Does the Introduction of Wind Turbines Have an Impact on Surrounding Property Prices?

A Hedonic Difference-In-Differences Approach

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Abstract

The Swedish government has the ambition to increase the usage of renewable energy sources in Sweden. Wind power development is one of many key elements needed to achieve that goal. This thesis has investigated if the introduction of wind turbines in an area have an impact on surrounding property prices. An extensive dataset covering the years 2010-2017 was used, which included 156 082 real estate transactions and 1 011 wind turbines located all over Sweden. Applying a hedonic difference-in-differences approach, our results indicate that property prices decline on average by 2-4% after a wind turbine has been introduced within 2 km of a property. We can also show that the effect increases in strength as the proximity to the wind turbine increases. This thesis contributes with some new insights into this issue, but more research on this topic is needed. Furthermore, our findings do not oppose further wind power development in Sweden. Instead, they illustrate an important issue that may increase in importance as Sweden is transforming its energy production towards renewable energy sources.

Keywords: Generalized Difference-In-Differences, Hedonic Pricing Model, Wind Turbines, Spatial Analysis, Swedish Housing Market.

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1. Introduction

In Sweden, the ambition is to increase the usage of renewable energy sources and decrease our dependence on nonrenewable alternatives, such as fossil fuels. In numbers, this means 50 percent more efficient energy use by year 2030 and 100 percent renewable electricity production by year 2040. The construction of new wind farms is an important part of this process, which will result in an increased dependence on this energy source in the future (Regeringskansliet, 2015).

The majority of all electricity production in Sweden comes from hydropower and nuclear power. Wind power still make up only around 10 percent of the total energy production, despite a marked increase since the 1980s. However, comparing the modest electricity production of 52 GWh in 1986 with 15 479 GWh in 2016 gives you a clear indication of the increased importance of wind power in Sweden (Statistics Sweden, 2016). Furthermore, the increase has been especially strong between 2010 and 2016, with almost a fivefold increase in electricity production from wind during this period (Figure A1 in the Appendix).

Although there has been a large increase in wind power, very little research has been conducted to investigate its impact on surrounding property prices in Sweden. For future wind farm projects, an understanding of the impact wind turbines have on their surroundings is of outmost importance for planning purposes and for answering the concerns among the general public. Several studies abroad have investigated the effects on property prices from the presence of wind turbines, but with various results.

The aim of this thesis is to better understand the economic effects of wind power development in Sweden with regards to its impact on the housing market. Our extensive dataset contains 156 082 transactions between 2010 and 2017 for residential properties located within a 10 km radius of 1 011 wind turbines. The wind turbines in this study were introduced between 2010 and 2017 and includes only land-based wind turbines. To estimate the impact on property prices from wind turbine exposure, a hedonic generalized difference-in-differences approach was applied, relying on the proximity from each sold property to the nearest wind turbine as a proxy for a property's wind turbine exposure. Our initial approach was later extended to include other ways of capturing wind turbine exposure by including multiple treatment effects and heterogeneous treatment effects.

The thesis is structured in the following way: Section 2 will review previous research that addresses the impact on residential property prices from wind turbine exposure, both in Scandinavia and in other countries. Section 3 will discuss the institutional background regarding wind power, such as the various negative environmental externalities[1] caused by wind turbines, the public opinion on wind power and the ownership structure regarding wind turbines in Sweden. Section 4 and 5 will review our hypothesis development, empirical strategy and the composition of our dataset. Our results are displayed in various tables and graphical illustrations, and these will be discussed and interpreted in Section 6. Section 7 concludes the thesis with a discussion of our most relevant findings and their implications, and ends with suggestions for future research within this area.

[1] In this thesis, negative environmental externalities are used as an umbrella term to describe visual disturbance, shadow flicker and noise pollution.

2. Literature Review

Many similar studies have been conducted with the aim of analyzing the effect on property prices from wind turbine exposure, but the evidence for any effect is mixed. This section contains a brief overview of some relevant previous studies that have influenced this thesis.

When trying to capture the impact on property prices, many different methods and approximations for wind turbine exposure have been used. The distance to a wind turbine is sometimes used as a proxy for the wind turbine exposure a property is subjected to. A study by Hoen et. al (2013) in the US applied this approach, but their results indicated no statistical evidence that home values close to a wind turbine were affected post-construction or post-announcement/pre-construction of the turbine. In Sweden, a non-academic study was conducted by Svensk Vindenergi (2010), applying a mixed approach of basic OLS regressions with distance as a proxy for wind turbine exposure, case studies and interviews. The study could not establish any negative relationship between house prices and the presence of wind farms in an area. However, the study did not have access to the same extensive wind farm database that we have and their empirical strategy differed from ours.

Other studies have tried to focus on the actual visual disturbance from a wind turbine and the various ways of assessing this. Lang et al. (2014) applied a hedonic difference-in-differences approach that incorporated both proximity, viewshed and contrast with surrounding development. Their results indicated no statistically significant negative impact on house prices from wind turbines. A similar study was conducted in Germany by Sunak and Madlener (2016). By using a quasiexperimental technique and a spatial difference-in-differences approach, they adopted a quantitative visual impact assessment. Their results indicate that the asking price for properties whose view was strongly affected by the construction of wind turbines decreased by about 9-14%. Properties with a minor or marginal view of the wind turbines experienced no devaluation.

Some studies have tried to make a more detailed assessment of the impact from wind turbines, including different aspects that may affect the amount of exposure a property is subjected to. Dröes and Koster (2016) looked at the effect on property prices in the Netherlands. They applied a difference-in-differences approach where distance, turbine characteristics (such as height, diameter of the blades, shadow areas and direct view) and multiple treatment effects were incorporated. They could show a 1,4% price decline for properties located within 2 km of a turbine. Another attempt to incorporate multiple forms of exposure was conducted in Denmark by Jensen et. al (2014). They tried to achieve a separation between the effects from noise and visual pollution. Their results indicated that wind turbines have a significant negative impact on the price schedule of neighboring residential properties. More specifically, their results indicate that noise pollution reduces the price with between 3% and 7%, and that visual pollution reduces the residential sales price by up to 3%.

3. Institutional Background

This section addresses the institutional setting for wind turbines in Sweden and will focus on the following: the negative environmental externalities caused by wind turbines and how they may affect residents living nearby, the public opinion regarding wind power, and lastly a quick review of the ownership structure for wind turbines in Sweden.

3.1. Visual and Noise Pollution

A wind turbine is a new form of industrial architecture that is different from many other elements in the landscape in terms of height and shape. Due to their size and the constant rotation of their blades, they become a dominating theme of the landscape. In order to be profitable, a wind turbine must be exposed to a lot of wind, and thus they should be located in an open area, and preferable on an elevated spot (Boverket, 2009).

Wind turbines may also give rise to so called shadow flicker and reflection effects. According to a report from Boverket (2009), shadows are noticeable 1,5 km from a wind turbine, but only in the form of a diffuse light change. The authors state that, based on previous experiences, no shadows are visible 3 km away from a turbine. According to a report prepared for the Department of Energy and Climate Change in the UK, 10 times the rotor diameter from a turbine is considered as an acceptable range to assess the impact of shadow flicker (Parsons Brinckerhoff, 2011).

Apart from the visual impact, wind turbines also generate noise. There are two kinds of noise emitted from a wind turbine: mechanical noise from the gear box or generator, and aerodynamic noise from the rotor blades. The aerodynamic noise is the dominant one of the two; mechanical noise is rarely a problem nowadays due to technical improvements. Aerodynamic noise arises when air passes through the rotor blades, generating a swishing sound which is physically very similar to the type of noise generated when wind blows through vegetation (Boverket, 2009). The level of noise is reduced the further away from the turbine you get, since the sound energy is spread out over a larger area. Meteorological conditions, such as air temperature and the wind direction around a wind turbine, are also important to consider when trying to estimate the noise impact. Furthermore, the prevailing soil conditions, with regards to how well the soil absorbs the noise, are also an important aspect to consider. When it comes to wind turbine development, authorities usually set the limit to 40 dB for the amount of noise surrounding residents should be allowed to experience (Boverket, 2009).

3.2. Noise and Health Effects

A related issue to noise pollution is the concerns regarding the health effects it gives rise to. The Swedish Environmental Protection Agency published a report in 2011 that investigates the health effects caused by noise from wind turbines. The report concludes that infra noise (1-20 Hz) generated from a wind turbine is unnoticeable up close, and that residential properties located nearby won't be affected by this. Thus, there are no indications that this type of noise would contribute to disturbance and negative health effects. Low frequency noise (20-200 Hz) from modern wind turbines is often noticeable at the prevalent noise limit target set by authorities for residential property areas. However, the noise generated by wind turbines doesn't contain more low frequency noise than that of other common sources of noise, such as road traffic. Larger wind turbines generate relatively more low frequency noise than smaller ones (Nilsson et al, 2011).

In a survey mentioned in the same report, around 10-20 percent of the residents claimed that they were fairly or very disturbed by noise from wind turbines at noise levels of 35-40 dB. The disturbance was mainly caused by the swishing sound generated from the rotor blades. This noise has a frequency of around 500-1000 Hz, and is not low frequency noise (Nilsson et al, 2011). Despite the documented experiences of disturbance from wind farms, no evident negative health effects have been proven. Furthermore, certain studies indicate a potential correlation between wind turbine noise and reported sleep quality, while other studies have found no such effect. There are also claims that infra and low-frequency noise from wind turbines could lead to serious negative health effects such as vibroacoustic disease or wind power syndrome, but based on a review of previous scientific studies within this area, no evidence of this could be found by the authors of the report (Nilsson et al, 2011). Although there is no clear evidence that low frequency noise from wind turbines pose a risk to local residents, the studies previously conducted have usually been based on turbines of less than 2-3 megawatts. Larger wind farms could deliver slightly higher amounts of low frequency noise (Swedish Environmental Protection Agency, 2017).

3.3. Societal Perspective - Public Opinion

The attitude towards wind power is something that is subjective and varies with both time and place. Usual aspects that concern people are the impact on the landscape, the noise from the turbines, lower property values and the impact on the natural environment. Research shows that people are worried the most about the potential disturbance from a wind turbine before construction, and that the actual level of disturbance once the wind turbine has been introduced is often smaller than expected. However, the amount of disturbance experienced varies a lot of from location to location. For instance, research conducted by Eja Pedersen at Halmstad University, indicates that there is also an interconnectedness between visual pollution and noise pollution in the way that the more visible a wind turbine becomes, the more bothered you become by the noise as well (Boverket, 2009).

In general, the attitude towards renewable energy is positive in Sweden, but the resistance towards a specific project can be significant (Boverket, 2009). In media, resistance towards planned projects are often reported. A recent example can be found in Härnösand, where plans to build two new wind turbines and a complimenting industrial road have raised a lot of concern. In a debate article, destruction of natural beauty, endangerment of flora and fauna, and the importance of the area for the city were raised as arguments for not building the turbines (Ahlström, 2017). In Norrköping, a group of residents expressed their opinions against the plans to build wind turbines in the area. One resident raised concerns about the amount of noise she would be exposed to. She had also made calculations on the amount of shadow she would be exposed to and claimed that during April and May as well as August and September, she would be exposed to 11 hours and 21 minutes of shadow per day. Many of those that had expressed concerns over the building plans worried mainly about the potential disturbance from low frequency noise and shadow flicker (Petersson, 2018). Although potential negative health effects from wind turbines seem to lack tangible scientific evidence, the concerns and discomfort among people about living next to a wind turbine are indeed present.

3.4. The Wind Energy Market in Sweden

The Swedish wind farm industry includes many different types of owners. Table A1 in the Appendix shows the distribution of different owner types in Sweden during 2013. The largest groups of owners are wind power companies and energy companies. Private individuals and economic associations still make up a very small part of the total capacity produced.

3.5. The Role of Landowners

The landowner has a strong position in the process of setting up a wind farm, and in practice it is the landowner that decides if a process is to be taken further. So far in Sweden, the landowners' attitudes have had a huge influence on where wind farms have been constructed.

Competition among wind turbine developers is fierce within areas listed by the municipality[2] as appropriate for wind power. Consequently, developers are actively looking for interested landowners that sit on suitable land for wind power (Boverket, 2009).

When a wind turbine is constructed on someone else's property, it is usually done through a leasing arrangement between the landowner and the future owner of the wind turbine. A wind turbine has a life cycle of 20 years or more, so the leasing arrangement should last for at least 25 years. One way to regulate the leasing fee is that the landowner receives a one-time payment for the intrusion on his or her property in the form of road construction, wirings and so forth. In addition to that, there can also be an annual compensation fee for persistent infringement on the property. The annual compensation is dependent on the amount of electricity produced by the wind turbines, such as a certain amount of compensation to the landowner for each installed megawatt or a certain percentage of the gross revenue generated by a wind turbine (Boverket, 2009).

In a EU-project focused on the financing of renewable energy projects, it was observed that economic benefits seem to be an important factor that can help increase the acceptance of wind power. Boverket (2009) points out that giving people living nearby a wind turbine an opportunity to own a share of it could be one way to create a more positive attitude towards wind power.

[2] Municipality refers to “kommun”. There are 290 municipalities in Sweden.

4. Theory and Methodology

This section covers our hypothesis development and reviews the empirical methods applied in this thesis. The backbone of the thesis is a hedonic pricing model, a method that is used to explain property prices. With the use of this hedonic pricing model, a generalized difference-in-differences approach is applied to investigate if there is a causal effect on property prices after the introduction of a wind turbine.

4.1. Hypothesis Development

Hypothesis 1: ***The presence of a wind turbine in an area is incorporated into the pricing of a property.***

The basic hypothesis underlying hedonic pricing models is that the price of a property can be derived from a willingness to pay for a bundle of characteristics (Xiao, 2017). Any form of increased visual and noise disturbance in an area should therefore, intuitively, impact the characteristics of a property, and thus affect the willingness to pay for it. Based on this background, our belief is that the negative environmental externalities from wind turbines will be incorporated into the pricing of properties.

Furthermore, we hypothesize:

Hypothesis 2: ***The effect on property prices increases as the proximity to the wind turbine increases.***

Thus, we expect the exposure to negative externalities to be more severe the closer a property is located to a wind turbine, implying a stronger effect on property prices.

4.2. Empirical Methodology

4.2.1. The Hedonic Pricing Model

The most commonly applied methods used to evaluate house prices can broadly be divided into two groups: traditional and advanced methods. Examples of traditional methods are the comparative method, the contractor's method, the residual method, the profits method and the investment method. Advanced methods include hedonic price modeling, artificial neural networks, case-based reasoning and spatial analysis methods. Out of these methods, the hedonic pricing model is the most commonly applied (Xiao, 2017).

The hedonic pricing model has the benefit of allowing the entire house expenditure to be broken down into individual components (Sirmans et al., 2005). The price of interest in this thesis is the price of a residential property. The hedonic pricing model can be defined in the following way:

$$Price = f(Physical\ Characteristics, Other\ Factors).$$

The equation above illustrates that the price of a house is a function of physical characteristics, such as size, location, various amenities and so forth, and other factors such as school quality and external factors (Sirmans et al., 2005). Determining variables in empirical studies have generally been grouped into four different subsets: structural attributes, locational attributes, neighborhood attributes and environmental attributes. Environmental attributes describe environmental quality and environmental amenities, such as air pollution, noise and aesthetic views (Xiao, 2017). It is the changes in environmental attributes that are of concern in this study, mainly in the form visual pollution, noise pollution and shadow flicker caused by wind turbines.

4.2.2. The Generalized Difference-In-Differences Model

In this thesis, we will adopt a difference-in-differences methodology to investigate if there is a causal effect on property prices after a wind turbine has been introduced in an area. This methodology is useful when data varies by state and time, and if you want to measure the effect from an intervention that will occur in only one of two different groups of observations (Cook et al., 2015).

The group exposed to the intervention is commonly referred to as the treatment group, while the group of observations that are not exposed to the intervention is often referred to as the control group. The classic difference-in-differences estimator is the difference between before and after differences for these two groups. For this thesis, this implies before and after differences for properties considered treated, and before and after differences for properties that belongs to the control group. A property is defined as treated after the construction of a wind turbine and if it is within a certain distance from this turbine. The idea behind this approach is that a simple pre-post design could lead to biased results due to unobserved factors that affect outcomes and that changed along with the treatment. If the unobserved factors also affected the control group of properties, the double differencing can isolate the treatment effect by removing the bias (Cook et al., 2015).

Since the wind turbines in our sample are located all over Sweden, properties will form several groups as they are clustered around the wind turbine closest to them.

Furthermore, since the wind turbines are introduced at different points in time, we are dealing with several dates of treatment happening around different wind turbines. The difference-in-differences approach can easily be applied to situations as the one mentioned above, with multiple groups and multiple time periods (Cook et al., 2015). This generalized difference-in-differences approach is the method used in this thesis.

The starting point is the standard difference-in-differences model, illustrated in the equation below:

(1) $$lnP_{it} = \beta * treatment_{it} + \eta * \delta_i + \nu * \sigma_t + \theta_t + \varepsilon_{it}$$

lnP_{it} is the natural logarithm of the price of property i at time t. θ_t are time (year-month) fixed effects, which are included to capture inflation in property prices. δ_i is a dummy variable that equals 1 if property i is within r km of a turbine, and 0 otherwise, and σ_t is a dummy variable that equals 1 if property i has been sold after a wind turbine has been introduced, and 0 otherwise. In practice, this means that a property is also treated if it is sold at the same date as the wind turbine was introduced. ε_{igt} is the error term. Our difference-in-differences estimator is $treatment_{it}$, which is formed by interacting δ_i and σ_t. Essentially, it is a variable that takes on the value 1 after a wind turbine is introduced within a r km radius from property i at time t, and 0 otherwise. β is the coefficient of interest, since it measures the effect of the construction of a new wind turbine. In Section 6, we will initially set $r = 2$, and then validate this choice. We will also test for $r = 1$ and $r = 3$ in our robustness checks. The remaining properties that are located outside the treatment range or in an area that has not yet received a wind turbine, would form the control group. In order to restrict our sample to the properties within a reasonable range of each wind turbine, we initially include properties within a 10 km radius of each wind turbine. This would give us a large control group to test out our model.

In equation 2, our model is extended to incorporate various control variables. X_{it} is a vector of control variables for property, demographic and environmental characteristics, which are described more in detail in Section 5.

(2) $$lnP_{it} = \beta * treatment_{it} + \eta * \delta_i + \nu * \sigma_t + \gamma' X_{it} + \theta_t + \varepsilon_{it}$$

In order to take time-invariant unobserved locational differences into account, 5-digit zip code fixed effects are included equation 3, labeled as a_g. Furthermore, we will introduce an interaction between market and time fixed effects, described more in detail in Section 6. In our robustness checks, we will estimate the impact from turbines on property prices in a repeat sales model. This will enable us to include property-specific fixed effects that will take into account all unobserved time-invariant property attributes (Lang et. al., 2014).

(3) $$lnP_{igt} = \beta * treatment_{it} + \eta * \delta_i + \nu * \sigma_t + \gamma' X_{igt} + a_g + \theta_t + \varepsilon_{igt}$$

In equation 4, we also estimate a model where the amount of properties included are restricted to a smaller radius of 4 km, which will make our control group more concentrated, and to a larger extent take local trends into account. The more precisely we can identify the cut off distance for treatment, the more we can restrict our sample and reduce bias from omitted variables (Dröes & Koster, 2016).

(4) $$lnP_{igt} = \beta * treatment_{it} + \eta * \delta_i + \nu * \sigma_t + \gamma' X_{igt} + a_g + \theta_t + \varepsilon_{igt} \leq 4 \text{ km}$$

We hypothesized that the effect on property prices increases as the proximity to a wind turbine increases. To investigate treatment cut-off points and to clearly illustrate the treatment effect over various distances, we created 1 km distance bands up to 3 km, where the 3 km to 4 km band was defined as the reference category. In this model, $treatment_{itd}$ takes on the value 1 after a wind turbine is introduced at time t and within the distance band d from property i, and 0 otherwise. We estimate:

(5) $$lnP_{igt} = \sum_d \beta_d * treatment_{itd} + \eta * \delta_i + \nu * \sigma_t + \gamma' X_{igt} + a_g + \theta_t + \varepsilon_{igt} \leq 4 \text{ km}$$

To validate our model and the assumptions behind it, we will extend it in Section 6, partly by testing for different treatment and control groups, fixed effects and interactions. Our model will also be extended by testing for heterogeneous treatment effects in the form of noise, shadow flicker and different turbine characteristics.

4.2.3. Miscellaneous Methodological Issues

This section contains a review of our definitions of treatment and the potential issues with our methodology and measurements.

4.2.3.1. Visual Pollution

In this thesis, the distance from a wind turbine functions as a proxy for a property's exposure to visual pollution. Certain wind turbines may be located fairly close to properties, but could still not be visible due to various local conditions, such as a very elevated terrain or other forms of obstacles that may obfuscate the view. However, since the majority of the turbines are very tall and located in open spaces, this problem may be of small significance for properties located close to a turbine. It would be preferable to visit each wind turbine, and on site try to evaluate how visible a turbine is from each property by using some form of qualitative ranking. However, due to both limited resources and time constraints, this was not possible for us to implement. Another approach would have been to make use of street view functions from map providers such as Google. However, the vast majority of the images available are too old to be of use to us, since they were taken before most turbines were introduced. Furthermore, most of the turbines are located on the countryside, where street view images are less available. Based on the discussion above, we deem distance to be an adequate proxy for visual pollution.

4.2.3.2. Noise Pollution

Furthermore, as described earlier, a wind turbine can also be a form of distraction due to noise pollution. Estimating noise pollution is not an easy task and would involve a subjective assessment of the exposure a certain property would experience. In order to account for noise pollution in our model, we manually adjusted each 10 km radius to capture only the properties located in the same direction from the wind turbine as the prevalent wind direction in the area. To be more specific, if the prevalent wind direction is from south west, properties located north east of the turbine would be considered exposed to both visual and noise pollution. With this approach, our aim was to create a contrast between properties that are only exposed to visual pollution and properties that are exposed to both visual pollution and noise pollution. However, our measure of the amount of noise exposure a property is exposed to is a rough approximation. In order to make more precise measurements, one would have to include more complex calculations that relies on more accurate assumptions and wind turbine data.

4.2.3.3. Exposure to Shadow Flicker

Sweden is located in the northern hemisphere, and thus, presumably, properties located to the north of each turbine would have a problem with shadow flicker. Furthermore, to measure how far from a wind turbine shadow flicker occurs, we used a rule of thumb approximation, which was 10 times the rotor blade diameter (Parsons Brinckerhoff, 2011). This generates a flexible radius for each turbine site, and at the same time it keeps us within the 1,5 km radius mentioned by Boverket (2009). However, it is important to bear in mind that this measurement would be a rough approximation of the exposure to shadow flicker.

4.2.3.4. Treatment from Multiple Turbines at Different Points in Time

Another issue arises when a property is treated by several turbines at different points in time. This could lead to a downward bias of the treatment effect, since a property may have been treated previously from a turbine that was introduced earlier but located further away. In more “turbine rich areas”, this problem is more prevalent. In this thesis, we make an approximation and measure the distance from each property to the nearest turbine as of 2017. To be more specific, within each 10 km radius, we measure the nearest distance from each property to the full set of turbines that have been introduced by 2017, and then reduce the dataset with those properties exposed to a turbine constructed before 2010. Since this measure may cause a downward bias to our estimates, we will also conduct a robustness test for this by only using properties exposed to a single turbine within the 10 km radius.

4.2.3.5. Anticipation and Adjustment Effects

One important aspect to consider is the time of treatment. One can distinguish between the time of announcement that a wind turbine or wind farm is going to be constructed, and the actual time of construction. It can take time for all the paperwork to be processed and approved, and potential appeals against the decision to build wind turbines might occur. An illustrative example of the timeline for a wind farm project is the Hjuleberg wind farm project in Falkenberg. The application for a permit was submitted on December 30, 2008. The permit was granted in 2011 and construction commenced in 2013. The wind farm was inaugurated on May 20, 2014 (Vattenfall, 2017).

Our dataset contains only the date of construction, i.e. when a wind turbine actually was introduced into an area. However, since the development of a wind turbine or wind farm can take a fairly long time, one could expect the prices to change slowly over the development process, i.e. there could be anticipation effects before a wind turbine has been built and adjustment effects after the wind turbine has been erected. If there is a gradual price change over time during the development process, our approach of only using the construction date would consequently underestimate the treatment effect, since the accumulated effect overtime would be larger. This issue is of great interest, but since we lack data over announcement dates and the fact that the development process can vary between different wind farm projects, we leave this issue to be investigated in future studies within this area.

4.2.3.6. Local Conditions and Shocks

One could also discuss different regional neighborhood characteristics. For instance, perhaps neighborhoods with higher property prices have inhabitants that are more concerned about the value of their properties, and thus would have easier to lobby against any plans to construct a wind turbine or wind farm in the area. As such, one could also discuss whether areas that are less attractive are chosen for wind farm development. However, the potential differences in property prices between areas will be captured in our model by the incorporation of 5-digit zip code fixed effects.

Another aspect to consider is that our model does not take into consideration other external shocks that occur in the same area and around the same time as a wind turbine is introduced. For instance, prices may go down in an area as a result of a new large building that disturbs the view or a new power line that is built close to a turbine site and around the same time as the wind turbine is being constructed. The cause behind a drop in property prices could then be attributed to this other form of disturbance, and not only from the introduction of a wind turbine or wind farm. However, we deem this issue to be unlikely and of negligible importance.

5. Data

The data for this thesis has been retrieved from several different sources and by using different methods. It can be divided into five different groups: wind turbine data, real estate transaction data, demographic data, environmental data and data retrieved from spatial analysis.

The wind turbine data was obtained from www.vindlov.se, a website that has been developed by around 20 governmental agencies in Sweden with the purpose of providing information regarding wind power in Sweden. Through their service "Vindbrukskollen", extensive information about wind farm projects located all over Sweden can be accessed. Through this service, we were able to obtain data on Swedish wind farms introduced between 1980 and 2017. The data retrieved contained information about the location of the wind turbines (SWEREF 99 TM coordinates), the date of construction (day, month, year), turbine characteristics (such as height, rotor blade diameter and annual electricity production) and if the turbine is land-based or water-based. In this study, we will only focus on land-based wind turbines. Water-based turbines were naturally excluded through our measurement methodology, since the water-based wind turbines were located too far away from the properties in our sample. Due to the availability of housing transaction data, only wind farms constructed between 2010 and 2017 entered our analysis. Regarding the quality of the data obtained from www.vindlov.se, we consider it to be reliable, due to the fact that it is provided by a number of governmental agencies in Sweden. However, we cannot assess the extent of data registration issues, since the dataset contains detailed information about wind turbines that is provided by the operators of the turbines.

Table 1 contains descriptive statistics for the wind turbines included in this study. Observe that not all characteristics are reported for all turbines, and that some of the variables have missing values. Our sample contains 1 011 wind turbines that were constructed between 2010 and 2017. The average construction year is 2013, indicating that fewer turbines have been built during the most recent years. This can be seen in Table A2 in the Appendix, which shows the distribution of the wind turbines by construction year. For example, in year 2017, only 25 of the total 1 011 turbines in our dataset were built. The maximum and minimum axis heights are 12 m and 150 m, respectively, with an average axis height of 96,62 m. The average diameter of the rotor blades is 90,65 m, with a minimum and maximum diameter of 6 m and 126 m, respectively. The average total height of the wind turbines is 140,99 m with a minimum and maximum of 15 m and 201 m, respectively. The average effect is 2,2 MW and the average annual production is 6,28 GWh. Furthermore, the average number of turbines in one single wind farm is 10,94 turbines. This mean is driven by the largest wind farms, where the total amount of turbines can be as many as 116. Thus, to note is the heterogeneity in the different turbine characteristics. In Figure A2 the spatial distribution of wind turbines across Sweden is illustrated.

Table 1
Descriptive Statistics: Wind Turbines

	Number of Observations	Mean	Std. Dev	Min	Max
Construction Year	1011	2013	2	2010	2017
Total Height (m)	998	140,99	31,04	15	201
Axis Height (m)	981	96,62	20,66	12	150
Rotor Diameter (m)	983	90,65	22,46	6	126
Effect (MW)	960	2,20	0,71	0,01	8,5
Annual Production (GWh)	868	6,28	1,99	0,01	12
Number of Turbines in Wind Farm	1 011	10,94	17,64	1	116
Total Number of Observations		1 011			

Notes: The table contains descriptive statistics on wind turbines constructed between 1 January, 2010 and 31 December, 2017. The dataset includes 408 wind farms and 1 011 wind turbines located in the study area. Due to missing values, some variables will contain less observations than the total number of observations.

The housing transaction data was obtained from the real estate transaction site www.booli.se. Since the data was not available for download, but free of charge, it was obtained through web scraping, a method in which content on a website is automatically retrieved by the use of a bot or web crawler (Vargiu & Urru, 2013). The programming language used was Python. We were able to retrieve every transaction in their database between 2010 and 2017, which involved a total of 1 094 172 observations, including also transactions for plots of land. In our analysis, land was excluded since few characteristics were available for this property type in comparison to residential properties. Also, two unspecified property type categories named “Other” and “House” were dropped. The property characteristics obtained from www.booli.se that were used in this study is the location of each transacted property (latitude and longitude), the transaction price of each property in SEK, the property size and plot size in square meters, the property type, and the date of each transaction. These will be described more thoroughly below.

In general, we consider the data obtained from www.booli.se to be reliable. However, when analyzing the data, we discovered some errors caused by data registration issues, such as the variable for property size sometimes taking the value of 1, measured in square meters. Since this data issue was discovered early in the research process, we were able to adjust for this bias by dropping observations showing signs of registration error. Furthermore, since the data was obtained through web scraping, registration errors might have occurred when extracting the information from www.booli.se. However, after comparing samples of the extracted information with the information found on the web page, we consider this not to be an issue.

Demographic data was obtained from Statistics Sweden's online database, www.statistikdatabasen.scb.se. This included data over the average income level for households, specified on a municipality level. However, the data over average income level was only available for 2011-2016. Since we needed data for 2010 and 2017 as well, we solved this issue by extrapolating the data from 2011 on 2010 and 2016 on 2017. Given minor relative changes between municipalities over the years, we deem this a suitable approximation. Information about the names and identification codes for all the counties[3] in Sweden was also obtained from Statistics Sweden's website. Being the main provider of statistical information in Sweden, we consider the data obtained from Statistics Sweden to be reliable.

Furthermore, other location characteristics for each property were obtained using distance measurement tools and spatial analysis in QGIS, a GIS software. These included distances in meters from each property to the nearest lake/watercourse, coastline and main road. The data was extracted using map data from SMHI and Lantmäteriet. In order to incorporate fine location fixed effects into our model, municipality and 5-digit zip code data for each property were also obtained using QGIS and shapefiles obtained from Lantmäteriet and ArcGIS hub respectively. The demographic information obtained from these sources was evaluated using different techniques, such as geocoding in Stata, which confirmed the quality of the data.

Table 2 illustrates descriptive statistics for the property transactions included in our dataset. There is large variation in the transaction prices, with a minimum of 50 000 SEK and a maximum of 10 400 000 SEK. The average transaction price is approximately 1 840 000 SEK. There is also large heterogeneity in the size of the transacted properties. The minimum size is 15 square meters, while the maximum size is 356 square meters, with the average being 103,88 square meters. Furthermore, the average plot size measures 1 376,97 square meters. This is a relatively large number, which is derived from the fact that the dataset contains a large amount of detached houses in rural areas. The average transaction year is

[3] County refer to "län". There are 21 counties in Sweden.

2014, and in Table A3 we can see that a large amount of all transactions in our dataset have taken place in the most recent years. The average disposable income for households is approximately 411 000 SEK, ranging from 293 000 SEK to 690 000 SEK. Moreover, the average distance to the nearest lake, coastline and main road from each property is 2,97 km, 24,93 km and 0,38 km, respectively. Table A4 also illustrates the distribution between the different types of properties included in this study. The majority of all transactions are for detached houses (57,82%), followed by apartments (22,82%).

Table 2
Descriptive Statistics: Property Transactions

	Mean	Std. Dev	Min	Max
Price (SEK)	1 843 516	1 411 697	50 000	10 400 000
Size (m2)	103,88	45,52	15	356
Plot Size (m2)	1 376,97	2 460,66	0	37 456
Transaction Year	2014	2	2010	2017
Average Disposable Income for Households (SEK)	410 717,50	59 364,53	293 000	690 000
Distance to Lake (km)	2,97	2,94	0,00	23,52
Distance to Coast (km)	24,93	36,17	0,00	233,81
Distance to Road (km)	0,38	0,47	0,00	9,23
Distance to Turbine (km)	5,53	2,39	0,00	10,02
Total Number of Observations		156 082		

Notes: The table contains descriptive statistics on properties located within 10 km of the nearest turbine and that was sold between 1 January, 2010 and 31 December, 2017. The majority of the apartments do not have any extra plot area; these observations are entered into the regression as 0.

Table 2 also presents the distance from each property to the nearest wind turbine, which was measured using QGIS and wind turbine and property coordinates obtained from www.vindlov.se and www.booli.se, respectively. The distance calculation was based on the Haversine formula with Lambert´s (1942) formula to correct for ellipsoidal flattening. Figure A3 illustrates the distance measurement procedure in QGIS. The average distance from each property to the nearest wind turbine is 5,53 km, with some considerable variation in distances.

Table 3 presents descriptive statistics for observations within and outside a 2 km radius from the nearest wind turbine. 9 868 transactions are reported to be within and 146 214 transactions are reported to be outside this radius. Note that the average transaction price is lower within 2 km of a wind turbine, compared to transactions outside this radius. This can give an early indication that house prices are lower in neighborhoods with a wind turbine in the surrounding area. However, this might also be explained by the fact that houses within this radius often are located in more rural areas, which commonly are associated with lower property prices compared to more urban environments. Table A5 illustrates that the total number of treated properties, defined as being within 2 km of wind turbine after the date of construction, amounts to 7 208, or 4,62% of the total sample. At the 1 km radius, the number of treated properties after the date of construction declines significantly to 1 229 or 0,79%.

Table 3
Descriptive Statistics: Treatment and Control Group

	Treatment Group (<= 2km)			Control Group (> 2km)		
	Mean	Min	Max	Mean	Min	Max
Price (SEK)	1 489 348	50 000	10 400 000	1 867 419	50 000	10 400 000
Size (m2)	108,07	15	350	103,59	15	356
Plot Size (m2)	2 264,66	0	37 331	1 317,06	0	37 456
Transaction Year	2014	2010	2017	2014	2010	2017
Income (SEK)	408 004	293 000	627 000	410 901	293 000	690 000
Distance to Lake (km)	4,20	0,00	23,52	2,88	0,00	22,81
Distance to Coast (km)	28,07	0,00	183,87	24,72	0,00	233,81
Distance to Road (km)	0,34	0,00	8,08	0,38	0,00	9,23
Distance to Turbine (km)	1,45	0,00	2,00	5,80	2,00	10,02
Total Number of Observations	9 868			146 214		

Furthermore, to incorporate noise pollution into our model, each 10 km radius around the wind turbines was manually adjusted in a manner that it would capture properties located in the same direction as the prevalent wind direction (Figure A4 in the Appendix). The prevalent wind direction for each location was obtained from www.globalwindatlas.info, a free web based application used to identify the wind direction in a specific area. Being a product of an international collaboration between The World Bank and other institutions, we consider this data source to be reliable. A picture of a wind rose obtained from www.globalwindatlas.info is given in Figure A5. The wind roses were used as guidance when drawing a noise adjusted radius.

Lastly, shadow flicker was incorporated by using WGS 84 coordinates for each turbine and property. If the latitude of the property was above the latitude of the nearest wind turbine and within the radius of 10 times the rotor diameter of the wind turbine, the property was considered exposed to shadow flicker.

6. Results

The result section is structured in the following way: Section 6.1 presents the main results for our hedonic pricing model, which later will be incorporated into the remaining models. Section 6.2 reviews the results of our base model regressions and the average treatment effect when applying various control variables and fixed effects. The model is then extended in Section 6.3 to include multiple treatments by testing the effect over multiple distance bands. Various robustness checks and sensitivity analyses are conducted in Section 6.4, followed by an analysis of heterogeneous treatment effects in Section 6.5. The result section ends with a brief reflection of our results by comparing them to the outcomes of some previous studies.[4]

6.1 The Hedonic Pricing Model

Table 4 presents our hedonic pricing model. Column (1) includes only property characteristics. Note that we use the natural logarithm of the variables *Size* and *Plot Size* to make their magnitude easier to grasp. The interpretation of the coefficient for *Size (ln)* is that if the size of a property increases by 1%, the price of a property increases by 0,8238%. The model generates a very modest adjusted R-squared of 0,19, due to a lack of other control variables and fixed effects.

Year-month fixed effects are added in column (2) to take time trends into account. In column (3), demographic characteristics are added in the form of a dummy variable that equals 1 if the average disposable household income level for the municipality the property is located in, exceeds 400 000 SEK, and 0 otherwise. This cut-off is around the average disposable household income level in our dataset (see Table 2) and was chosen to capture the difference between areas of "higher" and of "lower" income. Various environmental characteristics are then added in column (4) in the form of three dummy variables that equals 1 if a property is within 500 m, 1 000 m, and 200 m of the nearest lake, coastline and main road, respectively, and 0 otherwise.

The model improves significantly in column (5) when taking time-invariant unobserved locational differences into consideration by including 5-digit zip code fixed effects. To note is that the dummy variable representing vacation homes is no longer significant. In order to take into account trends over time within different markets, an interaction variable between market fixed effects and time fixed effects is included in column

[4] All regressions are robust for heteroskedasticity and multicollinearity through clustering at a 5-digit zip code level and since multicollinear variables would be omitted from the model.

(6). Market is defined as the county the property is located in and time is year-month fixed effects. The model's overall performance improves in terms of adjusted R-squared while the coefficients remain significant.

Table 4
Hedonic Model Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	Property Characteristics	Year-Month Fixed Effects	Demographic Characteristics	Environmental Characteristics	5-Digit Zip Code	Market-Time Interaction
Size (ln)	0.8238	0.8419	0.8112	0.8144	0.6985	0.6996
	(45.49)***	(46.98)***	(49.12)***	(52.62)***	(98.40)***	(98.77)***
Plot Size (ln)	-0.1504	-0.1550	-0.1405	-0.1238	0.0648	0.0644
	(11.92)***	(12.17)***	(12.38)***	(11.59)***	(15.02)***	(15.05)***
Vacation Home	0.0980	0.1496	0.1458	0.0660	0.0096	0.0097
	(4.00)***	(5.70)***	(6.61)***	(3.25)***	(0.71)	(0.73)
Country House	0.2347	0.2390	0.2773	0.2973	0.5764	0.5799
	(10.07)***	(10.24)***	(13.01)***	(14.07)***	(30.50)***	(30.71)***
Terrace House (1)	0.1660	0.1525	0.1413	0.1492	-0.0800	-0.0782
	(4.98)***	(4.61)***	(3.90)***	(4.25)***	(7.00)***	(7.45)***
Terrace House (2)	0.1770	0.1770	0.1552	0.1590	-0.0828	-0.0845
	(4.10)***	(4.09)***	(3.62)***	(3.81)***	(4.51)***	(4.76)***
Apartment	-0.6021	-0.6891	-0.5684	-0.4279	-0.1540	-0.1576
	(6.50)***	(7.32)***	(6.60)***	(5.14)***	(4.35)***	(4.53)***
Semi-Detached	0.2836	0.3300	0.2604	0.2734	-0.0238	-0.0259
	(8.56)***	(10.00)***	(7.00)***	(7.20)***	(1.57)	(1.71)*
Income			0.5291	0.5076	0.0221	0.0168
			(21.06)***	(20.21)***	(3.05)***	(2.31)**
Lake				-0.0445	0.1438	0.1446
				(1.40)	(10.80)***	(10.80)***
Coast				0.3700	0.2512	0.2516
				(10.41)***	(10.55)***	(10.95)***
Road				-0.1283	-0.0646	-0.0641
				(7.60)***	(11.59)***	(11.69)***
Property Charcs.	YES	YES	YES	YES	YES	YES
Year-Month FE	NO	YES	YES	YES	YES	YES
Demogr. Charcs.	NO	NO	YES	YES	YES	YES
Environ. Charcs.	NO	NO	NO	YES	YES	YES
5-Digit Zip FE	NO	NO	NO	NO	YES	YES
Year-Month x County	NO	NO	NO	NO	NO	YES
Number of Observations	156,082	156,082	156,082	156,082	156,082	156,082
Adjusted R-squared	0.1929	0.2146	0.2994	0.3323	0.7466	0.7518

Notes: The dependent variable is the natural logarithm of the property price. *Size (ln)* is the natural logarithm of the size of the property in m^2. *Plot Size (ln)* is the natural logarithm of the size of the land of the property, measured in m^2. *Vacation home* is a dummy variable that equals 1 if the property is a vacation home. *Terrace House (1)* is a dummy variable that equals 1 if the property is of the type Terrace House (1). *Terrace House (2)* is a dummy variable that equals 1 if the property is of the type Terrace House (2). See Table A4 for terrace house definitions. *Apartment* is a dummy variable that equals 1 if the property is an apartment. *Semi-Detached House* is a dummy variable that equals 1 if the property is a semi-detached house. The reference group is if a property is a detached house. *Income* is a dummy variable for the average disposable income for households specified on a municipality level, which equals 1 if the property is in a municipality with an average disposable income above 400 000 SEK. *Lake, Coast* and *Road* are dummy variables that equals 1 if the property is within 500 m, 1 000 m, and 200 m of the nearest lake/watercourse, coast line and main road, respectively. Standard errors are clustered at the 5-digit zip code level. Standard errors are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

6.2. The Difference-In-Differences Model – Average Treatment Effect

Table 5 contains our base model regressions, which are illustrated in equations 1 to 4 in Section 4.2.2. Column (1) presents our standard difference-in-differences model. *Within 2 km* is a dummy that indicates whether a property is within 2 km of a wind turbine. The coefficient is significant at the 1 percent significance level and could suggest that areas closer to a wind turbine have on average 13,94% lower property prices than areas that does not have a wind turbine nearby. This could be an indication that wind turbines are placed in less attractive areas. *Treatment* is our difference-in-differences estimator, which is negative and significant at the 10 percent significance level. The coefficient could indicate that property prices on average decrease by 8,66% after a wind turbine has been introduced within 2 km of a property. However, with a very low adjusted R-squared of 2,4%, derived from the absence of control variables and additional fixed effects, the results are unreliable.

In column (2), (3) and (4), control variables for property, demographic and environmental characteristics are added. In column (4), *Treatment* is now significant at the 1 percent significance level and the negative treatment effect has increased in magnitude, whereas the coefficient for *Within 2 km* is insignificant. When the 5-digit zip code fixed effects are added to the regression in column (5), the model improves significantly, which can be explained by the capturing of time-invariant unobserved locational differences. Note that, as the model improves in terms of adjusted R-squared, the variable *Within 2 kilometers* becomes insignificant and its coefficient converges towards zero. However, *Treatment* is now statistically significant at the 10 percent significance level and indicates that property prices decrease by 2,37% on average after a wind turbine is introduced within 2 km of property.

In column (6), we integrate the interaction between market fixed effects and time fixed effects into the regression. The treatment effect increases slightly to 2,61%. In column (7), we further extend the model with a restricted sample that only includes properties within a 4 km radius of a wind turbine, using properties within the distance range of 2 km to 4 km as control group. The intuition behind this is to further improve the model by a more concentrated control group, to account for other yet unobserved traits. This is based on the discussion in Section 4.2.2 regarding equation 4. The treatment effect increases and is statistically significant at the 5 percent significance level.

Table 5
Base Model Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Standard DID	Property Characteristics	Demographic Characteristics	Environmental Characteristics	5-Digit Zip Fixed Effects	Market-Time Interaction	2-4km Control Group
Within 2km	-0.1394	-0.0497	-0.0713	-0.0312	-0.0042	-0.0031	0.0053
	(2.83)***	(1.20)	(2.08)**	(0.94)	(0.25)	(0.19)	(0.31)
Time	0.1274	0.1388	0.1125	0.1140	-0.0132	0.0028	0.0123
	(3.54)***	(4.14)***	(4.05)***	(4.33)***	(1.78)*	(0.40)	(1.13)
Treatment	-0.0866	-0.1223	-0.0822	-0.1053	-0.0237	-0.0261	-0.0359
	(1.89)*	(3.13)***	(2.62)***	(3.29)***	(1.66)*	(1.83)*	(2.43)**
Size (ln)		0.8408	0.8103	0.8135	0.6985	0.6997	0.7160
		(47.12)***	(49.27)***	(52.69)***	(98.35)***	(98.74)***	(68.02)***
Plot Size (ln)		-0.1517	-0.1373	-0.1211	0.0648	0.0644	0.0602
		(11.94)***	(12.20)***	(11.44)***	(15.03)***	(15.06)***	(10.95)***
Vacation Home		0.1445	0.1415	0.0629	0.0095	0.0094	0.0124
		(5.53)***	(6.47)***	(3.14)***	(0.70)	(0.71)	(0.80)
Country House		0.2463	0.2840	0.3024	0.5767	0.5801	0.5811
		(10.64)***	(13.46)***	(14.46)***	(30.52)***	(30.73)***	(21.25)***
Terrace House (1)		0.1504	0.1397	0.1473	-0.0800	-0.0782	-0.0715
		(4.47)***	(3.81)***	(4.15)***	(6.99)***	(7.44)***	(4.35)***
Terrace House (2)		0.1707	0.1501	0.1541	-0.0826	-0.0845	-0.0797
		(3.93)***	(3.48)***	(3.66)***	(4.50)***	(4.76)***	(3.97)***
Apartment		-0.6785	-0.5581	-0.4202	-0.1538	-0.1574	-0.2425
		(7.26)***	(6.54)***	(5.09)***	(4.35)***	(4.53)***	(4.69)***
Semi-Detached House		0.3357	0.2658	0.2781	-0.0240	-0.0257	-0.0584
		(10.19)***	(7.18)***	(7.36)***	(1.59)	(1.70)*	(2.32)**
Income			0.5259	0.5045	0.0216	0.0168	0.0014
			(21.07)***	(20.31)***	(2.99)***	(2.32)**	(0.11)
Lake				-0.0498	0.1433	0.1440	0.1605
				(1.57)	(10.79)***	(10.80)***	(5.71)***
Coast				0.3671	0.2508	0.2511	0.2790
				(10.34)***	(10.51)***	(10.91)***	(7.74)***
Road				-0.1277	-0.0646	-0.0641	-0.0650
				(7.62)***	(11.58)***	(11.68)***	(7.12)***
Year-Month FE	YES	YES	YES	YES	YES	YES	YES
Property Charcs.	NO	YES	YES	YES	YES	YES	YES
Demogr. Charcs.	NO	NO	YES	YES	YES	YES	YES
Environ. Charcs.	NO	NO	NO	YES	YES	YES	YES
5-Digit Zip FE	NO	NO	NO	NO	YES	YES	YES
Year-Month x County	NO	NO	NO	NO	NO	YES	YES
2-4km Control Group	NO	NO	NO	NO	NO	NO	YES
Number of observations	156,082	156,082	156,082	156,082	156,082	156,082	48,760
Adjusted R-squared	0.0240	0.2189	0.3026	0.3351	0.7467	0.7518	0.7139

Notes: The dependent variable is the natural logarithm of the property price. The variable *Within 2km* is a dummy variable that equals 1 if a property was sold within 2km of a turbine, and 0 otherwise. *Time* is a dummy variable that equals 1 if a property has been sold after a wind turbine has been introduced, and 0 otherwise. *Treatment* is the difference-in-differences estimator. *Size (ln)* is the natural logarithm of the size of the property in m^2. *Plot Size (ln)* is the natural logarithm of the size of the land of the property, measured in m^2. *Vacation home* is a dummy variable that equals 1 if the property is a vacation home. *Terrace House (1)* is a dummy variable that equals 1 if the property is of the type Terrace House (1). *Terrace House (2)* is a dummy variable that equals 1 if the property is of the type Terrace House (2). See Table A4 for terrace house definitions. *Apartment* is a dummy variable that equals 1 if the property is an apartment. *Semi-Detached House* is a dummy variable that equals 1 if the property is a semi-detached house. The reference group is if a property is a detached house. *Income* is a dummy variable for the average disposable income for households specified on a municipality level, which equals 1 if the property is in a municipality with an average disposable income above 400 000 SEK. *Lake, Coast* and *Road* are dummy variables that equals 1 if the property is within 500 m, 1 000 m, and 200 m of the nearest lake/watercourse, coast line and main road, respectively. Standard errors are clustered at the 5-digit zip code level. Standard errors are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

6.3. Multiple Treatment Effects

Table A6 in the Appendix presents the results from our model for multiple treatment effects, which is illustrated in Section 4.2.2., Equation 5. Various distance bands were created using three dummy variables that equals 1 after a wind turbine is introduced within the distance band of between 0 to 1 km, 1 km to 2 km, and 2 km to 3 km from a property, respectively, and 0 otherwise. The distance band of 3 km to 4 km is the reference category.

The treatment effect for properties within the 1 km distance band is marked at -8,34% and is statistically significant at the 5 percent significance level. The treatment effect decreases for the 1 km to 2 km distance band, but is still significant at the 10 percent significance level. Between the 2 km to 3 km distance band, the treatment effect converges towards zero and becomes insignificant. The treatment effects are statistically significantly different from each other at the 10 percent significance level, with an *F*-value of 2,63 and a *P*-value of 0,0724. They are also statistically significantly different from zero at the 10 percent significance level, with an *F*-value of 2,6 and a *P*-value of 0,0508. A graphical illustration of the treatment effect over the distance bands is given in Figure 1. These results would indicate that the cut-off distance for treatment is around 2 km from a wind turbine, the distance used in our base model regressions to define treated properties.

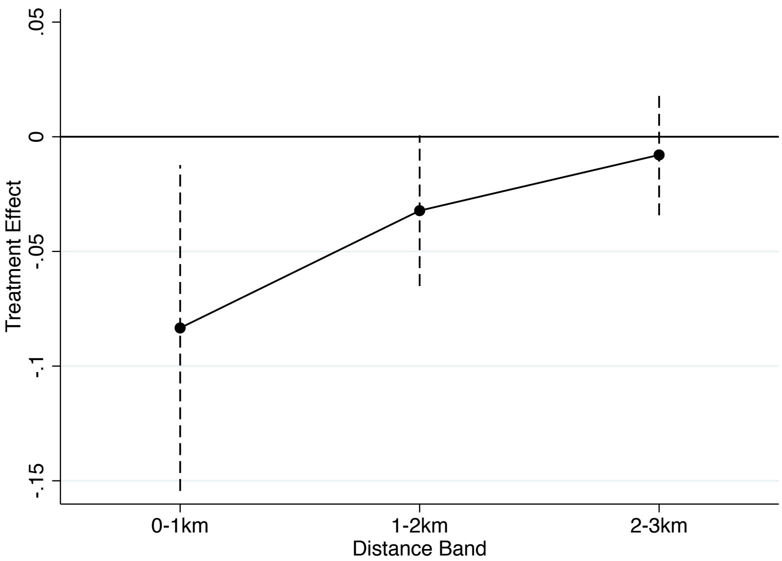

Figure 1. Multiple treatment effects derived from different distance bands. *Notes:* The dots represent the treatment coefficient for a given distance band (0-1km, 1-2km, and 2-3km). 95% confidence intervals are represented by the vertical dotted lines. The reference category consists of houses that are located in the range of 3-4km from a wind turbine.

6.4. Sensitivity Analysis and Robustness Checks

To make sure our results are robust, we also test for a number of different treatment and control group definitions in terms of distance. The results are presented in Table 6. In column (1), we define properties within 1 km of a wind turbine as treated, and properties located between the 1 km and 10 km distance band form the control group. The market-time interaction variable is excluded. The treatment effect increases compared to when using properties within 2 km as treatment group. The coefficient is significant at the 5 percent significance level and indicates that property prices decreases on average by 6,82% after a turbine has been introduced within 1 km of a property. In column (2), the model is extended with a restricted control group containing the properties located between 1 km and 4 km from a wind turbine. The results remain robust, with a slight increase in the negative treatment effect.

In column (3), we further extend the regression from column (2) with the interaction between market and time fixed effects. The treatment effect increases slightly in magnitude, and remains robust at the 5 percent significance level.

In column (4), we introduce a distance gap between the treatment group and control group into the model, by excluding properties from our dataset located further away than 1 km but within a 2 km radius of a wind turbine. The treatment effect becomes even more negative, increasing to 7,44%. This would indicate that there is a treatment effect in the range of 1 km and 2 km from a wind turbine, which also supports our previous results.

In column (5), the control group is restricted even further by only including properties within 3 km of a wind turbine. Treated properties are within 2 km of a wind turbine, resulting in a control group in the 2 km to 3 km range. The treatment effect remains robust at the 5 percent significance level. When increasing the control group restriction to 4 km in column (6), and also dropping observations located between 2 km and 3 km from a wind turbine, the treatment effect becomes slightly more negative. This would confirm that a cut-off point for treatment around 2 km is reasonable, but that the effect still exists to some extent beyond the 2 km radius.

Another question of interest is if properties within the 1 km radius are driving the effect when including properties within a 2 km range in the treatment group. To test for this, we drop all properties within 0 and 1 km of a wind turbine and only include properties within the 1 km to 2 km range in the treatment group. Properties in the 2 km to 4 km range will thus form our control group. As displayed in column (7), the treatment effect decreases slightly, but remains significant at the 5 percent significance level. Column (8) shows that the treatment effect becomes insignificant when using a treatment group within 3 km, supporting the idea of a cut-off distance for treatment at around 2 km.

Table 6
Robustness Checks for Different Treatment and Control Groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	0-1km TG, 1-10km CG	0-1km TG, 1-4km CG	0-1km TG, 1-4km CG (Interaction)	0-1km TG, 2-4km CG	0-2km TG, 2-3km CG	0-2km TG, 3-4km CG	1-2km TG, 2-4km CG	0-3km TG, 3-4km CG
Treatment 0-1km	-0.0682	-0.0696	-0.0725	-0.0744				
	(2.01)**	(2.01)**	(2.04)**	(2.06)**				
Treatment 0-2km					-0.0341	-0.0417		
					(2.10)**	(2.52)**		
Treatment 0-3km								-0.0193
								(1.59)
Treatment 1-2km							-0.0309	
							(2.02)**	
Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Property Charcs.	YES	YES	YES	YES	YES	YES	YES	YES
Demgr. Charcs.	YES	YES	YES	YES	YES	YES	YES	YES
Environ. Charcs.	YES	YES	YES	YES	YES	YES	YES	YES
5-Digit Zip FE	YES	YES	YES	YES	YES	YES	YES	YES
Year-Month x County	NO	NO	YES	YES	YES	YES	YES	YES
Number of observations	156,082	48,760	48,760	40,509	25,880	32,748	47,143	48,760
Adjusted R-squared	0.7467	0.7058	0.7139	0.7303	0.6866	0.7255	0.7193	0.7139

Notes: The dependent variable is the natural logarithm of the property price. The variable *Treatment 0-1km* is an interaction variable that equals 1 if a property has been sold within 1km of a wind turbine after it has been introduced. The variable *Treatment 0-2km* is an interaction variable that equals 1 if a property has been sold within 2 km of a wind turbine after it has been introduced. The variable *Treatment 0-3km* is an interaction variable that equals 1 if a property has been sold within 3km of a wind turbine after it has been introduced. The variable *Treatment 1-2km* is an interaction variable that equals 1 if a property has been sold within 2 km of a wind turbine after it has been introduced. When running the regression in column (7), observations within 1 km are dropped from the dataset. Lower order terms have been excluded to insure readability of the table. TG and CG stands for treatment group and control group, respectively. Standard errors are clustered at the 5-digit zip code level. Standard errors are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

In Table 7, we conduct a number of general robustness checks. Treated properties are within 2 km for all columns. One factor that may influence our results is the presence of outliers. In column (1), we adjust for outliers by removing observations below the 1st and above the 99th percentile with regards to the price, size and plot size for the properties. Our results are still significant at the 5 percent significance level and the negative treatment effect is 3,47%.

One could also discuss whether apartments are affected differently compared to other property types in our dataset. One thought could be that apartments would drive the effect as the ones on higher floors would have a clearer view than for instance detached houses. One could also argue that apartments could cause a downward bias, given that apartments are usually located in more urban environments where other forms of noise and visual disturbance are present, which in turn may obfuscate negative externalities from wind turbines. Furthermore, the lack of direct outdoor space in the form of a garden is another related factor here. In column (2), we test our model without apartments. Our results hardly change, with a slight decrease in the treatment effect compared to our base model regressions and a decrease in adjusted R-squared.

Our earlier regressions have defined market as the county the property is located in, interacting this with year-month fixed effects. One could argue that this interaction is not fine enough. However, the inclusion of finer fixed effects, such as the 5-digit zip code, would lead to a large amount of singleton observations, which could bias the estimates if not dropped from the regression (Correia, 2015). This would result in a much smaller dataset. To avoid the problem of having too many singletons dropped, and still show that a finer definition does not change our previous results, we interact market and time fixed effects at a finer level by defining market as the 2-digit zip code (column (3)). Singleton observations are excluded. Our results remain significant at the 5 percent level.

In all previous regressions, singleton observations have been kept due to the very small amount. However, to show that this has not biased our previous results, we test our base model adjusted for singleton observations in column (4). The results remain the same with a treatment effect of -3,59%, significant at the 5 percent significance level.

Table 7
General Robustness Checks

	(1)	(2)	(3)	(4)
	Adjusted for Outliers	Excluding Apartments	Year-Month & 2-Digit Zip Code Interaction	Base Model Adjusted for Singletons
Treatment	-0.0347	-0.0328	-0.0310	-0.0359
	(2.49)**	(2.16)**	(2.06)**	(2.43)**
Year-Month FE	YES	YES	YES	YES
Property Characteristics	YES	YES	YES	YES
Demographic Characteristics	YES	YES	YES	YES
Environmental Characteristics	YES	YES	YES	YES
5-Digit Zip FE	YES	YES	YES	YES
Year-Month x County	YES	YES	NO	YES
Year-Month x 2-Digit Zip Code	NO	NO	YES	NO
2-4km Control Group	YES	YES	YES	YES
Singleton Observations Dropped	NO	NO	YES	YES
Number of observations	46,546	39,141	47,945	48,510
Adjusted R-squared	0.7265	0.6921	0.7151	0.7117

Notes: The dependent variable is the natural logarithm of the property price. *Treatment* is the difference-in-differences estimator. Lower order terms have been excluded to insure readability of the table. Standard errors are clustered at the 5-digit zip code level. Standard errors are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

In Table 8, a number of alternative datasets are used. In column (1), we only keep the most recent transaction for those properties transacted more than once, reducing our dataset to 40 577 observations with a restricted sample of properties within a 4 km range. By doing this, we control for any bias that might arise from properties sold multiple times. The results remain robust, with a treatment effect of -3,16%, significant at the 5 percent level.

Another robustness check is to only use properties that has been sold more than once. This repeat sales model, described in Section 4.2.2., is presented in column (2). Since we now can incorporate property-specific fixed effects into the model, the adjusted R-squared increases significantly to 84,68%. Although the treatment effect becomes insignificant, the *P*-value is just above 10 percent (*P*-value of 11,7 percent). This could potentially indicate that our 5-digit zip code fixed effects don't capture unobserved locational differences adequately. However, the repeat sales dataset is very small, consisting of only 14 466 observations, which one should have in mind when drawing conclusions from these results.

As described in Section 4.2.3.1, the methodology applied so far could bias the impact on property prices due the fact that a property may be treated by several wind turbines at different points in time. To test for any possible bias, the sample is restricted in column (3) to include properties that are only treated by a single turbine. However, note that this will decrease the sample size significantly. The treatment effect is -7,28% and significant at the 5 percent significance level, supporting our theory of a downward bias when applying our main approach. However, due to the small number of observations, one should be careful when interpreting the results.

Table 8
Robustness Checks with Alternative Datasets

	(1)	(2)	(3)
	Most Recent Transactions	Repeat Sales Model	Robust Model
Treatment	-0.0316	-0.0375	-0.0728
	(1.97)**	(1.57)	(2.07)**
Year-Month FE	YES	YES	YES
Property Characteristics	YES	YES	YES
Demographic Characteristics	YES	YES	YES
Environmental Characteristics	YES	YES	YES
5-Digit Zip FE	YES	NO	YES
Year-Month x County	YES	YES	YES
2-4km Control Group	YES	YES	YES
Property-Specific FE	NO	YES	NO
Number of observations	40,577	14,466	8,086
Adjusted R-squared	0.7203	0.8468	0.6733

Notes: The dependent variable is the natural logarithm of the property price. *Treatment* is the difference-in-differences estimator. Lower order terms have been excluded to insure readability of the table. Standard errors are clustered at the 5-digit zip code level in column (1) and (3). In column (2), standard errors are clustered at a property level, and singletons are dropped to only keep properties transacted several times. Standard errors are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

6.5. Heterogeneous Treatment Effects

It is also of interest to analyze if there is a heterogeneity in the treatment effect. Table 9 presents the results from various interactions with the difference-in-differences estimator *Treatment*.[5] In column (1), we test for heterogeneity in treatment with regard to how many turbines the wind farm a property is exposed to contains. The intuition behind this robustness check is that properties exposed to larger wind farms should experience an additional price decline compared to properties exposed to a smaller wind farm.

Number of Turbines is a dummy variable that equals 1 if a wind farm contains more than 3 wind turbines. The reference category is thus wind farms with less than, or equal to, 3 wind turbines. When interacting *Number of Turbines* with our difference-in-differences estimator *Treatment*, the effect is highly insignificant. The treatment coefficients are not statistically significantly different from each other at the 5 percent significance level, with an *F*-value of 3,31. Therefore, we find no evidence supporting the idea that properties located closer to larger wind farms experience a larger negative treatment effect.

In column (2), *Treatment* is interacted with a dummy variable for the axis height of the turbine, that equals 1 if the height is above 110 meters. In column (3), *Treatment* is instead interacted with a dummy for the rotor blade diameter, that equals 1 if the diameter is

[5] Conducting F-tests, we find that all treatment effects for each model, respectively, are jointly statistically significantly different from zero.

larger than 110 meters. These two interactions test the idea that properties exposed to larger turbines would experience a larger effect. Both interactions decrease the sample size due to missing data for axis height and rotor diameter. Although the coefficients for the two interactions are negative, they are both highly insignificant. The treatment coefficients in column (2) are not jointly significant, with an F-value of 0,14. Furthermore, the treatment coefficients in column (3) are not jointly significant with an F-value of 0,2. Thus, we find no evidence indicating that properties exposed to larger wind turbines experience a stronger negative treatment effect.

Table 9
Heterogeneous Treatment Effects

	(1)	(2)	(3)	(4)	(5)
	Multiple Turbines	Turbine Height	Rotor Diameter	Noise Pollution	Shadow Flicker
Treatment	-0.0402	-0.0406	-0.0394	-0.0315	-0.0378
	(2.51)**	(2.55)**	(2.49)**	(2.06)**	(2.37)**
Treatment x Number of Turbines	0.0266				
	(0.96)				
Treatment x Turbine Height		-0.0647			
		(1.08)			
Treatment x Rotor Diameter			-0.0679		
			(1.14)		
Treatment x Noise Pollution				-0.0515	
				(1.10)	
Treatment x Shadow Flicker					-0.0545
					(0.85)
Property Characteristics	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES
Demographic Characteristics	YES	YES	YES	YES	YES
Environmental Characteristics	YES	YES	YES	YES	YES
5-Digit Zip FE	YES	YES	YES	YES	YES
Year-Month x County	YES	YES	YES	YES	YES
2-4km Control Group	YES	YES	YES	YES	YES
Number of observations	48,760	37,250	37,410	48,760	37,410
Adjusted R-squared	0.7141	0.6984	0.6994	0.7139	0.6994

Notes: The dependent variable is the natural logarithm of the property price. *Treatment* is the difference-in-differences estimator. *Treatment x Number of Turbines* is an interaction between *Treatment* and a dummy variable that equals 1 if the number of turbines in a wind farm is higher than 3, and 0 otherwise. *Treatment x Turbine Height* is and interaction between *Treatment* and a dummy variable that equals 1 if the axis height of a turbine is higher than 110 m, and 0 otherwise. *Treatment x Rotor Diameter* is an interaction between *Treatment* and a dummy variable that equals 1 if the rotor diameter of a turbine is larger than 110 m, and 0 otherwise. *Treatment x Noise Pollution* is an interaction between *Treatment* and a dummy variable that equals 1 if a property is within 1km of a wind turbine and is included in our noise exposure area, and 0 otherwise. *Treatment x Shadow Flicker* is an interaction between *Treatment* and a dummy variable that equals 1 if a property is within a radius of ten times the rotor diameter of the nearest wind turbine and situated to the north of the same turbine, and 0 otherwise. Lower order terms have been excluded to insure readability of the table. Standard errors are clustered at the 5-digit zip code level. Standard errors are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

In column (4) and (5), we test for heterogeneity in treatment with regards to noise pollution and shadow flicker. All properties that were included in our noise exposure area and within a 1 km range of a wind turbine were considered treated by noise pollution. For shadow flicker, all properties located to the north and within a 10 times the rotor diameter distance range of the wind turbine were considered exposed to shadow flicker. Since our measurements for capturing noise pollution and shadow flicker were very imprecise, our initial expectations of finding any effect was low. The results are highly insignificant for both noise pollution and shadow flicker. The treatment effects in the noise model (column (4)) are not statistically significantly different from each other, with an F-value of 0,7056. The treatment effects in the shadow flicker model (column (5)) are also not jointly significant, with an F-value of 0,8081. Therefore, we find no evidence that properties exposed to noise pollution and shadow flicker experience a larger negative treatment effect.

6.6. Our Results in Relation to Previous Research

This thesis has followed a similar structure as the study conducted by Dröes and Koster (2016) in the Netherlands. Our main results follow the same pattern as theirs, indicating that wind turbines may have a negative impact on surrounding property prices. However, to note is that their study was more extensive and was implemented in a more densely populated country. This may also explain why they were able to show statistically more significant results in comparison to our study. Furthermore, country differences and smaller sample sizes may also explain why studies such as the one conducted by Hoen et al. (2013) found no statistical evidence of wind turbines having a negative impact on property values.

The differences in terms of results between our study and the study conducted by Svensk Vindenergi (2010) may to some extent be explained by differences in methodology and the fact that they did not have access to the same extensive dataset that we have had. However, the heterogeneity in research findings within this topic emphasizes the need for more research, and that one should be careful to draw too strong conclusions from individual studies.

7. Conclusion

This thesis has investigated the impact on property prices from the introduction of wind turbines in Sweden. Our two hypotheses were that the presence of a wind turbine in an area is incorporated into the pricing of a property and that the effect on property prices increases as the proximity to the wind turbine increases. Our results indicate a statistically significant negative average treatment effect of around 2-4% on property prices after a wind turbine has been introduced within 2 km of a property. Furthermore, if a wind turbine is introduced within 1 km of a property, our results suggests a statistically significant negative average treatment effect of around 6-7% on property prices. We could not find any statistically significant negative treatment effect above a 2 km radius. Applying a model with various distance bands further underpins the conclusion that the negative treatment effect is stronger and statistically more significant for the distance bands closer to the wind turbine.

Our results suggest that economic value is destroyed when a wind turbine is introduced. However, when discussing the economic effects of wind power from a societal point of view, it is also important to consider potential benefits that arises from their presence. One clear benefit is reduced CO_2 emission by utilizing a green and renewable energy source. Furthermore, the production of electricity generates income for various parties, such as the owners of the turbines and the landowners, whom are compensated and earns income from letting others use his or her property for wind power purposes. To conclude, various aspects should be considered when determining the economic impact of wind turbines, not just the related decline in property values.

This thesis does not argue for stopping further wind power development in Sweden. Instead, we are trying to illustrate an important issue that may increase in importance as Sweden is transforming its energy production towards renewable energy sources. From a policy perspective, it can be of significant value to increase our understanding of how wind turbines affect property prices, and especially at which distances the exposure is most present. This could for instance help policy makers decide on where to build wind turbines in the future, and making more economically informed decisions when choosing energy sources.

As mentioned in the introduction of this thesis, more research on this topic is needed in Sweden. This thesis contributes with some new insights into this issue. However, measuring the effect on property values poses several methodological and empirical challenges. Many of these challenges have been discussed in this thesis and some suggested solutions to these issues have been provided. Future research should thus focus on finding other methods to better assess the various forms of wind turbine exposure, such as visual and noise pollution. Of interest, apart from looking at the impact on property prices, is to also focus on incorporating more extensive cost-benefit analyses that investigates the overall economic impact of wind turbine development.

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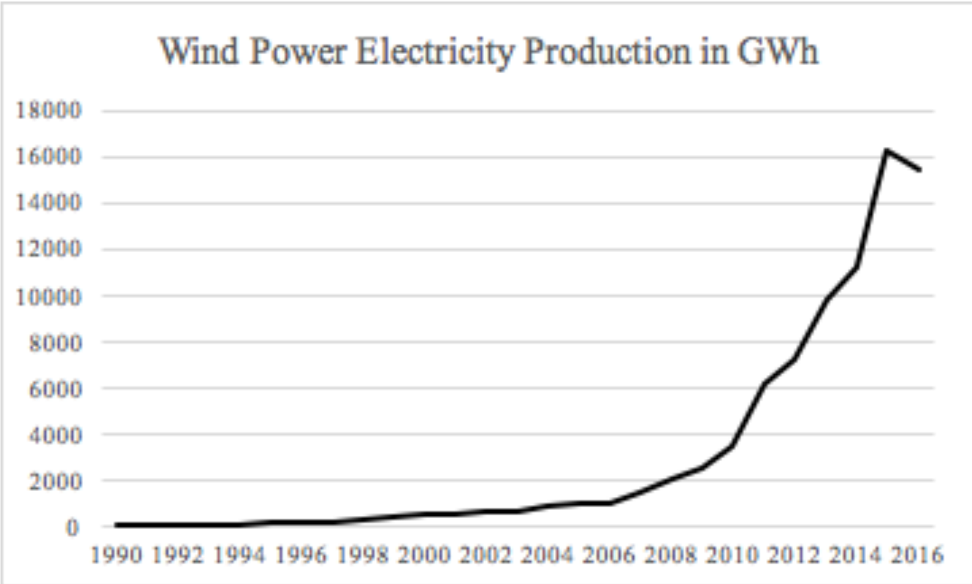
Appendix

Figure A1



Source: Statistics Sweden (2016)

Comment: The slight decline in energy production from wind in Sweden between 2015 and 2016, shown in the graph above, was partly caused by less windy conditions during that period.

Table A1

Wind Turbine Ownership Distribution

Type of Owner	Installed Production (TWh)	Percentage of Total Capacity (%)
Wind Power Companies	1,9	41,3
Energy Companies	1,3	29,3
Industrial Companies	0,6	12,2
Partnerships (Handelsbolag)	0,3	6,7
Property Companies (Bostadsbolag)	0,2	3,3
Local and Regional Authorities	0,1	2,3
Individuals	0,05	1,1
Economic Associations	0,03	0,6
Other	0,2	3,3
Total	4,6	100

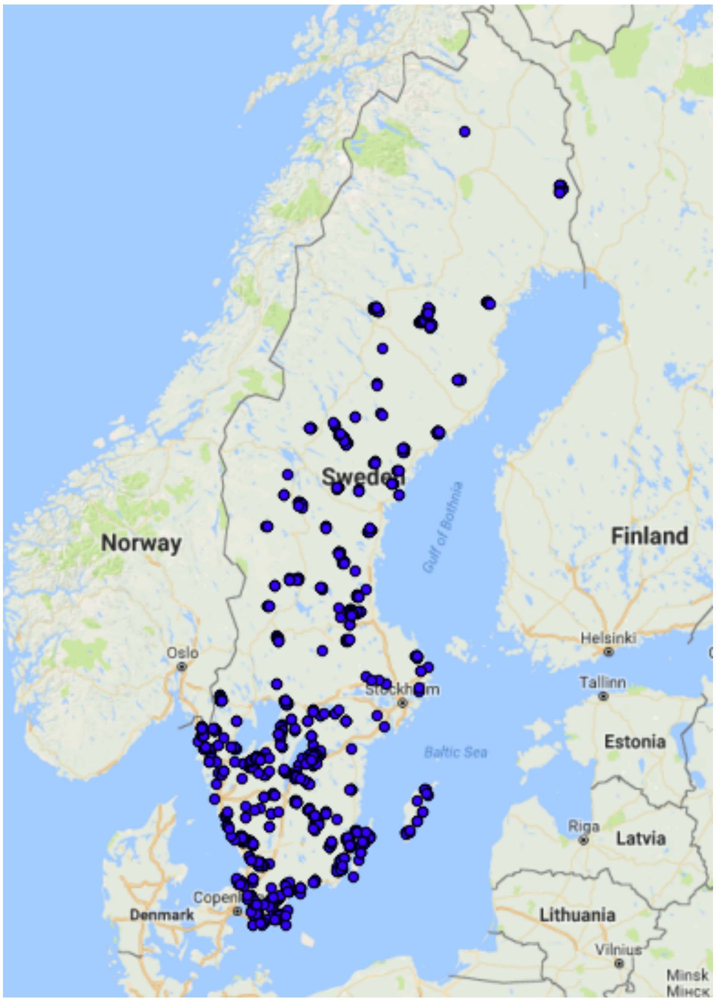
Source: Energimyndigheten (2015)

Table A2

Descriptive Statistics: Wind Turbines by Construction Year

Turbine Construction year	Number of Wind Turbines	Percent	Cum.
Year 2010	166	16,42	16,42
Year 2011	218	21,56	37,98
Year 2012	197	19,49	57,47
Year 2013	118	11,67	69,14
Year 2014	138	13,65	82,79
Year 2015	58	5,74	88,53
Year 2016	91	9	97,53
Year 2017	25	2,47	100
Total	1 011	100	

Figure A2



Comment: The picture illustrates the location of all the wind turbines in our sample. The majority of the turbines are located in the southern parts of Sweden.

Table A3

Property Transactions by Year

Transaction Year	Frequency	Percent	Cum.
Year 2010	13 439	8,61	8,61
Year 2011	12 739	8,16	16,77
Year 2012	13 535	8,67	25,44
Year 2013	19 809	12,69	38,14
Year 2014	22 108	14,16	52,3
Year 2015	24 870	15,93	68,23
Year 2016	24 781	15,88	84,11
Year 2017	24 801	15,89	100
Total	156 082	100	

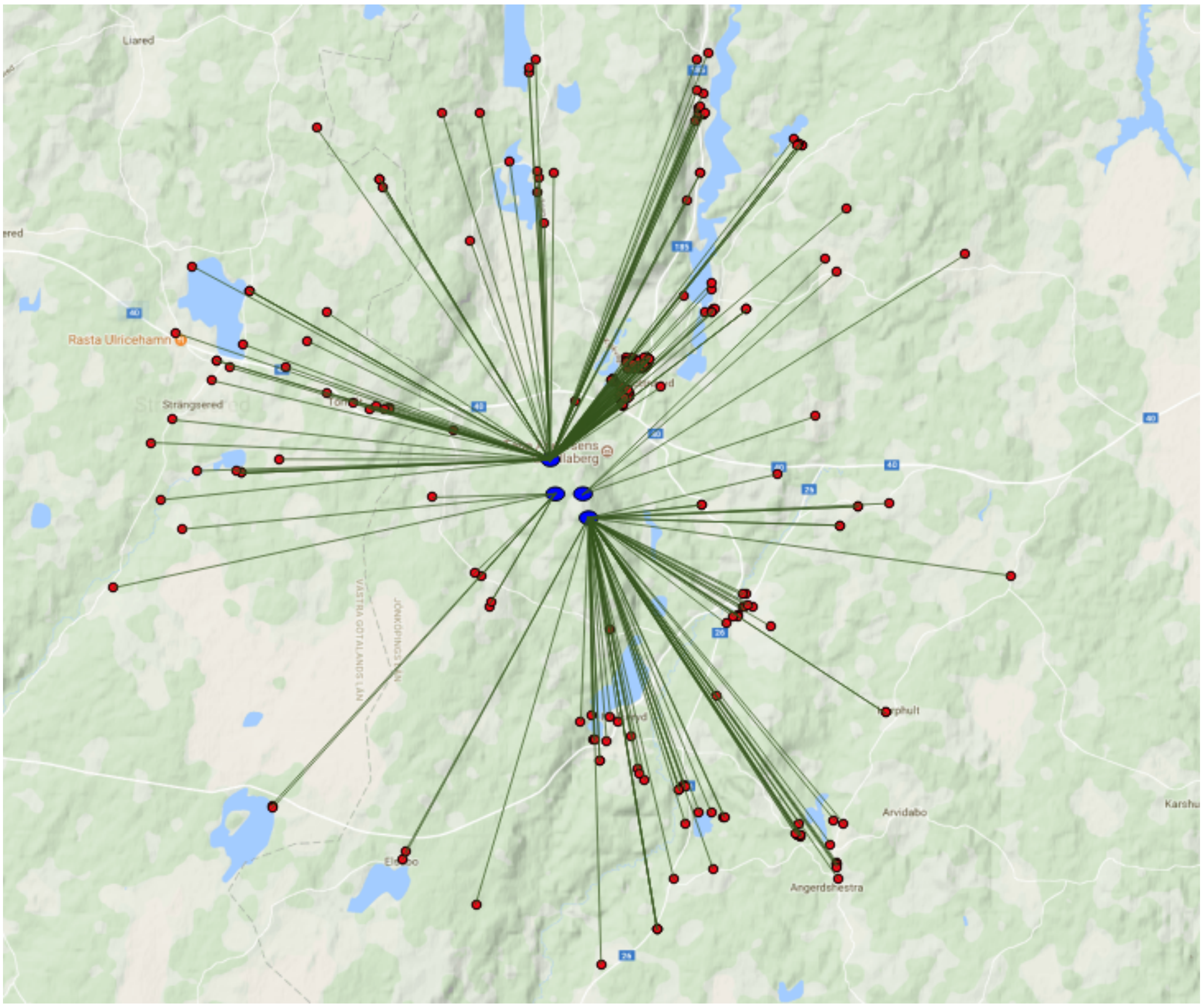
Table A4

Descriptive Statistics: Property Type

	Frequency	Percent
Vacation Home	10 703	6,86
Country House	5 770	3,7
Terrace House (1)	6 419	4,11
Terrace House (2)	6 694	4,29
Apartment	35 614	22,82
Semi-Detached House	636	0,41
Detached House	90 246	57,82
Total	156 082	100

Notes: The difference between "Terrace House 1" and "Terrace House 2" is that "Terrace House 2" consists of terrace houses that are only connected with a garage or similar.

Figure A3



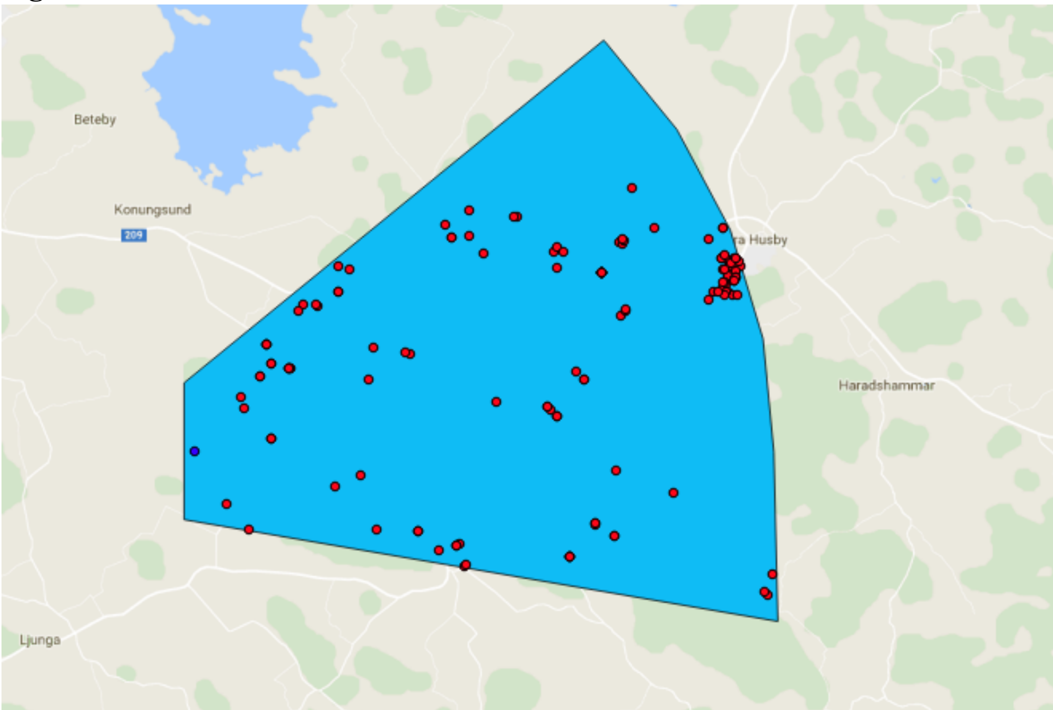
Comment: The figure above is an example of the distance measurement procedure. The dark blue dots are wind turbines, the red dots represent properties and the green lines connect each property to the nearest wind turbine.

Table A5

Descriptive Statistics: Treatment Group

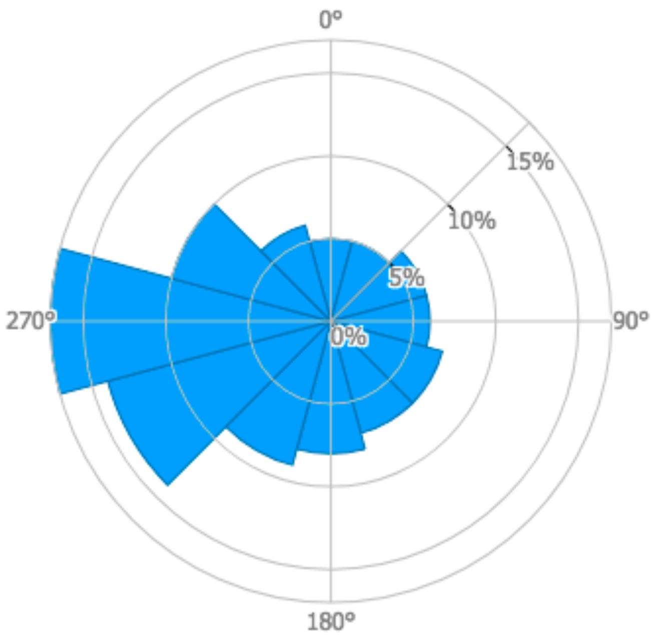
	Frequency	Percent
Within 2km	9 868	6,32
Within 2km, Post Treatment	7 208	4,62
Within 1km	1 617	1,04
Within 1km, Post Treatment	1 229	0,79

Figure A4



Comment: The figure above is an example of how the adjustment of the 10 km radius can look like when trying to capture noise pollution. The dark blue dot represents a wind turbine and the red dots are properties.

Figure A5



Comment: The figure above illustrates the wind rose used when adjusting our 10 km radius for noise pollution capturing.

Table A6
Multiple Treatment Effects

	(1)
	Distance Model
Within 1km	0.0064
	(0.18)
Between 1km & 2km	-0.0070
	(0.32)
Between 2km & 3km	-0.0138
	(0.86)
Time	0.0156
	(1.24)
Treatment 1km	-0.0834
	(2.30)**
Treatment 2km	-0.0322
	(1.92)*
Treatment 3km	-0.0079
	(0.59)
Size (ln)	0.7158
	(67.90)***
Plot Size (ln)	0.0604
	(10.99)***
Vacation Home	0.0121
	(0.78)
Country House	0.5816
	(21.27)***
Terrace House (1)	-0.0719
	(4.40)***
Apartment	-0.2420
	(4.68)***
Semi-Detached House	-0.0587
	(2.33)**
Terrace House (2)	-0.0801
	(4.00)***
Income	0.0014
	(0.12)
Lake	0.1598
	(5.72)***
Coast	0.2758
	(7.51)***
Road	-0.0646
	(7.09)***
Year-Month FE	YES
Property Characteristics	YES
Demographic Characteristics	YES
Environ. Characteristics	YES
5-Digit Zip FE	YES
Year-Month x County	YES
0-4km Sample	YES
Number of observations	48,760
F statistic	391.4
Adjusted R-squared	0.7140

Notes: The dependent variable is the natural logarithm of the property price. *Within 1km* is a dummy variable that equals 1 if a property is within 1 km of a wind turbine, and 0 otherwise. *Between 1km & 2km* is a dummy variable that equals 1 if a property is located between 1 km and 2 km of a wind turbine, and 0 otherwise. *Between 2km & 3km* is a dummy variable that equals 1 if a property is located between 2 km and 3 km of a wind turbine, and 0 otherwise. *Time* is a dummy variable that equals 1 if a property has been sold after a wind turbine has been introduced. The variable *Treatment 1km* is an interaction variable that equals 1 if a property has been sold within 1 km of a wind turbine after it has been introduced, and 0 otherwise. The variable *Treatment 2km* is an interaction variable that equals 1 if a property has been sold in the range of 1 to 2 km from a wind turbine after it has been introduced, and 0 otherwise. The variable *Treatment 3km* is an interaction variable that equals 1 if a property has been sold in the range of 2 to 3 km from a wind turbine after it has been introduced, and 0 otherwise. The reference category is defined as if a property has been sold in the range of 3 to 4km from a wind turbine. Standard errors are clustered at the 5-digit zip code level. Standard errors are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.