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Local Cost for Global Benefit: The Case of Wind Turbines

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Local Cost for Global Benefit: The Case of Wind Turbines

Abstract

Given the rapid expansion of wind power capacities in Germany, this paper estimates the effects of wind turbines on house prices using real estate price data from Germany's leading online broker. Employing a hedonic price model whose specification is informed by machine learning techniques, our methodological approach provides insights into the sources of heterogeneity in treatment effects. We estimate an average treatment effect (ATE) of up to -7.1% for houses within a one-kilometer radius of a wind turbine, an effect that fades to zero at a distance of 8 to 9 km. Old houses and those in rural areas are affected the most, while home prices in urban areas are hardly affected. These results highlight that substantial local externalities are associated with wind power plants.

JEL Classification: IQ21, D12, R31

Keywords: Wind power; hedonic price model

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1 Manuel Frondel, RWI and RUB; Gerhard Kussel, RWI and RUB; Stephan Sommer, RWI; Colin Vance, RWI and Jacobs University, Bremen. *– This work has been supported by the Collaborative Research Center "Statistical Modeling of Nonlinear Dynamic Processes" (SFB 823) of the German Research Foundation (DFG), within Project A3, "Dynamic Technology Modeling". We also gratefully acknowledge financial support by the German Federal Ministry of Education and Research (BMBF) within Kopernikus Project ENavi (grant 3SFK4B0) and Project DIPOL (grant 01LA1809C).* *– All correspondence to: Gerhard Kussel, RWI, Hohenzollernstraße 1/3, 45128 Essen, Germany, e-mail: gerhard.kussel@rwi-essen.de*

1 Introduction

Germany is widely seen as a global leader in efforts to mitigate climate change, having implemented an extensive feed-in-tariff scheme for renewable energy technologies whose aim is to contribute to the reduction of greenhouse gas (GHG) emissions by 40% in 2020 relative to 1990. Wind power is among the most promising renewable energy technologies, as it has a high generation potential with comparatively low costs. Between 2000, when feed-in-tariffs were introduced under Germany's Renewable Energy Act, and 2017, the number of onshore wind turbines roughly tripled, increasing from 9,359 to 28,675. Over the same interval, electricity generation from wind power increased from 9.5 to 106.6 billion kilowatthours, corresponding to a share of 18.8% of Germany's net electricity generation in 2017 (Data source: WindGuard).

Notwithstanding a broad-based popular acceptance of wind power, companies planning new wind turbines frequently meet massive resistance of local communities owing to negative externalities. In addition to posing hazards for birds and bats, the turbines make noise and affect the aesthetic appeal of the landscape by adding movement in the form of rotation and shadow flickers, leaving a more industrialized and less tranquil impression. Ultimately, such impacts may bear negatively on house prices. Yet, while there is some international evidence on the effect of nearby wind turbines on real estate prices, empirical evidence for Germany is scant.

Various methods can be availed for valuing external environmental costs, including stated-preference surveys, as well as by investigating revealed preferences as expressed via real estate prices. We add to the latter strand of the literature by analyzing the impact of wind turbines on the price of single-family houses. Drawing on a data set of asking prices from more than 2.7 million houses in Germany posted between 2007 and 2015 on the site of Germany's leading online broker, our approach employs a hedonic pricing model whose specification is informed by the causal forest machine leaning algorithm (**?**) to identify sources of heterogeneity.

We find an average treatment effect (ATE) of up to -7.1% for houses within a one-kilometer radius of a wind turbine, an effect that fades to zero at a distance between 8 and 9 km. As suggested by the causal forest algorithm, additional specifications are estimated that allow for differential effects of the wind turbines by the house's location and age. We find that very old houses and houses in rural areas suffer price reductions of up to 23%, probably due to stronger preferences for a pristine landscape, while house prices in urban areas are not affected at all. Our results illustrate that while electricity generation via wind turbines may have global benefits, these are accompanied by substantial local externalities.

The subsequent section provides a brief review of the literature on the effect of wind turbines on real estate prices. Section 3 concisely summarizes our database, followed by the description of our methodology in Section 4. We present and discuss our results in Section 5. The last section closes with a summary and conclusions.

2 Findings from the Literature

Growing global energy demand and the increased awareness of anthropogenic climate change have led to an increase in wind power capacities worldwide. The rising number of wind turbines, however, draws increasing attention to their negative externalities. Wind turbines not only endanger animals in their natural environment, notably birds and bats (Arnett et al., 2008; Barclay et al., 2007; Smallwood, 2007), but also make noise, create flicker effects, and negatively impact the scenery. Numerous stated-preference surveys suggest that people have a positive attitude towards wind power in general, but, at the same time, are concerned about external effects and environmental costs (Krekel and Zerrahn, 2017; Brennan and Van Rensburg, 2016; Meyerhoff et al., 2010; Swofford and Slattery, 2010).

Such surveys, however, may be subject to measurement error, particularly when respondents do not wish to state their true preferences. An alternative approach is to make use of peoples' revealed preferences, which are less prone to biases from strategic responses. Real estate prices consist of peoples' revealed willingness to pay for numerous housing, locality and environmental characteristics, leading to a hedonic house price model (Lancaster, 1966; Rosen, 1974). Adding the proximity to a wind turbine as a feature, peoples' valuation of corresponding externalities can be identified.

Following this basic idea, the effect of nearby wind turbines on housing prices has been analyzed in diverse settings, yielding mixed results. Lang et al. (2014), for instance, examine the impact of wind turbines on real estate prices in the U.S. state of Rhode Island. Employing a modified difference-in-difference approach, these authors find no effect of nearby wind turbines on real estate prices across model specifications. Similar results are obtained by Hoen et al. (2015), who model more than 50,000 real estate transactions from all over the U.S. by means of ordinary least squares and difference-in-difference estimation. Analyzing data from densely populated communities in the U.S. state of Massachusetts, the results of Hoen and Atkinson-Palombo (2016) also suggest that wind turbines have no effect on real estate prices. In contrast, employing a repeat sales fixed-effects approach, Heintzelman and Tuttle (2012) find a significantly negative effect in two of three analyzed municipalities in New York State.

While the empirical literature for the U.S. predominantly detects no effect of wind turbines on real estate prices, the available studies for European regions point to significantly negative impacts. Using a difference-in-difference methodology, Dröes and Koster (2016), for example, analyze Dutch house price data and estimate a small negative effect of -1.4% for wind turbines within a 2 km distance. With a similar approach for England and Wales, Gibbons (2015) finds a price reduction of up to 6% on houses having a wind turbine within 2 km, fading to zero at a distance of 8 to 14 km. Employing various estimators that distinguish separate effects of noise and visual pollution, Jensen et al. (2014) obtain an effect of similar size for Denmark. These authors attribute a 3% price reduction to visual disamenities and 3 to 7% to noise pollution, which only affects houses in immediate proximity to a turbine.

To the best of our knowledge, the only available evidence for Germany is provided by Sunak and Madlener (2015) and Sunak and Madlener (2016), who analyze the effect of wind turbines on real estate asking prices in a small semi-urban region. Using augmented spatial econometric models, Sunak and Madlener (2016) find a strong effect of -9 to -14% for the most affected houses. Providing the first comprehensive analysis for Germany as a whole, we add to this strand of the literature by offering insights into the sources of treatment effect heterogeneity.

3 Data

Our primary data source is drawn from ImmobilienScout24, Germany's leading online real estate platform. This data includes asking prices and building characteristics for more than 7 million residential units posted between 2007 and 2015. The focus of our analysis is on house sales, as the effect of amenities is presumably a less important factor for rental units. For the same reason, we exclude multi-family houses, instead solely focusing on single-family houses.

A potential drawback of the data is that the recorded prices are asking prices, rather than transaction prices. This would be problematic if the difference between asking and transaction prices is correlated with real estate or locality characteristics. Several recent studies using the ImmobilienScout24 data argue, however, that this concern is unfounded. These include an assessment of the effect of nuclear power plant shut downs on surrounding real estate prices by Bauer et al. (2017) and the analysis of the effect of national borders on house prices by Micheli et al. (2019). Frondel et al. (2019), who investigate the effect of mandatory disclosure of energy information in sales advertisements on German house prices, likewise explore this issue. They compare data on asking prices from ImmobilienScout24 with municipal data on transaction prices from Germany's capital Berlin, finding that (1) the difference between the two price series is moderate, with transaction prices being about 7% lower than asking prices, and that (2) this difference remains approximately constant over time.

While our sample consists of houses that were offered between 2007 and 2015, for estimation purposes, we pruned the data along several dimensions, excluding houses with (i) unusual prices below €20,000 or above €2,000,000, (ii) a reported living space of either less than 40 m^2 or more than 800 m^2, (iii) either less than 1 or more than 20 rooms and, (iv) a lot size smaller than 20 m^2 or larger than 5,000 m^2. As a result, our final data set comprises 2,855,466 observations.

The summary statistics reported in Table 1 indicate that the average asking price of the sample properties is about €274,000, the mean size is 154 m^2, and the mean number of rooms is 5.4. With about 55%, detached houses represent the majority of the sample properties, with another 17% of the properties being semidetached. With respect to the temporal dimension, the offers are almost equally split across the period 2007-2015.

Table 1: Descriptive Statistics of Real Estate Offers

	Mean	Standard Deviation	Minimum	Maximum
Asking price in €	273,786.4	203,136.9	20,000	2,000,000
Year of construction	1979.5	36.9	1300	2016
Living space in m^2	153.7	60.4	40	800
Lot size in m^2	676.4	536.3	20	5,000
Number of rooms	5.4	1.8	1	20
Detached house	0.55	-	0	1
Semidetached house	0.17	-	0	1
Other house type	0.08	-	0	1
Terrace house	0.04	-	0	1
Mid-terrace house	0.06	-	0	1
End-terrace house	0.04	-	0	1
Bungalow	0.03	-	0	1
Villa	0.03	-	0	1
Offer year 2007	0.08	-	0	1
Offer year 2008	0.15	-	0	1
Offer year 2009	0.13	-	0	1
Offer year 2010	0.12	-	0	1
Offer year 2011	0.11	-	0	1
Offer year 2012	0.09	-	0	1
Offer year 2013	0.11	-	0	1
Offer year 2014	0.11	-	0	1
Offer year 2015	0.10	-	0	1
Number of Observations:			2,855,466	

Separated descriptives for the treatment and control group are reported in Table A.1 in the appendix

In addition to the information on real estate characteristics, the data contains the exact coordinates of each house. This feature allows us to merge it with other georeferenced data sources, such as the database RWI-GEO-GRID (Breidenbach and Eilers, 2018), which provides high-resolution socio-demographic data on the scale of a 1x1 km grid. We make use of information on purchasing power per capita, population density, the unemployment rate, the share of foreigners, the number of buildings and demographic structure of the grid.[1]

To complete the locality characteristics, we add the distance to the center of the next city with more than 100,000 inhabitants and dummy variables for all German municipalities. Table 2 demonstrates substantial heterogeneity in the socio-demographic characteristics of the neighborhood. For instance, the purchasing power per capita ranges between €5,900 and €139,000. Moreover, we observe a large diversity in the population density, spanning as low as 1 inhabitant per km^2 in very rural areas to almost 27,000 inhabitants in highly urbanized areas.

Table 2: Descriptive Statistics of Locality Characteristics in 1x1 km Grids

	Mean	Standard Deviation	Minimum	Maximum
Purchasing power per capita (in €)	21,464.8	4,104.9	5,916.7	139,391.0
Total inhabitants per km^2	1,837.5	1,707.4	1.0	26,947.0
Unemployment rate (in %)	5.97	3.94	0.01	39.98
Foreigners (in %)	6.66	5.74	0.01	100.00
Number of buildings	434.8	306.2	1.0	2830.0
Share of inhabitants aged 0-20	19.52	2.66	0.18	38.67
Share of inhabitants aged 20-35	16.20	2.95	0.40	47.50
Share of inhabitants aged 35-45	14.44	2.16	0.35	42.22
Share of inhabitants aged 45-55	16.46	1.87	0.54	40.80
Share of inhabitants aged 55-65	12.70	1.86	0.27	35.44
Share of inhabitants aged 65+	20.68	1.86	3.17	97.96
Distance to city center (in km)	24.52	20.27	0.03	146.18
Distance to next wind turbine (in km)	8.43	6.28	0.02	54.83
Number of Observations:		2,855,466		

Separated descriptives for the treatment and control group are reported in Table A.1 in the appendix

Finally, we obtained geo-referenced data on wind turbines in Germany from the Re-

[1]The data is gathered by the commercial data provider *Micromarketing-Systeme und Consult GmbH (microm)* and is aggregated from more than one billion individual data points from various sources. Raw data are collected from companies acting in data intensive environments such as Creditreform and CEG Consumer Reporting, as well as from official institutions such as the Federal Office for Motor Traffic, the Statistical Offices of the Federation and the Federal States, and the Federal Employment Agency. Since RWI-GEO-GRID is only available for the years 2005 and 2009-2015, we interpolate the information for the years 2006-2008.

newable Energy Installations Core Data of the Federal Network Agency (BNetzA) and several regional authorities. The central register provided by BNetzA was introduced in August 2014. Hence, all information on the wind turbines that were installed after this date is retrieved from BnetzA, while all prior information is collected from federal state authorities. Both data sets are compatible and commonly encompass the construction year and the exact position of all wind turbines in Germany, but we dropped 2,373 observations due to missing information on the construction year.

At the beginning of our study period, 13,574 wind turbines were installed in 2007, mostly in the northeast owing to better wind conditions(Figure 1). This is the most propitious area for wind turbines, as average wind speeds are significantly higher compared to other regions in Germany. By the end of 2015, after stronger incentives in the form of higher feed-in tariffs for electricity produced from wind power were introduced, 7,883 wind turbines were additionally installed, also in less windy areas, such as the southeast of Germany.

While the mean distance of sample houses to the next wind turbine is about 8.4 km (Table 2) and the median amounts to 6.6 km, Figure 2 illustrates a great deal of heterogeneity: 8.9% of the properties have a wind turbine within a 2 km distance, whereas 0.6% are located more than 30 km away from a wind turbine.

Figure 1: Position of Wind Turbines

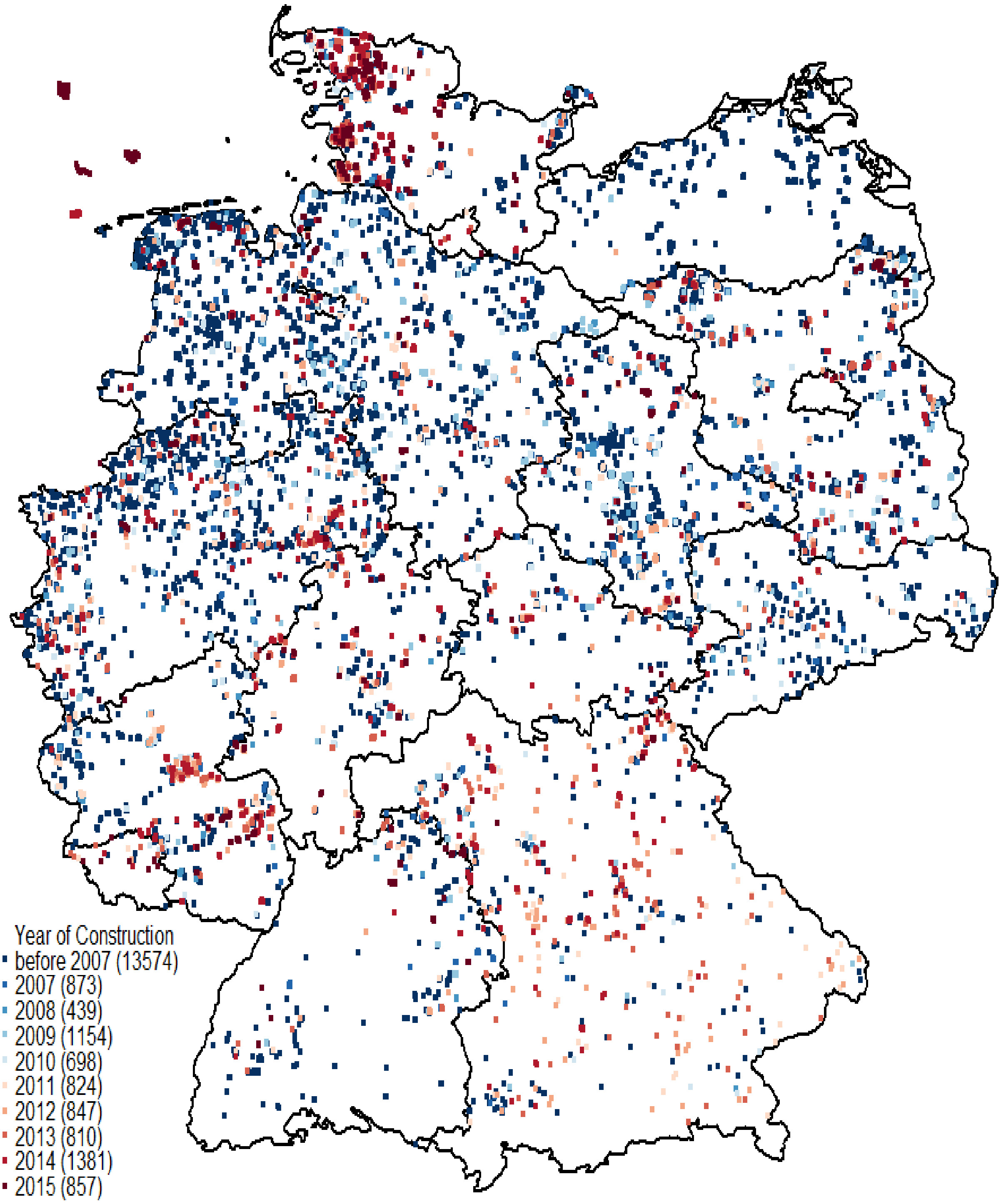
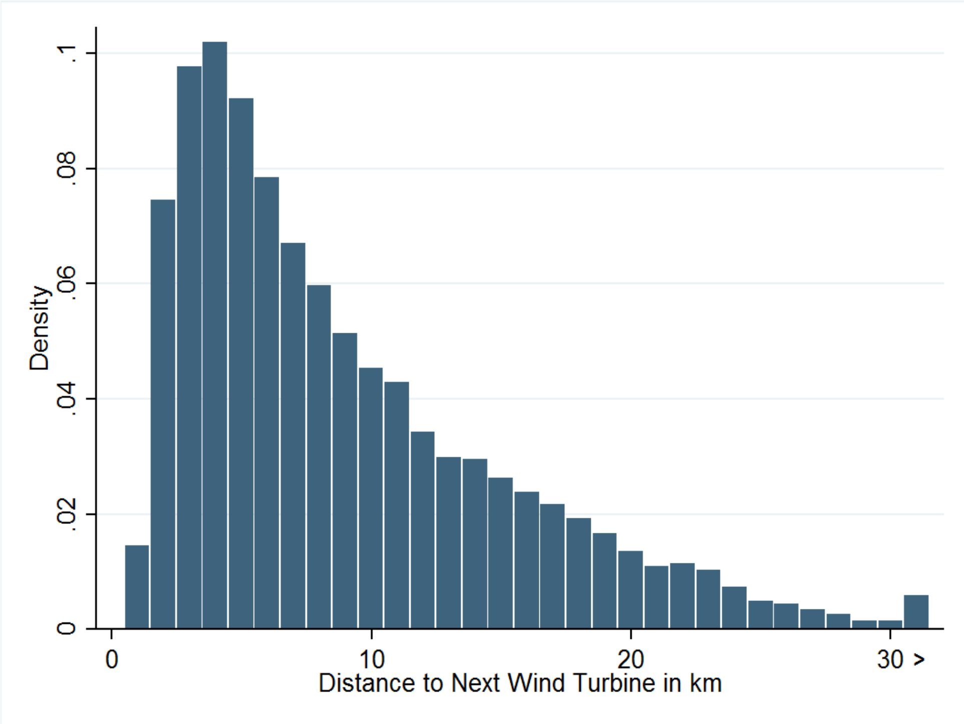


Figure 2: Distance to Wind Turbines



4 Methodology

To identify the impact of wind turbines on the prices of nearby houses, we estimate the following hedonic price model by Ordinary Least Squares (OLS):

$$\log(p_i) = distance_i^T \boldsymbol{\alpha} + \mathbf{x}_i^T \boldsymbol{\beta} + m_g + \tau_t + \varepsilon_i, \tag{1}$$

where $\log(p_i)$ is the natural logarithm of the asking price of house i and *distance* is a set of distance bands indicating whether the house is within the radius of 1, 2,...9 km distance to a wind turbine. $\mathbf{x}$ comprises house and locality characteristics, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are corresponding coefficient vectors, m_g and τ_t are fixed-effects for municipality g and time t, and ε_i is an error term that is independent and identically distributed. Our main focus is on coefficient vector $\boldsymbol{\alpha}$, which measures the average treatment effect for houses within 1, 2,...9 km distance to a wind turbine.

As we observe the asking price for a property either in presence (Y_{i1}) or in absence (Y_{i0}) of a wind turbine, but not in both states, we face the well-known evaluation problem (Holland 1986). Following the idea of Rubin's (1974) potential-outcome model:

$$Y_i = \begin{cases} Y_{i0} \; if \; W_i = 0 \\ Y_{i1} \; if \; W_i = 1, \end{cases} \tag{2}$$

where W is a binary indicator that equals unity when house i is in the range of a wind turbine and zero otherwise, the average treatment effect (ATE) is given by $ATE := E\left(Y(1)|W=1\right) - E\left(Y(0|W=0)\right)$. Accordingly, if the assignment of the treatment W were to be randomized, a situation that is implausible in observational studies, the causal effect of the treatment can easily be estimated by a simple comparison of mean outcomes. Yet, in our empirical example, it seems likely that wind turbines are more frequently placed in less wealthy neighborhoods, as land prices are lower and residents have less resources to oppose construction. At the same time, house prices in those areas are probably lower as well.

To identify the causal effect of the treatment, we need to assume unconfoundedness, i.e. that all determinants affecting the probability of the treatment (having a wind turbine nearby) and the outcome (house price) are captured by our covariates (X):

$$W_i \perp (Y_{i0}, Y_{i1})|X. \tag{3}$$

While this assumption is critical, it is not testable. Nevertheless, below we provide a supplementary analysis to increase the credibility of our estimates that is a based on a placebo-regression approach.

A final estimation issue concerns the possible existence of interaction terms that capture differential magnitudes in the effects of wind turbines. In this regard, it is conceivable that the effect of proximity to a wind turbine is dependent on other features of the house and of the surrounding landscape. It stands to reason, for example, that houses located in densely settled areas would be affected differently by wind turbines than those surrounded by pristine landscapes.

While theory can provide some guidance in identifying such sources of heterogeneity, the attempt to specify a complete set of interactions risks embarking on an iterative search for results that are, even if statistically significant, purely spurious (Assmann et al., 2000; Cook et al., 2004). Building on work by Athey and Imbens (2016), Wager and Athey (2018) develop a nonparametric machine learning algorithm to address this challenge. In essence, their approach draws on asymptotic normality theory to enable statistical inference using a forest-based method to generate predictions that are asymptotically unbiased. The method, which we implement using an R package provided by the authors, is akin to an adaptive nearest neighbor method, producing estimates of the conditional average treatment effect. We employ the method as an exploratory tool, using it to identify sources of heterogeneity in the estimation of treatment effects that we incorporate in the specification of Equation 1.

5 Empirical Results

Table 3 presents OLS estimates from a specification of hedonic price model 1 that excludes treatment heterogeneity, while Figure 3 allows visualization of the corresponding estimates of each distance band and its confidence interval. The figure illustrates that the average treatment effects are statistically and economically significant for houses that are within a distance of up to 8 km to a wind turbine. Unsurprisingly, the strongest effect is found for houses in the smallest radius of a one-kilometer distance, where the presence of turbines reduces house prices by 7.1% (= $100[exp(-0.0735)-1]$). In addition to impairing the scenery, wind turbines in such close proximity create audible noise and flicker effects. Although the treatment effects abate with distance, they remain statistically significant up to a radius between 7 to 8 kilometers, where noise should be irrelevant (Gibbons, 2015).

The coefficients on the remaining covariates are all statistically significant and exhibit the expected signs, albeit the effect sizes are small in many cases. Given the

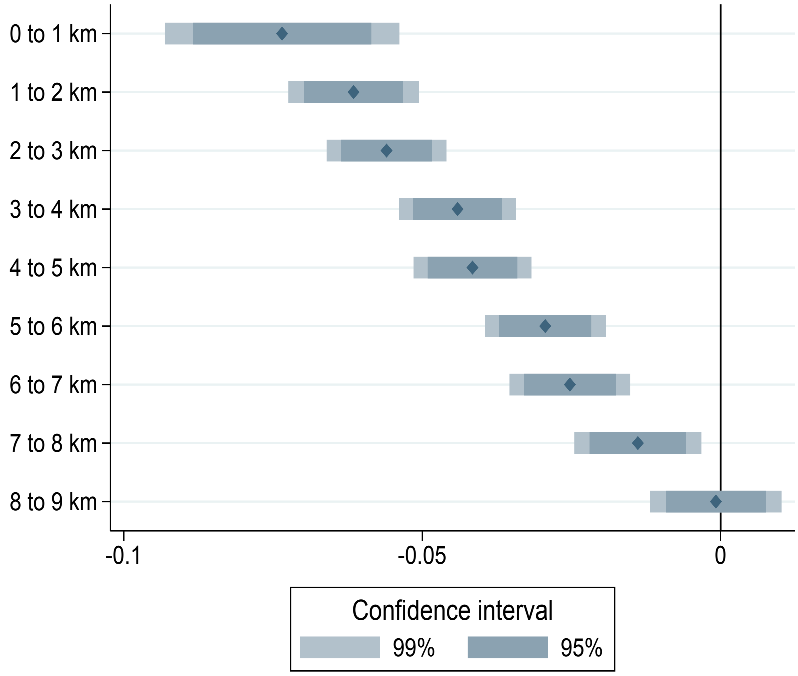
Table 3: OLS Regression Results of Equation 1

	Coefficients	Standard Errors
Wind turbine within		
1 km distance	-0.0735**	(0.00763)
1 to 2 km distance	-0.0615**	(0.00424)
2 to 3 km distance	-0.0560**	(0.00399)
3 to 4 km distance	-0.0441**	(0.00381)
4 to 5 km distance	-0.0416**	(0.00384)
5 to 6 km distance	-0.0294**	(0.00394)
6 to 7 km distance	-0.0253**	(0.00393)
7 to 8 km distance	-0.0139**	(0.00413)
8 to 9 km distance	-0.000786	(0.00427)
Housing characteristics:		
Year of construction	0.00453**	(0.0000479)
Living space (in m^2)	0.00410**	(0.0000298)
Lot size (in 100 m^2)	0.0122**	(0.00221)
Number of rooms	-0.0104**	(0.000801)
Detached house	0.0260**	(0.000993)
Semidetached house	-0.0601**	(0.000576)
Terrace house	-0.153**	(0.00114)
Mid-terrace house	-0.149**	(0.000895)
End-terrace house	-0.0838**	(0.00108)
Bungalow	0.0383**	(0.00114)
Villa	0.214**	(0.00122)
Locality characteristics:		
Purchasing power per capita (in 1,000 €)	0.0382**	(0.00106)
Total inhabitants (in 1,000)	0.031**	(0.00173)
Unemployment rate (in %)	-0.00452**	(0.0000849)
Foreigners (in %)	0.00407**	(0.000595)
Number of buildings	-0.00002*	(0.00000810)
Share of inhabitants aged 0-20	-0.0135**	(0.000905)
Share of inhabitants aged 20-35	0.00619**	(0.000594)
Share of inhabitants aged 35-45	0.00507**	(0.000981)
Share of inhabitants aged 45-55	-0.0148**	(0.000745)
Share of inhabitants aged 55-65	-0.0102**	(0.000824)
Distance to city center (in km)	-0.00420**	(0.000208)
Year dummies	Yes	
Municipality dummies	Yes	
Number of Observations:	2,855,466	
R^2	0.711	

Note: $**$ and $*$ indicate statistical significance at the 1% and 5% level,respectively; standard errors are clustered at the GEO-Grid level.

log-linear specification of the model, most of these estimates can be interpreted as the percentage change in the house price given a unit change in the explanatory variable. We see, for example, that each square meter increase in living space increases the house asking price by 0.4%, while each additional kilometer from the nearest city center decreases the price by about the same amount.

Figure 3: Effects of Wind Turbines on logged House Prices



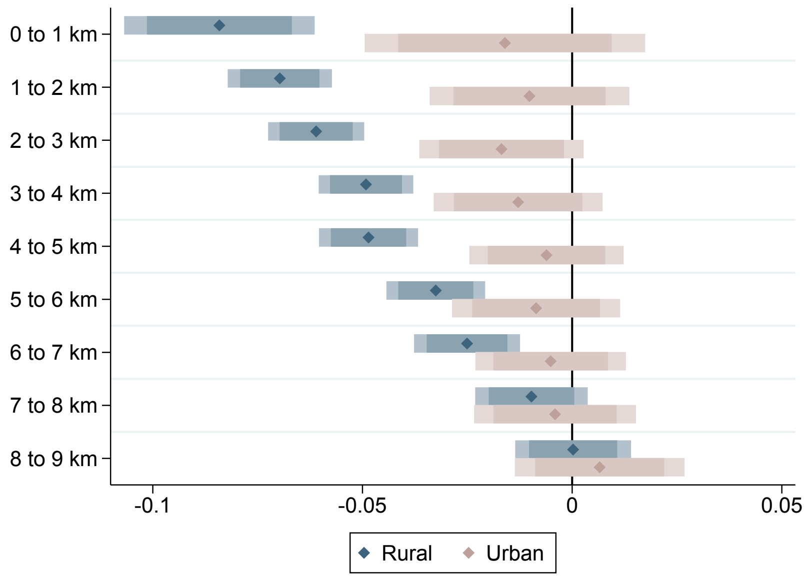
Note: Standard errors are clustered at the GEO-Grid level.

5.1 Heterogeneity in Treatment Effects

In principle, any of the control variables could be a source of heterogeneity in the treatment effects. To identify such sources, we plotted the results obtained from the causal forest algorithm applied to the covariates included in Equation 1. For this purpose, we collapsed the nine treatment dummies into a single dummy equaling unity if a wind turbine is within a distance of 8 kilometers of the home and zero otherwise. For the overwhelming majority of covariates, we find no significant mediating effect on the treatment dummy. Two exceptions are the distance to the next city center and the year of construction, both of which exacerbate the effect of proximity to a wind turbine. Specifically, as seen from Figures A4 and A5 in the appendix, there are rapid increases in the magnitude of the treatment effect for a distance to the next city center of more than 10 kilometers and construction years before 1950.

Based on these results, we construct an urban indicator that equals unity if the house offer is within a 10 km^2 radius around the next city center and zero otherwise, as well as an age indicator for houses that were built before 1950, and interact both indicators with the treatment dummies in Equation 1. Figure 4 illustrates the differences in the treatment effects between urban and rural areas. While there are substantial treatment effects in rural areas, the effect on prices of houses close to urban environments is considerably weaker and statistically insignificant at any conventional level.

Figure 4: Effects of Wind Turbines on logged House Prices in Rural and Urban Areas



Note: Standard errors are clustered at the GEO-Grid level. Coefficient estimates are reported in Table A.3 in the appendix.

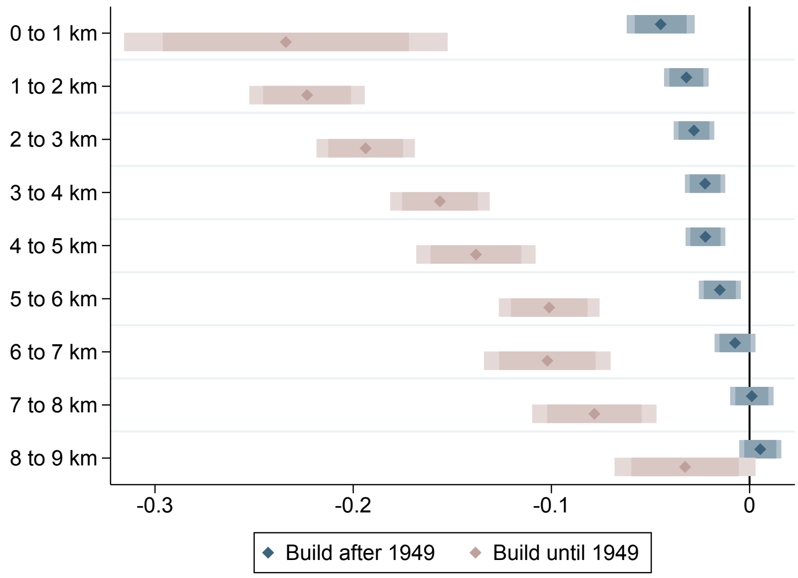
Contrasting with Dröes and Koster (2016), who find a stronger effect in urban environments, our finding seems intuitive given two potential explanations: First, to the extent that the urban landscape is already developed, the sight of a wind turbine might not change the overall impression of the landscape. Second, a more urban environment has a higher density of buildings that conceal the view of the wind turbine (Sunak and Madlener, 2015). This second explanation, however, does not apply to our data, as we control for the density of buildings. Hence, we conclude that the nativeness of the

[2] According to this definition 24,99% of the observations are located in urban areas. Results of robustness checks with alternative definitions (5 km, 9,19%; 20 km, 53,13%; and 50 km, 88,40%) are reported in the appendix (Figures A1 - A3).

landscape and the corresponding preferences of the residents seem to determine the effect size.

With respect to the age of buildings, Figure 5 shows a remarkable effect of up to -23% on the prices of houses built before 1950, whereas newer buildings are affected to a much lower extent. This effect may also be explained by preferences for a preindustrial impression of the building and the surrounding landscape.

Figure 5: Effects of a Wind Turbine on logged House Prices of Old Buildings and Newer Houses

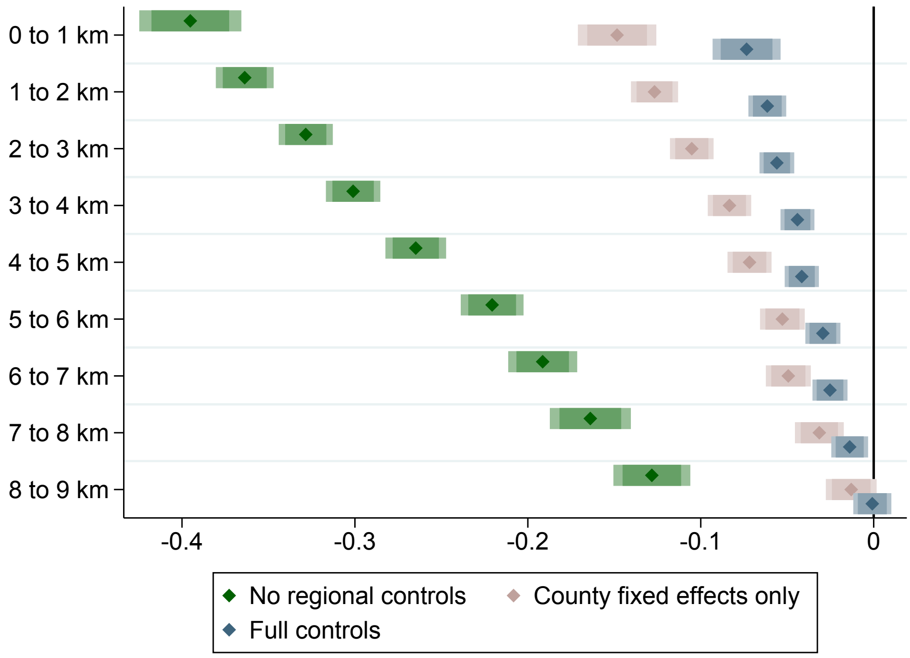


Note: Standard errors are clustered at the GEO-Grid level. Coefficient estimates are reported in Table A.4 in the appendix.

5.2 Unconfoundedness

As discussed in Section 4, our results can only be interpreted as causal if the unconfoundedness assumption holds, i.e. all determinants affecting the probability of the treatment – a nearby wind turbine – and the outcome – the house price – are captured by our covariates. To probe this assumption, we begin by estimating Equation 1 using three sets of control variables: First, Equation 1 is estimated without any local controls using only house characteristics and time fixed effects; second, we additionally include community fixed effects and, third, Equation 1 is estimated using all control variables. Figure 6 illustrates that the treatment effects shrink significantly when county fixed effects and the detailed RWI-GEO-GRID information are added. (Coefficient estimates are reported in Table A.2 in the appendix.) Apparently, when controls for locality characteristics are excluded in the estimation, the effects of wind turbines are overestimated, reflecting the fact that windmills tend to be installed in low-price regions.

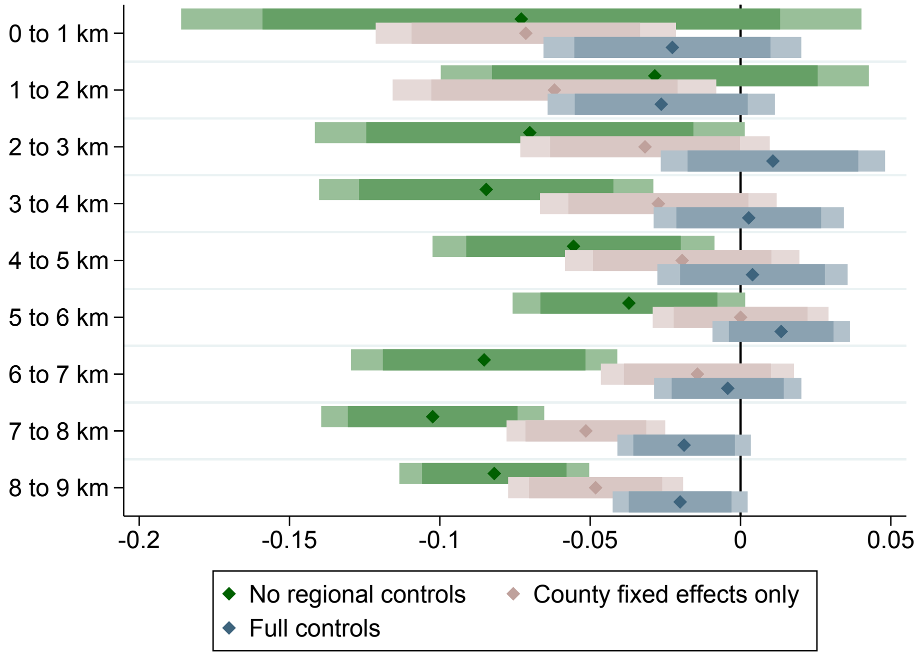
Figure 6: Effects of Wind Turbines on logged House Prices



Note: Standard errors are clustered at the GEO-Grid level.

To provide further evidence that the unconfoundedness assumption holds, we ran placebo regressions. In a first step, we drop from the estimation sample all "treated" houses, that is, those which had a wind turbine within 9 km when they were offered, instead focusing on houses where there was no turbine when they were offered, but where a turbine was constructed in the following years. We then estimate Equation 1 replacing the treatment dummies *distance* with placebo treatment dummies indicating the future presence of a wind turbine in a distance up to 9 km. To exclude anticipation effects, in addition to dropping actually treated houses, we also drop observations

Figure 7: Placebo Regression Results: Effects of Future Wind Turbines on logged House Prices



Note: Standard errors are clustered at the GEO-Grid level.

where a wind turbine was constructed within the two years following a house sale offer. Hence, there should be no treatment effect and the estimated coefficients can be interpreted as the selection effect of wind turbines in specific localities.

The resulting treatment effects are presented in Figure 7, while the OLS coefficient estimates are reported in Table A.5 in the appendix. The negative and significant coefficients on the treatment dummies in the "no local control setting" support the presumption that the placement of wind turbines is negatively correlated with surrounding house prices. However, the effects do not follow the decreasing pattern observed in our baseline estimation.

This finding still persists after adding municipality fixed effects, although the magnitude of many of the coefficients is lower. But, after including controls for our detailed small scale neighborhood characteristics from RWI-GEO-GRID, all coefficient estimates are not statistically different from zero. Also, there is no discernible pattern to the coefficient estimates, as they straddle both sides of zero. Hence, we are confident that we have captured all the factors influencing the placement of wind turbines that are associated with house prices via our detailed small-scale neighborhood data.

6 Summary and Conclusions

Wind power is among the most promising renewable energy technologies, as its high electricity generation potential is accompanied by relatively low generation cost. Yet, there is also increasing international evidence that wind turbines cause persistent negative externalities: In addition to posing hazards for birds and bats, turbines make noise and affect the aesthetic appeal of the landscape. Ultimately, these impacts may bear negatively on house prices. Despite the rapid expansion of wind power capacities in recent decades, though, empirical evidence on the effect of nearby wind turbines on real estate prices is scant for Germany.

Using asking prices from Germany's leading online broker and a hedonic pricing model coupled with a machine leaning algorithm, we fill this gap by analyzing the effect of wind turbines on prices of surrounding single-family houses. Accounting for detailed property and locality characteristics, we estimate an average treatment effect of up to 7.1% for houses within 1 km distance to the next wind turbine, an effect that fades out at a distance between 8 and 9 km.

Identifying the most important interaction terms by a machine leaning algorithm, we add to the literature by estimating heterogeneous treatment effects: While the prices of houses close to urban environments are not affected by nearby windmills, houses in rural areas suffer from remarkable devaluation. This effect is even more pronounced for old buildings built prior to 1949, whose asking prices decrease by up to 23%.

Our findings can be explained by differences in the appearance of the landscape and preferences of the local population. While the urban population is accustomed to living in an industrialized and dynamic environment, inhabitants of rural areas may lose the impression of pristine nature and tranquility when noise, rotation, and shadow flickers appear. Altogether, our results illustrate that while electricity generation via wind turbines may have global benefits, these are accompanied by substantial local externalities and environmental costs, primarily borne by rural communities close to wind turbines.

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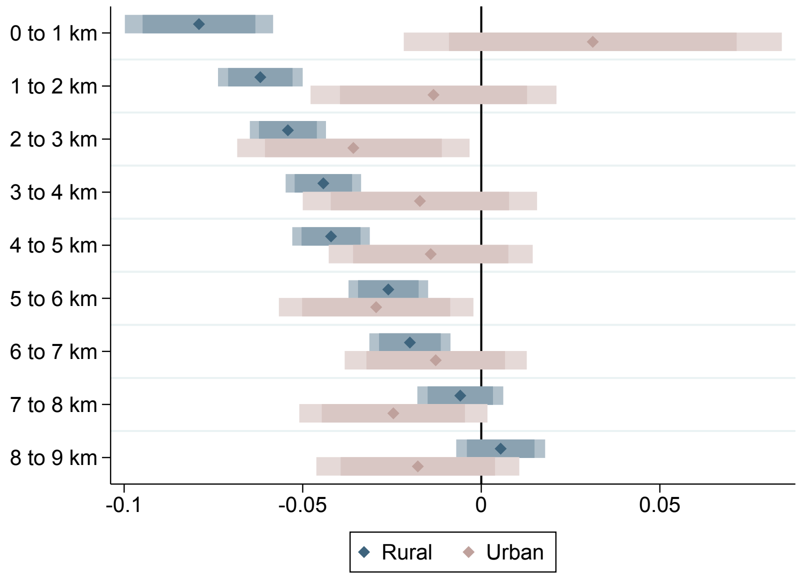
Appendix

Table A.1: Descriptive Statistics of the Treatment and Control Group

	Treatment Group		Control Group	
	Mean	Standard Deviation	Mean	Standard Deviation
Housing characteristics:				
Asking price in €	241,025.21	164,986.92	331,201.15	246,372.81
Year of construction	1979.24	37.19	1980.00	36.44
Living space in m^2	151.30	57.97	157.87	64.32
Lot size in m^2	704.85	557.34	626.62	493.40
Number of rooms	5.38	1.76	5.54	1.79
Detached house	0.60	-	0.54	-
Semidetached house	0.16	-	0.19	-
Other house type	0.06	-	0.07	-
Terrace house	0.03	-	0.04	-
Mid-terrace house	0.06	-	0.06	-
End-terrace house	0.03	-	0.04	-
Bungalow	0.03	-	0.02	-
Villa	0.03	-	0.04	-
Locality characteristics:				
Purchasing power per capita (in €)	20,808.36	3,588.27	22,615.24	4,662.33
Total inhabitants per km^2	1,684.74	1,588.06	2,105.22	1,868.65
Unemployment rate (in %)	6.39	3.96	5.23	3.78
Foreigners (in %)	6.02	5.43	7.79	6.08
Number of buildings	415.89	302.62	468.01	309.49
Share of inhabitants aged 0-20	19.61	2.72	19.37	2.57
Share of inhabitants aged 20-35	16.08	2.93	16.42	2.98
Share of inhabitants aged 35-45	14.29	2.12	14.71	2.20
Share of inhabitants aged 45-55	16.62	1.89	16.19	1.80
Share of inhabitants aged 55-65	12.76	1.88	12.59	1.84
Share of inhabitants aged 65+	20.64	1.86	20.72	1.87
Distance to city center (in km)	25.12	19.55	23.90	21.71
Number of Observations:	1,037,399		1,818,067	

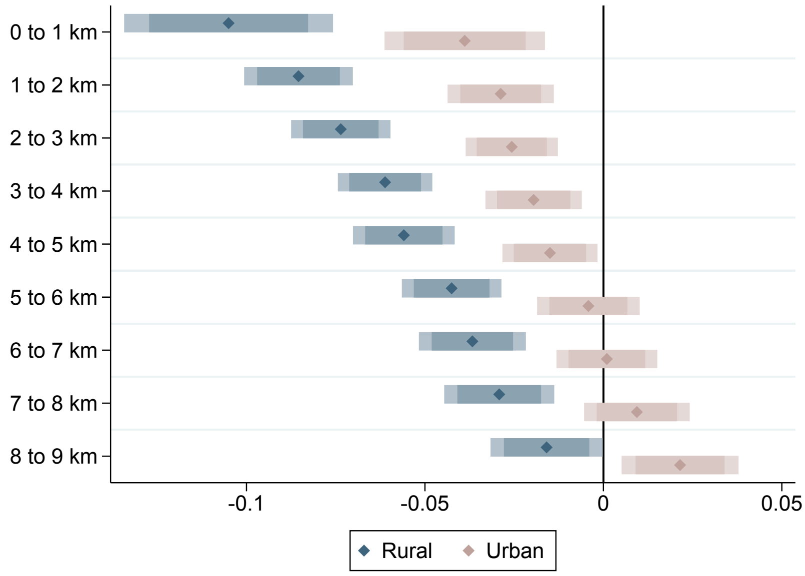
Note: Treatment group includes all houses with a wind turbine in 9 km, control group those further away than 9 km from the next turbine.

Figure A1: Effects of a Wind Turbine on logged House Prices of Rural and Urban Houses (5km Radius)



Note: Standard errors are clustered at the GEO-Grid level.

Figure A2: Effects of a Wind Turbine on logged House Prices of Rural and Urban Houses (20km Radius)



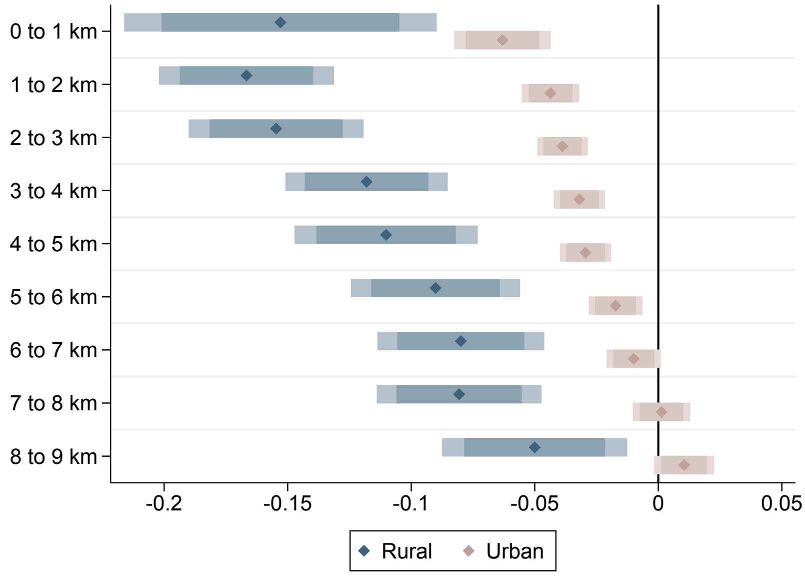
Note: Standard errors are clustered at the GEO-Grid level.

Table A.2: OLS Estimation Results of Equation 1 with Various Sets of Control Variables

	No Regional Controls		Local Fixed Effects Only		Full Controls	
	Coefficients	Standard Errors	Coefficients	Standard Errors	Coefficients	Standard Errors
Wind turbine within						
1 km distance	-0.395**	(0.0115)	-0.148**	(0.00881)	-0.0735**	(0.00763)
1 to 2 km distance	-0.364**	(0.00649)	-0.127**	(0.00529)	-0.0615**	(0.00424)
2 to 3 km distance	-0.328**	(0.00608)	-0.105**	(0.00490)	-0.0560**	(0.00390)
3 to 4 km distance	-0.301**	(0.00611)	-0.0834**	(0.00487)	-0.0441**	(0.00381)
4 to 5 km distance	-0.265**	(0.00682)	-0.0718**	(0.00494)	-0.0416**	(0.00384)
5 to 6 km distance	-0.221**	(0.00705)	-0.0528**	(0.00502)	-0.0294**	(0.00394)
6 to 7 km distance	-0.191**	(0.00775)	-0.0494**	(0.00505)	-0.0253**	(0.00393)
7 to 8 km distance	-0.164**	(0.00910)	-0.0314**	(0.00548)	-0.0139**	(0.00413)
8 to 9 km distance	-0.128**	(0.00863)	-0.0130	(0.00570)	-0.000786	(0.00427)
Housing characteristics	Yes		Yes		Yes	
Locality characteristics	No		No		Yes	
Year dummies	Yes		Yes		Yes	
Municipality dummies	No		Yes		Yes	
Number of Observations:	2,855,466		2,855,466		2,855,466	
R^2	0.435		0.667		0.711	

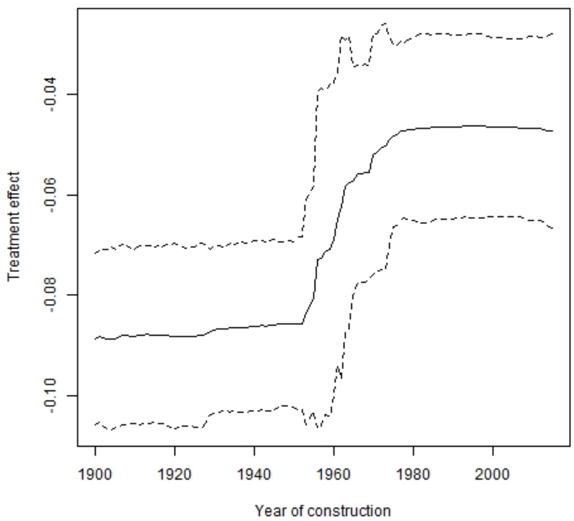
Note: $**$ and $*$ indicate statistical significance at the 1% and 5% level, respectively; standard errors are clustered at the GEO-Grid level.

Figure A3: Effects of a Wind Turbine on logged House Prices of Rural and Urban Houses (50km Radius)



Note: Standard errors are clustered at the GEO-Grid level.

Figure A4: Conditional Average Treatment Effect (CATE) of a Wind Turbine Conditional on the Year of Construction



Note: Confidence Intervals are given by dashed lines.

Table A.3: OLS Regression Results of Equation 1 with Rural/Urban Interaction

	Coefficients	Standard Errors
Wind turbine within		
1 km distance	-0.0841**	(0.00882)
1 to 2 km distance	-0.0697**	(0.00482)
2 to 3 km distance	-0.0610**	(0.00445)
3 to 4 km distance	-0.0492**	(0.00438)
4 to 5 km distance	-0.0486**	(0.00459)
5 to 6 km distance	-0.0325**	(0.00457)
6 to 7 km distance	-0.0251**	(0.00491)
7 to 8 km distance	-0.00971	(0.00521)
8 to 9 km distance	0.000229	(0.00536)
Interaction		
1 km distance * urban	0.0681**	(0.0153)
1 to 2 km distance * urban	0.0595**	(0.00997)
2 to 3 km distance * urban	0.0442**	(0.00845)
3 to 4 km distance * urban	0.0363**	(0.00866)
4 to 5 km distance * urban	0.0424**	(0.00817)
5 to 6 km distance * urban	0.0239**	(0.00881)
6 to 7 km distance * urban	0.0199*	(0.00834)
7 to 8 km distance * urban	0.00563	(0.00905)
8 to 9 km distance * urban	0.00634	(0.00935)
Housing characteristics	Yes	
Locality characteristics	Yes	
Year dummies	Yes	
Municipality dummies	Yes	
Number of Observations:	2,855,466	
R^2	0.687	

Note: $**$ and $*$ indicate statistical significance at the 1% and 5% level,respectively; standard errors are clustered at the GEO-Grid level.

Table A.4: OLS Regression Results of Equation 1 with Old/New Interaction

	Coefficients	Standard Errors
Wind turbine within		
1 km distance	-0.0449**	(0.00666)
1 to 2 km distance	-0.0319**	(0.00437)
2 to 3 km distance	-0.0281**	(0.00398)
3 to 4 km distance	-0.0225**	(0.00395)
4 to 5 km distance	-0.0223**	(0.00389)
5 to 6 km distance	-0.0150**	(0.00412)
6 to 7 km distance	-0.00735	(0.00400)
7 to 8 km distance	-0.00113	(0.00425)
8 to 9 km distance	0.00538	(0.00413)
Interaction		
1 km distance * build until 1949	-0.189**	(0.0314)
1 to 2 km distance * build until 1949	-0.191**	(0.0112)
2 to 3 km distance * build until 1949	-0.166**	(0.00949)
3 to 4 km distance * build until 1949	-0.134**	(0.00966)
4 to 5 km distance * build until 1949	-0.116**	(0.0116)
5 to 6 km distance * build until 1949	-0.0861**	(0.00987)
6 to 7 km distance * build until 1949	-0.0947**	(0.0125)
7 to 8 km distance * build until 1949	-0.0794**	(0.0121)
8 to 9 km distance * build until 1949	-0.0380**	(0..0134)
Housing characteristics	Yes	
Locality characteristics	Yes	
Year dummies	Yes	
Municipality dummies	Yes	
Number of Observations:	2,855,466	
R^2	0.689	

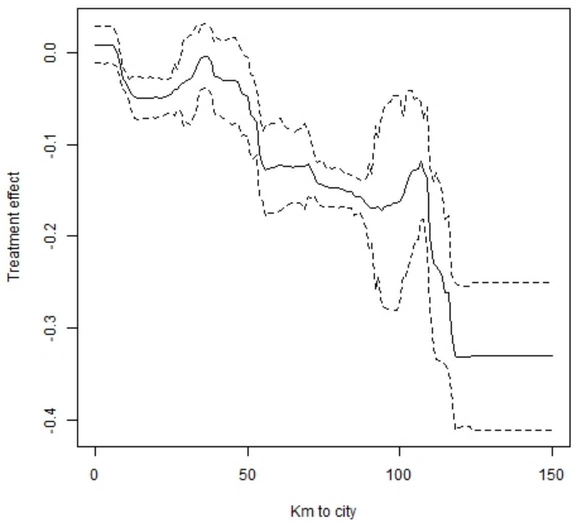
Note: $**$ and $*$ indicate statistical significance at the 1% and 5% level,respectively; standard errors are clustered at the GEO-Grid level.

Table A.5: OLS Estimation Results of Equation 1 with Placebo Treatment and Various Sets of Control Variables

	No Regional Controls		Local Fixed Effects Only		Full Controls	
	Coefficients	Standard Errors	Coefficients	Standard Errors	Coefficients	Standard Errors
No Wind turbine within						
1 km distance	-0.0729	(-1.66)	-0.0714**	(-3.68)	-0.0227	(-1.36)
1 to 2 km distance	-0.0285	(-1.03)	-0.0619**	(-2.96)	-0.0264	(-1.80)
2 to 3 km distance	-0.0701*	(-2.52)	-0.0318*	(-1.97)	0.0108	(0.74)
3 to 4 km distance	-0.0846**	(-3.92)	-0.0273	(-1.79)	0.00274	(0.22)
4 to 5 km distance	-0.0555**	(-3.05)	-0.0194	(-1.28)	0.00399	(0.32)
5 to 6 km distance	-0.0371*	(-2.47)	0.0000343	(0.00)	0.0135	(1.52)
6 to 7 km distance	-0.0853**	(-4.96)	-0.0143	(-1.15)	-0.00425	(-0.45)
7 to 8 km distance	-0.102**	(-7.11)	-0.0514**	(-5.02)	-0.0188*	(-2.18)
8 to 9 km distance	-0.0819**	(-6.68)	-0.0482**	(-4.27)	-0.0201*	(-2.30)
Housing characteristics	Yes		Yes		Yes	
Locality characteristics	No		No		Yes	
Year dummies	Yes		Yes		Yes	
Municipality dummies	No		Yes		Yes	
Number of Observations:	986,862		986,862		986,862	
R^2	0.400		0.686		0.733	

Note: ** and * indicate statistical significance at the 1% and 5% level, respectively; standard errors clustered on GEO-Grid level.

Figure A5: Conditional Average Treatment Effect (CATE) of a Wind Turbine Conditional on the Distance to the Next City



Note: Confidence Intervals are given by dashed lines.