Does the Presence of Wind Turbines Have Negative Externalities for People in Their Surroundings?

Evidence from Well-Being Data

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Abstract

Throughout the world, governments foster the deployment of wind power to mitigate negative externalities of conventional technologies, notably CO_2 emissions. Wind turbines, however, are not free of externalities themselves, particularly interference with landscape aesthetics. We quantify the negative externalities associated with the presence of wind turbines using the life satisfaction approach. To this end, we combine household data from the German Socio-Economic Panel Study (SOEP) with a novel panel dataset on over 20,000 installations. Based on geographical coordinates and construction dates, we establish causality in a difference-in-differences design. Matching techniques drawing on exogenous weather data and geographical locations of residence ensure common trend behaviour. We show that the construction of wind turbines close to households exerts significant negative external effects on residential well-being, although they seem both temporally and spatially limited. Robustness checks, including view shed analyses based on digital terrain models and placebo regressions, confirm our results.

Keywords

Externalities, Renewable Energy, Wind Power, Well-Being, Life Satisfaction, Social Acceptance, Spatial Analysis, SOEP

1. Introduction

Since the 1990s, there has been a world-wide trend towards renewable resources for electricity generation. In OECD countries, the share of renewables, excluding hydro power, quadrupled from 1.8% to 7.2% between 1990 and 2012 (IEA, 2013). Wind power has been a major driver of this development: in the same time period, capacity and production grew by more than 20% annually (IEA, 2013). In Germany, for example, more than 20,000 wind turbines contributed 9% to total electricity consumption in 2014 (BMWi, 2015). Also in non-OECD countries, wind power plays an ever increasing role, for example, in China, being the world's biggest market by 2012 (WWEA, 2013). The economic rationale behind this trend is to avoid negative environmental externalities common to conventional electricity generation technologies. Beyond noxious local emissions from burning fossil fuels, carbon dioxide emissions are responsible for global climate change. Nuclear power is subject to unclear long-term storage of waste and low-probability but high-impact accidents.

While wind power is largely free of emissions, waste, and risks, it is not free of externalities itself. Thereby, it is important to distinguish between *wind power* and *wind turbines*. Wind power, that is, electricity generated by wind turbines, might require costly changes within the electricity system, including the need to build more flexible backup capacities or expand the transmission grid. Wind turbines, in contrast to large centralised conventional power plants, which foster out-of-sight-out-of-mind attitudes, are more spatially dispersed and in greater proximity to consumers, increasing the salience of energy supply (Pasqualetti, 2000; Wüstenhagen et al., 2007). In fact, beyond unpleasant noise emissions (Bakker et al., 2012; McCunney et al., 2014) and impacts on wildlife (Pearce-Higgins et al., 2012; Schuster et al., 2015), most importantly, wind turbines have been found to have negative impacts on landscape aesthetics (Devine-Wright, 2005; Jobert et al., 2007; Wolsink, 2007). In general, no market prices exist for these negative externalities, so that they must be valued using alternative methods, such as stated preference (Groothuis et al., 2008; Jones and Eiser, 2010; Meyerhoff et al., 2010) or revealed preference approaches (Gibbons, 2015; Heintzelmann and Tuttle, 2012).

We investigate the effect of the presence of wind turbines on residential well-being and quantify their negative externalities using the so-called *life satisfaction approach*. To this end, we combine household data from the German Socio-Economic Panel Study (SOEP) with a novel panel dataset on more than 20,000 installations for the time period between 2000 and 2012. Trading off the decrease in life satisfaction caused by the presence of wind turbines against the increase caused by income, we value the negative externalities monetarily. As this approach has already been applied to various other environmental externalities, including air pollution (Ambrey et al., 2014; Ferreira et al., 2013; Levinson, 2012), landscape amenities (Kopmann and Rehdanz, 2013), noise pollution (Rehdanz and Maddison, 2008; van Praag and Baarsma, 2005), or flood disasters (Luechinger and Raschky, 2009), we contribute to a steadily growing stream of literature.

To estimate the causal effect of the presence of wind turbines on residential well-being, we employ a difference-in-differences design that exploits variation in wind turbine construction across space and over time: residents are allocated to the treatment group if a wind turbine is constructed within a pre-defined radius around their households, and to the control group otherwise. To ensure comparability of the treatment and control group, we apply, first, propensity-score matching based on socio-demographic characteristics, macroeconomic conditions, and exogenous weather data; and second, spatial matching techniques based on geographical locations of residence.

We show that the construction of a wind turbine within a radius of 4,000 metres has a significant negative and sizeable effect on life satisfaction. For larger radii, no negative externalities can be detected. Importantly, the effect seems to be transitory, vanishing after five years at the latest, and does not intensify with proximity or cumulation of installations. Robustness checks, including view shed analyses based on digital terrain models and placebo regressions, confirm these results. We arrive at a monetary valuation of the negative externalities for the current resident population between X1 and Y1 Euro per installation and year, depending on the specification. Complementing these numbers with results from hedonic housing regressions, we calculate that the total implicit willingness-to-pay of households in order to avoid wind turbine construction in their surroundings lies between X2 and Y2 Euro per installation and year.

To our knowledge, there exists only one working paper that investigates the effect of the presence of wind turbines on residential well-being, von Moellendorff and Welsch (2015), showing that they have a temporary negative impact. However, it differs from our paper in at least two important aspects: the authors do not account for self-selection of residents, and the data are only analysed at the post code level, i.e. life satisfaction is regressed on the number of wind turbines in a given post code area.

The rest of this paper is organised as follows. Section 2 reviews the literature on negative externalities of wind turbines and different valuation approaches. Section 3 describes the data, and Section 4 the empirical model. Results are presented in Section 5, and discussed in Section 6. Finally, Section 7 concludes and outlines avenues for future research.

2. Literature Review

2.1. Stated and Revealed Preference Approaches

Throughout contingent valuation studies, landscape externalities in form of visual disamenities are found to be a crucial trigger of opposition to particular wind turbine projects (Groothuis et al., 2008; Jones and Eiser, 2010; Meyerhoff et al., 2010). Opposition is found to be shaped by two potentially opposing forces: proximity and habituation. Concerning proximity, most studies find a significant willingness-to-pay to locate planned installations further away from places of residence (Drechsler et al., 2011; Jones and Eiser, 2010; Meyerhoff et al., 2010; Molnarova et al., 2012). Concerning habituation, evidence is more mixed: while some papers detect decreasing acceptance (Ladenburg, 2010; Ladenburg et al., 2013), others find unchanged attitudes (Eltham et al., 2008) or adaptation (Warren et al., 2005; Wolsink, 2007) over time.

Likewise, hedonic studies, drawing on variations in real estate prices, find evidence for negative externalities caused by the construction of wind turbines, for example, in the United States (Heintzelmann and Tuttle, 2012), Denmark (Jensen et al., 2013), the Netherlands (Dröes and Koster, 2014), Germany (Sunak and Madlener, 2014), and England and Wales (Gibbons, 2015). The decrease in real estate prices is found to range between 2% and 16%. Other studies do not detect significant effects (Lang et al., 2014; Sims et al., 2008).

2.2. Life Satisfaction Approach

The life satisfaction approach (LSA) is an alternative to stated and revealed preference approaches. It specifies a microeconometric function relating self-reported life satisfaction to the environmental disamenity to be valued, along with income and other variables. Parameter estimates are then used to calculate the implicit marginal rate of substitution, that is, the amount of income a resident is willing to pay in order to reduce the environmental disamenity by one unit (Frey et al., 2004).

Compared to contingent valuation studies, the LSA avoids bias resulting from the expression of attitudes or the complexity of valuation. Stated preference approaches, in particular, are subject to symbolic valuation: what is measured may be intrinsic attitudes rather than extrinsic preferences. At the same time, they are prone to framing and anchoring effects (Kahneman and Sugden, 2005). The LSA, in contrast, does not ask residents to monetarily value a complex environmental disamenity in a hypothetical situation, which reduces cognitive burden. Likewise, it does not reveal the relationship of interest, mitigating the incentive to answer in a strategic or socially desirable way (Kahneman and Sugden, 2005; van der Horst, 2007).

Compared to hedonic studies, the LSA avoids bias resulting from the misconception that the real estate market is in, or close to, equilibrium. Typically, this occurs in case of slow adjustment of prices, incomplete information, and transaction costs (especially direct and indirect migration costs). It also avoids potentially distorted future risk expectations common to market transactions, as well as bias resulting from the misprediction of utility (Frey et al., 2004; Frey and Stutzer, 2014).

Intuitively, the LSA is not entirely free of methodological issues itself. For subjective well-being data to constitute a valid approximation of welfare, they have to be at least ordinal. Moreover, the microeconometric function relating self-reported life satisfaction to the environmental disamenity has to be specified correctly. These requirements, however, are typically met in practice (Welsch and Kühling, 2009a).

3. Data

3.1. Data on Residential Well-Being

We use panel data from the German Socio-Economic Panel Study (SOEP) for the time period between 2000 and 2012. The SOEP is a representative panel of private households in Germany, covering almost 30,000 individuals in 11,000 households every year (Wagner et al., 2007, 2008). Importantly, it provides information on the geographical locations of the places of residence, allowing to merge data on residential well-being with data on wind turbines.[1] Our dependent variable is *satisfaction with life*, which is obtained from an eleven-point single-item Likert scale that asks "How satisfied are you with your life,

[1]The SOEP is subject to rigorous data protection legislation. It is never possible to derive the household data from coordinates since they are never visible to the researcher at the same time. See Goebel and Pauer (2014) for more information.

all things considered?". Conceptually, life satisfaction, which is equivalent to subjective well-being (Welsch and Kühling, 2009a) or experienced utility (Kahnemann et al., 1997), is defined as the cognitive evaluation of the circumstances of life (Diener et al., 1999).[2]

3.2. Data on Wind Turbines

At the heart of our analysis lies a novel panel dataset on onshore wind turbines in Germany. For its creation, we drew on a variety of dispersed sources, mostly the environmental authorities in the sixteen federal states. If data were not freely accessible, we contacted the body in charge for granting access and filed a request for disclosure.[3] We brought together data on more than 20,000 wind turbines with construction dates ranging between 2000 and 2012. The core attributes rendering an observation suitable for our empirical analysis are *(i)* the exact geographical coordinates, *(ii)* the exact construction dates, and *(iii)* information on the size of the installation.

The exact geographical coordinates constitute the distinctly novel feature of our dataset: postal codes or addresses, as provided by the public transparency platform on renewable energy installations in Germany, would render an exact matching between individuals and installations impossible.[4] Moreover, the exact construction dates of installations are required in order to contrast them with the interview dates of individuals. Finally, we focus only on installations that exceed a certain size threshold: small installations are less likely to interfere with landscape aesthetics; it is also more likely that they are owned by private persons. We could therefore measure effects other than negative

[2]In unreported regressions, we also examined whether wind turbine construction has an effect on health, using self-assessed health, as well as the mental and physical health items from the Short-Form (SF12v2) Health Survey, which has been incorporated into the SOEP. Overall, we find little evidence that these outcomes are affected.

[3]See Table C.11 in the Online Appendix for a detailed account and information on data protection.

[4]The public transparency platform on renewable energy installations can be found at `www.netztransparenz.de/de/Anlagenstammdaten.htm` (in German), accessed June 1, 2015.

externalities. Naturally, there is some degree of arbitrariness in determining a size threshold: beyond those without any information on size at all, we exclude all installations with a hub height of less than 50 metres or a capacity of less than 0.5 megawatts. In doing so, we focus only on large installations that are typically constructed by utilities.[5]

Out of more than 20,000, we are left with a set of 10,083 wind turbines relevant for our analysis. These constitute the *included group*.[6] The other 10,554 constitute the *excluded group*.

3.3. Merge

We merge the data on residential well-being with the data on wind turbines by calculating the distances between households and the nearest installation. Specifically, a treatment radius around each household is specified within which wind turbines of the *included group* trigger the household members to be allocated to the treatment group. If no such wind turbine is located within the treatment radius, the household members are allocated to the control group instead.

We subsequently check for each individual and year whether a wind turbine from the *excluded group* is located within the treatment radius at the interview date. Turbines from the *excluded group* receive special attention as households in their proximity should be discarded: they do not belong to either the treatment or control group. If both a turbine from the *included* and *excluded group* are present, however, then the individual is allocated to the treatment group if the first turbine built is from the *included group*, and discarded otherwise. See Figure C.3 in the Online Appendix for a graphical illustration.

Some further data adjustments are made. Due to currentness of data, only years up to 2010 are included for the state of *Mecklenburg-Vorpommern*, up to 2011 for *Saxony*, and

[5]We also focus only on installations that are built past 2000: before that, the SOEP does not provide information on the geographical locations of the places of residence.

[6]See Table B.1 in the Online Appendix for descriptive statistics.

up to 2012 for all other states. Moreover, we discard individuals for which the interview date is given with insufficient accuracy in the year in which the first wind turbine is constructed in their surroundings: for those individuals, we cannot be sure whether they should be allocated to the treatment or control group. Finally, we discard individuals who “start” in the treatment group, for example, if they enter the panel while a wind turbine is already present in their surroundings: for them, no pre-treatment information to base inference on is given. Note that the size of the treatment and control group depends on the treatment radius chosen.

4. Empirical Model

4.1. Treatment Radius

As default treatment radius, we choose 4,000 metres, motivated by three considerations. First, we consider this radius close enough for wind turbines to unfold negative impacts. Second, it allows for a sufficient sample size, especially when stratifying the final sample to study different sub-groups. Finally, there is no uniform legislation in Germany that could serve as reference. Across time and states, the so-called *impact radius*, based on which intrusions into the environment are evaluated, varies between 1,500 and 6,000 metres for a wind turbine with a hub height of 100 metres. Beyond the 4,000 metres default treatment radius, we carry out various sensitivity analyses with other radii.

In addition, to achieve a clear-cut distinction between treatment and control group at the margin, we introduce a ban radius of 8,000 metres, twice the length of the treatment radius: residents who experience the construction of a turbine within the ban radius, but outside the treatment radius, are discarded.

4.2. Identification Strategy

To establish causality, we have to make three identifying assumptions. First, the interview date is random and unrelated to the construction date. In other words, residents should not strategically postpone interviews due to construction. We checked the distribution of interviews, and it seems that this is not the case. Second, in the absence of treatment, treatment and control group would have followed a common trend in the outcome over time. Although this *common trend assumption* is not formally testable, as the counterfactual is not observable, we apply propensity-score and spatial matching techniques, as described in Sub-Section 4.3, to ensure comparability between treatment and control group. In addition, we control for confounders that could cause remaining differences in time trends.[7] Finally, conditional ignorability implies that, conditional on covariates, construction is independent of the outcome, and therefore exogenous. In our setting, endogeneity may arise through two channels: endogenous construction or endogenous residential sorting. In other words, for certain residents it could be systematically more likely that either new wind turbines are constructed in their surroundings, or that they move away from or towards existing installations. In both cases, estimates would be biased if such endogenous assignment to treatment or control group is correlated with the outcome. We argue that both channels are mitigated.

Concerning endogenous construction, we omit residents who live near small wind turbines, as such installations are more likely to be built and run by private persons. Instead, we focus only on large installations that are typically constructed by utilities. Moreover, we omit residents who are farmers: these are more likely to let land to commercial operators.[8] Finally, we control for individual fixed effects and a rich set of time-varying

[7]Implicitly, we also require the *stable unit treatment value assumption* to hold: whether a wind turbine is constructed in the surroundings of one household should not depend on the outcome of another housheold. There is no a priori reason to believe that this is the case. Moreover, there should be no variation in treatment intensity between households. Here, our size threshold ensures that treatment intensity is rather homogeneous.

[8]In unreported robustness checks, we do not find that wind turbine construction increases income from renting out or leasing of nearby residents. The results are robust to the inclusion of farmers.

observables at the micro level, originating from the SOEP, and at the macro level, originating from the Federal Statistical Office. The micro controls include demographic characteristics, human capital characteristics, and economic conditions at the individual level, as well as household characteristics and housing conditions at the household level; the macro controls include macroeconomic conditions and neighbourhood characteristics at the county level.[9] In doing so, we net out systematic differences between treatment and control group over time and at any point in time, ensuring common trend behaviour.[10]

In case of endogenous residential sorting, residents with lower (higher) preferences for wind turbines self-select into areas with greater (smaller) distances to them, whereby the preferences are correlated with the outcome. This can happen either prior to the observation period, so that we have an issue of *preference heterogeneity*, which we already account for by including individual fixed effects, or during the observation period, so that we have an issue of *simultaneity*. In our baseline specification, we work around simultaneity by excluding residents who move, motivated by two reasons. First of all, hypothesising that wind turbines exert a negative effect on residential well-being, most adversely affected individuals are most likely to move away from installations. Thus, our estimates can be interpreted as a lower bound, which is then consistent with the definition of our treatment variable: as it proxies the effect of the presence of wind turbines on residential well-being by distance, it implicitly assumes that every wind turbine is visible to every resident at any time, which is unlikely to be the case. For example, local topography might block the view from a household to a wind turbine.[11] On the other

[9]The results are robust to replacing the macro controls with state-year fixed effects. Moreover, they are robust to including linear and quadratic time trends, both individually and jointly, and to including month and quarter of year fixed effects.

[10]The results are robust to omitting all of these controls, which reinforces the notion of ignorability, that is, wind turbine construction as an exogenous event.

[11]We investigate this issue further in Sub-Section 5.6.

hand, households might adopt mitigating behaviour to block the view themselves, for example, by planting a tree or building a fence. Finally, we only have information on private households: some individuals, however, might spend considerable amounts of time outside their homes, for example, at work. They might therefore be less permanently affected, and so would be temporary visitors like tourists.

Besides that, endogenous residential sorting seems to be a minor issue: geographical mobility in Germany is traditionally low. As a matter of fact, in our final sample, only about 2% of all individuals move, and, most importantly, only about 3% of individuals in the treatment group. Moreover, from those 3%, 87% move for reasons that are not directly linked to their location.[12] In Sub-Section 5.7, we show that the results are indeed invariant to the inclusion of movers.

4.3. Matching Treatment and Control Group

Under the basic definition, the treatment group is relatively small, and concentrated in remote and rural areas, whereas the much larger control group is dispersed over the whole country. Individuals may thus not be comparable to each other, questioning the assumption of a common time trend between treatment and control group. We therefore restrict both treatment and control group to individuals living in rural areas, excluding individuals living in city counties (*kreisfreie Städte*) and counties ranked in the top two deciles according to population density.[13] Moreover, we use two types of matching,

[12] The SOEP includes an item that asks respondents whether they moved in the previous time period, as well as a follow-up item that asks them about the main reason for moving, including notice given by the landlord; buying a house or an apartment; inheritance; job reasons; marriage, breakup, or other family reasons; the size of the dwelling; the price of the dwelling; the standard of the dwelling; the standard of the location; the standard of the surroundings; and other reasons. We combine the standard of the location with the standard of the surroundings into one category that we assume not to be directly linked to the location of respondents.

[13] The results are robust to the inclusion of individuals living in urban areas.

prior to running our difference-in-differences regressions. See Figure C.4 in the Online Appendix for a graphical illustration of both types of matching.

The first type of matching is *propensity-score matching*. Specifically, we use one-to-one nearest-neighbour matching on macro controls, including the unemployment rate, average monthly net household income, and population density at the county level, as well as state dummies. We match residents on the mean values of these variables, taken over the entire observation period. Alternatively, one could match individuals on their values in either the first year of the observation period or, in case that individuals enter the panel at a later point, in the first year in which they enter the panel. The resulting point estimates are similar in terms of significance, and slightly smaller in size.[14] We also match on a variable that captures local wind power adequacy, defined as the average annual energy yield of a wind turbine in kilowatt hours per square metre of rotor area, based on weather data from 1981 to 2000 (German Meteorological Service (DWD), 2014). It encompasses a multitude of exogenous climatic and geographical factors. Specifically, it is based on wind velocity and aptitude, taking into account between-regional factors, such as coasts, and within-regional factors, such as cities, forests, and local topographies. Wind power adequacy is recorded on the basis of 1 kilometre $\times$ 1 kilometre tiles, distributed over the entire country. We match households with the nearest tile, and calculate the mean expected annual energy yield of a wind turbine from the 25 tiles surrounding it. See Figure C.5 in the Online Appendix for a graphical illustration of this calculation.

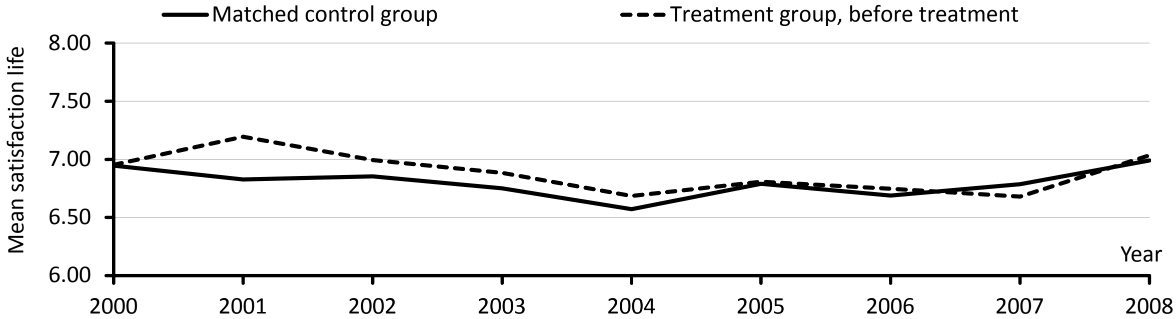
Figure 1 visualises how the dependent variable, *satisfaction with life*, evolves over time. The annual mean life satisfaction is shown for the matched control group (solid line) and the treatment group prior to treatment (dashed line).[15] All graphs control for

[14] The results are available upon request.

[15] The horizontal axis is restricted to the time period between 2000 and 2008. Thereafter, the pre-treatment group mean is based only on very few observations, and hardly delivers insightful information.

confounders. As can be seen, the matched control and pre-treatment group co-move in a similar pattern over time; there is no evidence for a diverging time trend.

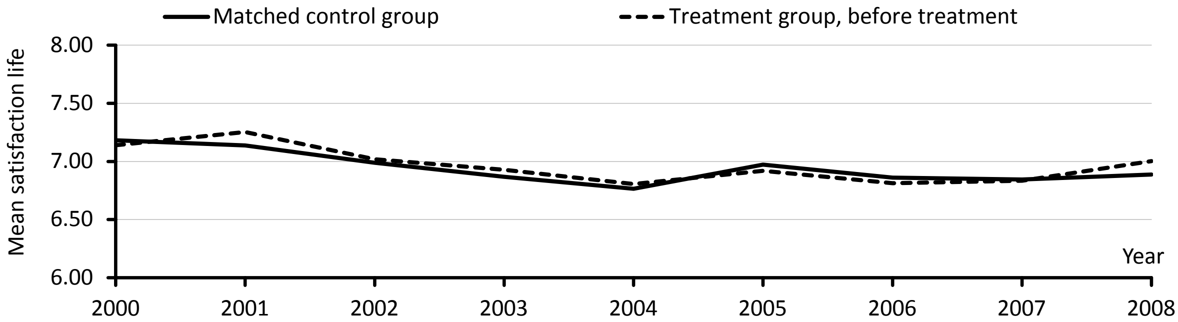
Figure 1: Common Time Trend (Propensity-Score Matching)



Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, own calculations

The second type of matching is *spatial matching.* It is based on the first law of geography, which states that closer things are more similar to each other. In this vein, it follows the idea that residents in close proximity to wind turbines are sufficiently similar to those living close but slightly farther away. We define a matching radius around each place of residence: individuals who are neither treated nor discarded, but experience the construction of a wind turbine within the matching radius, constitute the control group. In other words, we match residents who live close to an installation and close enough to be treated with those who live close but not close enough to be treated. We choose 10,000 and 15,000 metres as matching radii, whereby the latter serves as default. Through spatial matching, the scope of the analysis is narrowed down to residents who are comparable in terms of local living conditions. Likewise, potential positive effects of wind turbines, in particular local economic benefits, can be mitigated: while both treatment and control group could profit to a certain extent from a wind turbine, only the treatment group within 4,000 metres distance is likely to be negatively affected by its presence.

Figure 2: Common Time Trend (Spatial Matching, 15,000 metres)



Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, own calculations

Figure 2 is constructed analogously to Figure 1, using the default matching radius of 15,000 metres. Again, there is no evidence for a diverging time trend between matched control and pre-treatment group. A similar picture arises for the matching radius of 10,000 metres.

Finally, the descriptive statistics for the propensity-score matching specification are given in Table A.1:[16] it shows the means of all covariates, overall and separately for treatment and control group, along with their scale-free normalised differences. Imbens and Wooldridge (2009) suggest that a normalized difference above 0.25 indicates covariate imbalance. Clearly, this is not the case for any of our covariates. Thus, we conclude that the final sample is well-balanced on observables.[17]

Table A.1 about here

[16]See Table C.1 in the Online Appendix for the spatial matching specification.

[17]Note that covariance imbalance between treatment and control group would not necessarily be a threat to our identification strategy: we control for a rich set of time-varying observables. Moreover, including individual and year fixed effects net out systematic differences in both time-invariant observables and unobservables between individuals and years, respectively.

4.4. Regression Equation

We employ a linear model estimated by the fixed-effects (within) estimator.[18] The specification test by Wu (1973) and Hausman (1978), as well as the robust version by Wooldridge (2002) indicate that a fixed-effects specification is strictly preferable over a random-effects one: all tests reject the null of identical coefficients at the 1% significance level.[19] Robust standard errors are clustered at the federal state level.

Regression Equation (1) estimates the overall treatment effect, with $Construction_{it,r}$ as the regressor of interest. $Construction_{it,r}$ is a dummy variable that equals one in time period t if a wind turbine is present within treatment radius r around the household of individual i, and zero else. Regression Equation (2) estimates the treatment effect intensity, with the interaction $Construction_{it,r} \times Intensity_{it,r}$ as the regressor of interest. $Intensity_{it,r}$ is a place holder for different measures of treatment intensity: $InvDist_{it,r}$ is the inverse of the distance to the nearest installation in kilometres, $RevDist_{it,r}$ is the treatment radius minus the distance to the nearest installation, and $Cumul_{it,r}$ is the number of installation within the treatment radius. As more or more closely located wind turbines can be constructed during the observation period, the intensity can change over time. The two distance measures make different parametric assumptions. Regression Equation (3) estimates the treatment effect persistence. The regressor of interest, $Trans_{it-\tau,r}$, is a dummy variable that equals one in time period t, which is τ periods after

[18]Note that using a linear model introduces measurement error, as *satisfaction with life* is a discrete, ordinal variable. However, this has become common practice, as discrete models for ordinal variables are not easily applicable to the fixed-effects (within) estimator, and the bias resulting from this measurement error has been found to be negligible (see, for example, Ferrer-i-Carbonell and Frijters (2004) for panel data, and Brereton et al. (2008) and Ferreira and Moro (2010) for repeated cross-section data).

[19]The empirical values of the test-statistic, 204.20 and 220.38 under propensity-score matching and 211.12 and 243.20 under spatial matching, exceed the critical value 56.06 of the χ^2-distribution with 34 degrees of freedom.

the construction of the first turbine within the treatment radius, and zero else.

$$\begin{aligned} y_{it} &= \beta_0 + \mathbf{MIC'_{it}}\boldsymbol{\beta}_1 + \mathbf{MAC'_{it}}\boldsymbol{\beta}_2 + \delta_1 Construction_{it,r} + \\ &+ \sum_{n=1}^{12} \gamma_n Year_{2000+n} + \mu_i + \epsilon_{it} \end{aligned} \tag{1}$$

$$\begin{aligned} y_{it} &= \beta_0 + \mathbf{MIC'_{it}}\boldsymbol{\beta}_1 + \mathbf{MAC'_{it}}\boldsymbol{\beta}_2 + \delta_1 Construction_{it,r} \times Intensity_{it,r} + \\ &+ \sum_{n=1}^{12} \gamma_n Year_{2000+n} + \mu_i + \epsilon_{it} \end{aligned} \tag{2}$$

$$\begin{aligned} y_{it} &= \beta_0 + \mathbf{MIC'_{it}}\boldsymbol{\beta}_1 + \mathbf{MAC'_{it}}\boldsymbol{\beta}_2 + \sum_{\tau=1}^{9} \delta_\tau Trans_{it-\tau,r} + \\ &+ \sum_{n=1}^{12} \gamma_n Year_{2000+n} + \mu_i + \epsilon_{it} \end{aligned} \tag{3}$$

where y_{it} is *satisfaction with life* as the regressand; MIC_{it} and MAC_{it} are vectors of controls at the micro and macro level, respectively; and $Year_{2000+n}$ is a full set of yearly dummy variables. μ_i captures time-invariant unobserved heterogeneity at the individual level. ϵ_{it} is the idiosyncratic disturbance. $Construction_{it,r}$, $Construction_{it,r} \times Intensity_{it,r}$, and $Trans_{it-\tau,r}$ are the regressors of interest. The corresponding average treatment effects on the treated are captured by δ_1 and δ_τ.

5. Results

5.1. Overall Treatment Effect

Table A.2 reports the results of our difference-in-differences propensity-score and spatial matching specifications using the default treatment radius of 4,000 metres. For convenience, we only show our treatment variable here; detailed tables showing all covariates can be found in the Online Appendix.

Table A.2 about here

For both matching specifications, a central result emerges: the presence of a wind turbine within the default treatment radius of 4,000 metres around households has a significant negative effect on life satisfaction at the 1% and 5% level, respectively. The size of this effect is also economically significant: under propensity-score matching, for instance, life satisfaction decreases by 8% of a standard deviation. Combining the propensity-score with the spatial matching yields point estimates that are very similar to those of the standalone spatial matching specifications, regardless of matching radius chosen, and significant at the 5% level.[20]. The baseline specification thus provides evidence for significant negative local externalities.

What happens if we increase the treatment radius? For 8,000 and 10,000 metres under propensity-score matching, coefficient estimates are negative but considerably smaller in size, $\delta_1 = -0.0348$ and $\delta_1 = -0.0074$, respectively, and insignificant at any conventional level. Likewise, no effect can be detected in case of a 15,000 metres treatment radius.[21] An analogous result emerges for an increased treatment radius of 8,000 metres under spatial matching. This corroborates that we indeed systematically pick up negative local externalities triggered by the presence of wind turbines rather than local peculiarities: while closer proximity serves as a proxy for an undesired impact, for larger distances such an effect cannot be detected anymore.

5.2. Treatment Effect Intensity

We explore treatment effect intensity next. In Table A.3, for inverse distance, reverse distance, and cumulation, coefficient estimates have the expected sign, but none of them is significant for any matching specification.[22] It seems that the presence of a wind turbine

[20] See Table C.2 in the Online Appendix for the combined matching specification.

[21] For larger treatment radii, we apply no ban radius. See the Online Appendix for detailed results.

[22] The results for spatial matching with a 10,000 metres matching radius are analoguous. See the Online Appendix for detailed results.

itself is sufficient for negative externalities to arise, and specific intensity measures do not matter in addition.

Table A.3 about here

To explore this finding further, we investigate closer treatment radii below 4,000 metres under spatial matching (with propensity-score matching, the control group would have to be determined anew for each treatment radius, rendering comparability difficult). Specifically, we use 2,000, 2,500, and 3,000 metres as treatment radii, and in addition analyse different distance bands around treated individuals. For example, in band $[2,000; 3,000]$, only individuals experiencing wind turbine construction between 2,000 and 3,000 metres around their places of residence are assigned to the treatment group; residents with wind turbines in closer proximity are dropped. Analogously, we specify bands between 2,000 and 4,000 metres, 2,500 and 4,000 metres, and 3,000 and 4,000 metres. Table A.4 reports the results for both spatial matching radii. For distances below 4,000 metres, no significant effects are detected, and neither is for the $[2,000; 3,000]$ band. For larger bands, however, coefficient estimates are negative, significant at the 1% or 5% level, and large in size.[23]

Table A.4 about here

This finding can have several explanations. First, results can be driven by smaller sample sizes. In the baseline 4,000 metres specification, there are 506 treated individuals, decreasing to only 183 for 2,000 metres. Beyond such a potential statistical artefact, residents in closer proximity may exhibit certain peculiarities: some could effectively

[23]Alternatively, instead of estimating separate sub-samples, one could interact the main effect with a dummy variable for the respective distance band: the results remain qualitatively the same.

profit from installations, for instance, by directed compensation measures, as anecdotal evidence suggests. Alternatively, individuals in particularly close distance could also actively erect wind turbines in their surroundings, and profit monetarily.[24] Although we discarded small wind turbines that are unlikely to be built by utilities from our analysis, we cannot fully exclude this case since we do not have information on the ownership structure of particular installations.

Concerning size and significance of coefficient estimates, this result is in line with the treatment effect for the default 4,000 metres radius: while the effect is much stronger within the $[2,000; 4,000]$ band, it is insignificant for closer distances. Concerning directed compensation measures or active wind turbine erection by residents, results are in line with a lower-bound interpretation: as it cannot be excluded that some individuals in closer distances may profit, estimates are, if anything, attenuated, given that an significant negative overall treatment effect remains a robust finding. As discussed above, this lower-bound interpretation is consistent with the definition of the treatment variable.

In this respect, insignificant coefficient estimates for the different intensity measures are explained by non-significance of effects for smaller distances: if coefficients are insignificant for individuals living closer to wind turbines, treatment intensity increasing in proximity is obsolete.

5.3. Treatment Effect Transitoriness

Intuitively, the question arises whether the presence of wind turbines has a permanent or transitory effect on residential well-being. Table A.5 reports results on transitoriness for all matching specifications, including coefficient estimates for up to nine transition periods after the construction of a wind turbine within the default treatment radius of 4,000 metres. As can be seen, the effect seems to be temporally limited. It is significant

[24] In unreported robustness checks, we do not find that wind turbine construction decreases electricity costs of nearby residents.

at the 1% or 5% level from transition period two, that is, one year after the construction of a wind turbine, to at most transition period five. The size of the effect in each time period is somewhat larger than the size of the combined effect.

Note that a non-significant effect in transition period one is not surprising. While we use the construction date as reported in the data sources, in reality there might be some blur, which is picked up by the first-period coefficient: a wind turbine is usually not erected within a single day, and it is not stated explicitly whether the construction date marks the beginning or the end of the construction process. Additional sensitivity checks including a dummy variable for the time period before the construction of a wind turbine, on the contrary, provide no evidence of anticipation effects.[25]

Table A.5 about here

This finding can have several explanations. First, current residents may adapt to the presence of wind turbines in their surroundings (it is difficult to make any inference on future residents, or temporary visitors, as they do not appear in the data). Alternatively, they may adjust to their presence, for example, by adopting mitigating behaviour, such as planting a tree or building a fence. Second, the decay effect may be due to disamenities related to the construction process rather than the presence wind turbines. We believe that this is less likely to be the case, though, as the construction process of wind turbines is rather quick. Moreover, the non-significant effect in transition period one and the prolonged significant effects in transition periods thereafter point against this explanation. Finally, results may be driven by smaller sample sizes, as the treatment group size decreases over time. For a lag of nine years, construction from 2000 to 2003 is possible, whereas for shorter intervals more years are relevant. Note, however, that the

[25]See Sub-Section 5.6.

point estimates remain reasonably robust as significance decreases. Non-significance may thus arise as a statistical artefact due to loss of power rather than a genuine decay effect. Likewise, heavily affected residents might be excluded as they move away as time passes. Both explanations are, again, consistent with a lower-bound interpretation.

5.4. Heterogeneity Analysis

To gain a more diverse picture, we now apply our treatment effect analysis to different sub-groups. Table A.6 reports the results for residents who are house owners versus residents who are not, as well as for residents who are very concerned about the environment or climate change, respectively, versus residents who are not. The indicators on environmental and climate change concerns are obtained from single-item three-point Likert scales that ask respondents to rate how concerned they are about "environmental protection" or "climate change", respectively. We collapse these items into binary indicators that equal one for the highest category of concerns, and zero otherwise. Throughout all models, we use the difference-in-differences spatial matching specification with the default matching radius of 15,000 metres; results are robust to using the matching radius of 10,000 metres.

Table A.6 about here

Stratifying along real estate ownership, the coefficient estimate for house owners shows a significant negative effect (first column), which is not the case for non-house owners (second column). The size of the coefficient estimate is somewhat larger than at the aggregate level. One explanation for this finding may be that house owners, beyond negative local externalities due to a decrease in landscape aesthetics, suffer an additional monetary loss from a decrease in real estate prices. Sensitivity analyses including land price at the county level as an additional control leave results at the aggregate level and for the different sub-groups unchanged. Relating this result to hedonic pricing theory, it is in line with both classic economic theory and the critique of the hedonic method: if a negative externality was already completely priced into real estate values, there would be no scope for an additional effect. If, however, market frictions and transaction costs preclude full internalisation, then other methods can detect complementary effects.[26] We will turn to this issue in more detail in Sub-Section 6.

Stratifying along environmental concerns, coefficient estimates for non-concerned individuals show significant negative effects (fourth column for environment, sixth for climate change), which is not the case for concerned individuals (third and fifth column, respectively). Again, the size of coefficient estimates is higher than at the aggregate level. In this respect, we interpret environmental concerns as referring to more global rather than local impacts. Generally, wind turbines are regarded as environmentally friendly, and findings for residents who are environmentally aware are in line with that interpretation. Likewise, less environmentally aware individuals may have lower preferences for emission-free electricity production and, thus, be more sensitive towards intrusions into their surroundings.

5.5. Robustness: Placebo Tests

To check the robustness of our results regarding confounding factors, we conduct placebo tests. Specifically, we include up to three leads of the treatment variable, first individually and then jointly in combination with the contemporary treatment variable, in both our default difference-in-differences propensity-score and spatial matching specifications. Table A.7 reports the results.

Table A.7 about here

[26] In this context, Luechinger (2009) provides a discussion of this complementarity in the context of air pollutant emissions from fossil-fuelled power plants.

As can be seen, none of the leads is significant at any conventional level, neither in the propensity-score – first to third column – nor spatial – fifth to seventh column – matching specification. They are also much smaller in size, and in case of the third lead even of opposite sign. When included jointly in combination with the contemporary treatment variable – fourth and eighth column – they remain insignificant without clear pattern in terms of sign and size. The contemporary treatment variable, however, is still significant at the 1% level, negative, and large in magnitude. We take this as evidence that our estimates indeed systematically pick up the effect of wind turbine construction rather than confounding factors.[27]

5.6. Robustness: View Shed Analysis

To check the robustness of our results regarding actual visual relationships between households and installations, we combined our geographical information on households and wind turbines with a digital terrain model for Germany (Federal Agency for Cartography and Geodesy (BKG), 2016). This also provides further insight into disentangling the identified negative externalities into landscape aesthetics and other channels. To be clear, a digital terrain model includes only geographical barriers to visibility, such as location-specific elevated terrain, while excluding natural ones, such as forests and trees, as well as man-made structures, such as houses and fences, all of which may equally be barriers to visibility. However, to the extent that the latter are built on purpose in order to block visibility, individuals who built them are presumably those that are most adversely affected. Our estimates can thus be interpreted as a lower bound again.

We created an entirely new treatment group of households that are located within the default treatment radius of 4,000 metres and that have a direct view of wind turbines, as well as a corresponding new measure of treatment intensity – the visible height of wind

[27]This is also evidence that the construction of a wind turbine is a rather sudden, short-lived, and unanticipated event.

turbines from the viewpoint of households. Based on these, we performed a view shed analysis. The results are presented in Table A.8.

Table A.8 about here

As can be seen, the point estimates using the new treatment group definition are very similar to those using the old, in both our propensity-score – first column – and spatial – third column – matching specification. In fact, they are only slightly smaller in size and slightly less significant; the latter is most likely due to the loss of observations resulting from wind turbines covered by terrain. Moreover, the second and fourth column show that, when using the new treatment group definition and interacting the main effect with the visible height of the nearest installation, life satisfaction drops significantly for each metre rise in visibility. Interestingly, from all measures of treatment intensity, the visible height of wind turbines from the viewpoint of households is the only measure that turns out significant.[28]

We take this as evidence that the identified negative externalities associated with the construction of wind turbines are indeed foremost driven by negative impacts on landscape aesthetics. Moreover, the aggravating effect of the visible height of the nearest installation suggests that they are mainly driven by households that stand in direct visual relationship to them; however, the vast majority of households in our sample (about 92%) can see at least part of the nearest installation.

[28]We also recalculated all of our other intensity measures, including the inverse and reverse distance to the nearest installation, as well as the cumulative number of installations around the household, for the new treatment group. We did the same for our measures of treatment transitoriness. The results, which are available upon request, also confirm our baseline results.

5.7. Robustness: Residential Sorting

So far, we have excluded movers from all our analyses. The reason for this was twofold: assuming that individuals who move are those that are most adversely affected by wind turbines, excluding them means that our estimates can be interpreted as a lower bound. This, in turn, is then consistent with our treatment variable, which should be interpreted the same way. Besides that, only a very small share of individuals move in the first place: about 2% overall, and most importantly, about 3% of individuals in the treatment group. Of those 3%, when being asked about their main reason for moving, about 87% report to move for reasons unrelated to their surroundings.

To nevertheless check the robustness of our results regarding individuals who move, we perform two robustness checks. First, we re-estimate our difference-in-differences propensity-score and spatial matching specifications for a sample that includes both non-movers and movers. Second, we estimate linear probability models that regress the probability of moving in a given time period on the treatment variable. Other than that, these models build again on our usual specifications.

Table A.9 about here

Table A.9 reports the results for the first robustness check. ... . In the second robustness check, we do not find that the construction of a wind turbine in the default treatment radius of 4,000 metres around households has a significant effect on the probability of moving, in neither our difference-in-differences propensity-score nor spatial matching specification. The point estimates are close to zero, and if anything, negative.[29] We take this as evidence that endogenous residential sorting, if anything, is only a minor issue in our context.

[29]See Table C.10 in the Online Appendix for the results on the linear probability models.

6. Discussion

Our findings provide empirical evidence that the presence of wind turbines entails negative externalities, though limited in both time and space. This insight can add to the analysis of the transition towards renewables in electricity generation, which features high on the policy agenda in many countries. We put our findings into this context and draw some modest comparisons to the negative externalities that wind turbines are targeted to mitigate, in particular greenhouse gas emissions. Though necessarily remaining a somewhat ad-hoc back-of-the-envelope calculation, this assessment puts some intuition on our results.

To this end, we first monetise the identified negative externalities. Some caveats apply. First, regression coefficients capture marginal effects, while changes to be valued are greater than marginal. Likewise, the impact of income on life satisfaction may comprise more subtle aspects like relative comparisons to the past or to others. Moreover, evidence suggests that quantifications may overestimate the monetary effect of an environmental externality to be valued (Luechinger, 2009). Numbers derived here are thus an informed point of reference for comparisons.

We provide a lower and an upper bound for the monetised negative externalities. For the lower bound, we draw on results from the 10,000 metres radius matching, as in Table **??**, where only coefficient estimates for transition periods two to four are significant negative at a conventional level. Intuitively, the monetary valuation applies only to affected residents. In the final sample, each turbine affects approximately 0.2 residents. As wind turbines are concentrated in rural areas, the actual ratio is likely to be lower. Trading off the estimated coefficients against each other, summing over the three transition periods for which significant effects are found, and weighting results with the factor 0.2, the average monetised negative externality amounts to 181 Euro per wind turbine in total, 49 Euro for the second year, 58 for the third, and 74 for the fourth. Assuming a lifetime of a wind turbine of 20 years and, for simplicity, no discounting, this translates to 9 Euro per wind turbine and year. For the upper bound, we suppose a permanent effect and take the coefficient estimate largest in size from the propensity-score matching. Here, the average monetised negative externality amounts to 59 Euro per wind turbine and year.[30]

Next, we assess how much CO_2 emissions are avoided by a single wind turbine. To this end, we draw on the energy economics literature. The methodology consists in the numerical simulation of a counterfactual electricity system without wind power. To be clear, these numerical simulations depend in part on assumptions to which extent conventional technologies are replaced by renewables. Nevertheless, the literature delivers a narrow corridor of results for Germany, ranging between 650 and 790 grams of CO_2 per kilowatt hour of wind power between 2006 and 2010 (Weigt et al., 2013), and 720 grams for 2013 (Memmler et al., 2014).

Damage through CO_2 is world-wide and quantified by large integrated assessment models (see, for example, Pindyck (2013)). We assume a value of 50 Euro per ton (Foley et al., 2013; van den Bergh and Botzen, 2014, 2015). A modern wind turbine with a capacity of 2.5 megawatts (Memmler et al., 2014) and an average operating time of 1,600 full-load hours per year (BMWi, 2015) produces 4 gigawatt hours of electrical energy per year. With 700 grams of CO_2 displaced per kilowatt hour produced, a total of 2,800 tons of CO_2 is avoided. In other words, there is a total monetised *avoided negative externality* of 140,000 Euro per year. Even under very conservative assumptions, that is, a wind turbine with a capacity of 1 megawatt, operating time of 1,500 full-load hours, 650 grams of CO_2 displaced, and social costs of carbon dioxide emissions of 20 Euro per ton, the

[30]Or framed to the perspective of an affected resident, at the lower bound on average 906 EUR in total; 245, 292, and 369 EUR for the effective years respectively, and 45 EUR per year over a turbine's lifetime; and 293 EUR per year at the upper bound. This result is in line with Gibbons (2015) who finds that a household would be willing to pay around 600 GBP (861 EUR, converted as of July 17, 2015) per year to avoid having a wind farm of average size within 2km distance.

total monetised *avoided negative externality* amounts to 19,500 Euro per year.

Likewise, findings for wind power could be contrasted to other avoided externalities: SO_2 emissions, causing so-called *acid rain* (Luechinger, 2009, 2010), particulate matter, causing detrimental health impacts (Cesur et al., 2015), or nuclear power, which produces radioactive waste and is subject to low-probability but high-impact accidents, which do not only have negative local effects, but also significant spillovers on other countries (Goebel et al., 2015). Compared to these negative externalities, which are common to conventional technologies, the both spatially and temporally limited negative externalities caused by the presence of wind turbines are small. Taking the monetised valuation between 9 and 59 Euro per wind turbine and year at face value, annual benefits from displacing CO_2 emissions of up to over 100,000 Euro per year are disproportionately high. In total, for damage caused by CO_2 emissions, wind turbines saved between 1.1 and 3.7 billion Euro in Germany in 2013 alone, as opposed to 1.2 million Euro in monetised negative externalities.

A major implication for policy-makers is to communicate these findings. Besides that, the damage caused by CO_2 emissions is global, whereas the negative externalities caused by the presence of wind turbines are highly local. It is thus distributional issues that have to be balanced, for example, by organisationally or financially involving affected communities.

7. Conclusion

In many countries, wind power plays an ever increasing role in electricity generation. The economic rationale behind this trend is to avoid negative environmental externalities common to conventional technologies: wind power is largely free of emissions from fossil fuel combustion, as well as waste and risks from nuclear fission. For wind power to play an effective role, however, wind turbines must be constructed in large numbers, rendering them more spatially dispersed. In fact, the greater proximity of wind turbines to consumers has been found to have negative externalities itself, most importantly negative impacts on landscape aesthetics.

Against this background, we investigated the effect of the presence of wind turbines on residential well-being in Germany, combining household data from the German Socio-Economic Panel (SOEP) with a unique and novel panel dataset on more than 20,000 wind turbines for the time period between 2000 and 2012. In doing so, we quantified the negative externalities caused by the presence of wind turbines, using the life satisfaction approach. Employing a difference-in-differences design, which exploits the exact geographical coordinates of households and turbines, as well as their interview and construction dates, respectively, we established causality. To ensure comparability of the treatment and control group, we applied propensity-score and spatial matching techniques based, among others, on exogenous weather data and geographical locations of residence. We showed that the construction of a wind turbine in the surroundings of households has a significant negative effect on life satisfaction. Importantly, this effect is both spatially and temporally limited. The results are robust to using different model specifications.

We arrived at a monetary valuation of the negative externalities caused by the presence of an average wind turbine between 9 and 59 Euro per installation and year. Though non-negligible, this amount is substantially lower than the damage through CO_2 emissions of conventional power plants displaced by wind turbines. An average wind turbine *avoids* negative externalities of about 140,000 Euro per year under standard assumptions or 19,500 Euro per year under very conservative assumptions. From a policy perspective, nevertheless, opposition against wind turbines cannot be neglected: our results indicate a significant negative effect on residential well-being. It remains the task of the policy-maker to communicate benefits and moderate decision-making processes, and to consider distributional implications and potential compensation measures.

Several limitations and open points provide room for further research. First, we do not have data on view-sheds or concrete visibility of wind turbines from places of residence, as could be provided by digital surface models. Second, for convenience, we exclude residents who move from our analysis. Finally, we do not have data on the ownership structure of wind turbines. All three caveats, however, are consistent with a lower-bound interpretation of our findings: residents in the treatment group might actually not be affected, residents who are most adversely affected might be most likely to move away, and wind turbines in community ownership might have potentially positive monetary or idealistic effects on nearby residents. Beyond that, avenues for future research lie in the transfer of the empirical strategy applied in this study to other energy infrastructure, such as biomass plants or transmission towers.

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References

Ambrey, C., C. Fleming, and A. Y.-C. Chan, "Estimating the cost of air pollution in South East Queensland: An application of the life satisfaction non-market valuation approach," *Ecological Economics* 97 (2014), 172–181.

Batel, S., P. Devine-Wright, and T. Tangeland, "Social acceptance of low carbon energy and associated infrastructures: A critical discussion," *Energy Policy* 58 (2014), 1–5.

Bakker, R. H., E. Pedersen, G. P. van den Berg, R. E. Stewart, W. Lok, and J. Bouma, "Impact of wind turbine sound on annoyance, self-reported sleep disturbance and psychological distress," *Science of the Total Environment* 425 (2012), 42–51.

Brereton, F., J. P. Clinch, and S. Ferreira, "Happiness, geography and the environment," *Ecological Economics* 65(2) (2008), 386–396.

Chay, K. Y., and M. Greenstone, "Does Air Quality Matter? Evidence from the Housing Market," *Journal of Political Economy* 113(2) (2005), 376–424.

Federal Agency for Cartography and Geodesy (BKG), "Digitales Geländemodell Gitterweite 200 m ," (2016).

Federal Ministry for Economic Affairs and Energy (BMWi), "Zeitreihen zur Entwicklung der erneuerbaren Energien in Deutschland," (2015).

Cass, N., and G. Walker, "Emotion and rationality: The characterisation and evaluation of opposition to renewable energy projects," *Emotion, Space and Society* 2(1) (2009), 62–69.

Cesur, R, E. Tekin, and A. Ulker, "Air Pollution and Infant Mortality: Evidence from the Expansion of Natural Gas Infrastructure," *The Economic Journal* (forthcoming), doi: 10.1111/ecoj.12285.

Devine-Wright, P., "Beyond NIMBYism: towards an integrated framework for understanding public perceptions of wind energy," *Wind Energy* 8(2) (2005), 125–139.

Devine-Wright, P., and Y. Howes, "Disruption to place attachment and the protection of restorative environments: A wind energy case study," *Journal of Environmental Psychology* 30(3) (2010), 271–280.

Diener, E., E. M. Suh, R. E. Lucas, and H. L. Smith, "Subjective Well-Being: Three Decades of Progress," *Psychological Bulletin* 125(2) (1999), 276–302.

Drechsler, M., C. Ohl, J. Meyerhoff, M. Eichhorn, and J. Monsees, "Disruption to place attachment and the protection of restorative environments: A wind energy case study," *Energy Policy* 39(6) (2011), 3845–3854.

Dröes, M. I., and H. R. A. Koster, "Renewable Energy and Negative Externalities: The Effect of Wind Turbines on House Prices," *Tinbergen Institute Discussion Paper* 14-124/VIII (2014).

Eltham, D. C., G. Harrison, and S. J. Allen, "Change in public attitudes towards a Cornish wind farm: implications for planning," *Energy Policy* 36(1) (2008), 23–33.

Ferreira, S., A. Akay, F. Brereton, J. Cuñado, P. Martinsson, M. Moro, and T. F. Ningal, "Life satisfaction and air quality in Europe," *Ecological Economics* 88 (2013), 1–10.

Ferreira, S., and M. Moro, "On the Use of Subjective Well-Being Data for Environmental Valuation," *Environmental and Resource Economics* 46(3) (2010), 249–273.

Ferrer-i-Carbonell, A., and P. Frijters, "How Important is Methodology for the estimates of the determinants of Happiness?," *The Economic Journal* 114(497) (2004), 641–659.

Foley, D. K., A. Rezai, and L. Taylor, "The social cost of carbon emissions: Seven propositions," *Economics Letters* 121(1) (2013), 90–97.

Frey, B., S. Lüchinger, and A. Stutzer, "Valuing Public Goods: The Life Satisfaction Approach," *CREMA Working Paper* 2004-11 (2004).

Frey, B. S., and A. Stutzer, "Economic Consequences of Mispredicting Utility," *Journal of Happiness Studies* 15(4) (2014), 937–956.

Frey, B. S., *Happiness: A Revolution in Economics* (Cambridge, MA: The MIT Press, 2010).

Goebel, J., and B. Pauer, "Datenschutzkonzept zur Nutzung von SOEPgeo im Forschungsdatenzentrum SOEP am DIW Berlin," *Zeitschrift für amtliche Statistik Berlin-Brandenburg* 3 (2014), 42–47.

German Meteorological Service (DWD), "Karten zur Windkraftnutzungseignung in 80 Meter über Grund," (2014).

Gibbons, S., "Gone with the wind: Valuing the visual impacts of wind turbines through house prices," *Journal of Environmental Economics and Management* 72 (2015), 177-196.

Goebel, J., C. Krekel, T. Tiefenbach, and N. R. Ziebarth, "How natural disasters can affect environmental concerns, risk aversion, and even politics: evidence from Fukushima and three European countries," *Journal of Population Economics* 28(4) (2015), 1137–1180.

Groothuis, P. A., J. D. Groothuis, and J. C. Whitehead, "Green vs. green: Measuring the compensation required to site electrical generation windmills in a viewshed," *Energy Policy* 36(4) (2008), 1545–1550.

Hausman, J. A., "Specification Tests in Econometrics," *Econometrica* 46(6) (1978), 1251–1271.

Heintzelmann, M. D., and C. M. Tuttle, “Values in the Wind: A Hedonic Analysis of Wind Power Facilities,” *Land Economics* 88(3) (2012), 571–588.

Imbens, G. W., and Wooldridge, J. M., “Recent Developments in the Econometrics of Program Evaluation,” *Journal of Economic Literature* 47(1) (2009), 5-86.

International Energy Agency (IEA), *Renewables Information 2013* (Paris, France: OECD/IEA, 2013).

Jensen, C. U., T. E. Panduro, and T. H. Lundhede, “The Vindication of Don Quixote: The Impact of Noise and Visual Pollution from Wind Turbines,” *Land Economics* 90(2) (2013), 668-682.

Jobert, A., P. Laborgne, and S. Mimler, “Local acceptance of wind energy: Factors of success identified in French and German case studies,” *Energy Policy* 35(5) (2007), 2751–2760.

Jones, C. R., and J. R. Eiser, “Understanding ‘local’ opposition to wind development in the UK: How big is a backyard?,” *Energy Policy* 38(6) (2010), 3106–3117.

Kahneman, D., and R. Sugden, “Experienced Utility as a Standard of Policy Evaluation,” *Environmental & Resource Economics* 32(1) (2005), 161–181.

Kahnemann, D., P. P. Wakker, and R. Sarin, “Back to Bentham? Explorations of Experienced Utility,” *Quarterly Journal of Economics* 112(2) (1997), 375–406.

Kirchhoff, T., “Energiewende und Landschaftsästhetik,” *Naturschutz und Landschaftsplanung* 46(1) (2014), 10–16.

Kopmann, A., and K. Rehdanz, “A human well-being approach for assessing the value of natural land areas,” *Ecological Economics* 93 (2013), 20–33.

Krueger, A. B., and D. A. Schkade, "The reliability of subjective well-being measures," *Journal of Public Economics* 92(8–9) (2008), 1833–1845.

Ladenburg, J., "Attitudes towards offshore wind farms–The role of beach visits on attitude and demographic and attitude relations," *Energy Policy* 38(3) (2010), 1297–1304.

Ladenburg, J., M. Termansen, and B. Hasler, "Assessing acceptability of two onshore wind power development schemes: A test of viewshed effects and the cumulative effects of wind turbines," *Energy* 54(1) (2013), 45–54.

Lang, C., J. J. Opaluch, and G. Sfinarolakis, "The windy city: Property value impacts of wind turbines in an urban setting," *Energy Economics* 44 (2014), 413–421.

Levinson, A., "Valuing public goods using happiness data: The case of air quality," *Journal of Public Economics* 96(9–10) (2012), 869–880.

Lüchinger, S., "Valuing Air Quality Using the Life Satisfaction Approach," *The Economic Journal* 119(536) (2009), 482–515.

Lüchinger, S., "Life satisfaction and transboundary air pollution," *Economics Letters* 107(1) (2010), 4–6.

Lüchinger, S., and P. A. Raschky, "Valuing flood disasters using the life satisfaction approach," *Journal of Public Economics* 93(3–4) (2009), 620–633.

May, N., and O. A. Nilsen, "The Local Economic Impact of Wind Power Deployment," *IZA Discussion Paper* 9025 (2015).

McCunney, R. J., K. A. Mundt, W. D. Colby, R. Dobie, K. Kaliski, and M. Blais, "Wind Turbines and Health: A Critical Review of the Scientific Literature," *Journal of Occupational & Environmental Medicine* 56(11) (2014), 108–130.

Memmler, M., L. Schrempf, S. Hermann, S. Schneider, J. Pabst, and M. Dreher (Umweltbundesamt), "Emissionsbilanz erneuerbarer Energieträger - Bestimmung der vermiedenen Emissionen im Jahr 2013," Climate Change 29/2014 (2014).

Meyerhoff, J., C. Ohl, and V. Hartje, "Landscape externalities from onshore wind power," *Energy Policy* 38(1) (2010), 82–92.

Molnarova, K., P. Sklenicka, J. Stiborek, K. Svobodova, M. Salek, and E. Brabec, "Visual preferences for wind turbines: Location, numbers and respondent characteristics," *Applied Energy* 92 (2012), 269–278.

Pasqualetti, M. J., "Morality, Space, and the Power of Wind-Energy Landscapes ," *Geographical Review* 90(3) (2000), 381–394.

Pasqualetti, M. J., "Opposing Wind Energy Landscapes: A Search for Common Cause," *Annals of the Association of American Geographers* 101(4) (2011), 907–917.

Pearce-Higgins, J. W., L. Stephen, A. Douse, and R. H. W. Langston, "Greater impacts of wind farms on bird populations during construction than subsequent operation: results of a multi-site and multi-species analysis," *Journal of Applied Ecology* 49(2) (2012), 386–394.

Pindyck, R. S., "Climate Change Policy: What Do the Models Tell Us?," *Journal of Economic Literature* 51(3) (2013), 860–872.

Rehdanz, K., and D. Maddison, "Local environmental quality and life-satisfaction in Germany," *Ecological Economics* 64(4) (2008), 787–797.

Schuster, E., E. Bulling, and J. Köppel, "Consolidating the State of Knowledge: A Synoptical Review of Wind Energy's Wildlife Effects," *Environmental Management* 56(2) (2015), 300–331.

Sims, S., P. Dent, and G. R. Oskrochi, "Modelling the Impact of Wind Farms on House Prices in the UK," *International Journal of Strategic Property Management* 12(4) (2008), 251–269.

German Socio-economic Panel (SOEP), "Data for Years 1984-2012, Version 29," *SOEP* (2013).

Sunak, Y., and R. Madlener, "Local Impacts of Wind Farms on Property Values: A Spatial Difference-in-Differences Analysis," *FCN Working Paper* 1/2014 (2014).

van den Bergh, J. C. J. M., and W. J. W. Botzen, "A lower bound to the social cost of CO_2 emissions," *Nature Climate Change* 4 (2014), 253–258.

van den Bergh, J. C. J. M., and W. J. W. Botzen, "Monetary valuation of the social cost of CO_2 emissions: A critical survey," *Ecological Economics* 114 (2015), 33–46.

van der Horst, D., "NIMBY or not? Exploring the relevance of location and the politics of voiced opinions in renewable energy siting controversies," *Energy Policy* 35(5) (2007), 2705–2714.

van Praag, B. M. S., and B. E. Baarsma, "Using Happiness Surveys to Value Intangibles: The Case of Airport Noise," *The Economic Journal* 115(500) (2005), 224–246.

von Möllendorff, C., and H. Welsch, "Measuring Renewable Energy Externalities: Evidence from Subjective Well-Being Data," *SOEPpapers on Multidisciplinary Panel Data Research* 779 (2015).

Vorkinn, M., and H. Riese, "Environmental Concern in a Local Context: The Significance of Place Attachement," *Environment and Behavior* 33(2) (2001), 249–263.

Wagner, G. G., J. R. Frick, and J. Schupp, "The German Socio-economic Panel Study

(SOEP): Scope, Evolution and Enhancements," *Schmollers Jahrbuch* 127(1) (2007), 139–170.

Wagner, G. G., J. Goebel, P. Krause, R. Pischner, and I. Sieber, "Das Sozio-oekonomische Panel (SOEP): Multidisziplinäres Haushaltspanel und Kohortenstudie für Deutschland -– Eine Einführung (für neue Datennutzer) mit einem Ausblick (für erfahrene Anwender)," *AStA Wirtschafts- und Sozialstatistisches Archiv* 2(4) (2008), 301–328.

Warren, C. R., C. Lumsden, S. O'Down, and R. V. Birnie, "'Green On Green': Public perceptions of wind power in Scotland and Ireland," *Journal of Environmental Planning and Management* 48(6) (2005), 853–875.

Weigt, H., D. Ellerman, and E. Delarue, "CO_2 abatement from renewables in the German electricity sector: Does a CO_2 price help?," *Energy Economics* 40 (2013), S149–S158.

Welsch, H., "Environmental welfare analysis: A life satisfaction approach," *Ecological Economics* 62(3–4) (2007), 544–551.

Welsch, H., and J. Kühling, "Using Happiness Data for Environmental Valuation: Issues and Applications," *Journal of Economic Surveys* 23(2) (2009), 385–406.

Wolsink, M., "Wind power implementation: The nature of public attitudes: Equity and fairness instead of 'backyard motives'", *Renewable & Sustainable Energy Reviews* 11(6) (2007), 1188–1207.

Wooldridge, J. M., *"Econometric Analysis of Cross Section and Panel Data,"* (Cambridge, MA: The MIT Press, 2002).

Wu, D.-M., "Alternative Tests of Independence Between Stochastic Regressors and Disturbances," *Econometrica* 41(4) (1973), 733–775.

Wüstenhagen, R., M. Wolsink, and M. J. Bürer, "Social acceptance of renewable energy innovation: An introduction to the concept," *Energy Policy* 35(5) (2007), 2683–2691.

World Wind Energy Association (WWEA), "World Wind Energy Report 2012," (Bonn, Germany: WWEA, 2013).

Zöllner, J., P. Schwarzer-Ries, and C. Wemheuer, "Public acceptance of renewable energies: Results from case studies in Germany," *Energy Policy* 36(11) (2008), 4136–4141.

Appendix A. Tables

Table A.1: Descriptive Statistics for Propensity-Score Matching (PSM)

	Mean		
	Treatment Group	Control Group, PSM	Normalised Difference
Variables	(T)	(C)	(T)-(C)
Micro Controls			
Age	54.2053	52.3441	0.0875
Is Female	0.4991	0.5026	0.0050
Is Married	0.7829	0.7216	0.1006
Is Divorced	0.0481	0.0654	0.0530
Is Widowed	0.0735	0.0733	0.0006
Has Very Good Health	0.0566	0.0631	0.0194
Has Very Bad Health	0.0433	0.0481	0.0163
Is Disabled	0.1447	0.1243	0.0421
Has Migration Background	0.0881	0.0845	0.0089
Has Tertiary Degree	0.2828	0.3065	0.0369
Has Lower Than Secondary Degree	0.1844	0.1773	0.0130
Is in Education	0.0101	0.0184	0.0498
Is Full-Time Employed	0.3758	0.3779	0.0030
Is Part-Time Employed	0.1112	0.0770	0.0829
Is on Parental Leave	0.0068	0.0060	0.0069
Is Unemployed	0.0732	0.0954	0.0566
Log Monthly Net Individual Income[a]	6.4513	6.3143	0.1009
Has Child in Household	0.2277	0.2652	0.0616
Log Annual Net Household Income[a]	10.3718	10.2929	0.0984
Lives in House[b]	0.5538	0.5283	0.0376
Lives in Small Apartment Building	0.0896	0.0866	0.0067
Lives in Large Apartment Building	0.1589	0.1745	0.0312
Lives in High Rise	0.0113	0.0145	0.0211
Number of Rooms per Individual	1.7996	1.7686	0.0245
Macro Controls			
Unemployment Rate	12.0116	13.7700	0.2139
Average Monthly Net Household Income[a]	1,364.0120	1,311.0680	0.1959
Number of Observations	3,975	2,662	-
Number of Individuals	498	488	-

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	Mean		
	Treatment Group	Control Group, PSM	Normalised Difference
Variables	(T)	(C)	(T)-(C)

[a] In Euro/Inflation-Adjusted (Base Year 2000), [c] Detached, Semi-Detached, or Terraced

Note: The third column shows the normalised difference, which is calculcated as $\triangle x = (\bar{x}_t - \bar{x}_c) \div \sqrt{\sigma_t^2 + \sigma_c^2}$, where $\bar{x}_t$ and $\bar{x}_c$ is the sample mean of the covariate for the treatment and control group, respectively. σ^2 denotes the variance. As a rule of thumb, a normalised difference greater than 0.25 indicates a non-balanced covariate, which might lead to sensitive results (Imbens and Wooldridge, 2009). All figures are rounded to four decimal places.
Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, own tabulations.

Table A.2: Results - FE Models, Propensity-Score (PS) and Spatial (S) Matching
$Construction_{it,4000}$

Dependent Variable: Satisfaction With Life

Regressors	PS	S ($10,000m$)	S ($15,000m$)
$\text{Construction}_{\text{it},4000}$	-0.1405***	-0.1088***	-0.1138**
	(0.0399)	(0.0222)	(0.0366)
Micro Controls	yes	yes	yes
Macro Controls	yes	yes	yes
Number of Observations	6,637	8,609	16,378
Number of Individuals	986	1,317	2,586
of which in treatment group	498	506	506
of which in control group	488	811	2,080
Adjusted R^2	0.0657	0.0678	0.0632

Robust standard errors clustered at the federal state level in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{\text{it},4000}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a treatment radius of 4,000 metres in interview year t, and zero else. The dependent variable is life satisfaction on a 0/10 scale. All regression equations include dummy variables for interview years, individual fixed effects, and a constant. See Table A.1 for the complete list and descriptive statistics of the micro and macro controls. All figures are rounded to four decimal places.

Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Table C.11 of Online Appendix, own calculations.

Table A.3: Results - FE Models, Propensity-Score (PS) and Spatial (S) Matching
Construction$_{it,4000}$ × Intensity

Dependent Variable: Satisfaction With Life

	PS			S (15,000m)		
Regressors\Intensity Measure	InvDist$_{it,4000}$	RevDist$_{it,4000}$	Cumul$_{it,4000}$	InvDist$_{it,4000}$	RevDist$_{it,4000}$	Cumul$_{it,4000}$
Construction$_{\mathrm{it,4000}}$ × Intensity	-0.2090	-0.0128	-0.0178	-0.1862*	-0.0181	-0.0174
	(0.1605)	(0.0550)	(0.1556)	(0.0940)	(0.0338)	(0.0106)
Micro Controls	yes	yes	yes	yes	yes	yes
Macro Controls	yes	yes	yes	yes	yes	yes
Number of Observations	6,637	6,637	6,637	16,378	16,378	16,378
Number of Individuals	986	986	986	2,586	2,586	2,586
of which in treatment group	498	498	498	506	506	506
of which in control group	488	488	488	2,080	2,080	2,080
Adjusted R^2	0.0650	0.0646	0.0659	0.0630	0.0629	0.0630

Robust standard errors clustered at the federal state level in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

Note: Construction$_{\mathrm{it,4000}}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a treatment radius of 4,000 metres in interview year t, and zero else. The intensity measures are defined as follows: InvDist$_{it,4000}$ is the inverse distance, RevDist$_{it,4000}$ is equal to four minus the distance to the next wind turbine in kilometres, Cumul$_{it,4000}$ is equal to the number of wind turbines within a treatment radius of 4,000 metres, all in interview year t. The dependent variable is life satisfaction on a 0/10 scale. All regression equations include dummy variables for interview years, individual fixed effects, and a constant. See Table A.1 for the complete list and descriptive statistics of the micro and macro controls. All figures are rounded to four decimal places.

Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Table C.11 of Online Appendix, own calculations.

Table A.4: Results - FE Models, Closer Proximity and Distance Bands, Spatial (S) Matching $Construction_{it,r/b}$

Dependent Variable: Satisfaction With Life

Treatment radius r	S $(10,000m)$ Construction$_{it,r}$	S $(15,000m)$ Construction$_{it,r}$	# treated
2,000	-0.0254	0.0232	183
	(0.1278)	(0.1107)	
2,500	-0.0119	-0.0169	274
	(0.0717)	(0.0613)	
3,000	-0.0450	-0.0442	356
	(0.0575)	(0.0589)	
4,000	-0.1088***	-0.1138**	506
	(0.0222)	(0.0366)	
Treatment band b	**Construction$_{it,b}$**	**Construction$_{it,b}$**	**# treated**
$[2,000; 3,000]$	-0.0783	-0.0827	243
	(0.0549)	(0.0614)	
$[2,000; 4,000]$	-0.1711***	-0.1749**	411
	(0.0423)	(0.0551)	
$[2,500; 4,000]$	-0.1860**	-0.1869**	329
	(0.0635)	(0.0754)	
$[3,000; 4,000]$	-0.1735**	-0.1799*	232
	(0.0725)	(0.0842)	

Robust standard errors clustered at the federal state level in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: $\mathrm{Construction_{it,r}}$ ($\mathrm{Construction_{it,b}}$) is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a treatment radius of r metres (treatment band b in metres) in interview year t, and zero else. The treatment band $[\mathrm{x_1}; \mathrm{x_2}]$ comprises only those households that are located between $\mathrm{x_1}$ and $\mathrm{x_2}$ metres from the wind turbine. The dependent variable is life satisfaction on a 0/10 scale. All regression equations include micro controls, macro controls, dummy variables for interview years, individual fixed effects, and a constant. See Table A.1 for the complete list and descriptive statistics of the micro and macro controls. All figures are rounded to four decimal places.

Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Table C.11 of Online Appendix, own calculations.

Table A.5: Results - FE Models, Propensity-Score (PS) and Spatial (S) Matching
$Trans_{it\text{-}\tau,4000}$

Dependent Variable: Satisfaction With Life

	PS		S $(10,000m)$	S $(15,000m)$	
Regressors\Transitoriness Measure	$\text{Trans}_{it-\tau,4000}$	# treated	$\text{Trans}_{it-\tau,4000}$	$\text{Trans}_{it-\tau,4000}$	# treated
$\text{Trans}_{it-1,4000}$	-0.0546	498	-0.0401	-0.0392	506
	(0.0642)		(0.0657)	(0.0642)	
$\text{Trans}_{it-2,4000}$	-0.1616**	444	-0.1212**	-0.1262**	450
	(0.0697)		(0.0482)	(0.0697)	
$\text{Trans}_{it-3,4000}$	-0.192**	424	-0.1381***	-0.1506**	430
	(0.0609)		(0.0411)	(0.0609)	
$\text{Trans}_{it-4,4000}$	-0.2242**	376	-0.1808**	-0.1902*	382
	(0.0917)		(0.0687)	(0.0917)	
$\text{Trans}_{it-5,4000}$	-0.2253**	335	-0.1311	-0.1472	341
	(0.0924)		(0.0837)	(0.0924)	
$\text{Trans}_{it-6,4000}$	-0.2637	288	-0.1664	-0.1519	291
	(0.1495)		(0.1264)	(0.1495)	
$\text{Trans}_{it-7,4000}$	-0.2215	240	-0.0963	-0.0744	243
	(0.1271)		(0.0941)	(0.1271)	
$\text{Trans}_{it-8,4000}$	0.0305	204	0.1847	0.2104	207
	(0.1846)		(0.1483)	(0.1846)	
$\text{Trans}_{it-9,4000}$	-0.0679	167	0.0378	-0.0778	170
	(0.2816)		(0.2452)	(0.2816)	
Micro Controls	yes		yes	yes	
Macro Controls	yes		yes	yes	
Number of Observations	6,637		16,378	16,378	
Number of Individuals	986		1,317	2,586	
of which in control group	488		811	2,080	
Adjusted R^2	0.0659		0.0680	0.0635	

Robust standard errors clustered at the federal state level in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Trans}_{it-\tau,4000}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a 4,000 metres treatment radius in interview year $t-\tau$, and zero else. For example, $\text{Trans}_{it-3,4000}$ is the treatment dummy in the third year after the construction of the wind turbine. The dependent variable is life satisfaction on a 0/10 scale. All regression equations include dummy variables for interview years, individual fixed effects, and a constant. See Table A.1 for the complete list and descriptive statistics of the micro and macro controls. All figures are rounded to four decimal places.

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	PS	S $(10,000m)$	S $(15,000m)$

Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Table C.11 of Online Appendix, own calculations.

Table A.6: Results - Sub-Samples, FE Models, Spatial Matching ($15,000m$)
$Construction_{it,4000}$

Dependent Variable: Satisfaction With Life

Regressors	(1)	(2)	(3)	(4)	(5)	(6)
$\mathrm{Construction}_{\mathrm{it,4000}}$	-0.1261**	-0.0937	-0.0711	-0.1356**	0.0634	-0.2127***
	(0.0488)	(0.1132)	(0.0686)	(0.0436)	(0.0499)	(0.0605)
Micro Controls	yes	yes	yes	yes	yes	yes
Macro Controls	yes	yes	yes	yes	yes	yes
Number of Observations	12,570	3,808	3,934	12,350	5,469	10,909
Number of Individuals	2,047	700	1,380	2,400	722	1,864
of which in treatment group	388	155	308	488	148	358
of which in control group	1,659	545	1,072	1,912	587	1,506
Adjusted R^2	0.0635	0.0733	0.0668	0.0636	0.0669	0.0650

Robust standard errors clustered at the federal state level in parentheses

**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

(1) House-owners, (2) Non-house-owners, (3) Worries environment high, (4) Worries environment not high,

(5) Worries climate change high, (6) Worries climate change not high

Note: $\mathrm{Construction}_{\mathrm{it,4000}}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a treatment radius of 4,000 metres in interview year t, and zero else. The dependent variable is life satisfaction on a 0/10 scale. All regression equations include dummy variables for interview years, individual fixed effects, and a constant. See Table A.1 for the complete list and descriptive statistics of the micro and macro controls. All figures are rounded to four decimal places.

Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Table C.11 of Online Appendix, own calculations.

Table A.7: Results - Robustness (Placebo Tests), FE Models, Propensity-Score (PS) and Spatial (S) Matching
$Construction_{it,4000}$

Dependent Variable: Satisfaction With Life

	PS				S $(15,000m)$			
Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathrm{F3.Construction}_{\mathrm{it},4000}$ *(Third Lead)*			0.0806	0.0956			0.0772	0.1083
			(0.0894)	(0.1109)			(0.0843)	(0.1119)
$\mathrm{F2.Construction}_{\mathrm{it},4000}$ *(Second Lead)*		-0.0208		-0.0470		-0.0163		-0.0335
		(0.0535)		(0.1104)		(0.0399)		(0.1008)
$\mathrm{F1.Construction}_{\mathrm{it},4000}$ *(First Lead)*	-0.0650			0.0474	-0.0593			0.0421
	(0.0505)			(0.0949)	(0.0536)			(0.0939)
$\mathrm{Construction}_{\mathrm{it},4000}$				-0.1354***				-0.1239***
				(0.0396)				(0.0313)
Micro Controls	yes	yes	yes	yes	yes	yes	yes	yes
Macro Controls	yes	yes	yes	yes	yes	yes	yes	yes
Number of Observations	6,189	5,843	5,274	5,274	15,235	14,408	12,988	12,988
Number of Individuals	897	872	819	819	2,306	2,246	2,090	2,090
of which in treatment group	496	492	479	479	504	500	486	486
of which in control group	401	380	340	340	1,802	1,746	1,604	1,604
Adjusted R^2	0.0536	0.0517	0.0499	0.0503	0.0561	0.0541	0.0531	0.0532

Robust standard errors clustered at the federal state level in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: $\mathrm{Construction}_{\mathrm{it},4000}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a treatment radius of 4,000 metres in interview year t, and zero else. The dependent variable is life satisfaction on a 0/10 scale. All regression equations include dummy variables for interview years, individual fixed effects, and a constant. See Table A.1 for the complete list and descriptive statistics of the micro and macro controls. All figures are rounded to four decimal places.

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Dependent Variable: Satisfaction With Life

	PS				S $(15,000m)$			
Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)

Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Table C.11 of Online Appendix, own calculations.

Table A.8: Results - Robustness (View Shed Analysis), FE Models, Propensity-Score (PS) and Spatial (S) Matching
$Construction_{it,4000}$

Dependent Variable: Satisfaction With Life

	PS		S $(15,000m)$	
Regressors	(1)	(2)	(3)	(4)
$\text{ConstructionVisible}_{\text{it},4000}$	-0.1388**		-0.1082**	
	(0.0471)		(0.0381)	
$\text{ConstructionVisible}_{\text{it},4000} \times \text{HeightVisible}_{\text{it},4000}$		-0.0013**		-0.0010**
		(0.0005)		(0.0004)
Micro Controls	yes	yes	yes	yes
Macro Controls	yes	yes	yes	yes
Number of Observations	6,273	6,273	16,013	16,013
Number of Individuals	939	939	2,538	2,538
of which in treatment group	451	451	458	458
of which in control group	488	488	2,080	2,080
Adjusted R^2	0.0623	0.0624	0.0615	0.0616

Robust standard errors clustered at the federal state level in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{ConstructionVisible}_{\text{it},4000}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a treatment radius of 4,000 metres in interview year t and the household has a direct view on it, and zero else. $\text{HeightVisible}_{\text{it},4000}$ is the corresponding visible height of the wind turbine from the viewpoint of the household in metres. The dependent variable is life satisfaction on a 0/10 scale. All regression equations include dummy variables for interview years, individual fixed effects, and a constant. See Table A.1 for the complete list and descriptive statistics of the micro and macro controls. All figures are rounded to four decimal places.

Source: Federal Agency for Cartography and Geodesy (BKG) (2016), SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Table C.11 of Online Appendix,

own calculations.

Table A.9: Robustness (Residential Sorting - Sample Includes Movers) - FE Models, Propensity-Score (PS) and Spatial (S) Matching, $Construction_{it,4000}$

Dependent Variable: Satisfaction With Life

Regressors	PS	S $(10,000m)$	S $(15,000m)$
$\mathrm{Construction}_{\mathrm{it},4000}$			
Micro Controls	yes	yes	yes
Macro Controls	yes	yes	yes
Number of Observations			
Number of Individuals			
of which in treatment group			
of which in control group			
Adjusted R^2			

Robust standard errors clustered at the federal state level in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

Note: $\mathrm{Construction}_{\mathrm{it},4000}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a treatment radius of 4,000 metres in interview year t, and zero else. The dependent variable is life satisfaction on a 0/10 scale. All regression equations include dummy variables for interview years, individual fixed effects, and a constant. See Table A.1 for the complete list and descriptive statistics of the micro and macro controls. All figures are rounded to four decimal places.

Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Table C.11 of Online Appendix, own calculations.

Appendix B. Online

Appendix B.1. Descriptive Statistics for Wind Turbines in the Included Group

Table B.1: Descriptive statistics

	[#]	Capacity [kW]			Total height [m]			Share
		min	max	average	min	max	average	
Germany	10083	200	7500	1571	51	239	123	49 %
Baden-Württemberg	309	500	3000	1425	66	186	124	77 %
Bavaria	434	500	3370	1705				68 %
Berlin	1			2000			138	100 %
Brandenburg	2401	500	7500	1683	83	239	133	71 %
Bremen	2	2000	2500	2250	118	143	131	3 %
Hamburg	7	270	6000	3096	66	198	156	12 %
Hesse	343	500	3000	1616	85	186	138	51 %
Lower Saxony	631	300	2500	1674	67	170	118	34 %
Mecklenburg-Vorpommern	726	500	2500	1005				59 %
North Rhine-Westphalia	956	500	2500	1358				33 %
Rhineland-Palatinate								0 %
Saarland	2	2300	2300	2300	145	145	145	1 %
Saxony	491	299	3158	1528	51	186	116	59 %
Saxony-Anhalt	2029	300	7500	1683	56	199	126	77 %
Schleswig-Holstein	1489				63	183	106	55 %
Thuringia	262	600	3075	1741				41 %

Note: capacity, total height, and shares rounded to integers. Blanks if no information available. The share describes the percentage of turbines in the *included group* within each federal state of Germany.

Source: see Table C.11.

Appendix C. Tables

Table C.1: Descriptive Statistics for Spatial Matching (S)

	Mean				
	Treatment Group	Control Group, S ($10,000m$)	Control Group, S ($15,000m$)	Normalised Difference	Normalised Difference
Variables	(T)	(C1)	C(2)	(T)-(C1)	(T)-(C2)
Micro Controls					
Age	54.1815	53.2244	53.1816	0.0455	0.0474
Is Female	0.5009	0.5078	0.5131	0.0098	0.0172
Is Married	0.7793	0.7637	0.7613	0.0263	0.0303
Is Divorced	0.0479	0.0365	0.0411	0.0403	0.0233
Is Widowed	0.0744	0.0573	0.0689	0.0487	0.0152
Has Very Good Health	0.0577	0.0645	0.0690	0.0202	0.0329
Has Very Bad Health	0.0429	0.0402	0.0390	0.0098	0.0139
Is Disabled	0.1446	0.1525	0.1372	0.0157	0.0149
Has Migration Background	0.0874	0.0830	0.1253	0.0112	0.0871
Has Tertiary Degree	0.2829	0.2333	0.2813	0.0803	0.0024
Has Lower Than Secondary Degree	0.1840	0.1727	0.1715	0.0210	0.0232
Is in Education	0.0100	0.0159	0.0142	0.0367	0.0274
Is Full-Time Employed	0.3745	0.3508	0.3752	0.0349	0.0009
Is Part-Time Employed	0.1109	0.1034	0.1067	0.0171	0.0095
Is on Parental Leave	0.0067	0.0056	0.0101	0.0099	0.0260
Is Unemployed	0.0749	0.0682	0.0590	0.0184	0.0450
Log Monthly Net Individual Income[a]	6.4477	6.4098	6.4792	0.0279	0.0230
Has Child in Household	0.2262	0.2374	0.2623	0.0187	0.0595
Log Annual Net Household Income[a]	10.3719	10.3546	10.4101	0.0215	0.0468

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	Mean				
	Treatment Group	Control Group, S $(10,000m)$	Control Group, S $(15,000m)$	Normalised Difference	Normalised Difference
Variables	(T)	(C1)	C(2)	(T)-(C1)	(T)-(C2)
Lives in House[b]	0.5537	0.6099	0.6011	0.0829	0.0699
Lives in Small Apartment Building	0.0886	0.0853	0.0855	0.0073	0.0071
Lives in Large Apartment Building	0.1593	0.1306	0.1320	0.0574	0.0544
Lives in High Rise	0.0112	0.0113	0.0123	0.0007	0.0071
Number of Rooms per Individual	1.8012	1.8657	1.8712	0.0496	0.0532
Macro Controls					
Unemployment Rate	12.0172	10.4592	10.1886	0.1988	0.2314
Average Monthly Net Household Income[a]	1,363.3050	1,403.8010	1,428.5320	0.1451	0.2252
Number of Observations	4,005	4,604	12,373	-	-
Number of Individuals	506	811	2,080	-	-

[a] In Euro/Inflation-Adjusted (Base Year 2000), [c] Detached, Semi-Detached, or Terraced

Note: The third column shows the normalised difference, which is calculcated as $\triangle x = (\bar{x}_t - \bar{x}_c) \div \sqrt{\sigma_t^2 + \sigma_c^2}$, where $\bar{x}_t$ and $\bar{x}_c$ is the sample mean of the covariate for the treatment and control group, respectively. σ^2 denotes the variance. As a rule of thumb, a normalised difference greater than 0.25 indicates a non-balanced covariate, which might lead to sensitive results (Imbens and Wooldridge, 2009). All figures are rounded to four decimal places.

Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, own tabulations.

Figure C.3: Households around which a wind turbine of the *excluded group* is constructed first are discarded, the others are allocated to either the treatment or control group

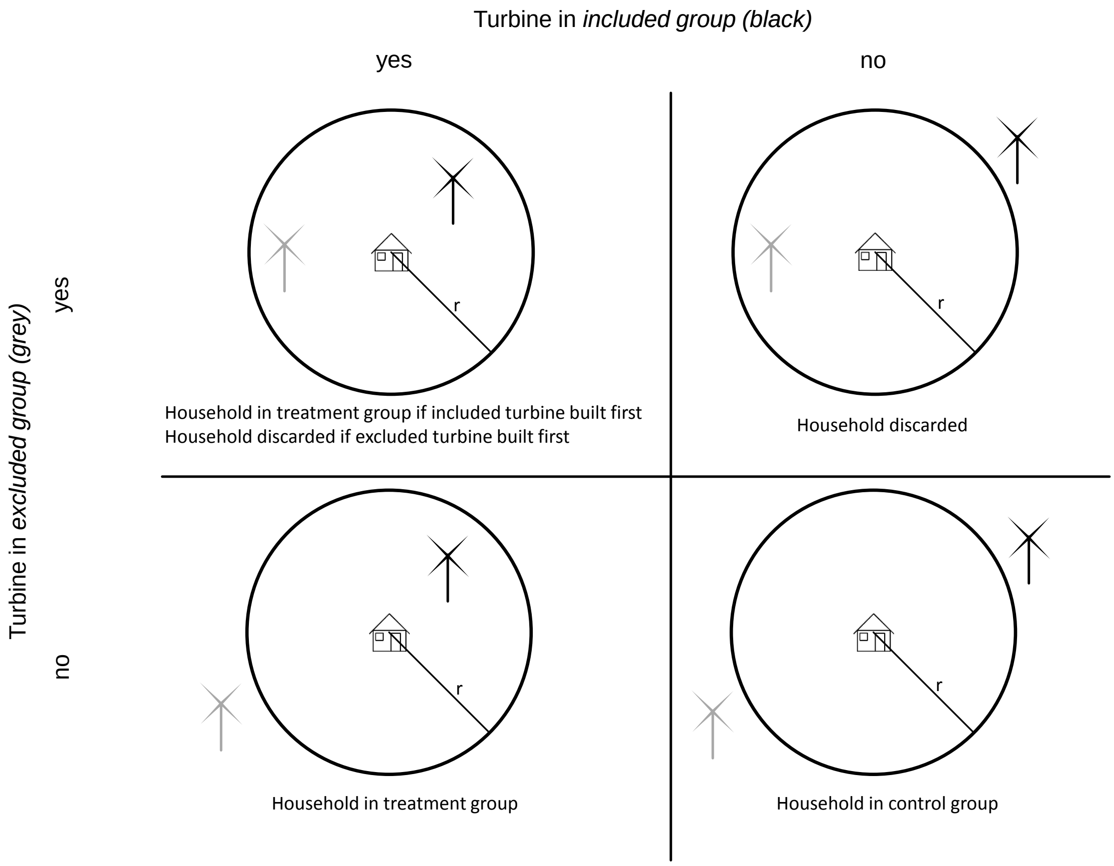


Figure C.4: Empirical Model - Matching Strategy

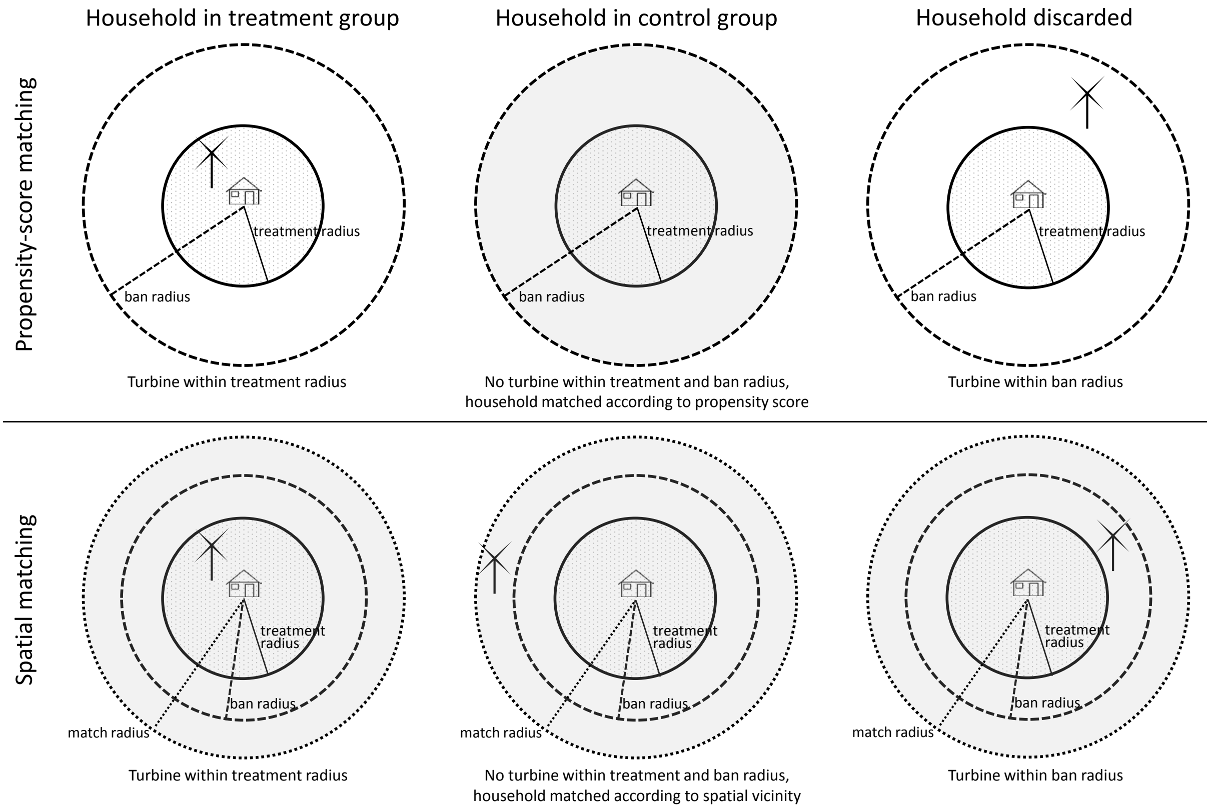
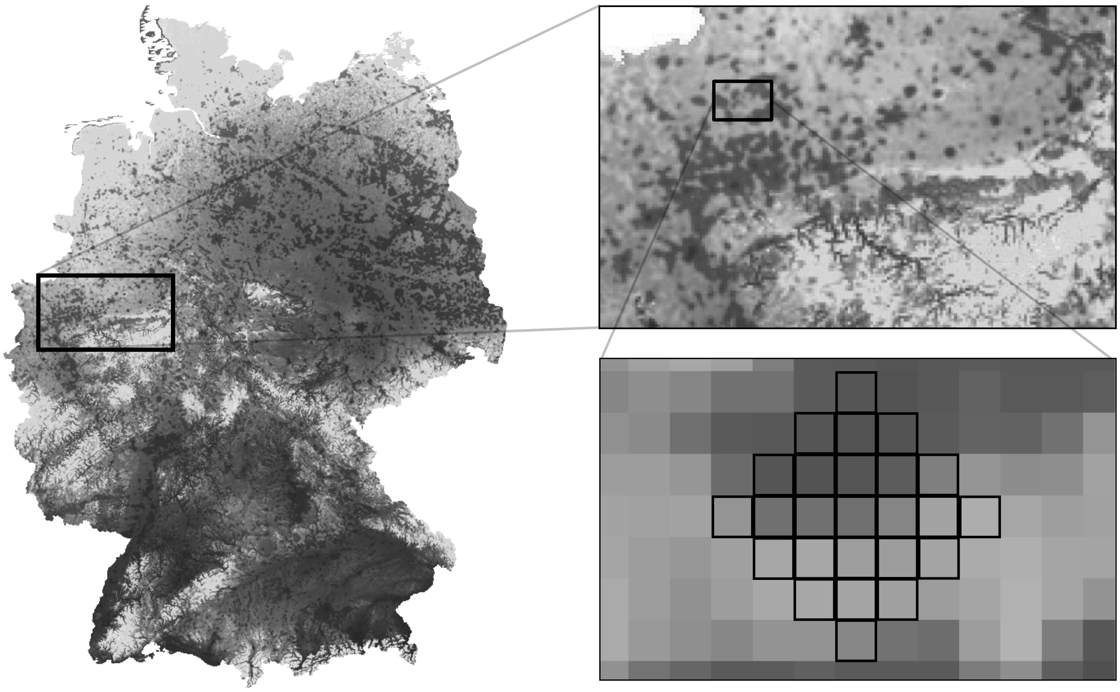


Figure C.5: Calculation of Mean Expected Annual Energy Yield



Note: Calculation for each household of the mean expected annual energy yield of a wind turbine from the 25 one kilometre times one kilometre tiles surrounding it. Coding ranging from dark (lowest expected annual wind yield) to light (highest expected annual wind yield).

Source: German Meteorological Service (DWD) (2014)

Appendix C.1. Detailed Results

Table C.2: Results - FE Models, Combining Propensity-Score (PS) With Spatial (S) Matching $Construction_{it,4000}$

Dependent Variable: Satisfaction With Life

Regressors	PS + S $(10,000m)$	PS + S $(15,000m)$
$\text{Construction}_{\text{it},4000}$	-0.1136**	-0.1173**
	(0.0453)	(0.0476)
Micro Controls	yes	yes
Macro Controls	yes	yes
Number of Observations	4,812	5,731
Number of Individuals	631	774
of which in treatment group	498	498
of which in control group	133	276
Adjusted R^2	0.0405	0.0412

Robust standard errors clustered at the federal state level in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{\text{it},4000}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a treatment radius of 4,000 metres in interview year t, and zero else. The dependent variable is life satisfaction on a 0/10 scale. All regression equations include dummy variables for interview years, individual fixed effects, and a constant. See Table A.1 for the complete list and descriptive statistics of the micro and macro controls. All figures are rounded to four decimal places.

Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Table C.11 of Online Appendix, own calculations.

Table C.3: Results - FE Models, Propensity-Score (PS) and Spatial (S) Matching
$Construction_{it,4000}$

Dependent Variable: Satisfaction With Life

Regressors	PS	S $(10,000m)$	S $(15,000m)$
$\text{Construction}_{\text{it},4000}$	-0.1405***	-0.1088***	-0.1138**
	(0.0399)	(0.0222)	(0.0366)
Age	-0.0689	-0.0792***	-0.0142
	(0.0425)	(0.0197)	(0.0199)
Age Squared	0.0001	0.0002	-0.0001
	(0.0004)	(0.0002)	(0.0002)
Is Female			
Is Married	0.0903	-0.1502	0.1175
	(0.1449)	(0.1856)	(0.2095)
Is Divorced	0.2802	-0.0721	0.1241
	(0.4173)	(0.0945)	(0.2315)
Is Widowed	-0.1891	-0.7490**	-0.2608
	(0.2035)	(0.3319)	(0.2513)
Has Very Good Health	0.2967***	0.2833***	0.3674***
	(0.0693)	(0.0536)	(0.0424)
Has Very Bad Health	-1.3187***	-1.2854***	-1.2141***
	(0.1184)	(0.0887)	(0.1000)
Is Disabled	-0.0137	-0.0101	-0.2080**
	(0.1113)	(0.0881)	(0.0691)
Has Migration Background			
Has Tertiary Degree	-0.0087	-0.0303	-0.1976
	(0.1926)	(0.2628)	(0.1660)
Has Lower Than Secondary Degree	-0.0008	0.1677	0.2274
	(0.3042)	(0.2073)	(0.2062)
Is in Education	0.3740	0.1739	0.3345
	(0.4008)	(0.2544)	(0.2033)
Is Full-Time Employed	0.0001	0.0213	0.0841
	(0.1182)	(0.0780)	(0.0655)
Is Part-Time Employed	-0.1220	-0.0534	-0.0426
	(0.1056)	(0.0904)	(0.0644)
Is on Parental Leave	0.0709	-0.0308	0.1516
	(0.2157)	(0.2097)	(0.1289)
Is Unemployed	-0.5000***	-0.4325***	-0.4542***
	(0.1233)	(0.0864)	(0.0772)
Log Monthly Net Individual Income[a]	0.0538	0.0523	0.0385
	(0.0539)	(0.0436)	(0.0282)
Has Child in Household	0.1555*	0.1997***	0.0897**
	(0.0741)	(0.0521)	(0.0374)
Log Annual Net Household Income[a]	0.1738	0.2503***	0.2003***
	(0.1173)	(0.0695)	(0.0537)
Lives in House[b]	-0.0135	0.0057	0.0086
	(0.0954)	(0.0484)	(0.0414)
Lives in Small Apartment Building	0.0051	0.0234	0.0159
	(0.0935)	(0.0575)	(0.0395)
Lives in Large Apartment Building	-0.0262	-0.0060	0.0144
	(0.0765)	(0.0421)	(0.0298)
Lives in High Rise	0.1176	0.0925	0.0720
	(0.2136)	(0.2107)	(0.1805)
Number of Rooms per Individual	0.0011	-0.0157	0.0136
	(0.0416)	(0.0402)	(0.0210)
Unemployment Rate	-0.0199	-0.0353***	-0.0081
	(0.0133)	(0.0102)	(0.0105)
Average Monthly Net Household Income[a]	0.0008	0.0004	-0.0006
	(0.0006)	(0.0008)	(0.0005)
Number of Observations	6,637	8,609	16,378
Number of Individuals	986	1,317	2,586
of which in treatment group	498	506	506

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Dependent Variable: Satisfaction With Life

Regressors	PS	S $(10,000m)$	S $(15,000m)$
of which in control group	488	811	2,080
F-Statistic	2,462.5200	9,891.2100	5,251.8600
R^2	0.0704	0.0715	0.0652
Adjusted R^2	0.0657	0.0678	0.0632

[a] In Euro/Inflation-Adjusted (Base Year 2000), [b] Detached, Semi-Detached, or Terraced

Robust standard errors clustered at the federal state level in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{\text{it},4000}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a treatment radius of 4,000 metres in interview year t, and zero else. The dependent variable is life satisfaction on a 0/10 scale. All regression equations include dummy variables for interview years, individual fixed effects, and a constant. See Table A.1 in Main Appendix for the complete list and descriptive statistics of the micro and macro controls. All figures are rounded to four decimal places.

Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Table C.11, own calculations.

Table C.4: Results - FE Models, Propensity-Score Matching
$Construction_{it,8000/10000/15000}$

Dependent Variable: Satisfaction With Life

Regressors	r=8000	r=10000	r=15000
$\mathrm{Construction}_{\mathrm{it,r}}$	-0.0348	-0.0074	0.1303
	(0.0508)	(0.0645)	(0.1858)
Age	-0.2886	0.0093	-0.0512
	(0.0373)	(0.0192)	(0.0559)
Age Squared	0.0000	-0.0004	-0.0003
	(0.0002)	(0.0003)	(0.0004)
Is Female			
Is Married	-0.2568	-0.6604	-0.6631
	(0.2547)	(0.4986)	(0.6816)
Is Divorced	0.1843	-0.1972	-0.2746
	(0.2606)	(0.5383)	(0.6366)
Is Widowed	-0.6568*	-0.6836	-0.8520
	(0.3032)	(0.4503)	(0.6821)
Has Very Good Health	0.3276***	0.3398***	0.2804**
	(0.0814)	(0.0781)	(0.0872)
Has Very Bad Health	-1.3464***	-1.3147***	-1.2396***
	(0.1025)	(0.1574)	(0.2896)
Is Disabled	-0.0255	-0.1951	-0.2450**
	(0.0873)	(0.1407)	(0.0861)
Has Migration Background			
Has Tertiary Degree	-0.0026	-0.2182	-0.9182
	(0.1907)	(0.3084)	(0.7468)
Has Lower Than Secondary Degree	0.0054	1.1626**	-0.7703***
	(0.1663)	(0.4427)	(0.1394)
Is in Education	-0.1457	0.6630	0.6402
	(0.1904)	(0.4731)	(0.3646)
Is Full-Time Employed	0.0649	0.1354	-0.0820
	(0.1087)	(0.1375)	(0.1928)
Is Part-Time Employed	0.0473	-0.0249	-0.0756
	(0.0927)	(0.1128)	(0.2193)
Is on Parental Leave	0.0912	0.0431	0.0286
	(0.1369)	(0.1654)	(0.2412)
Is Unemployed	-0.4316***	-0.5374**	-0.4905***
	(0.1183)	(0.2060)	(0.0978)
Log Monthly Net Individual Income[a]	-0.0017	-0.0169	-0.0445
	(0.0444)	(0.0485)	(0.0677)
Has Child in Household	0.1246	0.2017	-0.0008
	(0.0927)	(0.1189)	(.01474)
Log Annual Net Household Income[a]	0.2628***	0.2074**	0.1571
	(0.0482)	(0.0736)	(0.1164)
Lives in House[b]	0.0011	-0.0209	0.0106
	(0.0617)	(0.0469)	(0.1294)
Lives in Small Apartment Building	0.0152	-0.0098	0.0156
	(0.0752)	(0.0.0626)	(0.1340)
Lives in Large Apartment Building	-0.0178	-0.0356	0.0303
	(0.1077)	(0.0867)	(0.1010)
Lives in High Rise	0.0437	-0.0186	0.1251
	(0.1478)	(0.0008)	(0.3441)
Number of Rooms per Individual	0.0418	0.0643	0.0491
	(0.0292)	(0.0368)	(0.0469)
Unemployment Rate	-0.0376***	-0.0270*	-0.0455***
	(0.0089)	(0.0132)	(0.0116)
Average Monthly Net Household Income[a]	-0.0012*	-0.0009	0.0006
	(0.0006)	(0.0008)	(0.0009)
Number of Observations	9,389	6,254	2,767
Number of Individuals	1,357	939	423

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Dependent Variable: Satisfaction With Life

Regressors	r=8000	r=10000	r=15000
of which in treatment group	684	474	212
of which in control group	673	465	211
F-Statistic	5,951.5600	7,431.9500	1,373.6400
R^2	0.0698	0.0816	0.0798
Adjusted R^2	0.0665	0.0766	0.0683

[a] In Euro/Inflation-Adjusted (Base Year 2000), [b] Detached, Semi-Detached, or Terraced

Robust standard errors clustered at the federal state level in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{\text{it,r}}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a treatment radius of r metres in interview year t, and zero else. The dependent variable is life satisfaction on a 0/10 scale. All regression equations include dummy variables for interview years, individual fixed effects, and a constant. See Table A.1 in Main Appendix for the complete list and descriptive statistics of the micro and macro controls. All figures are rounded to four decimal places.

Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Table C.11, own calculations.

Table C.5: Results - FE Models, Spatial Matching (S) (10,000m, 15,000m)
$Construction_{it,8000}$

Dependent Variable: Satisfaction With Life

Regressors	S $(10,000m)$	S $(15,000m)$
$\text{Construction}_{\text{it,8000}}$	-0.0642	-0.0452
	(0.0372)	(0.0447)
Age	-0.0242	-0.0030
	(0.0266)	(0.0248)
Age Squared	-0.0001	-0.0001
	(0.0002)	(0.0002)
Is Female		
Is Married	-0.4424	-0.0844
	(0.5476)	(0.4607)
Is Divorced	-0.0619	0.0909
	(0.4789)	(0.5164)
Is Widowed	-0.8117	-0.4189
	(0.5315)	(0.4720)
Has Very Good Health	0.3484***	0.3920***
	(0.0741)	(0.0518)
Has Very Bad Health	-1.3571***	-1.2564***
	(0.1412)	(0.1378)
Is Disabled	-0.0327	-0.1994**
	(0.1207)	(0.0831)
Has Migration Background		
Has Tertiary Degree	-0.1510	-0.2413
	(0.1510)	(0.2108)
Has Lower Than Secondary Degree	0.1362	0.2324
	(0.1975)	(0.1761)
Is in Education	-0.0400	0.2268
	(0.2082)	(0.1824)
Is Full-Time Employed	0.1017	0.1417
	(0.0831)	(0.0779)
Is Part-Time Employed	0.0588	0.0545
	(0.0783)	(0.0597)
Is on Parental Leave	-0.0244	0.0714
	(0.1257)	(0.0862)
Is Unemployed	-0.4511***	-0.4796***
	(0.0998)	(0.0747)
Log Monthly Net Individual Income[a]	0.0188	0.0056
	(0.0373)	(0.0395)
Has Child in Household	0.2174**	0.0976
	(0.0760)	(0.0568)
Log Annual Net Household Income[a]	0.2354**	0.1812***
	(0.0793)	(0.0453)
Lives in House[b]	0.0098	0.0172
	(0.0230)	(0.0413)
Lives in Small Apartment Building	0.0534	0.0102
	(0.0539)	(0.0432)
Lives in Large Apartment Building	-0.0571	-0.0008
	(0.0368)	(0.0580)
Lives in High Rise	0.1087	0.0110
	(0.0820)	(0.1546)
Number of Rooms per Individual	0.0095	0.0230
	(0.0210)	(0.0185)
Unemployment Rate	-0.0445***	-0.0230**
	(0.0080)	(0.0070)
Average Monthly Net Household Income[a]	-0.0005	-0.0010*
	(0.0007)	(0.0005)
Number of Observations	8,643	14,485
Number of Individuals	1,241	2,193

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Dependent Variable: Satisfaction With Life

Regressors	S $(10,000m)$	S $(15,000m)$
of which in treatment group	698	698
of which in control group	543	1,495
F-Statistic	26,893.1900	14,555.3300
R^2	0.0740	0.0676
Adjusted R^2	0.0704	0.0654

[a] In Euro/Inflation-Adjusted (Base Year 2000), [b] Detached, Semi-Detached, or Terraced

Robust standard errors clustered at the federal state level in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{\text{it},8000}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a treatment radius of 8,000 metres in interview year t, and zero else. The dependent variable is life satisfaction on a 0/10 scale. All regression equations include dummy variables for interview years, individual fixed effects, and a constant. See Table A.1 in Main Appendix for the complete list and descriptive statistics of the micro and macro controls. All figures are rounded to four decimal places.

Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Table C.11, own calculations.

Table C.6: Results - FE Models, Propensity-Score Matching

$Construction_{it,4000}$ × Intensity, $Trans_{it\text{-}\tau,4000}$

Dependent Variable: Satisfaction With Life

Regressors\Intensity or Transitoriness Measure	Intensity $InvDist_{it,4000}$	$RevDist_{it,4000}$	$Cumul_{it,4000}$	Transition $Trans_{it-\tau,4000}$	# treated
$Construction_{it,4000}$ × Intensity	-0.2090	-0.0128	-0.0178		
	(0.1605)	(0.0550)	(0.1556)		
$Trans_{it-1,4000}$				-0.0546	498
				(0.0642)	
$Trans_{it-2,4000}$				-0.1616**	444
				(0.0697)	
$Trans_{it-3,4000}$				-0.192**	424
				(0.0609)	
$Trans_{it-4,4000}$				-0.2242**	376
				(0.0917)	
$Trans_{it-5,4000}$				-0.2253**	335
				(0.0924)	
$Trans_{it-6,4000}$				-0.2637	288
				(0.1495)	
$Trans_{it-7,4000}$				-0.2215	240
				(0.1271)	
$Trans_{it-8,4000}$				0.0305	204
				(0.1846)	
$Trans_{it-9,4000}$				-0.0679	167
				(0.2816)	
Age	-0.0738	-0.0790	-0.0738	-0.0672	
	(0.0438)	(0.0446)	(0.0444)	(0.0413)	
Age Squared	0.0001	-0.0001	0.0001	0.0010	
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	
Is Female					
Is Married	-0.0946	0.1056	0.1116	0.0986	
	(0.1456)	(0.1451)	(0.1399)	(0.1530)	
Is Divorced	0.2825	0.2913	0.3020	0.3110	
	(0.4115)	(0.4110)	(0.4142)	(0.4034)	
Is Widowed	-0.1842	-0.1696	-0.1615	-0.1833	
	(0.2078)	(0.2079)	(0.2026)	(0.2078)	
Has Very Good Health	0.2967***	0.2955***	0.2963***	0.2971***	
	(0.0694)	(0.0698)	(0.0696)	(0.0694)	
Has Very Bad Health	-1.3164***	-1.3166***	-1.3222***	-1.3280***	
	(0.1189)	(0.1201)	(0.1197)	(0.1135)	
Is Disabled	0.0149	0.0137	0.0128	0.0212	
	(0.1101)	(0.1103)	(0.1099)	(0.1132)	
Has Migration Background					
Has Tertiary Degree	-0.0016	0.0038	0.0035	-0.0284	
	(0.1923)	(0.1920)	(0.1915)	(0.1914)	
Has Lower Than Secondary Degree	0.0029	0.0032	-0.0021	-0.0131	
	(0.3066)	(0.3092)	(0.3069)	(0.3061)	
Is in Education	0.3658	0.3658	0.3670	0.3770	
	(0.4006)	(0.4004)	(0.4029)	(0.3998)	
Is Full-Time Employed	-0.0022	-0.0024	-0.0046	0.0022	
	(0.1181)	(0.1180)	(0.1178)	(0.1120)	
Is Part-Time Employed	-0.0154	-0.0156	-0.0148	-0.0113	
	(0.1052)	(0.1059)	(0.1064)	(0.1056)	
Is on Parental Leave	0.0743	0.0768	0.0784	0.0727	
	(0.2203)	(0.2242)	(0.2201)	(0.2144)	
Is Unemployed	-0.5049***	-0.5080***	-0.5075***	-0.5013***	
	(0.1224)	(0.1208)	(0.1209)	(0.1241)	
Log Monthly Net Individual Income[a]	0.0540	0.0541	0.0539	0.0532	
	(0.0536)	(0.0532)	(0.0533)	(0.0552)	
Has Child in Household	0.1509	0.1491*	0.1479*	0.1546*	

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Regressors\Intensity or Transitoriness Measure	Intensity $\text{InvDist}_{it,4000}$	$\text{RevDist}_{it,4000}$	$\text{Cumul}_{it,4000}$	Transition $\text{Trans}_{it-\tau,4000}$	# treated
	(0.0742)	(0.0753)	(.0743)	(0.0791)	
Log Annual Net Household Income[a]	0.1720	0.1726	0.1760	0.1744	
	(0.1181)	(0.1170)	(0.1178)	(0.1184)	
Lives in House[b]	-0.0134	-0.0144	-0.0134	-0.0136	
	(0.0957)	(0.0958)	(0.0958)	(0.0954)	
Lives in Small Apartment Building	0.0043	0.0028	0.0041	0.0046	
	(0.0945)	(0.0960)	(0.0954)	(0.0927)	
Lives in Large Apartment Building	-0.0260	-0.0264	-0.0255	-0.0272	
	(0.0769)	(0.0774)	(0.0770)	(0.0761)	
Lives in High Rise	0.1176	0.1180	0.1181	0.1120	
	(0.2107)	(0.0774)	(0.2103)	(0.2111)	
Number of Rooms per Individual	0.0007	0.0002	0.0006	0.0008	
	(0.0415)	(0.0411)	(0.0413)	(0.0421)	
Unemployment Rate	-0.0222	-0.0241	-0.0237	-0.0159	
	(0.0142)	(0.0146)	(0.0148)	(0.0127)	
Average Monthly Net Household Income[a]	0.0008	0.0008	0.0007	0.0009	
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	
Number of Observations	6,637	6,637	6,637	6,637	
Number of Individuals	986	986	986	986	
of which in treatment group	498	498	498		
of which in control group	488	488	488	488	
F-Statistic	3,052.8700	2,800.3000	2,605.900	8,865.0800	
R^2	0.0698	0.0694	0.0697	0.0719	
Adjusted R^2	0.0650	0.0646	0.0659	0.0659	

[a] In Euro/Inflation-Adjusted (Base Year 2000), [b] Detached, Semi-Detached, or Terraced

Robust standard errors clustered at the federal state level in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{\text{it},4000}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a treatment radius of 4,000 metres in interview year t, and zero else. The intensity measures are defined as follows: $\text{InvDist}_{it,4000}$ is the inverse distance, $\text{RevDist}_{it,4000}$ is equal to four minus the distance to the next wind turbine in kilometres, $\text{Cumul}_{it,4000}$ is equal to the number of wind turbines within a treatment radius of 4,000 metres, all in interview year t. $\text{Trans}_{it-\tau,4000}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a 4,000 metres treatment radius in interview year $t-\tau$, and zero else. For example, $\text{Trans}_{it-3,4000}$ is the treatment dummy in the third year after the construction of the wind turbine. The dependent variable is life satisfaction on a 0/10 scale. All regression equations include dummy variables for interview years, individual fixed effects, and a constant. See Table A.1 in Main Appendix for the complete list and descriptive statistics of the micro and macro controls. All figures are rounded to four decimal places.

Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Table C.11, own calculations.

Table C.7: Results - FE Models, Spatial Matching (10,000m)
$Construction_{it,4000}$ × Intensity, $Trans_{it\text{-}\tau,4000}$

Dependent Variable: Satisfaction With Life

Regressors\Intensity or Transitoriness Measure	Intensity $\text{InvDist}_{it,4000}$	$\text{RevDist}_{it,4000}$	$\text{Cumul}_{it,4000}$	Transition $\text{Trans}_{it-\tau,4000}$	# treated
$\text{Construction}_{\text{it},4000}$ × Intensity	-0.1604	-0.0078	-0.0142		
	(0.1038)	(0.0411)	(0.0113)		
$\text{Trans}_{it-1,4000}$				-0.0401	506
				(0.0657)	
$\text{Trans}_{it-2,4000}$				-0.1212**	450
				(0.0482)	
$\text{Trans}_{it-3,4000}$				-0.1381***	430
				(0.0411)	
$\text{Trans}_{it-4,4000}$				-0.1808**	382
				(0.0689)	
$\text{Trans}_{it-5,4000}$				-0.1311	341
				(0.0837)	
$\text{Trans}_{it-6,4000}$				-0.1644	291
				(0.1264)	
$\text{Trans}_{it-7,4000}$				-0.0963	243
				(0.0941)	
$\text{Trans}_{it-8,4000}$				0.1847	207
				(0.1483)	
$\text{Trans}_{it-9,4000}$				0.0378	170
				(0.2452)	
Age	-0.0821***	-0.0853***	-0.0818***	-0.0793***	
	(0.0204)	(0.0210)	(0.0206)	(0.0199)	
Age Squared	-0.0002	0.0002	0.0002	0.0002	
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	
Is Female					
Is Married	-0.1501	-0.1450	-0.1400	-0.1467	
	(0.1841)	(0.1831)	(0.1837)	(0.1970)	
Is Divorced	-0.0729	-0.0686	-0.0606	-0.0546	
	(0.0969)	(0.1003)	(0.0948)	(0.0970)	
Is Widowed	-0.7476**	-0.7395*	-0.7347*	-0.7428*	
	(0.3327)	(0.3314)	(0.3292)	(0.3372)	
Has Very Good Health	0.2839***	0.2839***	0.2842***	0.2834***	
	(0.0537)	(0.0543)	(0.0539)	(0.0539)	
Has Very Bad Health	-1.2847***	-1.284***	-1.2884***	-1.2901***	
	(0.0891)	(0.0897)	(0.0895)	(0.0862)	
Is Disabled	-0.0099	-0.0110	-0.0113	-0.0037	
	(0.0874)	(0.0874)	(0.0863)	(0.0911)	
Has Migration Background					
Has Tertiary Degree	-0.0253	-0.0214	-0.0218	-0.0495	
	(0.2624)	(0.2616)	(0.2620)	(0.2641)	
Has Lower Than Secondary Degree	0.1702	0.1709	0.1672	0.1619	
	(0.2083)	(0.2090)	(0.2078)	(0.2104)	
Is in Education	0.1693	0.1695	0.1696	0.1811	
	(0.2552)	(0.2554)	(0.2078)	(0.2554)	
Is Full-Time Employed	0.0203	0.0206	0.0187	0.0273	
	(0.0776)	(0.0770)	(0.0777)	(0.0803)	
Is Part-Time Employed	-0.0544	-0.0537	-0.0541	-0.0492	
	(0.0905)	(0.0910)	(0.0913)	(0.0920)	
Is on Parental Leave	-0.0255	0.1514	-0.0219	-0.0315	
	(0.2121)	(0.2139)	(0.2114)	(0.2087)	
Is Unemployed	-0.4343***	-0.4450***	-0.4360***	-0.4321***	
	(0.0878)	(0.0883)	(0.0881)	(0.0882)	
Log Monthly Net Individual Income[a]	0.0526	0.0529	0.0527	0.0519	
	(0.0434)	(0.0432)	(0.0434)	(0.0441)	
Has Child in Household	0.1969***	0.1958***	0.1951***	0.1958***	

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Regressors\Intensity or Transitoriness Measure	Intensity $\text{InvDist}_{it,4000}$	$\text{RevDist}_{it,4000}$	$\text{Cumul}_{it,4000}$	Transition $\text{Trans}_{it-\tau,4000}$	# treated
	(0.0525)	(0.0525)	(0.0519)	(0.0551)	
Log Annual Net Household Income[a]	0.2497***	0.2506***	0.2523***	0.2492***	
	(0.0702)	(0.0698)	(0.0700)	(0.0709)	
Lives in House[b]	0.0056	0.0049	0.0057	0.0052	
	(0.0483)	(0.0482)	(0.0486)	(0.0481)	
Lives in Small Apartment Building	0.0229	0.0220	0.0229	0.0225	
	(0.0575)	(0.0575)	(0.0576)	(0.0569)	
Lives in Large Apartment Building	-0.0062	-0.0068	-0.0060	-0.0066	
	(0.0421)	(0.0422)	(0.0486)	(0.0420)	
Lives in High Rise	0.0919	0.0915	0.0922	0.0947	
	(0.2100)	(0.2101)	(0.2103)	(0.2103)	
Number of Rooms per Individual	-0.0158	-0.0160	-0.0160	-0.0155	
	(0.0402)	(0.0404)	(0.0403)	(0.0401)	
Unemployment Rate	-0.0360***	-0.0362***	-0.0369***	-0.0323**	
	(0.0096)	(0.0097)	(0.0100)	(0.0113)	
Average Monthly Net Household Income[a]	0.0004	0.0004	0.0004	0.0004	
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	
Number of Observations	8,609	8,609	8,609	8,609	
Number of Individuals	1,317	1,317	1,317	1,317	
of which in treatment group	506	506	506		
of which in control group	811	811	811	811	
F-Statistic	10,029.0400	9,702.5400	9,832.3100	10,774.6900	
R^2	0.0711	0.0709	0.0711	0.0725	
Adjusted R^2	0.0704	0.0672	0.0674	0.0680	

[a] In Euro/Inflation-Adjusted (Base Year 2000), [b] Detached, Semi-Detached, or Terraced

Robust standard errors clustered at the federal state level in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{\text{it},4000}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a treatment radius of 4,000 metres in interview year t, and zero else. The intensity measures are defined as follows: $\text{InvDist}_{it,4000}$ is the inverse distance, $\text{RevDist}_{it,4000}$ is equal to four minus the distance to the next wind turbine in kilometres, $\text{Cumul}_{it,4000}$ is equal to the number of wind turbines within a treatment radius of 4,000 metres, all in interview year t. $\text{Trans}_{it-\tau,4000}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a 4,000 metres treatment radius in interview year $t-\tau$, and zero else. For example, $\text{Trans}_{it-3,4000}$ is the treatment dummy in the third year after the construction of the wind turbine. The dependent variable is life satisfaction on a 0/10 scale. All regression equations include dummy variables for interview years, individual fixed effects, and a constant. See Table A.1 in Main Appendix for the complete list and descriptive statistics of the micro and macro controls. All figures are rounded to four decimal places.

Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Table C.11, own calculations.

Table C.8: Results - FE Models, Spatial Matching (15,000m)
$Construction_{it,4000}$ × Intensity, $Trans_{it\text{-}\tau,4000}$

Dependent Variable: Satisfaction With Life

Regressors\Intensity or Transitoriness Measure	Intensity $\text{InvDist}_{it,4000}$	$\text{RevDist}_{it,4000}$	$\text{Cumul}_{it,4000}$	Transition $\text{Trans}_{it-\tau,4000}$	# treated
$\text{Construction}_{\text{it},4000}$ × Intensity	-0.1862*	-0.0181	-0.0174		
	(0.0940)	(0.0338)	(0.0106)		
$\text{Transition}_{it-1,4000}$				-0.0392	506
				(0.0642)	
$\text{Transition}_{it-2,4000}$				-0.1262**	450
				(0.0697)	
$\text{Transition}_{it-3,4000}$				-0.1506**	430
				(0.0609)	
$\text{Transition}_{it-4,4000}$				-0.1902*	382
				(0.0917)	
$\text{Transition}_{it-5,4000}$				-0.1472	341
				(0.0924)	
$\text{Transition}_{it-6,4000}$				-0.1519	291
				(0.1495)	
$\text{Transition}_{it-7,4000}$				-0.0744	243
				(0.1271)	
$\text{Transition}_{it-8,4000}$				0.2104	207
				(0.1846)	
$\text{Transition}_{it-9,4000}$				-0.0778	170
				(0.2816)	
Age	-0.0158	-0.0176	-0.0156	-0.0146	
	(0.0204)	(0.0207)	(0.0202)	(0.0193)	
Age Squared	-0.0001	-0.0001	-0.0001	-0.0001	
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	
Is Female					
Is Married	0.1184	0.1217	0.1231	0.1194	
	(0.2084)	(0.2069)	(0.2088)	(0.2104)	
Is Divorced	0.1241	0.1262	0.1298	0.1356	
	(0.2309)	(0.2069)	(0.2305)	(0.2302)	
Is Widowed	-0.2560	-0.2547	-0.2532	-0.2566	
	(0.2503)	(0.2486)	(0.2498)	(0.2524)	
Has Very Good Health	0.3675***	0.3673***	0.3675***	0.3673***	
	(0.0426)	(0.0428)	(0.0425)	(0.0423)	
Has Very Bad Health	-1.2137***	-1.2141***	-1.2161***	-1.216***	
	(0.1001)	(0.1002)	(0.1001)	(0.0991)	
Is Disabled	-0.2078**	-0.2083**	-0.2086**	-0.2042**	
	(0.0687)	(0.0686)	(0.0687)	(0.0715)	
Has Migration Background					
Has Tertiary Degree	-0.1954	-0.1934	-0.1934	-0.2098	
	(0.1668)	(0.1674)	(0.1673)	(0.1681)	
Has Lower Than Secondary Degree	0.2284	0.2286	0.2266	0.2234	
	(0.2061)	(0.2062)	(0.2061)	(0.2076)	
Is in Education	0.3323	0.3327	0.3327	0.3395	
	(0.2027)	(0.2025)	(0.2036)	(0.2021)	
Is Full-Time Employed	0.0833	0.0830	0.0822	0.0873	
	(0.0656)	(0.0657)	(0.0659)	(0.0650)	
Is Part-Time Employed	-0.0434	-0.0434	-0.0431	-0.0408	
	(0.0642)	(0.0643)	(0.0647)	(0.0640)	
Is on Parental Leave	0.1517	0.1514	0.1525	0.1525	
	(0.1291)	(0.1293)	(0.1294)	(0.1299)	
Is Unemployed	-0.4554***	-0.4562***	-0.4565***	-0.4542***	
	(0.0774)	(0.0773)	(0.0774)	(0.0766)	
Log Monthly Net Individual Income[a]	0.0386	0.0388	0.0386	0.0383	
	(0.0281)	(0.0281)	(0.0282)	(0.0280)	
Has Child in Household	0.0881**	0.0875**	0.0868**	0.0867**	

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Regressors\Intensity or Transitoriness Measure	Intensity $\text{InvDist}_{it,4000}$	$\text{RevDist}_{it,4000}$	$\text{Cumul}_{it,4000}$	Transition $\text{Trans}_{it-\tau,4000}$	# treated
	(0.0373)	(0.0374)	(0.0371)	(0.0381)	
Log Annual Net Household Income[a]	0.2002***	0.2009***	0.2021***	0.1994***	
	(0.0541)	(0.0539)	(0.0540)	(0.0538)	
Lives in House[b]	0.0086	0.0083	0.0087	0.0083	
	(0.0415)	(0.0417)	(0.0417)	(0.0412)	
Lives in Small Apartment Building	0.0157	0.0153	0.0158	0.0153	
	(0.0397)	(0.0398)	(0.0396)	(0.0394)	
Lives in Large Apartment Building	0.0144	0.0141	0.0146	0.0140	
	(0.0301)	(0.0304)	(0.0302)	(0.0297)	
Lives in High Rise	0.0715	0.0710	0.0716	0.0732	
	(0.1780)	(0.1795)	(0.1798)	(0.1808)	
Number of Rooms per Individual	0.0135	0.0133	0.0134	0.0138	
	(0.0210)	(0.0211)	(0.0211)	(0.0211)	
Unemployment Rate	-0.0083	-0.0082	-0.0089	-0.0059	
	(0.0100)	(0.0098)	(0.0098)	(0.0112)	
Average Monthly Net Household Income[a]	-0.0006	-0.0006	-0.0006	-0.0006	
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	
Number of Observations	16,378	16,378	16,378	16,378	
Number of Individuals	2,586	2,586	2,586	2,586	
of which in treatment group	506	506	506		
of which in control group	2,080	2,080	2,080	2,080	
F-Statistic	4,299.3200	4,088.2000	5,747.9200	8,860.9700	
R^2	0.0650	0.0650	0.0649	0.0659	
Adjusted R^2	0.0630	0.0629	0.0630	0.0635	

[a] In Euro/Inflation-Adjusted (Base Year 2000), [b] Detached, Semi-Detached, or Terraced

Robust standard errors clustered at the federal state level in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{\text{it},4000}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a treatment radius of 4,000 metres in interview year t, and zero else. The intensity measures are defined as follows: $\text{InvDist}_{it,4000}$ is the inverse distance, $\text{RevDist}_{it,4000}$ is equal to four minus the distance to the next wind turbine in kilometres, $\text{Cumul}_{it,4000}$ is equal to the number of wind turbines within a treatment radius of 4,000 metres, all in interview year t. $\text{Trans}_{it-\tau,4000}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a 4,000 metres treatment radius in interview year $t-\tau$, and zero else. For example, $\text{Trans}_{it-3,4000}$ is the treatment dummy in the third year after the construction of the wind turbine. The dependent variable is life satisfaction on a 0/10 scale. All regression equations include dummy variables for interview years, individual fixed effects, and a constant. See Table A.1 in Main Appendix for the complete list and descriptive statistics of the micro and macro controls. All figures are rounded to four decimal places.

Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Table C.11, own calculations.

Table C.9: Results - Sub-Samples, FE Models, Spatial Matching ($15,000m$)
$Construction_{it,4000}$

Dependent Variable: Satisfaction With Life

Regressors	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Construction}_{\text{it},4000}$	-0.1261**	-0.0937	-0.0711	-0.1356**	0.0634	-0.2127***
	(0.0488)	(0.1132)	(0.0686)	(0.0436)	(0.0499)	(0.0605)
Age	-0.0188	0.0025	-0.1069**	0.0043	-0.0388	-0.0004
	(0.0166)	(0.0446)	(0.0410)	(0.0259)	(0.0270)	(0.0332)
Age Squared	-0.0001	0.0001	0.0006**	-0.0003	0.0002	-0.0003
	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Is Female						
Is Married	0.0589	0.3851	-0.0522	0.0620	0.3197	-0.0734
	(0.0946)	(0.7317)	(0.1953)	(0.1471)	(0.4429)	(0.1527)
Is Divorced	0.0391	0.4838	-0.5064	0.1950	-0.0679	0.2127
	(0.2112)	(0.6903)	(0.8270)	(0.3434)	(0.4314)	(0.2987)
Is Widowed	-0.5247*	0.0895	-0.9141	-0.2729	-0.4955	-0.3157
	(0.2652)	(0.7342)	(0.7701)	(0.1820)	(0.8712)	(0.2506)
Has Very Good Health	0.3674***	0.3737**	0.4583***	0.3490***	0.3639***	0.3686***
	(0.0503)	(0.1615)	(0.1345)	(0.0449)	(0.0636)	(0.0658)
Has Very Bad Health	-1.3017***	-1.0011***	-1.1366***	-1.2267***	-1.3264***	-1.1695***
	(0.1269)	(0.1538)	(0.2749)	(0.1051)	(0.1891)	(0.0952)
Is Disabled	-0.1545	-0.3634*	-0.3932	-0.1647	-0.3259***	-0.1430
	(0.0934)	(0.1811)	(0.2154)	(0.1039)	(0.0691)	(0.1332)
Has Migration Background						
Has Tertiary Degree	-0.2054	-0.3403	-0.4993*	-0.0646	-0.2762	-0.1930
	(0.1951)	(0.2783)	(0.2485)	(0.1469)	(0.3597)	(0.1417)
Has Lower Than Secondary Degree	0.3635*	-0.3660	0.6399	0.2814	-0.1533	0.4471*
	(0.1882)	(0.3417)	(1.0752)	(0.1900)	(0.3664)	(0.2403)
Is in Education	0.1265	1.0588**	0.6272	0.3490*	0.3120	0.3212
	(0.1735)	(0.3595)	(0.5650)	(0.1690)	(0.2717)	(0.2403)
Is Full-Time Employed	-0.0462	0.6159***	0.1730	0.1174*	0.0846	0.0753
	(0.0871)	(0.0913)	(0.1622)	(0.0620)	(0.1230)	(0.0699)
Is Part-Time Employed	-0.0561	0.0547	-0.0196	-0.0034	-0.1111	0.0057
	(0.0602)	(0.1327)	(0.1663)	(0.0853)	(0.1104)	(0.0932)
Is on Parental Leave	0.1815	0.2686	0.1355	0.1546	0.0187	0.2277*
	(0.1016)	(0.4238)	(0.2755)	(0.1321)	(0.2173)	(0.1239)
Is Unemployed	-0.4953***	-0.2808*	-0.3720	-0.4486***	-0.4415**	-0.4850***
	(0.1131)	(0.1304)	(0.2070)	(0.0720)	(0.1523)	(0.1133)
Log Monthly Net Individual Income[a]	0.0693	-0.0393	0.0789	0.0094	0.0771	0.0149
	(0.0399)	(0.0767)	(0.0890)	(0.0331)	(0.0541)	(0.0380)
Has Child in Household	0.1105*	-0.0186	0.1073	0.1133**	0.0124	0.1367**

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Dependent Variable: Satisfaction With Life

Regressors	(1)	(2)	(3)	(4)	(5)	(6)
	(0.0555)	(0.1371)	(0.1434)	(0.0477)	(0.0738)	(0.0509)
Log Annual Net Household Income[a]	0.2405***	0.1759	0.0596	0.2240***	0.3090***	0.1357**
	(0.0645)	(0.1271)	(0.0938)	(0.0599)	(0.0905)	(0.0439)
Lives in House[c]	-0.0099	0.0679	-0.0006	0.0145	-0.0116	0.0175
	(0.0455)	(0.0678)	(0.0807)	(0.0594)	(0.0497)	(0.0602)
Lives in Small Apartment Building	-0.0011	0.0506	-0.0312	0.0232	0.0047	0.0204
	(0.0521)	(0.0871)	(0.0898)	(0.0522)	(0.0741)	(0.0518)
Lives in Large Apartment Building	-0.0091	0.0335	-0.0251	0.0277	-0.0076	0.0262
	(0.0310)	(0.0816)	(0.0873)	(0.0460)	(0.0682)	(0.0515)
Lives in High Rise	0.0597	0.1164	0.2536	0.0279	0.0481	0.0819
	(0.1908)	(0.3136)	(0.3930)	(0.1849)	(0.3097)	(0.1575)
Number of Rooms per Individual	0.0216	0.0104	-0.0228	0.0132	-0.0330	0.0302
	(0.0229)	(0.0493)	(0.0697)	(0.0231)	(0.0505)	(0.0333)
Unemployment Rate	-0.0081	-0.0178	-0.0259	-0.0102	-0.0113	-0.0037
	(0.00149)	(0.0155)	(0.0360)	(0.0155)	(0.0163)	(0.0104)
Average Monthly Net Household Income[a]	-0.0003	-0.0019	-0.0004	-0.0007	-0.0011**	-0.0002
	(0.0005)	(0.0012)	(0.0012)	(0.0006)	(0.0004)	(0.0007)
Number of Observations	12,570	3,808	3,934	12,350	5,469	10,909
Number of Individuals	2,047	700	1,380	2,400	722	1,864
of which in treatment group	388	155	308	488	148	358
of which in control group	1,659	545	1,072	1,912	587	1,506
F-Statistic	3,393.8100	1,464.5000	1,796.3600	25,074.9900	2,300.6900	4,097.3100
R^2	0.0660	0.0816	0.0749	0.0662	0.0728	0.0679
Adjusted R^2	0.0635	0.0733	0.0668	0.0636	0.0669	0.0650

[a] In Euro/Inflation-Adjusted (Base Year 2000), [b] Detached, Semi-Detached, or Terraced

(1) House-owner subsample, (2) Non-house-owner subsample, (3) Worries environment high, (4) Worries environment not high, (5) Worries climate change high, (6) Worries climate change not high

Robust standard errors clustered at the federal state level in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{\text{it},4000}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a treatment radius of 4,000 metres in interview year t, and zero else. The dependent variable is life satisfaction on a 0/10 scale. All regression equations include dummy variables for interview years, individual fixed effects, and a constant. See Table A.1 in Main Appendix for the complete list and descriptive statistics of the micro and macro controls. All figures are rounded to four decimal places.

Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Table C.11, own calculations.

Table C.10: Robustness (Residential Sorting - Linear Probability Models) - FE Models, Propensity-Score (PS) and Spatial (S) Matching, $Construction_{it,4000}$

Dependent Variable: Moving

Regressors	PS	S $(10,000m)$	S $(15,000m)$
$\text{Construction}_{\text{it},4000}$	-0.0072	-0.0060	-0.0051
	(0.0069)	(0.0061)	(0.0054)
Micro Controls	yes	yes	yes
Macro Controls	yes	yes	yes
Number of Observations	6,613	8,571	16,316
Number of Individuals	978	1,313	2,580
of which in treatment group	498	506	506
of which in control group	480	807	2,074
Adjusted R^2	0.0102	0.0097	0.0046

Robust standard errors clustered at the federal state level in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{\text{it},4000}$ is a treatment dummy variable based on the exact interview date that is equal to one if a wind turbine is present within a treatment radius of 4,000 metres in interview year t, and zero else. The dependent variable is a dummy variable that is equal to one in the time period in which an individual moves, and zero else; thus, we are estimating linear probability models here. All regression equations include dummy variables for interview years, individual fixed effects, and a constant. See Table A.1 for the complete list and descriptive statistics of the micro and macro controls. All figures are rounded to four decimal places.

Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Table C.11 of Online Appendix, own calculations.

Table C.11: Data Sources for Wind Turbines and Data Protection

Data for several wind turbines is taken from the renewables installations master data (EEG Anlagenstammdaten) for Germany, which the German transmission system operators (TSOs) are obliged to publish. This dataset collects all renewables installations which are subject to the Renewable Energy Act support scheme. However, it comprises geographical coordinates only for a small number of installations. Sources:

TSO: 50Hertz Transmission
`http://www.50hertz.com/de/EEG/Veroeffentlichung-EEG-Daten/EEG-Anlagenstammdaten` (in German), accessed June 1, 2015.
TSO: Amprion
`http://www.amprion.net/eeg-anlagenstammdaten-aktuell` (in German), accessed June 1, 2015.
TSO: TenneT TSO
`http://www.tennet.eu/de/kunden/eegkwk-g/erneuerbare-energien-gesetz/eeg-daten-nach-52.html` (in German), accessed June 1, 2015.

For geographical information, we largely rely on data by State offices for the environment of the German federal states and counties, which we report on state or county (*Landkreis*) level in the following. If a German disclaimer applies, we provide the original text and an own translation. An asterisk indicates freely accessible sources; all other data were retrieved on request and may be subject to particular non-disclosure requirements.

Baden-Württemberg*:
Basis: data from the spatial information and planning system (RIPS) of the State Office for the Environment, Land Surveying, and Nature Conservation Baden-Württemberg (LUBW). [Grundlage: Daten aus dem Räumlichen Informations- und Planungssystem (RIPS) der Landesanstalt für Umwelt, Messungen und Naturschutz Baden-Württemberg (LUBW)]
`http://udo.lubw.baden-wuerttemberg.de/public/pages/home/welcome.xhtml` (in German), accessed June 1, 2015.

Berlin*:
NEB Neue Energie Berlin GmbH & Co. KG. `http://www.windenergie-berlin.de/index.htm` (in German), accessed June 1, 2015. Coordinates retrieved via Open Street Maps.

Brandenburg:

State Office for the Environment, Public Health, and Consumer Protection Brandenburg (Landesamt für Umwelt, Gesundheit und Verbraucherschutz Brandenburg)

Bremen:

Senator for the Environment, Construction and Transportation

Hamburg:

Office for Urban Development and the Environment

Hesse:

Data source: Hessian State Information System Installations (LIS-A) – Hessian Ministry for the Environment, Energy, Agriculture, and Consumer Protection (Datengrundlage: Hessisches Länderinformations-system Anlagen (LIS-A) - Hessisches Ministerium für Umwelt, Energie, Landwirtschaft und Verbraucherschutz)

Lower Saxony:

Administrative district Ammerland: Construction Office

Administrative district Aurich: Office for Construction and Nature Conservation

Administration Union Greater Braunschweig (Zweckverband Großraum Braunschweig)

Administrative district Cloppenburg

City of Delmenhorst: Municipal Utilities Delmenhorst

Administrative district Harburg: Administrative Department for District and Business Development

Administrative district Holzminden

Administrative district Lüchow-Dannenberg: Office for Construction, Immission Control, and Monument Preservation

Administrative district Oldenburg

City of Osnabrück: Office for the Environment and Climate Protection

Administrative district Osterholz: Construction Office

Administrative district Osterode: Energieportal (energy gateway)

Administrative district Peine

Administrative district Stade: Office for Construction and Immission Protection

Administrative district Vechta: Office for Planning, the Environment, and Construction

Mecklenburg-Vorpommern*:

State Office for the Environment, Nature Conservation, and Geology (Landesamt für Umwelt, Naturschutz und Geologie). http://www.umweltkarten.mv-regierung.de/atlas/script/index.php (in German), accessed June 1, 2015.

North Rhine-Westphalia:

State Office for Nature Conservation, the Environment, and Consumer Protection NRW (Landesamt für Natur, Umwelt und Verbraucherschutz NRW)

Rhineland-Palatinate:

Ministry for Economic Affairs, Climate Protection, Energy, and State Planning Rhineland-Palatinate (Ministerium für Wirtschaft, Klimaschutz, Energie und Landesplanung Rheinland-Pfalz)

Saarland:

State Office for Land Surveying, Geographical Information, and Regional Development (Landesamt für Vermessung, Geoinformation und Landentwicklung)

Saxony:

Saxon Energy Agency – SAENA GmbH (Sächsische Energieagentur – SAENA GmbH)

Saxony-Anhalt:

State Administration Office Saxony-Anhalt (Landesverwaltungsamt Sachsen-Anhalt)

Schleswig-Holstein:

State Office for Agriculture, the Environment and Rural Areas (Landesamt für Landwirtschaft, Umwelt und ländliche Räume Schleswig Holstein)

Thuringia:

Thuringian State Administration Office (Thüringer Landesverwaltungsamt),

Thüringer Energienetze*

www.thueringer-energienetze.com/Kunden/Netzinformationen/Regenerative_Energien.aspx (in German), accessed June 1, 2015.