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# Wind turbines, solar farms, and house prices

Martijn Dröes and Hans Koster

INTERNATIONAL TRADE AND REGIONAL ECONOMICS



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# Abstract

This paper examines the effect of wind turbines - with a particular focus on turbine height - 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 (\textgreater150m) 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 rather than wind turbines does not seem to be a way to avoid the external effects of renewable energy production.

JEL Classification: R31, Q42, Q15, L95

Keywords: wind turbines, solar farms, House Prices

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# Wind Turbines, Solar Farms, and House Prices<sup>\*</sup>

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February 26, 2021

#### Abstract

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#### 1 Introduction

Renewable energy is on the rise. While global demand is still strongly increasing, the demand for fossil fuels has actually strongly declined (IEA 2020). Furthermore, the current Covid-19 crisis has made clear the downsides of fossil fuels: the effective use of fossil fuels depend heavily on storage capacity and transportation (Science 2020). Instead, renewable energy is typically produced locally and could be a viable alternative to fossil fuels. Two important sources of renewable energy production are wind turbines and commercial solar farms.

Renewable energy production may have external effects on local residents (Meyerhoff et al. 2010, Groth & Vogt 2014). Wind turbines make noise, cast shadows, and create flickering. Moreover, turbines can visually pollute the landscape, particularly if they are tall. Solar panels can reflect sound and sunlight and are also usually not considered to be aesthetically pleasing. In line with a large literature on hedonic pricing, we would expect that such externalities capitalize into house prices. Increasing our understanding of these external effects is policy-relevant for at least two reasons. First, it provides insight in what could be a more efficient allocation of renewable energy production facilities (Rodman & Meentemeyer 2006). Second, because the effects of wind turbines and solar farms are local, the effect on house prices is indicative that the burden of renewable energy production is not necessarily distributed equally within society.

The aim of this paper is to examine the effect of wind turbines and solar farms on house prices. We employ a quantitative, revealed-preferences approach, to measure this effect. We contribute to the existing literature in several ways. First, this paper explicitly focuses on the role of turbine height on house prices. In particular, we investigate whether tall turbines have a larger effect on house prices and at a larger distance. Given the substantial increase in wind turbine height in the last years, we would expect heterogeneity in the effect of turbines of different heights on house prices. This is important for spatial policies regarding the placement of wind turbines.<sup>1</sup>

Second, to identify a causal effect of renewable energy production facilities on house prices is not straightforward, as turbines and solar farms are mostly located in sparsely populated areas with

<sup>&</sup>lt;sup>1</sup>Some studies find effects of turbines up to 14%, while others do not find any effect (see Section ?? for an extensive review). One potential explanation is that previous studies did not take into account that large turbines may lead to larger decreases in housing values. A notable exception is Dröes & Koster (2016), who show that in the Netherlands turbines larger than 100m lead to an additional price decline of 2.2%. In addition, Dröes & Koster (2016) only analyze a handful of tall turbines and it remains unclear whether the spatial extent of negative externalities for turbines of different heights is the same. We would expect they are not.

lower house prices. That is, the placement of renewable energy production sites is not random. To mitigate endogeneity concerns many studies use a differences-in-differences design based on comparison with a local control group (Gibbons 2015, Dröes & Koster 2016, Jensen et al. 2018). A key identifying assumption is that there are *parallel trends* between treated and control areas, which may be restrictive and is an assumption that is hard to test.<sup>2</sup> Instead, we exploit *temporal variation* in the openings of turbines and solar farms. That is, we employ a hedonic regression design that compares price changes in areas that have received a wind turbine or solar farm; to areas that will receive a turbine or solar farm in the future.By examining the causal effect on *house prices* we aim to measure the (revealed) preferences of households regarding the placement of wind turbines and solar farms.<sup>3</sup>

Third, to the best of our knowledge, we are among the first to investigate the impact of solar farms on house prices. For solar farms, we use essentially the same identification strategy as for wind turbines. However, the effects of solar farms are expected to be more local than those of wind turbines, as visual pollution is likely to be more localized. Additionally, we compare the results of solar farms to those of wind turbines. Many previous studies only focus on a single type of renewable energy production facility.

This paper relies on detailed housing transactions data from the Netherlands between 1985-2019, which we combine with data on all wind turbines and solar farms that have been placed during this period. The Netherlands is typically seen as a fairly urbanized country and thus provides an ideal study area to examine the external effects of wind turbines and solar farms on house prices.<sup>4</sup>

The results in this paper show that the construction of a wind turbine leads to a decrease in local house prices of 1.8%. In particular, we find that a turbine taller than 150m decreases prices within 2km by 5.4%, while the effect of low turbines (<50m) is statistically indistinguishable from zero. Also, the effect of tall wind turbines does not extend much beyond 2km, but we do find evidence that the impact radius is smaller (<1km) for low wind turbines. Various additional robustness checks support the main findings. Regarding solar farms, we find that house prices

<sup>&</sup>lt;sup>2</sup>For a more elaborate discussion, see Bertrand et al. (2004), Abadie (2005), and Donald & Lang (2007).

 $<sup>^{3}</sup>$ More specifically, house prices are a useful monetary measure of household preferences (Rosen 1974).

 $<sup>^{4}</sup>$ The Netherlands (an E.U. member state) is more than twice the size of the San Francisco Bay Area (U.S.) but has a comparable population density ( $488/km^{2}$  versus  $430/km^{2}$ , respectively).

decrease by about 2.6% after opening. The effect is confined to 1km, so it is more localized than that of wind turbines.

Finally, we show that the total loss in housing values as a result of the placement of wind turbines is about  $\in$ 5 billion, while solar farms imply a total loss of  $\in$ 800 million. Yet, 1% of the turbines cause almost 50% of the total loss in housing values. These are turbines that are placed too close to residential areas. The median loss per installed megawatt-hour (MWh) is  $\in$ 53, with taller turbines having a much lower median loss per MWh (*i.e.*  $\in$ 277 for a turbine <50m versus  $\in$ 11 for a turbine >150m). Hence, it seems much more efficient to build taller, more powerful, turbines. We further find that the average loss per MWh for a solar farm is of the same order of magnitude as that of a wind turbine.

From a policy perspective, our results thus imply that building solar farms instead of wind turbines will not mitigate the external effects of renewable energy production. Our results further highlight the importance of avoiding the placement of wind turbines and solar farms near urban areas.

The remainder of this paper is structured as follows. Section 2 provides a discussion of the international and Dutch policy context. Section 3 discusses the data, while the methodology is discussed in Section 4. Section 5 highlights the regression results and Section 6 concludes.

# 2 Policy context

Wind turbines are an important source of renewable energy with 30% of its capacity located in Europe and 17% in the U.S. in 2018. Especially China has invested heavily in wind energy, overtaking the E.U. already in 2015 as being the largest producer of wind energy. Currently, 36% of worldwide capacity is located in China (GWEC 2019). Many other Western and Asian countries have been increasing their capacity over the past decades as well. Technological change fueled by an increased demand for energy has led wind turbines to become taller over time (as taller turbines produce more energy). Where turbines in the 1980s were still around 30m, the newest generation of wind turbines is currently well above 100m.<sup>5</sup>

A relatively new phenomenon is the commercial production of renewable energy via solar farms,

 $<sup>^{5}</sup>$ The average power a turbine <50m generates is 0.14 MW, while it is 4.15 MW for a turbines >150m. These are large differences in potential energy output.

which are large fields of solar panels. The first solar farm was constructed in 1982 in California. Yet, with advances in technology, it has become attractive to commercially exploit solar farms only in the last decade or so. Many countries, like India, China, and the United States have heavily invested in very large solar farms.<sup>6</sup>

In 2019, the renewable energy capacity captured 27% of total electricity production with solar photovoltaics capturing still only 2.8% of the total production, about half that of wind turbines. Hydropower is still one of the largest contributors. By contrast, last year's growth in solar photovoltaics capacity was about twice that of wind turbines (REN21 2020). Whether the current surge in the construction of tall wind turbines and solar farms will continue remains to be seen, but some countries have already suggested that the economic recovery after Covid-19 should be a green one (Associated Press 2020).

In this study, we focus on the Netherlands (which is an E.U. member state). The E.U. has extended its energy efficiency directive in 2018 posing new targets for 2030. According to the national energy and climate plans of the different member states, many European countries will rely on wind and solar energy to meet those targets. In 2013, the Dutch government reached an energy agreement with many central stakeholders in the Dutch society (*i.e.* labor unions, environmental organizations, financial institutions) to reduce  $CO_2$  emissions by 2020-2023. An important pillar of this agreement is to construct about 1,300 wind turbines on land (SER 2013).<sup>7</sup>

In 2019, this ambition was extended and a National Climate Agreement was reached to reduce  $CO_2$  emissions by 49% in 2030 compared to 1990. To achieve this goal, about 50% of renewable energy production should be realized on land (35 of the 84 TWh), while the remainder will be produced offshore. Furthermore, a large-scale subsidy program is now in operation for which 30 Dutch regions are required to develop energy production plans. From this, it is clear that wind and solar energy produced on land will play a major role in reaching the renewable energy goals (National Climate Agreement 2019). Although the Dutch government aims to ensure the participation of local residents in developing renewable energy production sites, there have been

<sup>&</sup>lt;sup>6</sup>Currently, the largest solar farm in the world is 40km<sup>2</sup>, located in Bhadla, India.

<sup>&</sup>lt;sup>7</sup>In 2019, the Dutch government lost a major court case against the non-profit environmental organization Urgenda because it did not fulfill its climate goals set for 2020. This event created a precedent for other related court cases in other E.U. member states (Supreme Court 2019), and has created a sense of urgency to increase renewable energy production more quickly.

a lot of protests, particularly against tall wind turbines (Telegraaf 2020). Our study is therefore very societally relevant.

# 3 Data

#### 3.1 Data on wind turbines and housing values

The locations of wind turbines, as well as the axis height, diameter of the blades, and the power (MW) of the turbine come from www.windstats.nl. We define *turbine height* as the axis height plus half the diameter of the rotor blades (*i.e.* the so-called tip height).<sup>8</sup> There is a very high correlation ( $\rho = 0.918$ ) between height of the turbine and the power it generates. For example, a turbine of 3MW (with a height of about 150m) produced 6.5 million kWh, while a turbine of 2MW (115m) only provides 4.5 million kWh.

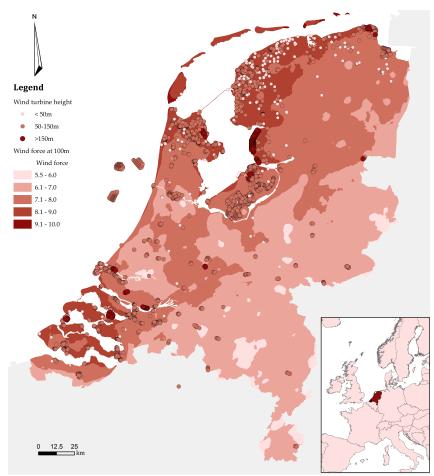
The total number of wind turbines up to and including mid-2019 is 2,695. This study focuses on the 2,406 turbines that have been built on land.<sup>9</sup> Of the turbines that have been built on land, 614 were built after 2011. Many of these new turbines are close to the locations where wind turbines have previously been installed. Figure 1 shows the locations of wind turbines. The map highlights that wind turbines are often concentrated in coastal areas (which have a lot of wind). Figure 2 shows that there is clearly an upward trend in the height of turbines. In 2000 the average height of new turbines was still around 80m. Towards the end of the sample period, the average height is about 140m with a maximum of 200m. Interestingly, the trend seems to stabilize as of 2016. Currently, low turbines (<50m) account for about 10% of the turbines, medium-sized (50-150m) for about 80% and tall turbines (>150) for the remaining 10%.

The dataset concerning house prices has been provided by Brainbay. The data cover approximately 70% of the market.<sup>10</sup> The data contain sales of existing properties between 1985-(mid)2019. In addition to property prices, the dataset includes information on many different property features. Based on this, we can calculate the distance to the nearest existing wind turbine for each (transacted) home in our sample. The descriptive statistics are reported in Table 1.

<sup>&</sup>lt;sup>8</sup>Dröes & Koster (2016) use axis height and the diameter of rotor blades separately, but the effect of these are difficult to measure as height and diameter of the blades are highly correlated (*i.e.* there are no high turbine with tiny blades).

<sup>&</sup>lt;sup>9</sup>The *Princess Amalia, Egmond aan Zee, Luchterduinen, and Gemini offshore wind farms are therefore not included in our analysis, Gemini is missing from the map shown here because it is far from the coast.* 

<sup>&</sup>lt;sup>10</sup>The sales that are not included are by real estate agents that are not a member of the NVM real estate organization, but most of them are.



*Notes*: We obtain data on solar farms from windstats. Data on wind speeds is from the KNMI. The map is compiled by the authors.

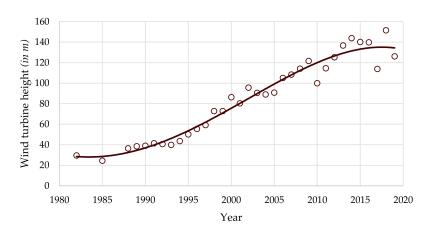


FIGURE 1 - THE LOCATION OF WIND TURBINES

Notes: We obtain data on the height of wind turbines from <code>Windstats</code>. The solid line indicates the non-linear trend line.

Figure 2 - Average height of NeW wind turbines

The average house price between 1985 and 2019 is  $\in$  214.178. This is based on more than 3 million transactions (2.7 million homes). The average house price is slightly lower ( $\notin$  206.658)

(1)	(2)	(3)	(4)
Mean	St.dev.	Min	Max
$214,\!180$	121,704	$25,\!000$	1,000,000
0.0506	0.2192	0	1
117.9	37.71	26	250
4.384	1.340	1	25
0.317	0.465	0	1
0.281	0.449	0	1
0.128	0.334	0	1
0.331	0.471	0	1
0.976	0.154	0	1
0.866	0.341	0	1
0.891	0.312	0	1
0.00618	0.0784	0	1
0.0717	0.258	0	1
0.150	0.357	0	1
0.169	0.374	0	1
0.138	0.345	0	1
0.126	0.332	0	1
0.109	0.311	0	1
	$\begin{array}{c} 214,180\\ 0.0506\\ 117.9\\ 4.384\\ 0.317\\ 0.281\\ 0.128\\ 0.331\\ 0.976\\ 0.866\\ 0.891\\ 0.00618\\ 0.0717\\ 0.150\\ 0.169\\ 0.138\\ 0.126\end{array}$	MeanSt.dev. $214,180$ $121,704$ $0.0506$ $0.2192$ $117.9$ $37.71$ $4.384$ $1.340$ $0.317$ $0.465$ $0.281$ $0.449$ $0.128$ $0.334$ $0.331$ $0.471$ $0.976$ $0.154$ $0.866$ $0.341$ $0.891$ $0.312$ $0.00618$ $0.0784$ $0.0717$ $0.258$ $0.150$ $0.357$ $0.169$ $0.374$ $0.138$ $0.345$ $0.126$ $0.332$	MeanSt.dev.Min $214,180$ $121,704$ $25,000$ $0.0506$ $0.2192$ $0$ $117.9$ $37.71$ $26$ $4.384$ $1.340$ $1$ $0.317$ $0.465$ $0$ $0.281$ $0.449$ $0$ $0.128$ $0.334$ $0$ $0.331$ $0.471$ $0$ $0.976$ $0.154$ $0$ $0.866$ $0.341$ $0$ $0.00618$ $0.0784$ $0$ $0.150$ $0.357$ $0$ $0.169$ $0.374$ $0$ $0.138$ $0.345$ $0$ $0.126$ $0.332$ $0$

TABLE 1 – DESCRIPTIVES: HOUSE PRICES AND WIND TURBINES

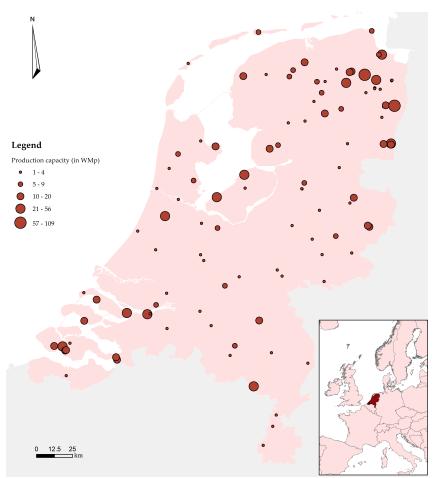
*Notes:* The number of observations is 3,389,903. The data covers the period 1985-(mid)2019 Apartments are the reference group for the type of residence. Houses built before 1945 are the reference category for the building year.

within 2km of an existing wind turbine, suggesting there is a slight tendency to built turbines in areas with lower prices. In Appendix A.2 we provide more details on differences between treated and control areas.

Finally, the average distance of properties to wind turbines in 2019 is 8.7km. This distance has been decreasing for years; in 1995 for example the distance was still 26.6km. However, for many households, wind turbines are still relatively far away. Only 5.1% of the housing transactions between 1985 and 2019 occur within 2km wind turbines *after* they have become operational. Yet, the total number of transactions near all wind turbines present in 2019 is 290,002 (238,164 houses).

#### 3.2 Data on solar farms and housing values

The data on solar farms come from Zon op Kaart, compiled by ROM3D.We have double-checked these data through OpenStreetMap. Furthermore, using OpenStreetMap, we geocode the data so that we have exact information on the size and geographic demarcation of solar farms. The number of solar farms (107) included in the analysis is much lower than the number of wind



*Notes*: We obtain data on solar farms from Zon op Kaart. The first solar farm was built in 2004. The map is compiled by the authors.

FIGURE 3 – THE LOCATIONS OF SOLAR FARMS (UNTIL MID-2019)

### $turbines.^{11}$

Figure 3 shows the location and opening year of solar farms in the Netherlands until mid-2019. The first solar farm in our dataset is *Ecopark Waalwijk* (4.2 thousand panels) which opened in 2004. The locations of the solar farms are not randomly distributed in the Netherlands. As solar farms are land-intensive, many solar farms are located in areas with a low population density because of land availability.

The largest solar farm currently is located in Vlagtwedde (Groningen) and consists of 320,000 solar panels (approximately  $1 \text{km}^2$ ) with a total nominal peak power of 109 MWP.<sup>12</sup> It appears

<sup>&</sup>lt;sup>11</sup>Importantly, we disregard solar panels on roofs of industrial or agricultural buildings and only consider land-based solar farms.

<sup>&</sup>lt;sup>12</sup>This solar farm produces about  $0.85 \times 1,000,000 \times 109 = 92$  million kWh per year (see Tenten Solar 2019). For comparison purposes, an (average) wind turbine of 3 MW delivers around 8 million kWh; the park is therefore roughly equal to 14 wind turbines.

	(1)	(2)	(3)	(4)
	Mean	St.dev.	Min	Max
Transaction price $(\in)$	$249,\!586$	$124,\!274$	$25,\!000$	1,000,000
Solar farm $<1km$	0.00118	0.0343	0	1
House size in $m^2$	116.8	37.70	26	250
Number of rooms	4.453	1.398	1	24
Terraced	0.313	0.464	0	1
Semi-detached	0.277	0.448	0	1
Detached	0.122	0.327	0	1
Garage	0.314	0.464	0	1
Garden	0.970	0.170	0	1
Maintenance state is good	0.867	0.340	0	1
Central heating	0.881	0.323	0	1
Monumental status	0.00636	0.0795	0	1
Construction year 1945-1959	0.0704	0.256	0	1
Construction year 1960-1970	0.133	0.339	0	1
Construction year 1971-1981	0.139	0.346	0	1
Construction year 1981-1990	0.114	0.317	0	1
Construction year 1991-2000	0.119	0.324	0	1
Construction year $>2000$	0.203	0.402	0	1

TABLE 2 – DESCRIPTIVES: HOUSE PRICES AND SOLAR FARMS

*Notes:* The number of observations is 1,470,808. The data is as of 2009. Apartments are the reference group for the type of residence. Houses built before 1945 are the reference category for the building year.

that new solar farms generally contain more panels, so the size of solar farms has increased over time. Using the data on property transactions, we calculate the distance of each property to the edge of the nearest solar farm.

Although the first solar farm was opened in 2004 we do not observe transactions within 1km after the opening of this solar farm. 97 solar farms were opened in 2017, 2018, and 2019. Because almost all solar farms have been opened in recent years, we use the transactions data from the last 10 years (*i.e.* from 2009-2019). The descriptive statistics are reported in Tabel 2.

The average property price between 2009 and mid-2019 is  $\in$ 249,586. The other descriptive statistics regarding housing characteristics are almost identical to those of wind turbines. The number of transactions in the Netherlands between 2009 and 2019 is about 1.5 million. Yet, there are not that many observations nearby solar farms. In particular, within 1km there are 1,736 transactions *after* the placement of a solar farm (0.118% of the data). Fortunately, the total number of transactions within 1km of all solar farms that are present in 2019 is 12,650 (11,843 houses).

Similarly to wind turbines, house prices within 1km of a solar farms are lower ( $\leq 226,000$ ) than

the sample average. These, and other descriptive statistics, are discussed in more detail in Appendix A.2.

# 4 Methodology

#### 4.1 Measuring the price effect of wind turbines

To measure the effect of wind turbines on house prices, we employ a difference-in-differences hedonic price method in which house price developments nearby wind turbines are compared with house price developments further away. In particular, we estimate:

$$\log P_{it} = \beta w_{it-1} + \gamma X_{it} + \lambda_j + \lambda_t + \epsilon_{it}, \tag{1}$$

where  $P_{it}$  is the transaction price of property *i* sold in year *t*,  $w_{it-1}$  is an indicator that is 1 if a property is sold within 2km in all years *after* placement of a wind turbine (for now we focus on the nearest wind turbine),  $X_{it}$  are housing characteristics,  $\lambda_j$  are location fixed effects at the postcode 6-digit level (containing about a half a street and on average just over 20 households, but fewer in rural areas),  $\lambda_t$  are month and year time dummies that control for overall price trends and seasonality,  $\epsilon_{it}$  contains characteristics of properties or locations that are unobserved. These are assumed to be uncorrelated with the placement of a turbine.<sup>13</sup>

We control for any time-constant price difference across locations. This is important as differences in prices may arise because amenities may differ between locations (for example, the presence of schools, etc.). To alleviate the concern that the location fixed effects are not detailed enough we will also show robustness using a repeat sales approach, completely absorbing time-invariant property and location characteristics. We use 2km around turbines as treatment areas, as most of the noise (<500m), flickering (<1000m), and landscape pollution (<2000m) typically falls within this area (Dröes & Koster 2016). Nevertheless, we will also explicitly investigate whether the effect reaches beyond 2km.

We are particularly interested in  $\beta$ , which measures the percentage change in property value relative to a (local) control group. We start our analysis by using transactions in the rest of the

<sup>&</sup>lt;sup>13</sup>Note that the location fixed effects capture time-invariant price differences between control and treatment areas (*e.g.* the selection effect of wind turbines being placed in low-priced areas). The time fixed effects capture time trends, such as general economic trends affecting house prices).

Netherlands as the control group and subsequently examine the effect using 3-5km and 2-3km as control group areas.

Still, one may be concerned that properties that are further away than 2km may have different price trends. For example, they may be located closer to city centers, which are prone to relatively strong price increases due to inelastic housing supply and gentrification. Our preferred specification therefore only keeps observations within 2km of a (future) wind turbine, implying that we only use the variation in the opening dates of wind turbines. We are then comparing the price development in areas in which wind turbines are opened to locations where they will be opened in the future. This is possible because there is variation in the opening date of wind turbines.

This approach is a version of a difference-in-differences strategy, but one in which unobserved price trends are much more likely to be very similar in treatment and control areas, and much less restrictive than the standard parallel trend assumption between spatially differentiated treatment and control groups that is usually applied in standard differences-in-differences methodologies. In particular, in Appendix A.3 we show that this is equivalent to a model with *non-parallel trends (i.e.* we implicitly control for differences in income, unemployment trends, etc.) between control and treatment groups.

Finally, it is important to control for housing characteristics because certain types of homes are more often located closer to wind turbines. A possible decrease in value could then mistakenly be attributed to the placement of a wind turbine. We will show various robustness tests showing the validity of our research design.

Furthermore, we are particularly interested to examine heterogeneity in the impact of wind turbines by allowing the price effect to differ between low (<50m), medium-sized (50-150m), and tall (>150) turbines. The specification to be estimated is then:

$$\log P_{it} = \sum_{h=1}^{3} \beta_h w_{iht-1} + \gamma X_{it} + \lambda_j + \lambda_t + \epsilon_{it}, \qquad (2)$$

where  $w_{iht-1}$  is a dummy that equals one when the nearest turbine falls in height category hand is within 2km in t-1, and  $\beta_h$  are the coefficients to be estimated for each height category. We will also examine whether the impact radius differs for turbines with different heights.

#### 4.2 Measuring the price effect of solar farms

For solar farms we initially assume an impact radius of 1km, which we realize is somewhat arbitrary. We will therefore also investigate the spatial extent of the effect. To measure the impact of the opening of a solar farm on property values, we use the same methodology as that for wind turbines. We estimate the following equation:

$$\log P_{it} = \zeta s_{it-1} + \gamma X_{it} + \lambda_i + \lambda_t + \eta_{it}, \tag{3}$$

where  $P_{it}$  is again the transaction price of property *i* sold in year *t*,  $s_{it-1}$  is an indicator that is 1 if a property is sold within 1km in all years after opening of a solar farm (again we look at the nearest solar farm),  $X_{it}$  are property characteristics,  $\lambda_j$  are postcode fixed effects,  $\lambda_t$  are month dummies, and  $\eta_{it}$  again captures unobserved heterogeneity.

We are particularly interested in  $\zeta$ . This coefficient measures the percentage change in property values due to the placement of a solar farm relative to a (local) control group. The initial control group consists of transactions from the whole of the Netherlands. We improve on this by selection transactions within 2-5km and 1-2km. As there are much fewer solar farms as compared to wind turbines, we expect that just using temporal variation in the opening of solar farms (*i.e.* only using observations within 1km of a solar farm) will lead to somewhat imprecise estimates.

# 5 Results

#### 5.1 Baseline estimates: wind turbines and house prices

Table 3 shows the regression results based on equation (1). In column (1) we use the whole dataset. The results suggest that the opening of a wind turbine within 2km of the property is associated with a house price decrease of 1.9% (= (e<sup>-0.0192</sup> - 1) × 100%). This effect is statistically significant at the 1% significance level. Using the whole of the Netherlands as a control group is unlikely to yield unbiased results, as price trends between rural areas (where turbines are often placed) and urban areas are most likely different.<sup>14</sup>

 $<sup>^{14}</sup>$ Yet, the equation including controls and fixed effects seems to capture a considerable amount of the variation in house prices, as we can explain 93% of the variation in house prices. This high fit is mainly due to the inclusion

	(1)	(2)	(3)	(4)
	Full sample	Control group (3-5km)	Control group (2-3km)	Temporal variation only
Wind turbine placed $<2km$	$-0.0192^{***}$ (0.0041)	$-0.0256^{***}$ (0.0045)	$-0.0214^{***}$ (0.0048)	-0.0183*** (0.0068)
Housing characteristics	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Postcode fixed effects	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Year and month fixed effects	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Observations	3,389,780	$1,\!488,\!276$	710,703	290,002
$R^2$	0.92	0.92	0.92	0.92

TABLE 3 – AVERAGE EFFECT OF WIND TURBINES ON HOUSE PRICES (Dependent variable: the logarithm of house prices)

Notes: This table is based on data between 1985 and 2019. Standard errors are clustered at the neighborhood level and are in parentheses. Significance levels: \*\*\* p<0.01, \*\* p<0.05, \* p<0.10.

In columns (2) and (3) we change the control group to include transactions within 3-5km and 2-3km of a wind turbine, respectively. The effect becomes a bit higher; -2.5%, using the 3-5km control group and -2.1% in case of the 2-3km control group. The fact that the effect we find is relatively robust and remains statistically significant even with a substantially smaller sample and different control groups suggests that it is plausible we are capturing a causal effect of the opening of wind turbines on house prices.

Finally, we estimate a version of equation (1) which is based on the sample of transactions within 2km of all existing wind turbines in 2019. That is, we measure the effect conditional on the placement of wind turbines in particular areas. This should capture any selection effect concerning the location of wind turbines. The regression estimate in column (4) shows that house prices within 2km of a wind turbine decrease by 1.8% *relative* to areas in which a wind turbine has not yet been constructed. The effect is statistically significant at the one percent significance level. We consider this to be strong evidence that wind turbines affect nearby house prices.<sup>15</sup>

of highly detailed PC6 fixed effects.

<sup>&</sup>lt;sup>15</sup>In principle, this specification is equivalent to a difference-in-differences model that allows for non-parallel trends between the control and treatment groups. In Appendix A.3 we show that a classical difference-in-differences (DID) model based on the model estimated in column (3) (2-3km control group), but allowing for such non-parallel trends indeed yields identical point estimates. Only the standard errors are (marginally) smaller as they are (artificially) lowered by adding the control group transactions. We, therefore, prefer the results reported in Table 3, column (4).

#### 5.2 Robustness checks

In Appendix A.3, we discuss several sensitivity analyses concerning the results. First, we estimate a repeat sales model, which conditions out all time-invariant housing and location characteristics by differencing prices between pairs of consecutive transactions of the same house. The estimated coefficient is still very close to the baseline estimate suggesting that the detailed location fixed effects we have used before seem to capture unobserved housing and location characteristics well.

Second, we test whether anticipation effects are important. Such anticipation effects may arise because house prices already adjust before the construction of a turbine, e.g. because the planning phase may take several years. We show that the treatment effect controlling for any anticipation effects is -2.1%. The effect is still statistically significant at the one percent significance level. Prices start to decline about 3 years before the opening of a turbine.

Third, we investigate whether regional trends may be correlated with the placement of turbines. We estimate a specification with travel-to-work-area (TTWA) fixed effects interacted with time trends. The treatment effect remains very stable (*i.e.* it is -2.1%).

Fourth, we examine wind turbine removals and show that house prices increase by 1.1% if a turbine is removed. However, due to a low number of removed turbines, the estimate is somewhat imprecise and not statistically significant at conventional levels.

Fifth, we study the effect of multiple turbines. We show that it is particularly the first turbine that has an effect on house prices. When more turbines are built within 2km turbines, the additional turbines generally have a negative effect but the effect is less than 1% and statistically insignificant. From a policy perspective, these results imply that to reduce external effects on house prices it is best to cluster turbines in wind farms.

Finally, one may be concerned that the perception regarding wind turbines may have changed. We, therefore, test whether the willingness to pay to live nearby turbines is constant across the study period. It appears that we cannot reject the null hypothesis that the effect is constant over time.

#### 5.3 Demography and sorting

One may wonder what type of households are the most affected by the placement of wind turbines. We explore this in Appendix A.4, where we gather data from Statistics Netherlands on various demographic characteristics at a very spatially disaggregated postcode 6-digit level. The results do confirm that turbines are built in sparsely populated areas with about 30% lower population densities. Interestingly, we find that the median income is only 2% lower within 2km of a turbine. Hence, the households that are affected are not necessarily those at the lower end of the income distribution. Moreover, the share of people receiving income assistance is the same between treated and untreated areas.

Finally, we further investigate whether preference-based sorting occurs after the placement of a wind turbine. We find small effects changes in population density, household size, and the share of foreigners after a wind turbine is placed. Although statistically significant, these effects are economically small. Hence, we do not find evidence that the demographic composition changes considerably after turbine construction.

#### 5.4 Wind turbine height

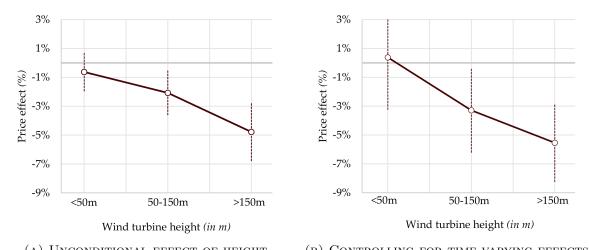
Up until now, we have ignored the effect of turbine height and assumed that the effect of turbines is confined to 2km. As shown, turbines have become taller over time, which may, in turn, have exacerbated visual pollution, as well as the potential reach of noise pollution, flickering and shadow. We would expect that this increases the treatment effect and also affects the overall impact radius.<sup>16</sup> We, therefore, estimate several regression based on equation (2), using temporal variation only (see Table 3, column(4)), and show the results in several figures.<sup>17</sup>

In Figure 4a we show that taller turbines indeed have a larger effect on house prices. Small turbines (<50m) on average have an effect of less than -1%. while this effect is not statistically significant. For a medium-sized turbine (50-150m) the effect is around 2% and statistically significant.<sup>18</sup> For turbines taller than 150m the effect is around 5% and also statistically significant, even

<sup>&</sup>lt;sup>16</sup>For example, at a distance of 2km a turbine of 100m in height has a perceived height of 5cm. Instead, a 200m high turbine at that distance has already a perceived height of 10cm. The view of such a turbine might well be less obscured by features of the (urban) landscape.

 $<sup>^{17}</sup>$  The underlying regression table is reported in Appendix A.3.

<sup>&</sup>lt;sup>18</sup>We also considered splitting this category up even further but did not find statistically significant differences between those turbines.



(A) UNCONDITIONAL EFFECT OF HEIGHT (B) CONTROLLING FOR TIME-VARYING EFFECTS *Notes:* The dotted lines represent the 95% confidence intervals. These regressions include observations within 2km of a (future) turbine and control for housing characteristics, postcode fixed effects, as well as year and month fixed effects. The number of observations is 290,002 and the  $R^2$  in both regressions is 0.92.

FIGURE 4 – PRICE EFFECTS FOR DIFFERENT TURBINE HEIGHTS

though the confidence bands are a bit wider due to a lower number of observations.<sup>19</sup> The effect ranges between 3-7% and it is clear that the effect is considerably stronger than the effect of low turbines.

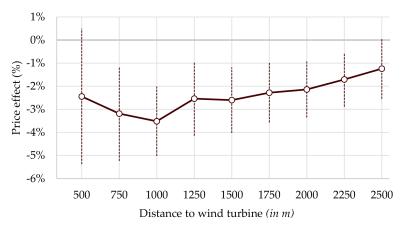
In Figure 4b, we control for time-varying effects of turbines, as to control for any potential changes in perception over time. We find very similar effects for small, medium and tall wind turbines. The effect of a medium-sized turbine is now about -3% and the effect of a tall turbine is also a bit larger and -5.4%. These effects are still statistically significant, but note that the confidence bands are now somewhat wider.

#### 5.5 Impact area of turbines

Distance to a wind turbine is likely an important factor in determining the possible decrease in prices. Within 5 times the axis height there is a possible effect of sound and for the average turbine up to 1km there is also possible shadow. Up to 2km (and beyond), there is potentially visual pollution.

In Figure 5 we, therefore, show a specification where we interact the effect of turbines by 250m distance band dummies. Hence, we estimate the treatment effect for different distance bands. The number of observations increases as we now include housing transaction prices within

<sup>&</sup>lt;sup>19</sup>In the Netherlands, turbines larger than 150m also need to have a flashing light (white during the day, red during the night). This might increase the experienced nuisance and visibility of those wind turbines.



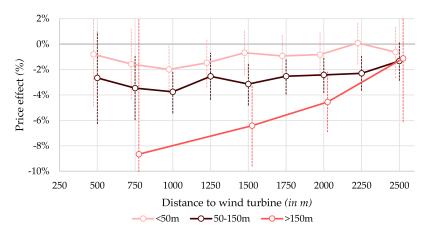
Notes: The dotted lines represent the 95% confidence intervals. This regression includes observations within 2.5km of a (future) turbine and controls for housing characteristics, postcode fixed effects, as well as year and month fixed effects. The number of observations is 491, 337 and the  $R^2$  is 0.92.

FIGURE 5 – WIND TURBINES: PRICE EFFECTS AT DIFFERENT DISTANCES (1985-2019)

2.5km of a (future) turbine. Figure 5 shows that within 500m the confidence bands are large because the number of observations is low. Hence, we cannot precisely determine the effect of the opening of a wind turbine on transaction prices within short distances. Between 500-750m the effect is about -3%. The effect gradually decreases until at 2500m the effect is small and indistinguishable from zero. Hence, the impact area of turbines seems to be maximally 2250m.

Although the average effect across all turbine heights is of interest, it is important to investigate whether the impact area is different for tall turbines. As such, we re-estimate the regression but now allow the effects to vary by wind turbine height *and* distance. Even with this large dataset, the number of observations for tall turbines is small. Hence, we aggregate the distance bins for the tallest turbines by 500m instead of 250m. The results are depicted in Figure 6. Small turbines only have a statistically significant effect of about 2% at 1km and the effect is essentially zero beyond 1km. At 500m and 750m the effects are imprecisely measured.

A turbine with a height between 50 and 150m yields a statistically significant effect of -3.4% at 750m. The effect decreases over distance, but at a relatively low rate. At 2500m the effect is no longer statistically significant. For the tallest wind turbines, the effect is again larger than for small turbines. At 750m the effect is -8.3%, albeit very imprecise due to the low number of observations (within 500m of a turbine exceeding 150m there are even no transactions available). The effect again decreases with distance, but more rapidly, and the effect is small and no longer statistically significant at 2500m. Note that the confidence bands for different



Notes: The dotted lines represent the 95% confidence intervals. This regression includes observations within 2.5km 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 491, 337 and the  $R^2$  is 0.92.

FIGURE 6 – DISTANCE AND WIND TURBINE HEIGHT

heights are overlapping in most cases, except when comparing the largest and smallest turbines, which suggests that measuring the effect of height and distance to a turbine demands a lot from the data.

Overall, our results imply that taller turbines have higher effects on house prices and we find evidence that the effect also reaches just beyond 2km, up to 2250m, but not beyond 2.5km. Moreover, we show that low turbines (<50m) have a small impact on house prices that is confined to about 1km.

#### 5.6 Solar farms and house prices

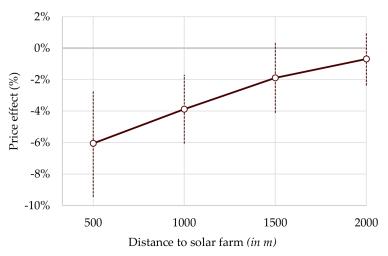
In Table 4 we report results regarding solar farms, based on equation (3). Column (1) shows the effect of the opening of a solar farm within 1km of a home using the full extent of our data. This effect is -3.7% (= (e<sup>-0.0380</sup> - 1) × 100%) and statistically significant at the 1% significance level. However, this specification does not take into account local price trends that may be correlated with the placement of solar farms. Moreover, it is not a priori clear that the effect is confined to 1km.

To take these issues into account, a specification is estimated in column (2) in which the control group are transactions that take place within 2-5km of a solar farm. The effect now becomes -4.6% and it is still highly statistically significant. Finally, in column (3) we decompose the effect for 500m distance bands. In Figure 7 we show that the effect within 500m is -5.9%. It is

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole Netherlands	Control group	Distance	Control group	+ Wind turbine	Temporal
	Netnerianas	2-5km	profile	1-2km	treatment	variation only
Solar farm placed $<1 \mathrm{km}$	$-0.0380^{***}$ (0.0093)	$-0.0469^{***}$ (0.0099)	see Fig. 7	$-0.0263^{***}$ (0.0090)	$-0.0263^{***}$ (0.0090)	-0.0156 (0.0253)
Wind turbine placed $<2km$					0.0018 (0.0166)	
Housing characteristics	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Postcode fixed effects	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Year and month fixed effects	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Observaties	1,470,808	355,235	405,164	62,579	$62,\!579$	12,650
$R^2$	0.90	0.90	0.90	0.89	0.89	0.90

TABLE 4 – AVERAGE EFFECTS OF SOLAR FARMS ON PROPERTY PRICES (2009-2019) (Dependent variable: the logarithm of house prices)

*Notes:* This table is based on data between 2009-2019. Standard errors are clustered at the neighborhood level and are within parentheses. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.10



*Notes:* The dotted lines represent the 95% confidence intervals. This regression includes observations within 5km of solar farms present in 2019 and controls for housing characteristics, postcode fixed effects, as well as year and month fixed effects. The number of observations is 405, 164 and the  $R^2$  is 0.90.

FIGURE 7 – PRICE EFFECTS AT DIFFERENT DISTANCES, SOLAR FARMS (2009-2019)

-3.8% up to 1km and it approaches zero and is no longer statistically significant beyond 1km. Next, we undertake some robustness checks. In column (4) we consider a more local control group by only including observations within 2km of a (future) solar farm. The estimated coefficient is somewhat smaller: house prices decrease on average by 2.6% after the opening of a solar farm. The effect is highly statistically significant. We consider this estimate as our preferred estimate as it is rather conservative and the control group more local.

Furthermore, it could be argued that the effect of solar farms picks up the effect of wind turbines,

because they might be located close to each other. Hence, we add a dummy indicating whether there is a wind turbine within 2km in column (5). The effect of solar farms is still -2.6%. This is not too surprising as the correlation between wind turbine locations within 2km and solar farms within 1km is only 0.005. The negative effect of wind turbines is statistically insignificant because the sample only includes very few turbines.

Finally, we identify the effect based on variation in the opening dates of solar farms only. The result is reported in column (6). In this case, the point estimate is still -1.5% but the effect is no longer statistically significant. This is not surprising as we include just 12,650 observations in the regression. More importantly, given the standard error, this estimate is not statistically significantly different from our preferred estimate.

We interpret these findings as robust evidence that property values decrease within 1km of solar farms. The coefficient estimates range between -1.5% and -5.9%, depending on the specification. Again, we see the results in column (4) as our preferred model estimate: it takes into account possible unobserved trends and includes enough observations to accurately estimate the effect. The effect is of the same order of magnitude as for turbines, but more localized.

#### 5.7 Overall losses in property values

Given the regression estimates, we can calculate the 'back-of-the-envelope' total loss in housing values as a result of the construction of wind turbines and solar farms in the Netherlands. For wind turbines, we use the estimates that discriminate between the height of a turbine and the distance of a property to the nearest turbine reported in Figure 6. For solar farms, we rely on the estimate reported in column (4) in Table 4.

Using data from BAG (*i.e.* the Building Register) we calculate the number of residential properties in each distance band from each wind turbine and solar farm. Furthermore, we calculate real average house prices (in 2019 prices) within 2km of a wind turbine and 1km of each solar farm using the NVM data. We then multiply the estimated price effects with real prices and the number of residential properties around each turbine or solar farm. Before we move to the results, we caution that the numbers should be interpreted as back-of-the-envelope calculations as we have to make several simplifying assumptions. First, we assume that the relative price decrease estimated for the owner-occupied housing market carries over to the rental market.

	(1)	(2)	(3)	(4)	(5)
		Wind t	urbines		Solar farms
	All	$\leq 50m$	50-150m	$\geq 150m$	All
Total loss in $\in$ (in millions)	4,993	427	3,789	777	800
Average loss in $\in$ per turbine/farm Average loss in $\in$ per MWh	4,153,672 953.14	2,102,069 2,191.89	4,271,443 1033.84	6,939,494 763.82	7,477,965 835.59
Median loss in $\in$ per turbine/farm Median loss in $\in$ per MWh	$140,175 \\ 53.41$	250,599 276.96	$114,562 \\ 34.15$	$116,\!652 \\ 11.30$	1,901,138 364.80

TABLE 5 – WIND TURBINES AND SOLAR FARMS: TOTAL EFFECTS ON HOUSE PRICES

*Notes:* We assume that a wind turbine of 1 MW delivers  $365 \times 24 \times 0.304 = 2,663$  MWh, where 0.304 represents the capacity factor, which we obtain from the Energey Information Agency. A solar farm with a nominal peak power of 1 MWh delivers  $0.85 \times 1,000,000 \times 1 = 0.85$  million kWh.

Second, we assume that the average price effects of turbines and solar farms apply to properties throughout the Netherlands; so we abstract from any heterogeneity in the price effect other than the heterogeneity in distance to and height of the wind turbine. The results are still informative as they point towards the overall economic magnitude of the effect.

The results for wind turbines, reported in Table 5 show that the total loss in housing value is about  $\in 5$  billion, which is substantial.<sup>20</sup>

Because there are so few properties within 500m of a turbine, only 0.7% of the total loss accrues to properties within 500m of a turbine, while 10% of the loss is borne by properties within 1km of a turbine. The average loss per turbine built on land is  $\in$ 4.1 million. The average loss per MWh is about  $\in$ 1 thousand. These results suggest that when placing wind turbines it is important to take into account the additional external costs.

However, the average loss per turbine may be somewhat misleading as most of the total loss is due to a few turbines that are close to residential neighborhoods. More specifically, it appears that just 25 turbines account for almost 50% of the total loss. This shows that it is very important to build turbines not too close to residential properties. Indeed, the median loss per turbine is much lower and about  $\in$ 140 thousand, or about  $\in$ 53 per MWh. Given the construction costs of about  $\in$ 1.27 million per MW, we calculate the median loss in housing values as 16.5% of the construction costs.<sup>21</sup>

<sup>&</sup>lt;sup>20</sup>For comparison purposes, the Dutch GDP was about 725 billion in 2017.

 $<sup>^{21}</sup>$ For each turbine, we calculate the loss per MW. We then take the median of this loss.

Note that the median loss per MWh varies considerably across turbines of different heights. For example, because tall turbines generate more power, the median loss per MWh is about  $\in 11$ , while it is  $\in 277$  for low turbines. Hence, despite the smaller effects of low turbines, the loss in power does not make it more efficient to build low turbines.

Let us now consider the impact of solar farms. Because there are yet much fewer solar farms constructed, the total loss is just over  $\in 800$  million. The *average loss* per solar farm is of the same order magnitude as the external costs of wind turbines. Here it also seems more informative to look at the median loss of a solar farm, which amounts to about  $\in 2$  million, which is considerably larger than the median loss for one turbine. However, this is mainly because solar farms are generally larger and generate more energy. In addition, the median loss per MWh is  $\in 365$ , which is also considerably larger than the median loss of a wind turbine. The reason is that solar farms are often large so that it is hardly avoidable to have a solar farm that is not close to residential properties. Indeed, the median number of properties within 1km is 178, while this is just 3 properties for wind turbines.<sup>22</sup>

These results seem to suggest that – even though the impact areas is smaller – building solar farms does not mitigate the external effects of renewable energy production in comparison to wind turbines, at least given the current spatial distribution and available technology. Still, the large differences between the average and median loss per turbine/solar farm strongly confirm that choosing sparsely populated areas to build turbines/solar farms is important. For solar farms, these areas may be easier to find, as the impact area of solar farms seems to be confined to 1km instead of about 2km for turbines. On the other hand, the land beneath solar farms cannot be used for other purposes, while land close to turbines can be used for crops or livestock farming.

# 6 Conclusions and Policy Implications

Producing energy sustainably is an important step towards a climate-neutral economy with net-zero greenhouse gas emissions. Wind and solar energy are important sources of renewable energy. However, while reductions in  $CO_2$  emissions benefit the whole population, external effects are borne only by households living close to production sites. Hence, insights into these external

 $<sup>^{22}</sup>$ Within 2km of a turbine, the median number of properties is 15.5. This stark difference is also due to regulations that prohibit wind turbine construction close to residential properties.

effects is paramount for renewable energy policy as the size of external effects is informative on whether there is local support for the opening of production sites, such as wind turbines and solar farms. In this study, a panel dataset on house prices between 1985 and 2019 from the Netherlands is used to measure the effect of the proximity of wind turbines and solar farms on property values.

Our results suggest that the opening of a wind turbine decreases local house prices by 1.8%. The impact of turbines does not reach beyond 2250m. It is particularly the first turbine that reduces house prices; hence to mitigate external effects, turbines should be concentrated in wind farms. Moreover, we are particularly interested in the effects of turbine height, as turbines have become much taller over time. For a turbine taller than 150m we find that the effect is on average -5.4%. The impact area is about 2km. Instead, a small turbine below 50m has only a small effect which at most distances is statistically insignificant and quickly dissipates beyond 1km. Thus, turbine height is an important source of heterogeneity in the effect of turbines on property values.

This study also investigates the impact of solar farms on house prices. Due to possible noise disturbance, the reflection of the sun, but also visual pollution, a solar farm can have a negative impact on property values. The effects of this are expected to be more local because these solar farms are less visible than wind turbines; and noise reflection also probably does not reach that far. We find evidence of a decrease in property values of about 2.6% after the placement of a solar farm. This effect is confined to 1km.

Our back-of-the-envelope calculations document that the total loss in house value as a result of wind turbines is about  $\in 5$  billion, which is about equal to the replacement costs. Interestingly, 1% of the turbines account for almost 50% of the loss in housing values. This confirms that the choice where to build turbines is key; to mitigate losses in housing values turbines should be placed in sparsely populated areas. The median loss per MWh produced is  $\in 53$ , but this varies considerably across turbines of different heights. For example, for tall turbines, the median loss per MWh is about  $\in 11$ . This suggests that it is worthwhile to build tall turbines. The median loss per MWh for solar farms is  $\in 365$ , which is much higher than the median loss for wind turbines (but note that the average losses are about the same). Hence, building solar farms instead of wind turbines will not mitigate the external effects of renewable energy production.<sup>23</sup>

<sup>&</sup>lt;sup>23</sup>For future research and renewable energy policy, it would be useful to also compare the results with the

The results in this paper highlight that careful placement of wind turbines and solar farms is paramount as the total loss in housing wealth can quickly increase if turbines and solar farms are built too close to residential properties. We argue that the external costs of wind turbines and solar farms should be taken into account when constructing such renewable energy production facilities and this study clarifies what those potential costs are. However, whether and to what extent homeowners should be compensated for the loss in housing values is a political question. Currently, the Dutch government compensates homeowners for losses in housing values due to area redevelopment exceeding 2% and this will be increased to 4% in 2022. Homeowners are only compensated for a loss in housing value over and above the threshold. We showed that only close to turbines or solar farms, the loss in housing values exceeds 4%, so that this compensation scheme, at least for most homeowners, will be of limited use in the future.

potential negative external effects of other (non-renewable) energy production alternatives.

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# **Online 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.<sup>24</sup> 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

 $<sup>^{24}</sup>$ 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.

et al. (2019) find potentially large effects of visibility in Germany and Greece, respectively. The 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.<sup>25</sup> 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.<sup>26</sup>

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

<sup>&</sup>lt;sup>25</sup>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.

<sup>&</sup>lt;sup>26</sup>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.

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 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.<sup>27</sup>

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).

 $<sup>^{27}</sup>$ Interestingly, they find that gas plants also have a negative effect on house prices and biomass plants have a positive effect.

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 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 ( $\approx \in 8,000$ ). 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 ( $\approx \in 23,000$ ). 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.

		Wind turbines				Solar	farms	
	< 2km		$\geq 2km$		< 1 km		$\geq 1 km$	
	mean	sd	mean	sd	mean	sd	mean	$\operatorname{sd}$
Transaction price	206,654	114,489	214,882	122,333	226,024	100,052	249,790	$124,\!444$
Size in m <sup>2</sup>	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

TABLE A1 – Additional descriptives: wind turbines and solar farms

*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 of

(Dependent variable: the logar	
	(1)
	Non-parallel
	trends
Wind turbine placed $<2km$	$-0.0183^{***}$ (0.0068)
Housing characteristics	$\checkmark$
Postcode fixed effects	$\checkmark$
Year and month fixed effects	$\checkmark$
Treatment group $\times$ controls	$\checkmark$
Observations	710,703
$R^2$	0.92
<i>Note:</i> This table is based on data	from the Dutch Associ-

Table $A2 -$	Non	PARALLEL	TRENDS	DID	MODEL,
	2-3K	M CONTROL	L GROUP		

=

*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.

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

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

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.

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.<sup>28</sup>

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. Conse-

<sup>&</sup>lt;sup>28</sup>The average height of removed turbines is just 77m, while it is 98m for the whole sample of onshore turbines.

	(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	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	
Postcode fixed effects	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	
Year and month fixed effects	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	
Observations	290,002	290,002	290,002	491,337	491,337	
$R^2$	0.92	0.92	0.92	0.92	0.92	

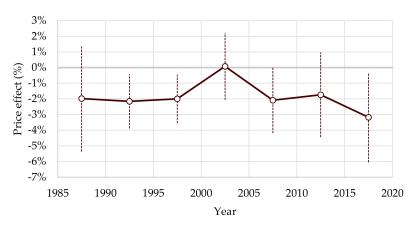
TABLE A4 – TURBINE HEIGHT, IMPACT AREA AND HOUSE PRICES (Dependent variable: the logarithm of house prices)

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.

quently, 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.



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

A possible explanation might be that preferences for turbines are different during a housing 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.<sup>29</sup> 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.

 $<sup>^{29}{\</sup>rm Because}$  we lack recent data, and because most solar farms are built in recent years, we cannot repeat the analysis for solar farms.

TABLE AD - DESCRIPT	ITVES: DE	MOGRAP	HIC VARI	ABLES
	(1)	(2)	(3)	(4)
	Mean	St.dev.	Min	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 $(in \in)$	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

TADLE  $\Delta 5 = Descriptives$ , Democraphic variables

*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.

In Table A5 we report descriptive statistics. We find an average population density of 82.6 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.<sup>30</sup> 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

<sup>&</sup>lt;sup>30</sup>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.

	(1)	(1) (2) (3) (4)			(5)
	Population	Household	Share	Median	Share income
PANEL A: UNCONDITIONAL REGRESSIONS	$density \ (log)$	$size \ (log)$	For eigners	income (log)	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	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
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	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Year fixed effects	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Observations	183,290	169,440	166,821	119,899	20,084
$R^2$	0.9933	0.9014	0.8598	0.8348	0.8893

TABLE A6 – WIND TURBINES, DEMOGRAPHY AND SORTING

*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.

(i.e. -2%). The share of people receiving income assistance is not higher or lower in treated areas (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.