LR Exhibit 7

DISCUSSION PAPER SERIES

DP15023

WIND TURBINES, SOLAR FARMS, AND HOUSE PRICES

Martijn Dröes and Hans Koster

INTERNATIONAL TRADE AND REGIONAL ECONOMICS

ISSN 0265-8003

WIND TURBINES, SOLAR FARMS, AND HOUSE PRICES

Martijn Dröes and Hans Koster

Discussion Paper DP15023
Published 10 July 2020
Submitted 08 July 2020

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

WIND TURBINES, SOLAR FARMS, AND HOUSE PRICES

Abstract

To cope with the increasing demand for renewable energy, wind turbines have become taller over time. In addition, with advances in solar cell technology the commercial exploitation of solar farms has increased considerably in recent years. This paper adds to the existing literature by examining 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 (>150m) decreases house prices within 2km by 5.4%, while a small turbine (<50m) has an effect of 2% at most and the effect quickly dissipates after 1km. Further results indicate that solar farms seem to lead to a decrease in house prices within 1km of about 2-3%. By comparing the overall impact on house prices, we show that 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

Martijn Dröes - m.i.droes@uva.nl
University of Amsterdam

Hans Koster - h.koster@vu.nl
Vrije Universiteit Amsterdam and CEPR

Acknowledgements
The paper benefited from a research grant from the Dutch Ministry of Economic Affairs and Climate Policy. We thank Brainbay for providing data from NVM on housing transactions. We thank Jos van Ommeren and several members of a discussion group organized by the Ministry of Economic Affairs and Climate Policy for thoughtful comments on a previous version of this paper.

Wind Turbines, Solar Farms, and House Prices*

Martijn I. Dröes[†] Hans R.A. Koster[‡]

June 26, 2020

Abstract

Abstract — To cope with the increasing demand for renewable energy, wind turbines have become taller over time. In addition, with advances in solar cell technology the commercial exploitation of solar farms has increased considerably in recent years. This paper adds to the existing literature by examining 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 (>150m) decreases house prices within 2km by 5.4%, while a small turbine (<50m) has an effect of 2% at most and the effect quickly dissipates after 1km. Further results indicate that solar farms seem to lead to a decrease in house prices within 1km of about 2-3%. By comparing the overall impact on house prices, we show that building solar farms rather than 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.

*The paper benefited from a research grant from the Dutch Ministry of Economic Affairs and Climate Policy. We thank Brainbay for providing data from NVM on housing transactions. We thank Jos van Ommeren and several members of a discussion group organized by the Ministry of Economic Affairs and Climate Policy for thoughtful comments on a previous version of this paper.

[†]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, and affiliated to the Centre for Economic Policy Research.

1 Introduction

Renewable energy is on the rise. While global demand is still strongly increasing amidst the Covid-19 pandemic, the demand for fossil fuels has actually strongly declined (IEA 2020). Furthermore, the current 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 more locally and could be a viable alternative to fossil fuels.

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 EU 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 to wind turbines becoming taller over time, as taller turbines produce more energy. Where turbines in the 1980s were still around 30m the newest generation of wind turbines are currently well above 100m.[1]

In addition, a relatively new phenomenon is the commercial production of renewable energy via solar farms, which are large fields of solar panels. The first solar farm was constructed in 1982 in California. Yet, with advances in technology, it has only become attractive to commercially exploit solar farms in the last decade or so. Many countries, like India, China, and the United States have heavily invested in very large solar farms.[2]

In 2019, the renewable energy capacity captured 27% of total electricity production with solar photovoltaics (including self-consumption) 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).

[1] 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. As we will explain later, turbine height is defined as the axis height plus half the diameter of the rotor blades.

[2] Currently, the largest solar farm in the world is 40km^2, located in Bhadla, India.

Yet, wind turbines and solar panels may have external effects on local residents. Wind turbines make noise, cast shadows, and create flickering. Moreover, they can visually pollute the local landscape, which particularly may hold for tall turbines. 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 important as to gain insight in the optimal allocation of renewable energy production facilities. Moreover, as housing wealth constitutes a large part of overall wealth and the effect of wind turbines and solar farms is arguably local, the effect on house prices is indicative that the burden of renewable energy production may not be distributed equally within society.

The aim of this paper is to examine the effect of wind turbines and solar farms on house prices. We contribute to the existing literature in several ways. First, this is the first paper that 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 sizes on house prices. Some studies find average effects of turbines up to 14%, while others do not find any effect at all (see for a more elaborate discussion, Section 2). Besides other differences in *e.g.* sample composition and identification strategies, a potential explanation for the differences in the results is that previous studies did not take into account that large turbines may lead to substantially larger decreases in housing values.[3]

Second, to identify a causal effect of renewable energy production facilities on house prices is not straightforward, as the spatial distribution of wind turbines and solar farms is not random; turbines and solar farms are mostly located in sparsely populated areas with lower house prices. To the extent one does not adequately address omitted variable bias, one is predisposed to mismeasure the impact of turbines and solar farms on house prices. To mitigate endogeneity concerns many studies use some form of a differences-in-differences design (Gibbons 2015, Dröes & Koster 2016, Jensen et al. 2018). A key identifying assumption is that there are *parallel trends* between treated and control areas (for a more elaborate discussion see Bertrand et al.

[3]Using data on recent years enables us to test this explicitly, as there are simply many more tall wind turbines than in the past.

2004, Abadie 2005, Donald & Lang 2007), which may be restrictive and is an assumption that is hard to test. Instead, we improve on the literature by *only* exploiting temporal variation in the openings of turbines and solar farms. That is, we compare price changes in areas that have received, for example, a wind turbine to areas which will receive a turbine in the future. Unobserved price trends are most likely very similar in those areas.

Third, to the best of our knowledge, we are among the first to investigate the impact of solar farms on house prices. We use essentially the same identification strategy as for wind turbines. 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. We will further compare the overall loss in house values for homeowners as result of wind turbines and solar farms.

This paper relies on a 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 therefore provides an ideal study area to examine the effect of wind turbines and solar farms on house price as many turbines/solar farms are located close to residential areas and we thus observe many housing transactions in those areas.[4]

The results in this paper show a decrease in house prices after the construction of a wind turbine within 2km of a property of 1.8%, on average. This effect is slightly higher than the 1.4% found by Dröes & Koster (2016), which was based on a differences-in-differences set-up with spatially differentiated local control groups. We hypothesize that an explanation for the increase in the effect is the fact that turbines have become taller. Indeed, we find that a turbine taller than 150m decreases prices within 2km by 5.4%, while the effect of low turbines (<50m) is, *on average*, statistically indistinguishable from zero. We further find that turbines have larger effects when properties are close. We do not find evidence that the effect of tall wind turbines reaches beyond about 2km, although we do find some evidence that the impact radius is smaller (<1km) for low wind turbines. In particular, we observe a negative and statistically significant effect between 0.75 and 1km of about 2%, but the effect dissipates beyond 1km. Various additional robustness checks support the main findings.

[4]The Netherlands is more than twice the size of the San Francisco Bay Area but has a comparable population density (488/km^2 versus 430/km^2, respectively).

Regarding solar farms, our results suggest that house prices decrease by about 2-3% after the opening of a solar farm within 1km of the property. Hence, the effect is indeed more localized than that of wind turbines. As mentioned, solar farms are also a relatively new phenomenon, implying that we have much fewer observations on solar farms. Using a design with local control groups, we find that the effects are only weakly statistically significant, and therefore should be interpreted with caution. When only relying on temporal variation in the placement of solar farms, the effect is still negative and of the same order of magnitude, but imprecisely estimated.

Finally, we compare the results and show that the total loss in housing values as a result of the placement of wind turbines is about €4.5 billion, while solar farms imply a total loss of €84 million. The number of properties in the vicinity of turbines and solar farms is paramount, as 1% of the turbines cause about 45% 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 €89. However, the loss varies considerably between turbines of different heights, with taller turbines having a much lower median loss per MWh (€844 for a turbine <50m versus €10 for a turbine >150m). Hence, it seems much more efficient to build taller, more powerful, turbines. We find that the losses of solar farms are of the same order of magnitude, as the median loss per installed MWh is €63. Hence, building solar farms instead of wind turbines does not seem to be a way to avoid external effects of renewable energy production.

The remainder of this paper is structured as follows. Section 2 provides a literature overview on the effects of wind turbines and solar farms on property prices. Section 3 and Section 4, respectively, discuss the data and methodology used in this study. Section 5 highlights our key regression results and Section 6 concludes.

2 Wind turbines, solar farms, and house prices

2.1 Wind turbines and housing values

Major interventions in the landscape or the living environment almost always lead to changes in house prices. This is because households' preferences capitalize into house prices. Let us consider a simple example: imagine a potential buyer comparing two nearly identical homes; one is at some point near a wind turbine, while the other is far away from a turbine. The difference in price of the home then measures the willingness to pay to *not* live near a turbine. This price difference is conditional on hedonic characteristics (*i.e.* house and location attributes).

In the literature that use hedonic pricing methods, there are already a host of studies looking at the effects of wind turbines on housing prices. 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) focuses 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) focuses on wind turbines in Massachusetts. None of these studies find a statistically significant effect of wind farms on house prices. For the Netherlands, a study by Van Marwijk et al. (2013), which only looks at four research locations, finds no unequivocal effects.

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) finds a point estimate of -2.4% in house prices within 2.5km. However, they focus on just 10 turbines in Rhode Island. The estimated effects are therefore imprecise. Similarly, Vyn & McCullough (2014) uses data of one wind farm in Canada and finds, not entirely surprisingly, no statistically significant effects, although in some cases the point estimates are negative.

Ladenburg & Dubgaard (2007) does 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 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 a 3-7% reduction due to noise pollution. Vyn (2018) argues that one reason for the different effect sizes may be that there are large spatial differences in the resistance to wind turbines. He finds, for example, in Canada that municipalities where there is a lot of 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.[5]

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%. We think that the difference in results arises from the fact that essentially all of these studies rely on relatively small datasets covering a handful of wind turbines and/or wind farms. 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.

The study by Gibbons (2015) is, however, a good example of a convincing study that links plausible research design to a very large dataset. The study relies 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 locations that are comparable, but where wind farms are not visible. A concern with Gibbons's study is that it does not has 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.

A previous study by Dröes & Koster (2016) relies 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 turbines, they show that house prices decreased 1.4-2.3% within 2km of wind turbine. They also

[5] 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.

provide some suggestive evidence that wind turbine height may matter, but their results did not differentiate in terms of impact radius and were 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.[6]

Another study by Jensen et al. (2018) focuses on Denmark. They find 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 for the Netherlands not including detailed location fixed effects leads to an effect that is considerably higher than when location fixed effects are controlled for.

2.2 Solar farms and housing values

The above-mentioned review indicates that a large number of studies have been undertaken into 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, despite the fact that concerns have been expressed that solar farms may have an impact on property values (Jones et al. 2014).

There is one report 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%. 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.

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 (MWh) of the turbine come from `www.windstats.nl`. We define *turbine height* as the axis height plus half the diameter of the rotor blades.[7] There appears to be a very high correlation ($\rho = 0.918$) between height of the turbine and the power it generates. For example a turbine of

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

[7] Dröes & Koster (2016) use axis height, but the effect of this might be difficult to measure as height and diameter of the blades are likely highly correlated (*i.e.* there are no high turbine with tiny blades).

3MW (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.[8] 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 the wind turbines. The map highlights that wind turbines are often concentrated in windy coastal areas. As coastal areas are different than inland areas, it is important to use local control groups to capture any unobserved heterogeneity. 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. The average towards the end of the sample period is around 140m with a max of 200m. Interestingly, the trend seems to stabilize as of 2016.

The dataset concerning house prices has been provided by `Brainbay`. The data covers approximately 70% of the market. The data mainly contains 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.

The average house price between 1985 and 2019 is €214.178. This is based on more than 3 million transactions (2.7 million homes). The average house price is slightly lower (€206.658) within 2km of an existing wind turbine. That is, wind turbines are not randomly built in the Netherlands. Such selection effects based on house prices are typically taken into account within the difference-in-differences framework. The average distance (of the homes sold) 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 of a wind turbine *after* it is operational (*i.e.* about 150 thousand homes in our dataset).

[8]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 because it is far from the coast.

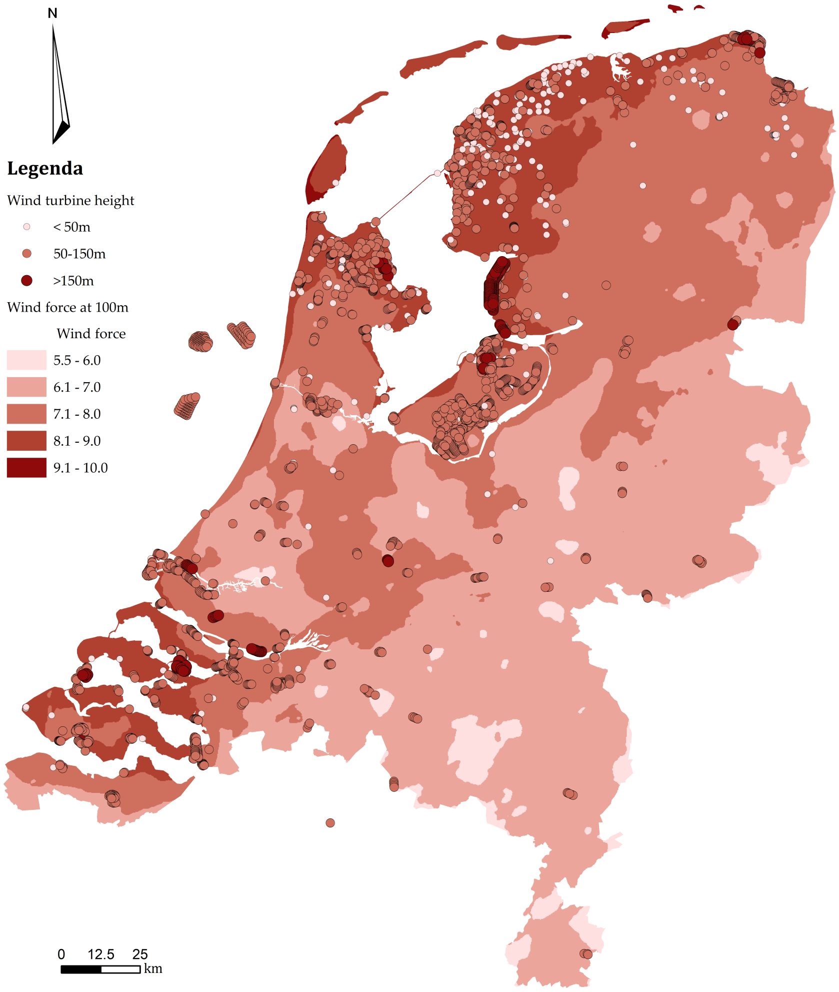


Figure 1 – The location of wind turbines

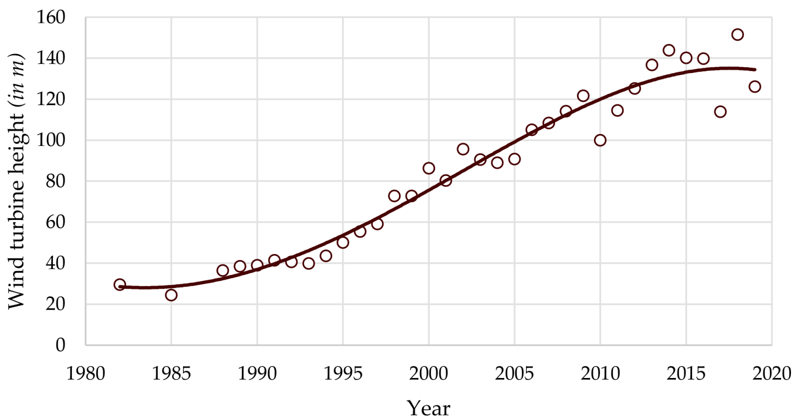


Figure 2 – Average height of new wind turbines

Table 1 – Descriptives: house prices and turbines

	(1) Mean	(2) St.dev.	(3) Min	(4) Max
Transaction price *(€)*	214,180	121,704	25,000	1,000,000
Wind turbine, <2km	0.0506	0.2192	0	1
House size in m^2	117.9	37.71	26	250
Number of rooms	4.384	1.340	1	25
Terraced	0.317	0.465	0	1
Semi-detached	0.281	0.449	0	1
Detached	0.128	0.334	0	1
Garage	0.331	0.471	0	1
Maintenance state is good	0.866	0.341	0	1
Central heating	0.891	0.312	0	1
Listed building	0.00618	0.0784	0	1
Construction year 1945-1959	0.0717	0.258	0	1
Construction year 1960-1970	0.150	0.357	0	1
Construction year 1971-1981	0.169	0.374	0	1
Construction year 1981-1990	0.138	0.345	0	1
Construction year 1991-2000	0.126	0.332	0	1
Construction year >2000	0.109	0.311	0	1

Notes: The number of observations is 3,389,903. Apartments are the reference group for the type of residence. Houses build before 1945 are the reference category for the building year.

3.2 Data on solar farms and housing values

The data on solar farms come from Wikipedia. We have double checked and supplemented these data through various internet sources. Importantly, we disregard solar panels on roofs of industrial or agricultural buildings and only consider land-based solar farms. The number of solar farms (48) included in the analysis is much lower than the number of wind turbines.

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 location of the solar farms are clearly 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 $1km^2$) with a total nominal peak power of 109 MWP. This is approximately $0.85 \times 1,000,000 \times 109 = 92$ million kWh per year (see Tenten Solar 2019). For comparison purposed, an (average) wind turbine of 3 MW delivers around 8 million kWh; the park is therefore roughly equal to 14 wind turbines. It appears that new solar farms generally contain more panels, so the size of solar farms has increased over time.

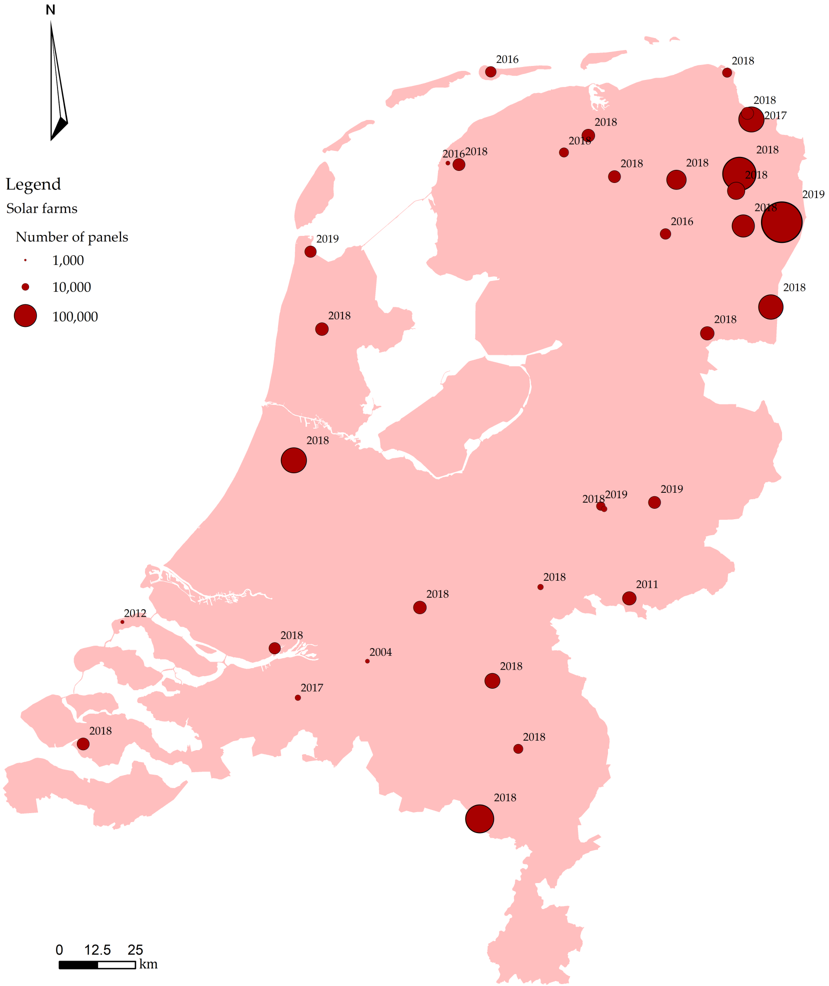


Figure 3 – The locations of solar farms (until mid-2019)

The property price data that is used to measure the effect of the placement of solar farms on property prices are the same as that of wind turbines and are also from Brainbay. Based on the location of the centroid of solar farms and the location of housing transactions, the distance between homes and the the nearest solar farm can be calculated. Note that we have no information about the precise size of a solar farm. Hence, if a solar farm is very large, a home can be far from the centroid, but still close to a solar farm if the solar farm is large. The distance to the centroid is therefore an overestimate of the actual distance to a solar farm. This type of measurement error will typically imply that we will underestimate the actual effect of

Table 2 – Descriptives: house prices and solar farms

	(1) Mean	(2) St.dev.	(3) Min	(4) Max
Transaction price *(€)*	249,586	124,274	25,000	1,000,000
Solar farm <1km	0.00017	0.0132	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

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

solar farms.

Although the first solar farm was opened in 2004 we do not observe transactions within 1km radius after the opening of this solar farm. The majority of the solar farms (40), were opened in 2017, 2018 and 2019. Given that the data in this study runs until mid-2019, it is clear that the impact of solar farms on house prices can only be measured to a limited extent. 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 €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 1.4 million. For solar farms we initially assume an impact radius of 1km. However, there is no clear guideline with regard to the impact area of solar farms; and there is no particular reason why the effect should extend beyond 1km. Unfortunately, there are hardly any observations left at 500m, but even at 1km the number of transactions after installing a solar farm is very limited: we only observe 256 transactions (0.017% of the data) within 1km *after* the placement of a solar farm.

4 Methodology

4.1 Measuring the price effect of wind turbines

To measure the effect of wind turbines on house prices, we employ a hedonic price method in which the house price is regressed on the presence of a wind turbine in year preceding the transaction:

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

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 a year *after* placement of a wind turbine (for now we focus on the nearest wind turbine), X_{it} are housing characteristics, λ_j are location fixed effects at the postcode 6-digit level (about a half a street and on average just over 20 households), λ_t are monthly time dummies, ϵ_{it} contains characteristics of properties or locations that are unobserved. These are assumed to be uncorrelated with the placement of a turbine.

It is important to correct for housing characteristics because different types of homes may be sold in each year or because certain types of homes are more often located closer to wind turbines. A possible relative decrease in value could then be mistakenly attributed to the placement of a wind turbine. Correcting for average prices between locations is also important via the inclusion of location fixed effects, as wind turbines may be built in locations with lower house prices. Differences in prices may arise because amenities may differ between locations (for example, the presence of schools, etc.). In addition, economic developments can take place at national level that influence house prices (such as those due to economic cycles). This is addressed by including month fixed effect.

We are particularly interested in β. This coefficient measures the percent change in property value relative to a (local) control group. We start our analysis by using transactions in the rest of the Netherlands as 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 because they are, for example, 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. Hence, the identifying assumption is that the placement of turbines *within eventually targeted locations* is uncorrelated to price trends. We think this assumption is reasonable, and much less restrictive than the parallel trend assumption between spatially differentiated treatment and control groups that is usually applied in the literature.

Our particular interest is to allow for heterogeneity in the impact of wind turbines by allowing for low, medium-sized and tall turbines. Low turbines (<50m) account for about 10% of the turbines, medium-sized (50-150m) for about 80% and tall turbines (>150) for about the upper 10%. The specification to be estimated is then:

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

where w_{iht-1} is a dummy that equals one when the nearest turbine falls in height category $h$and is within 2km in $t-1$. β_h are the coefficients to be estimated for each height category.

We will show robustness of the results by examining the impact area of tall, medium-sized, and lower turbines; testing whether the effects of turbines is constant over time; correcting for anticipation effects; examining the effect of wind turbine demolitions; and looking at properties with multiple treatments.

4.2 Measuring the price effect of solar farms

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:

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

where P_{it} is 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 one year after opening of a solar farm (again we look at the nearest solar farm), X_{it} are property characteristics, λ_j are location fixed effects at postcode 6 level, λ_t

Table 3 – Average effect of wind turbines on house prices
(Dependent variable: the logarithm of house prices)

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

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.

are month dummies, and η_{it} again captures unobserved heterogeneity.

We are particularly interested in ζ. This coefficient measures the percent change in property value relative to a (local) control group. The initial control group consists, of all transactions throughout the Netherlands, then of transactions within 2-5km and 1-2km. For robustness purposes, we also estimate the effect using observation within 1km only, but the number of observations is then very low and, therefore, the estimate is expected to be imprecise. Furthermore, we will test the spatial extent of the effect by allowing ζ to differ by distance to a solar farm.

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% ($= (e^{-0.0192} - 1) \times 100\%$). This effect is statistically significant at the 1% significance level. Using the whole of the Netherlands as 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.[9]

In columns (2) and (3) we change the control group to include transactions within 3-5km and

[9] Yet, the equation including controls and fixed effects seem 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 of highly detailed PC6 fixed effects. Other studies that have used such detailed location fixed effects (*e.g.* Dröes & Koster (2016)) have shown that the results are essentially the same as using repeat sales.

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 with regard to location. The regression estimate in column (4) shows that house prices within 2km of a wind turbines decline 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.[10]

5.2 Some robustness checks

Before moving on to the regressions where we allow the effect of turbines to vary by height and distance to the turbine, we aim to show robustness of the estimated average impact of turbines. Table 4 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, it is suggested by Dröes & Koster (2016) that house prices are already decreasing two years prior to the placement of a wind turbine. In column (1), Table 4, we therefore exclude transactions occurring in two year prior the opening of a wind turbine within 2km. The effect is -2.4%, which is indeed slightly higher than the baseline estimate of -1.8%. The effect is still highly statistically significant.

Second, 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

[10] In principle this specification is equivalent to a difference-in-differences model that allows for non-parallel trends between the control and treatment groups, by allowing the year fixed effects and control variables coefficients to differ between those groups. In the Appendix 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 non-parallel trends 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).

Table 4 – Robustness: wind turbines and house prices
(Dependent variable: the logarithm of house prices)

	(1)	(2)	(3)	(4)
	Corrected for anticipation effects	*Removed turbines*	*No closer turbines*	*Multiple treatment*
Wind turbine placed <2km	-0.0240***		-0.0183***	-0.0162**
	(0.0079)		(0.0068)	(0.0076)
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	✓	✓	✓	✓
Year and month fixed effects	✓	✓	✓	✓
Observations	267,576	26,483	289,083	290,002
R^2	0.92	0.91	0.92	0.92

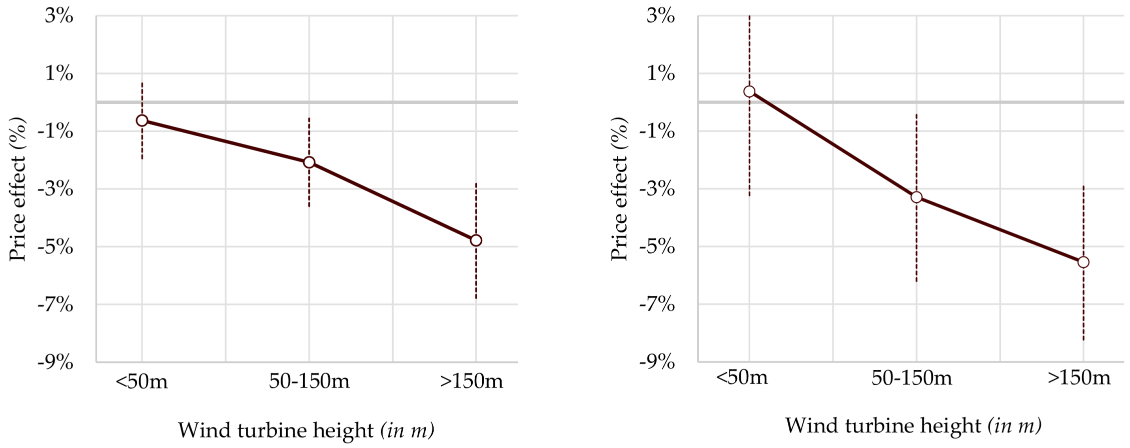
Notes: This table is based on data from the Dutch Association of Realtors (provided by Brainbay) between 1985 en 2019. The same data as in Table 3, column (4) is used although in column (1), (2) and (3) some additional restrictions are imposed. Standard errors are clustered at the neighborhood level and are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

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 be removed and removed ones. Column (2) shows the results. The effect of turbine removals is positive, as expected. Although the coefficient is imprecisely estimated, the point estimate is surprisingly similar to wind turbine construction, in particular because removed turbines are generally smaller.[11]

Third, we focus on the construction of the first wind turbine within 2km. If a wind turbine is built within 2km of a property it could happen that a subsequent turbine is placed even closer. In only 919 of the transactions in our database a wind turbine is placed closer to a house after there was already a turbine within 2km. Not surprisingly, in column (3) we show that the effect remains the same if we exclude those observations.

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

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



(a) Unconditional effect of height (b) Controlling for time 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

quently, column (4) 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 home. From a policy perspective, if the aim is to reduce external effects on house prices, these results suggest that it is best to cluster turbines in wind farms.

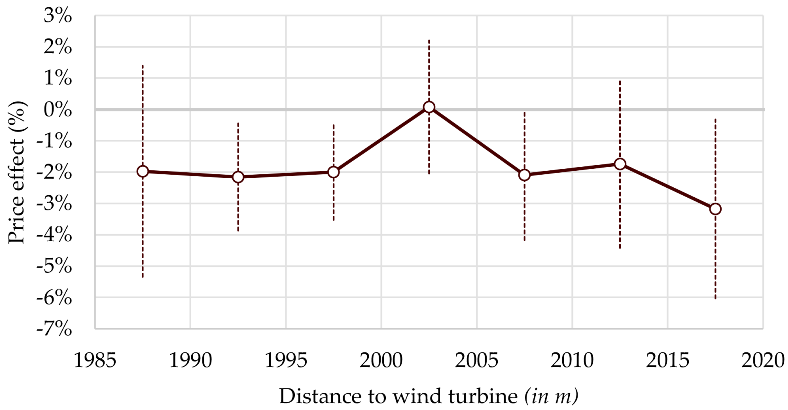
5.3 Wind turbine height

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 increased 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.[12] We, therefore, estimate several regression based on (equation 2). We summarize the results in several figures.[13]

In Figure 4a we show that taller turbines indeed seem to have a larger effect on house prices. Small turbines (<50m) on average have an effect of less than -1%. while this effect is not

[12]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.

[13]The underlying regression table is reported in the Appendix.



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.

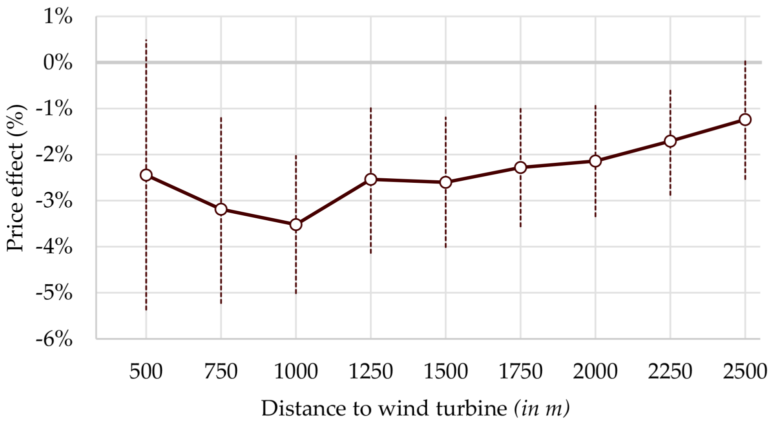
Figure 5 – The effect of wind turbines in different time periods

statistically significant. For a medium-sized turbine (50-150m) the effect is around 2% and statistically significant.[14] For turbines larger taller than 150m the effect is around 5% and also statistically significant even though the confidence bands are a bit wider due to a low number of observations.[15] The effect ranges between 3-7% and it is clear that the effect is considerably stronger than the effect of low turbines.

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

[14] We also considered splitting this category up even further but did not find statistically significant differences between those turbines.

[15] 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.



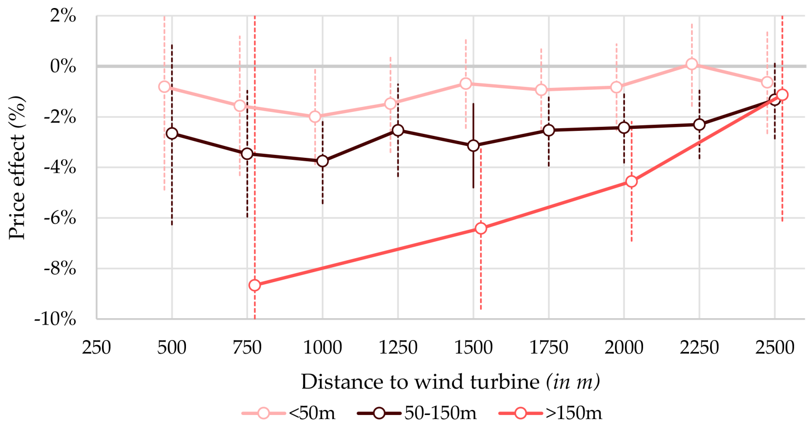
Notes: The dotted lines represent the 95% confidence intervals. This regression includes observations within 2.5km of a (future) turbine and controls for housing characteristics, postcode fixed effects, as well as year and month fixed effects. The number of observations is $491,337$ and the R^2 is 0.92.

FIGURE 6 – PRICE EFFECTS AT DIFFERENT DISTANCES (1985-2019)

Going back to the effect of wind turbine height, in Figure 4b, we control for the time period effects (*i.e.* see Figure 5), as to control for any potential changes in perception. We find very similar effects of 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.

5.4 Impact area of turbines

Distance to a wind turbine is likely an important factor in determining the possible decrease in prices. Dröes & Koster (2016) assume an impact radius of 2km. 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 there is potentially visual pollution. Their results show that indeed up to 2km there is an effect on average across all turbines. In Figure 6 we 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 observations increases as we now include housing transaction prices within 2.5km of a (future) turbine. Figure 6 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 seem to be maximally 2250m.



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 7 – DISTANCE AND WIND TURBINE HEIGHT

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 7. 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 category of wind turbines the effect is again larger than the smaller categories. At 750m the effect is -8.3% albeit very imprecise. 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 heights are overlapping in most cases, except maybe for the largest versus smallest category of 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

Table 5 – Average effects of solar farms on property prices (2009-2019)
(Dependent variable: the logarithm of house prices)

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole Netherlands	*Control group 2-5km*	*Distance profile*	*Control group 1-2km*	*+ Wind turbine treatment*	*Temporal variation only*
Solar farm placed <1km	-0.0609***	-0.0278*	-0.0282*	-0.0318*	-0.0325*	-0.0184
	(0.0163)	(0.0163)	(0.0167)	(0.0170)	(0.0167)	(0.0253)
Solar farm placed 1-2km			0.0173			
			(0.0153)			
Wind turbine placed <2km					-0.0550	
					(0.0380)	
Housing characteristics	✓	✓	✓	✓	✓	✓
Postcode fixed effects	✓	✓	✓	✓	✓	✓
Year and month fixed effects	✓	✓	✓	✓	✓	✓
Observaties	1,470,808	85,329	98,010	15,203	15,203	2,519
R^2	0.90	0.89	0.89	0.87	0.87	0.87

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

to about 1km.

5.5 *Solar farms and house prices*

In Table 5 we report results regarding the impact of solar farms, based on equation (3). Column (1) shows the effect of the opening of a solar farm within 1km of a home compared to the property value development of homes throughout the Netherlands. This effect is approximately -6% and statistically significant at the 1% significance level. However, it is clear that 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 -2.7% and is only statistically significant at the 10% significance level. Column (3) also examines the treatment effect between 1-2km, still using the same control group. The results show that within 1km the effect is -2.8%. The effect is somewhat imprecise and again statistically significant only at the 10% significance level. There is no statistically significant effect at 1-2km (if anything, the effect is slightly *positive*).

Next, in column (4) we consider an even more local control group by only including observations within 2km of a (future) solar farm only. The results are similar: house prices decrease on average by 3.1% after the construction of a solar farm. The effect is again marginally significant.

Furthermore, it could be argued that the effect of solar farms actually pick 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 −3.2% and again marginally statistically significant. This is not too surprising as the correlation between wind turbine locations within 2km and solar farms within 1km is only 0.02. The negative effect of wind turbines is statistically insignificant because the sample only includes very few turbines. Interestingly, the point estimate is larger than the baseline estimate. Looking more closely at the turbines in this sample confirms that these are generally newer and taller turbines.

Finally, we identify the effect based on variation the the opening dates of solar farms only. The result is reported in column (6). In this case the point estimate is still −1.8% but the effect is no longer statistically significant. This is not surprising as now we only include 2,519 observations in the regression.

Overall, these results show that there is suggestive, albeit robust, evidence, that property values decrease by 2-3% within 1km of a solar farms. Hence, the effect is of the same order of magnitude, but more localized than the effect of wind turbines. The number of transactions and homes within 1km is, however, much more limited. Future research, possibly in other countries and at a later date, should determine whether the results found here are robust.

5.6 Overall losses in property values

Given the regression estimates we can calculate the 'back-of-the-envelop' 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 7. For solar farms we rely on the estimate reported in column (4) in Table 5.

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 within 2km of a wind turbine and 1km of each solar farm. Before we move to the results, we caution that the numbers should be interpreted as back-of-the-envelop

Table 6 – Wind turbines and solar farms: total effects on house prices

	(1)	(2)	(3)	(4)	(5)
	Wind turbines				Solar farms
	All	*≤50m*	*50-150m*	*≥150m*	*All*
Total loss in €(*millions*)	4,419	193	3,238	988	84
Average loss in €	3,676,000	948,000	3,651,000	8,819,000	2,808,000
Average loss in € per MWh	923	2,907	923	996	276
Median loss in €	166,000	246,000	145,000	109,000	476,000
Median loss in € per MWh	89	844	45	10	63

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.

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. 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 for wind turbines, reported in Table 6 show that the total loss in housing value is about €4.4 billion, which is substantial. The replacement (construction) cost of 3,506MW installed capacity of wind turbines on land in 2019 is roughly €4.5 billion. So the overall loss in house values is about equal to the overall construction costs. 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 €3.7 million. The average loss per MWh is about €3.5 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 €166 thousand, or about €89 per MWh. Given the construction costs of about €1.27 million per MW, and the median installed capacity of 3MW, the median loss in housing values is about 4.4% of median construction costs.

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 €10, while it is €844 for low turbines. Hence, despite smaller effects of low turbines, the loss in power do 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 €84 million. However, the average loss per solar farm is of the same order magnitude as the costs of wind turbines. Here it also seems more informative to look at the median loss of a solar farm, which amounts to about €0.5 million, which is somewhat larger than the median loss for one turbine. However, this is mainly because solar farms are generally larger and generate more capacity. The median loss per MWh is €63, which is in the same order of magnitude as the median loss per MWh for wind turbines (€89).

Given that the estimates for solar farms are imprecise, these results seem to suggest that when looking at the average loss in housing values per MWh, it does not matter much whether solar farms or wind turbines are constructed. Still, the large differences between the average and median loss per turbine/solar farm strongly confirms 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

Producing energy in a sustainable way 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 benefits the whole population, external effects are borne only by households living close to production sites. Hence, insights into these external effects is paramount as the size of external effects is directly informative on the local support for the opening of production sites, such as wind turbines and solar farms. In this study, a long 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 turbines decreases house prices within 2km by 1.8%, on average. 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 the variation in turbine height may partly explain why different studies find considerably different estimates. Moreover, tall wind turbines become an increasingly common sight in recent years. 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 not statistically significant and the effect quickly dissipates after 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, 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 suggestive evidence of a decrease in property values of on average 2-3% after the placement of a solar farm. This effect is confined to 1km. However, our data shows that the number of property transactions within 1km of solar farms is still very limited, which is mainly because most of these solar farms have only been realized in recent years. The low number of treated observations imply that our estimates are only marginally statistically significant.

Our back-of-the-envelope calculations document that the total loss in house value as a result of wind turbines is about €4 billion, which is about equal to the replacement costs. Interestingly, 1% of the turbines account for about 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 €89, but this varies considerably across turbines of different heights. For example, for tall turbines the median loss per MWh is about €10. This suggests that it is worthwhile to build tall turbines. The median loss per MWh for solar farms is €63, so the losses in housing values are in the same order of magnitude as the median loss for wind turbines. Hence, building solar farms instead of wind turbines does not necessarily seem to be a way to avoid external effects of renewable energy production.

References

Abadie, A. (2005), 'Semiparametric difference-in-differences estimators', *Review of Economic Studies* **72**, 1–19.

Associated Press (2020), 'Germany, Britain call for 'green recovery' from pandemic', *Associated Press Berlin - Online* . https://apnews.com/2272fa23e1a514be5ab7043bdc589959.

Bertrand, M., Duflo, E. & Mullainathan, S. (2004), 'How Much Should We Trust Differences-In-Differences Estimates?', *The Quarterly Journal of Economics* **119**(1), 249–275.

Carter, J. (2011), 'The Effect of Wind Farms on Residential Property Values in Lee County, Illinois', *Preliminary draft, Spring 2011, Illinois State University* .

Castleberry, B. & Greene, J. S. (2018), 'Wind Power and Real Estate Prices in Oklahoma', *International Journal of Housing Markets and Analysis* **11**(5), 808–827.

Daams, M. N. & Sijtsma, F. J. (2019), 'Windparken en Woningprijzen in Groningen en Drenthe', *Rapportage in opdracht van RTV Noord en RTV Drenthe* .

Donald, S. & Lang, K. (2007), 'Inference with Difference-in-Differences and other Panel Data', *Review of Economics and Statistics* **89**, 221–233.

Dröes, M. & Koster, H. (2016), 'Renewable Energy and Negative Externalities: The Effects of Wind Turbines on House Prices', *Journal of Urban Economics* **96**, 121–141.

Eichholtz, P., Kok, N., Langen, M. & Van Vulpen, D. (2018), 'Clean Electricity, Dirty Electricity: The Effect on Local House Prices', *SSRN working paper* .

Gibbons, S. (2015), 'Gone With the Wind: Valuing the Local Impacts of Wind Turbines Through House Prices', *Journal of Environmental Economics and Management* **72**, 177–196.

GWEC (2019), 'Global Wind Report 2018', *Global Wind Energy Council* . https://gwec.net/global-wind-report-2018/.

Hoen, B. & Atkinson-Palombo, C. (2016), 'Wind Turbines, Amenities and Disamenitites: A study of Home Value Impacts in Densely Populated Massachusetts', *Journal of Real Estate Research* **38**(4), 473–504.

Hoen, B., Wiser, R., Cappers, P., Thayer, M. & Sethi, B. (2010), 'Wind Energy Facilities and Residential Properties: The Effect of Proximity and View on Sales Prices', *American Real Estate Society Annual Conference, Naples, Florida, 14-17 April 2010* .

IEA (2020), 'Global energy review 2020', *Report* . https://www.iea.org/reports/global-energy-review-2020.

Jensen, C. A., Panduro, T. E. & Hedemark-Lundhede, T. (2014), 'The Vindication of Don Quixote: The Impact of Noise and Visual Pollution from Wind Turbines', *Land Economics* **90**(4), 668–682.

Jensen, C. A., Panduro, T. E., Hedemark-Lundhede, T., Elberg-Nielsen, A. S., Dalsgaard, M. & Jellesmark-Thorsen, B. (2018), 'The Impact of On-shore and Off-shore Wind Turbine Farms on Property Prices', *Energy Policy* **116**, 50–59.

Jones, P., Hillier, D. & Comfort, D. (2014), 'Solar farm Development in the United Kingdom', *Property Management* **32**(2), 176–184.

Ladenburg, J. & Dubgaard, A. (2007), 'Willingness to Pay for Reduced Visual Disamenities from Offshore Wind Farms in Denmark', *Energy Policy* **35**, 4059–4071.

Lang, C., Opaluch, J. & Sfinarolakis, G. (2014), 'The Windy City: Property Value Impacts of Wind Turbines in an Urban Setting', *Energy Economics* **44**, 413–421.

Maddison, D., Ogier, R. & Beltran, A. (2019), 'The Disamenity Impact of Solar Farms: A Hedonic Analysis', *Work-in-progress presented at UK's Network of Environmental Economics* .

REN21 (2020), 'Renewables 2020 Global Status Report', *REN21* . https://www.ren21.net/reports/global-status-report/.

Science (2020), 'Renewable power surges as pandemic scrambles global energy outlook, new report finds', *Science magazine* . 30-04-2020, https://www.sciencemag.org/news/2020/04/renewable-power-surges-pandemic-scrambles-global-energy-outlook.

Sims, S., Dent, P. & Oskrochi, R. (2008), 'Modelling the Impact of Wind Farms on House Prices in the UK', *International Journal of Strategic Property Management* **12**, 251–269.

Skenteris, K., Mirasgedis, S. & Tourkolias, C. (2019), 'Implementing Hedonic Pricing Models for Valuing the Visual Impact of Wind Farms in Greece', *Economic Analysis and Policy* **64**, 248–258.

Sunak, Y. & Madlener, R. (2016), 'The Impact of Wind Farm Visibility on Property Values: A Spatial Difference-in-Differences Analysis', *Energy Economics* **55**, 79–91.

Tenten Solar (2019), 'Zonnepanelen: van Wp naar kWh'.
URL: *https://www.tentensolar.nl/semi-overheid/dossiers/item/zonnepanelen-van-wp-naar-kwh.html*

Van Marwijk, R., Levkovich, O. & Rouwendal, J. (2013), Invloed van Windturbines op Woningprijzen, Technical report, Agentschap NL, Amsterdam.

Von Möllendorf, C. & Welsch, H. (2017), 'Measuring Renewable Energy Externalities: Evidence from Subjective Well-Being Data', *Land Economics* **93**, 109–126.

Vyn, R. J. (2018), 'Property Value Impacts of Wind Turbines and the Influence of Attitudes toward Wind Energy', *Land Economics* **94**, 496–516.

Vyn, R. & McCullough, R. (2014), 'The Effects of Wind Turbines on Property Values in Ontario: Does Public Perception Match Empirical Evidence?', *Canadian Journal of Agricultural Economics* **62**, 365–392.

Appendix

Table A1 – 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 A2 – 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. 5	see Fig. 4b	see Fig. 6	see Fig. 7
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.