Wind Turbines, Solar Farms, and House Prices

APPENDIX*

Martijn I. Dröes† Hans R.A. Koster‡

Abstract — This paper examines the effect of wind turbines and solar farms on house prices. Using detailed data from the Netherlands between 1985-2019, the results show that tall wind turbines have considerably stronger effects on house prices, as compared to small turbines. For example, a tall turbine (>150m) decreases house prices within 2km by 5.4%, while a small turbine (<50m) has an effect of maximally 2% and the effect dissipates after 1km. Further results indicate that solar farms lead to a decrease in house prices within 1km of about 2.6%. By comparing the overall impact on house prices, we show that the external effects of solar farms per unit of energy output are comparable to those of wind turbines. Thus, building solar farms instead of wind turbines does not seem to be a way to avoid the external effects of renewable energy production.

Keywords — wind turbines, solar farms, house prices.

JEL codes — R31, Q42, Q15, L95.

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†Corresponding author. Amsterdam Business School, Faculty of Economics and Business, University of Amsterdam, Plantage Muidergracht 12, 1018 TV Amsterdam, e-mail: m.i.droes@uva.nl. Martijn is also affiliated to the Amsterdam School of Real Estate (ASRE) and the Tinbergen Institute.

‡Department of Spatial Economics, Vrije Universiteit Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, email: h.koster@vu.nl. Hans is also research fellow at the National Research University, Higher School of Economics in St. Petersburg and the Tinbergen Institute, the Netherlands.

Appendix

A.1 Literature review: wind turbines, solar farms and house prices

A.1.1 Wind turbines and housing values

Major interventions in the landscape almost always lead to changes in house prices. This is because households' preferences capitalize into house prices.[1] This price difference is typically examined by controlling for differences in hedonic characteristics (*i.e.* house and location attributes). In the literature that uses hedonic pricing methods, there are already a host of studies looking at the effects of wind turbines on housing prices. We discuss here the ones that are most relevant for our study. Many studies focus on just a few wind turbines in a small geographical area. For example, Sims et al. (2008) and Carter (2011) investigate the effect of a single wind farm on house prices in the United Kingdom and the United States respectively, while Castleberry & Greene (2018) focus on Western Oklahoma. Hoen et al. (2010) investigate the effect on house prices of 24 wind farms in 9 states in the U.S. A study by Lang et al. (2014) looks at different individual wind turbines on Rhode Island. Vyn & McCullough (2014) look at the influence of a wind farm in Ontario on house prices and Hoen & Atkinson-Palombo (2016) focus on wind turbines in Massachusetts. For the Netherlands, a study by Van Marwijk et al. (2013) looks at four research locations. None of these studies find a statistically significant effect of wind turbines on house prices.

However, it would be incorrect to conclude that there is no effect of wind turbines on house prices, as the results are often too imprecise to draw strong conclusions. For example, Lang et al. (2014) find a point estimate of -2.4% within 2.5km. However, they focus on just 10 turbines in Rhode Island. The estimated effects are therefore imprecise. Similarly, Vyn & McCullough (2014) use data of one wind farm in Canada and also find no statistically significant effects, although in a few cases the point estimates are negative.

Ladenburg & Dubgaard (2007) do find evidence that households in Denmark are willing to pay to avoid living near an offshore wind farm. Studies by Sunak & Madlener (2016) and Skenteris et al. (2019) find potentially large effects of visibility in Germany and Greece, respectively. The

[1] Let us consider a simple example: imagine a potential buyer comparing two nearly identical homes; one is near a wind turbine, while the other is far away from a turbine. The difference in house price between these two homes then measures the willingness to pay to *not* live near a turbine. The willingness to pay (WTP) is the maximum amount of money a consumer is willing to pay for a particular characteristic of a property he or she consumes.

decrease in property values in these studies range from 9-14%. However, we again caution that Sunak & Madlener (2016) and Skenteris et al. (2019) only consider a few wind farms. Jensen et al.'s (2014) analysis relies on 22 sites in Denmark. They find significant reductions in property values. More specifically, the results point towards a 3% reduction due to visual pollution and an additional 3-7% reduction due to noise pollution.[2] Vyn (2018) argues that one reason for the different effect sizes may be that there are large spatial differences in the local support for wind turbines. Using Canadian data, he finds, for example, that municipalities where there is a lot of local resistance there is a decrease in housing values, while that is not the case for municipalities where there is little or no resistance. However, Vyn (2018) does not include location fixed effects, which correct for unobserved characteristics of locations. Because wind turbines are often built in areas where prices are lower, the results could be partly explained by this.[3]

Hence, while there have been quite a few papers measuring the effects of wind turbines on housing prices, the results are quite ambiguous, ranging from 0 to 20%. A possible explanation is that many of these studies rely on relatively small datasets covering a handful of wind turbines and/or wind farms. We particularly aim to improve on this including all (2,400) turbines in the Netherlands in our analysis. Moreover, most studies rely on a standard differences-in-differences strategy. The most important assumption underpinning this research design is that there are parallel trends between treated and control areas. As wind turbines are particularly built in sparsely populated areas outside of large cities, this assumption is debatable.

We think the study by Gibbons (2015) is a rather convincing study that employs a plausible research design and relies on a very large dataset (as it uses information on all residential transactions and wind turbines in England and Wales). Gibbons (2015) finds that home prices are 5-6% lower within 2km of a *visible* wind farm. His study compares changes in house prices at locations where wind farms are visible with otherwise similar locations, but where wind farms are not visible. A concern with Gibbons's study is that it does not use precise information on the exact location of wind turbines in England and Wales; only on the location of the centroid

[2]Another class of studies uses stated choice experiments to identify external effects. Meyerhoff et al. (2010), for example, shows that negative landscape externalities would arise from expanding wind power in Germany. Lutzeyer et al. (2018) finds that rental prices of vacation homes decrease by 5% for offshore wind farms.

[3]A recent Dutch policy report by Daams & Sijtsma (2019) analyzes the changes in prices for locations that have a view of turbines *that still have to be built* in Groningen and Drenthe. The report seems to suggest that there are major decreases in property value of about 10% within 2.5km (or even higher in some measurements), but these results are questionable because only a few wind farms are considered and, as mentioned, these still need to be built.

of a wind farm. This implies a measurement error in the distance to the nearest wind turbine because wind farms can be quite large. Our study is somewhat different from Gibbons (2015), as we look at many wind turbines at many different locations, some of them being part of a wind farm, some of them standing alone. Moreover, we explicitly focus on differences in wind turbine height, which are expected to have different effects on house prices.

In a related study, Dröes & Koster (2016) rely on all turbines and about 70% of housing transactions in the Netherlands between 1985 and 2011. Using a difference-in-differences strategy combined with local control groups (defined as transactions located between 2 and 3km of a wind turbine), they show that house prices decreased 1.4-2.3% within 2km of a wind turbine. They also provide some suggestive evidence that wind turbine height may matter, but their results did not measure the impact radius of tall turbines. Moreover, their results on turbine height are also quite imprecise because few tall turbines existed before 2012. A recent paper by Eichholtz et al. (2018) confirms the overall price decline due to wind turbine construction in the Netherlands.[4]

Another study by Jensen et al. (2018) focuses on Denmark. They find negative price effects between 3-6% for homes within 3km of an installed turbine. However, their results are not conditional on spatial fixed effects and, as such, do not control for time-invariant unobserved heterogeneity. This implies that Jensen et al.'s (2018) estimates are most likely overestimates, as Dröes & Koster (2016) show that not including detailed location fixed effects leads to an effect that is considerably higher than when one controls for location fixed effects.

A.1.2 Solar farms and housing values

The above-mentioned review indicates that a large number of studies have been undertaken studying the effects of wind turbines on house prices. It is therefore surprising that there are hardly any studies measuring the effects of solar farms on house prices, even though concerns have been expressed that solar farms may have an impact on property values as well (Jones et al. 2014).

There do exist two studies. The first is by Maddison et al. (2019) on the influence of solar farms on property values using English data. Their preliminary findings seem to point towards a

[4]Interestingly, they find that gas plants also have a negative effect on house prices and biomass plants have a positive effect.

negative price effect of -4 to -8%. Al-Hamoodah et al. (2018) show that a majority of survey respondents expect no impact of solar farms, while some estimated a negative impact associated with close distances between the home and the facility, in particular for larger solar farms. Finally, a study by Von Möllendorf & Welsch (2017) does not look at the effects of solar farms on house prices, but at data on subjective well-being. They find no effects of solar farms on well-being.

A.2 Additional descriptive statistics wind turbines and solar farms

In Table A1 the house price data is reported for the treatment areas of wind turbines (<2km) and solar farms (<1km) and the rest of the Netherlands. It is clear that close to wind turbines house prices are considerably lower (≈€8,000). In line with this, houses are also smaller. Regarding house types, there are relatively many terraced, semi-detached, and detached properties, located nearby wind turbines. The reason is that turbines are typically not built close to dense areas with higher shares of apartments. The state of maintenance for both samples is similar. The same applies to the presence of central heating.

House prices near solar farms (<1km) are considerably lower (≈€23,000). This might reflect that for solar farms a lot of space is necessary such that there are built mostly in rural areas in which house prices are low. This is also reflected in that houses are larger and more often have gardens. As with properties nearby wind turbines, there are relatively few apartments near solar farms.

Solar farms and wind turbines seem to be built in areas with similar characteristics. Turbines and solar farms typically can be found in more rural areas, although in the Netherlands 'rural' areas are still typically quite densely populated (*i.e.* see Appendix A.4). Wind turbines are built more closely to coastlines though, while we do not observe this for solar farms.

Because of clear spatial differences in terms of property characteristics it is important to use a difference-in-differences design with local control groups or to focus on treatment areas only; as well as control for housing characteristics in the regressions.

TABLE A1 – ADDITIONAL DESCRIPTIVES: WIND TURBINES AND SOLAR FARMS

	Wind turbines				*Solar farms*			
	<2km		*≥2km*		*<1km*		*≥1km*	
	mean	sd	mean	sd	mean	sd	mean	sd
Transaction price	206,654	114,489	214,882	122,333	226,024	100,052	249,790	124,444
Size in m^2	117.4	35.88	118.0	37.88	123.7	33.58	116.7	37.73
Number of rooms	4.425	1.253	4.380	1.348	4.741	1.227	4.450	1.399
Terraced property	0.362	0.480	0.313	0.464	0.354	0.478	0.312	0.463
Semi-detached property	0.287	0.452	0.280	0.449	0.361	0.480	0.276	0.447
Detached property	0.141	0.348	0.127	0.333	0.184	0.388	0.121	0.326
Property has garage	0.313	0.464	0.333	0.471	0.411	0.492	0.313	0.464
Property has garden	0.972	0.166	0.976	0.152	0.952	0.215	0.970	0.170
Maintenance state is good	0.865	0.342	0.866	0.341	0.870	0.336	0.867	0.340
Property has central heating	0.882	0.322	0.891	0.311	0.892	0.311	0.881	0.324
Property is (part of) listed building	0.00534	0.0729	0.00626	0.0789	0.00316	0.0561	0.00639	0.0797
Construction year 1945-1959	0.0639	0.245	0.0724	0.259	0.0651	0.247	0.0704	0.256
Construction year 1960-1970	0.136	0.343	0.151	0.358	0.102	0.302	0.133	0.340
Construction year 1971-1980	0.150	0.357	0.170	0.376	0.151	0.358	0.139	0.346
Construction year 1981-1990	0.140	0.347	0.138	0.344	0.147	0.354	0.113	0.317
Construction year 1991-2000	0.134	0.340	0.126	0.331	0.183	0.387	0.119	0.324
Construction year > 2000	0.133	0.339	0.106	0.308	0.200	0.400	0.203	0.402

Notes: This table shows the descriptive statistics of the house price dataset within (and outside) the treatment area for wind turbines (2km) and solar panels (1km). The data covers 1985-(mid)2019. The solar farm sample is as of 2009. The number of observations for each category is 290,002, 3,099,778, 12,650, and 1,458,158, respectively.

A.3 Robustness checks

In Table A2 we show a 'classical' difference-in-differences (DID) model based on the specification estimated in column (3), Table 3. However, we allow for non-parallel trends. We show that this yields identical point estimates as the preferred specification for wind turbines (*i.e.* column (4)). Only the standard errors are (marginally) smaller as they are (artificially) lowered by adding the control group transactions.

In this Appendix Section, we further aim to show the robustness of the estimated average impact of turbines. Table A3 contains several robustness checks based on our preferred specification where we only use temporal variation in the placement of turbines (reported in Table 3, column (4)).

First, in the previous specification, we only include a limited amount of housing and location characteristics. Moreover, one may be concerned that postcode fixed effects are larger in rural areas so that we do not only identify the effects based on temporal variation in the placement of turbines. Instead, in column (1), we show the results of a repeat sales model, in which we control for all time-invariant housing and location characteristics. In particular, we difference out these characteristics by taking the difference in house prices between consecutive transactions of the same house. However, a repeat-sales approach comes at the cost of focusing on a subsample

TABLE A2 – NON PARALLEL TRENDS DID MODEL, 2-3KM CONTROL GROUP

(Dependent variable: the logarithm of house prices)

	(1)
	Non-parallel trends
Wind turbine placed <2km	-0.0183***
	(0.0068)
Housing characteristics	✓
Postcode fixed effects	✓
Year and month fixed effects	✓
Treatment group × controls	✓
Observations	710,703
R^2	0.92

Note: This table is based on data from the Dutch Association of Realtors (provided by Brainbay) between 1985 en 2019. Standard errors are clustered at the neighborhood level and are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

TABLE A3 – ROBUSTNESS: WIND TURBINES AND HOUSE PRICES
(Dependent variable: the logarithm of house prices)

	(1)	(2)	(3)	(4)	(5)	(6)
	Repeat sales	*Anticipation effects*	*NUTS 3 FE + Time Trends*	*Removed turbines*	*No closer turbines*	*Multiple treatment*
Wind turbine placed <2km	-0.0227***	-0.0211***	-0.0208**		-0.0183***	-0.0162**
	(0.0065)	(0.0061)	(0.0103)		(0.0068)	(0.0076)
Wind turbine placed <2km × opened, $t-2$		-0.0176***				
		(0.0047)				
Wind turbine placed <2km × opened, $t-3$		-0.0089*				
		(0.0048)				
Wind turbine placed <2km × opened, $t-4$		-0.0051				
		(0.0053)				
Wind turbine placed <2km × opened, $t-5$		-0.0059				
		(0.0057)				
Wind turbine placed <2km × opened, $< t-5$		0.0035				
		(0.0089)				
Wind turbine removed <2km				0.0112		
				(0.0115)		
Wind turbine placed <2km × 2 turbines						-0.0057
						(0.0063)
Wind turbine placed <2km × 3 turbines						0.0015
						(0.0070)
Wind turbine placed <2km × 4 turbines						-0.0059
						(0.0104)
Wind turbine placed <2km × 5 turbines						-0.0096
						(0.0099)
Housing characteristics	–	✓	✓	✓	✓	✓
Postcode fixed effects	–	✓	–	✓	✓	✓
TTWA-by-5 year fixed effects	–	–	✓	–	–	–
Year and month fixed effects	✓	✓	✓	✓	✓	✓
Observations	51,838	290,002	290,002	26,483	289,083	290,002
R^2	0.78	0.92	0.83	0.91	0.92	0.92

Notes: In column (1), the dependent variable as well as the treatment variable are first-differenced. This table is based on data from the Dutch Association of Realtors (provided by Brainbay) between 1985 en 2019. The same subsample as in Table 3, column (4) is used, although in some cases with additional restrictions. Standard errors are clustered at the neighborhood level and are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

of transactions of properties that we observe at least twice. Yet, our findings are robust as the repeat sales estimate suggests a price decline of -2.2%.

Second, going from the planning stage to the final construction can take years (including an assessment study, meetings with local residents, etc.). Although we do not have data on the duration of the planning phase, we use a revealed preference approach to empirically measure how many years in advance prices start to decline. We observe in column (2) that three years in advance prices decline by 0.9%, although this effect is only statistically significant at the ten percent significance level. Before that time the effects are not statistically significant. Two years in advance the effect is already -1.7%. Finally, the treatment effect controlling for this anticipation effect is -2.1% and is still statistically significant at the one percent significance level. These findings seem to be in line with earlier studies (see *e.g.* Dröes & Koster 2016).

Third, although the results comparing treatment areas with a local control group should filter out any unobserved trends (*e.g.* income, unemployment, regional policies) that might be correlated with wind turbine construction, one may be concerned that differential trends in labor markets bias our results. In column (3) we, therefore, replace postcode fixed effects – which capture time-invariant variation – with more aggregate location fixed effects that are allowed to vary over time by 5-year periods. More specifically, we include travel-to-work-area (NUTS3) by five-year fixed effects. The treatment effect is now -2.1% which is in line with the preferred specification.

Fourth, the lifespan of a wind turbine is roughly 25 years. This implies that towards the end of the sample period (as of 2011) some turbines have been demolished. About 229 of the $1,239$ turbines that were within 2km of housing were demolished. We are particularly interested in those turbines that have not been replaced by a new turbine and did not have another turbine within 2km. Only 0.3% of the transactions are close to such turbines *after* they have been removed. To properly identify the effect we only keep observations near actual turbines that will be eventually removed or have been removed. Column (4) shows the results. The effect of turbine removals is positive, as expected. Although the coefficient is imprecisely estimated, the point estimate is lower than that for newly constructed wind turbines, in particular because removed turbines are generally smaller.[5]

Fifth, we focus on the construction of the first wind turbine within 2km. If a wind turbine is built within 2km of a property a subsequent turbine might be placed even closer. In only 919 transactions in our dataset, a wind turbine is placed closer to a house after there was already a turbine within 2km. Not surprisingly, in column (5) we show that the effect remains the same if we exclude those observations.

Sixth, more generally, the price of a property may be influenced by multiple turbines. Con-

[5]The average height of removed turbines is just 77m, while it is 98m for the whole sample of onshore turbines.

TABLE A4 – TURBINE HEIGHT, IMPACT AREA AND HOUSE PRICES
(Dependent variable: the logarithm of house prices)

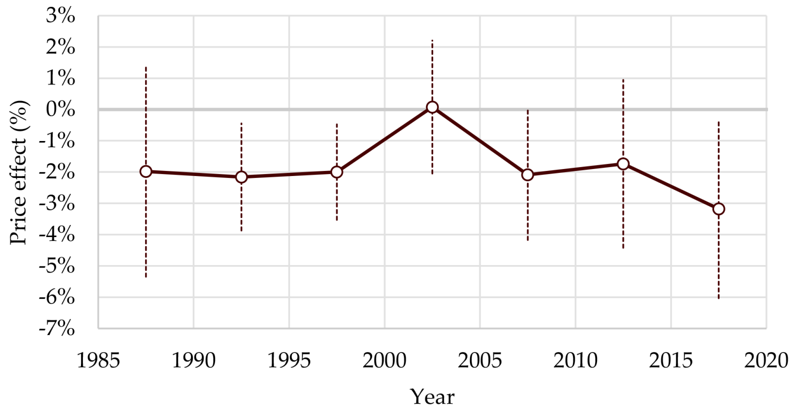
	(1)	(2)	(3)	(4)	(5)
	Turbine height	*Time periods*	*Height (+ time periods)*	*Distance (<2.5km)*	*Distance & height*
Wind turbine placed <2km	see Fig. 4a	see Fig. A1	see Fig. 4b	see Fig. 5	see Fig. 6
Housing characteristics	✓	✓	✓	✓	✓
Postcode fixed effects	✓	✓	✓	✓	✓
Year and month fixed effects	✓	✓	✓	✓	✓
Observations	290,002	290,002	290,002	491,337	491,337
R^2	0.92	0.92	0.92	0.92	0.92

Note: This table is based on data from the Dutch Association of Realtors (provided by Brainbay) between 1985 en 2019. Columns (1)-(3) are based on the (time variation only) model presented in Table 3, column (4). Column 3 adds interaction effects between the treatment indicator and 5-year time periods (see column 1). Columns (4) and (5) are also based on time variation in opening dates only but include transactions up to 2.5km of the nearest wind turbine. Standard errors are clustered at the neighborhood level and are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

sequently, column (6) includes interaction effects with the number of wind turbines that are placed within 2km. In our sample, this never exceeds 5 turbines. In line with Dröes & Koster (2016), the regression results suggest that there is no evidence that beyond the first turbine there is an additional price effect of more turbines placed close to a property. From a policy perspective, if the aim is to reduce external effects on house prices, the latter result suggests that it is best to cluster turbines in wind farms.

Seventh, in Table A4 we show the different specifications where we allow the effect to vary with *(i)* turbine height, *(ii)* time periods, *(iii)* height and time periods, *(iv)* distance, and *(v)* distance and height. These results are discussed in the main body of the paper.

One may be concerned that, because tall turbines have been built in recent years, the larger effect of tall turbines may capture changes in perception. In Figure A1 we, therefore, test whether the willingness to pay to live nearby turbines is more or less constant across the study period. We report the result using interaction effects with 5-year time period dummies (*i.e.* 1985-1989, 1990-1994, etc.). Again, we re-estimate our preferred regression model based on temporal variation in wind turbine construction, but allow the effect of turbines to vary over time. We do see that the point estimate in the last 5-year period in our sample (2015-2019) is indeed a bit higher, at about -3%. Interestingly, between 2000 and 2004 the effect was around zero. It is unclear why this is the case, but this was a period of strong house price growth. A possible explanation might be that preferences for turbines are different during a housing



Notes: The dotted lines represent the 95% confidence intervals. This regression includes observations within 2km of a (future) turbine and controls for housing characteristics, postcode fixed effects, as well as year and month fixed effects. The number of observations is $290,002$ and the R^2 is 0.92.

FIGURE A1 – THE EFFECT OF WIND TURBINES IN DIFFERENT TIME PERIODS

market boom. However, if we take into account the confidence bands we cannot reject the null hypothesis that the effect is constant over time.

A.4 Demography and sorting

To investigate whether certain demographic groups are disproportionally affected by the placement of wind turbines we gather additional data on demographic characteristics from Statistics Netherlands. Because the impact of wind turbines is local, it is very important to gather these data at the lowest level of spatial aggregation possible.

It appears that Statistics Netherlands publishes infrequently data at the postcode 6-digit level in 2004, 2008, 2010, 2014, 2015 and 2016.[6] Although the data covers a shorter time period than the real estate data, the upside is that it covers all postcodes in the Netherlands (rather than only postcodes where transactions occur), so that we expect to have sufficient identifying variation. We focus on 5 demographic variables: population density, average household size, the share of foreigners, monthly income, and the share of people that receive income assistance. The latter two variables are particularly interesting because this enables us to say something on whether the house price decrease is carried by the rich or the poor and so may impact income inequality.

In Table A5 we report descriptive statistics. We find an average population density of 82.6

[6]Because we lack recent data, and because most solar farms are built in recent years, we cannot repeat the analysis for solar farms.

TABLE A5 – DESCRIPTIVES: DEMOGRAPHIC VARIABLES

	(1) Mean	(2) St.dev.	(3) Min	(4) Max
Population density *(per ha)*	82.64	108.5	0	1,500
Household size	2.284	0.630	1	34.25
Share foreigners	0.146	0.177	0	1
Median monthly income *(in €)*	2,248	752.5	500	10,000
Share income assistance	0.218	0.136	0.00649	1
Wind turbine placed <2km	0.0689	0.253	0	1
Solar farm placed <1km	8.32e-05	0.00912	0	1

Notes: We have 2,092,303 observations on population density, 1,929,359 observations on household size, 1,895,223 observations on the share of foreigners in the postcode, 1,392,511 observations on the median monthly income, and 291,244 observations on the share of people receiving income assistance. The number of observations that are within 2km of a wind turbine is 181,339 and within 1km of a solar farm 219.

persons per hectare. The average household size is 2.3, while the share of foreigners is on average 15%. Furthermore, the median monthly income is 2,248, while the share of people receiving income assistance is 22%. Please note that the number of observations per variable varies considerably. This is because of confidentiality, observations are removed if an individual's information could be identified. This particularly holds for the share of people with income assistance, for which we have only 291 thousand observations.

The first question we aim to answer is whether turbines are disproportionally placed in areas with certain demographic characteristics. Panel A in Table A6 therefore looks at unconditional regressions of the variable of interest on whether a wind turbine has been placed within 2km, as well as year fixed effects.[7] Unsurprisingly, we find that population density is considerably lower in areas where a turbine is placed. More specifically, the coefficient indicates that the difference in population density is $\exp(-0.347) - 1 = -29\%$. This confirms the consensus that turbines are placed in rural, sparsely populated, areas.

In line with this, we find that the household size is 2.8% higher and the share of foreigners 2.6 percentage point lower, in line with the idea that farmer families tend to be somewhat larger and more often are natives.

Interestingly, we find in column (4) that median incomes are only a little lower in treated areas (*i.e.* -2%). The share of people receiving income assistance is not higher or lower in treated areas

[7] Usually, it would be sufficient to compare means across treated and untreated areas. However, because measurement of some variables changes over time (such as the share of foreigners and median income), unconditional means are not so informative.

TABLE A6 – WIND TURBINES, DEMOGRAPHY AND SORTING

	(1)	(2)	(3)	(4)	(5)
PANEL A: UNCONDITIONAL REGRESSIONS	*Population density (log)*	*Household size (log)*	*Share Foreigners*	*Median income (log)*	*Share income assistance*
Wind turbine placed <2km	-0.3468***	0.0273***	-0.0257***	-0.0208**	-0.0019
	(0.0641)	(0.0073)	(0.0095)	(0.0088)	(0.0035)
Year fixed effects	✓	✓	✓	✓	✓
Observations	2,055,208	1,929,359	1,896,223	1,392,511	291,244
R^2	0.0028	0.0034	0.0644	0.0637	0.2155
PANEL B: CONDITIONAL REGRESSIONS	(1)	(2)	(3)	(4)	(5)
Wind turbine placed <2km	-0.0104**	-0.0091***	-0.0117*	0.0073	0.0010
	(0.0045)	(0.0033)	(0.0061)	(0.0083)	(0.0051)
Postcode fixed effects	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓
Observations	183,290	169,440	166,821	119,899	20,084
R^2	0.9933	0.9014	0.8598	0.8348	0.8893

Notes: This table is based on data from 2004, 2008, 2010, 2014, 2015 and 2016. In Panel B we only keep observations within 2km of a wind turbine in 2019. Standard errors are clustered at the neighborhood level and are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

(column (5)). Hence, it seems that the placement of turbines is unlikely to generate substantial distributional effects, although future research could also consider the impact on (net) wealth and overall welfare.

While Panel A is informative on differences in the demographic composition between affected and unaffected areas, it does not tell us how demographics change *as a result of* the placement of wind turbines. To investigate whether preference-based sorting occurs, we pursue a similar strategy as with house prices, implying that we include year *and postcode* fixed effects. The latter fixed effects should capture any selection effects. Further, we only keep observations within 2km of a wind turbine in 2019.

In Panel B we find very small sorting effects. Column (1) suggests that population density decreases by 1%, which may be due to a reduction in the average household size of about 1%. The share of foreigners reduces further by 1.2 percentage points. Importantly, we do not find that median income or the share of people receiving is affected by the placement of a turbine. Hence, we do not find any evidence that the construction of turbines triggers a process of neighborhood deprivation.

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