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

Evidence from Well-Being Data

Christian Krekel, Alexander Zerrahn

German Institute for Economic Research (DIW Berlin), Mohrenstraße 58, 10117 Berlin, Germany

ckrekel@diw.de, azerrahn@diw.de

Abstract

Throughout the world, governments foster the deployment of wind power. The economic rationale behind these policies is to reduce negative externalities of conventional technologies, most 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 (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 both temporally and spatially limited. Their monetary valuation is, however, several magnitudes lower than the avoided externalities from CO_2 emissions.

Keywords: Well-Being, Life Satisfaction, Social Acceptance, Renewable Energy, Wind Turbines, Externalities, SOEP, Spatial Analysis

JEL: C23, Q42, Q51, R20

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 to expand the transmission grid. Wind turbines, in contrast to large centralised conventional power plants, which foster out-of-sight-out-of-mind attitudes, must be constructed in large numbers for wind power to play an effective role. This renders them more spatially dispersed and therefore 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 (Lehnert et al., 2014; Pearce-Higgins et al., 2012), most importantly, wind turbines have been found to have negative impacts on landscape aesthetics for residents living close by (Devine-Wright, 2005; Jobert et al., 2007; Wolsink, 2007). In general, no market prices exist for these negative externalities. Therefore, they are typically valued using stated preference (Groothuis et al., 2008; Jones and Eiser, 2010; Meyerhoff et al., 2010) or revealed preference approaches (Gibbons, 2014; 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 (SOEP) with a unique and novel panel dataset on more than 20,000 wind turbines in Germany 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 (see, for example, Welsch (2007)). 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.

Using a treatment effect analysis, we allocate residents to the treatment group if a wind turbine is constructed within a pre-defined radius around their household, and to the control group otherwise. We establish causality in a difference-in-differences design that exploits variation in time and space. 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, novel 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 effect on life satisfaction. The size of the effect is also economically significant, accounting for up to a fourth of the effect of being unemployed. For larger radii, no negative externalities can be detected. Importantly, the effect is transitory, vanishing after five years at the latest, and does not intensify with proximity or cumulation of wind turbines. Contrasting the monetary valuation of the imposed negative externalities with the avoided negative externalities through reduced CO_2 emissions, wind power is a favourable technology. In fact, the avoided damage exceeds the valuation of the spatially and temporally limited negative externalities by several magnitudes.

To our knowledge, there exists only one working paper that investigates the effect of wind turbines on residential well-being (von Moellendorff and Welsch, 2014), finding that the presence of wind turbines has temporary negative effects. However, it differs from our paper in at least two important aspects: the authors do not account for self-selection of residents into particular geographical locations, and the data is analysed at the post code level, rendering a clear-cut treatment-effect interpretation difficult. As we argue, we overcome both shortcomings and thus contribute to the literature in several ways. First, we investigate the effect of wind turbines on residential well-being for the first time based on exact distances. Second, we use a difference-in-differences design in combination with propensity-score and novel spatial matching techniques, ensuring comparability of the treatment and control group, to establish causality. Third, we add to the ongoing debate on the political economy of renewable energy by providing figures on negative externalities, which can be contrasted with those of conventional electricity generation technologies. Finally, we provide an assessment from a macro perspective as our results are not site-specific, compared to most previous research.

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 put into perspective in Section 6. Finally, Section 7 concludes and outlines avenues for future research.

2. Literature Review

2.1. Stated and Revealed Preference Approaches

Throughout stated preference 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 wind turbines 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), other papers find unchanged attitudes (Eltham et al., 2008) or adaptation (Warren et al., 2005; Wolsink, 2007) over time.

Environmental psychology provides deeper explanations for the underlying rationales: a preference for a traditional landscape instead of an industrialised appeal (Kirchhoff, 2014), and a positive emotional bond between people and places, which develops over time and which generates meaning and belonging (Devine-Wright and Howes, 2010; Vorkinn and Riese, 2001). A disruption of such place-bound identities can cause negative emotions and reduce subjective well-being (Cass and Walker, 2009; Pasqualetti, 2011).

Likewise, hedonic studies, drawing on variations in real estate prices, find evidence for significant negative externalities caused by wind turbines for the United States (Heintzelmann and Tuttle, 2012), Denmark (Jensen et al., 2013), the Netherlands (Dröes and Koster, 2014), England and Wales (Gibbons, 2014), and Germany (Sunak and Madlener, 2014). The decrease in real estate prices due to the construction of wind turbines is estimated 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 increasingly used as an alternative to stated and revealed preference approaches. It specifies a microeconometric function relating 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 decrease the environmental disamenity by one unit (Frey et al., 2004).

Compared to stated preference approaches, the LSA avoids bias resulting from the expression of attitudes or the complexity of valuation. On that note, stated preference approaches are subject to symbolic valuation. For wind turbines, Batel et al. (2014) point at subtle differences in the wording of questionnaires driving results. What is measured may thus be intrinsic attitudes rather than extrinsic preferences. At the same time, this approach is prone to framing and anchoring effects (Kahneman and Sugden, 2005). Instead of asking residents to monetarily value a complex environmental disamenity in a hypothetical situation, the LSA does not rely on the ability to consider all relevant consequences, 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 revealed preference approaches, the LSA avoids bias resulting from the assumption that the market for the private good taken as complement of the environmental disamenity is in equilibrium. Typically, this assumption is violated in case of slow adjustment of prices, incomplete information, transaction costs, and a low variety of private goods, as is the case for wind turbines and real estate. It also avoids potentially distorted future risk expectations common to market transactions (Frey et al., 2004). Finally, it avoids bias resulting from the misprediction of utility, which is common to both stated and revealed preference approaches (Frey and Stutzer, 2013).

Intuitively, the LSA is not entirely free of methodological issues itself. For data on self-reported well-being to constitute a valid approximation of welfare, they have to be at least ordinal. Moreover, the microeconometric function that relates life satisfaction to the environmental disamenity to be valued 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 (SOEP) for the time period between 2000 and 2012. The SOEP is an extensive and representative panel study of private households in Germany, covering almost 11,000 households and 22,000 individuals annually (Wagner et al., 2007, 2008). Most importantly, it provides information on the geographical locations of places of residence, allowing to merge data on well-being with data on wind turbines.[1] Our dependent variable is *satisfaction with life* as an indicator of life satisfaction in general. It is obtained from an eleven-point single-item Likert scale that asks "How satisfied are you with your life, 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).

3.2. Data on Wind Turbines

At the heart of our analysis lies a unique and novel panel dataset on 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,

[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. For more information, see Goebel and Pauer (2014).

we contacted the body in charge for granting access and filed a request for data disclosure. See Appendix C for a detailed account and information on data protection. We brought together data on more than 20,000 wind turbines with construction dates ranging between 1985 and 2012. The core attributes rendering an observation suitable for our empirical analysis are *(i)* the exact geographical coordinates, *(ii)* the construction dates, *(iii)* construction past 2000, and *(iv)* some indicator for the size of the installation.

Concerning *(i)*, the exact locations constitute the distinctly novel feature of our dataset. Zip codes or postal addresses, as provided in the public transparency platform on renewable energy installations in Germany[2], would render an exact matching between turbines and individuals impossible. All turbines in our sample, in contrast, are recorded with exact coordinates. Concerning *(ii)*, construction dates must be available to contrast them with interview dates of households in the SOEP. Construction past 2000, *(iii)*, has pragmatic reasons: geographic coordinates of households are only available from 2000 onwards. Concerning *(iv)*, we focus on turbines that exceed a certain size threshold. Very small installations are less likely to interfere with landscape aesthetics. Moreover, it is more likely that they are owned by residents in immediate proximity to the site. We could therefore measure an effect other than a negative externality. Naturally, there is some degree of arbitrariness in determining a size threshold. Beyond those without any information on size at all, we exclude all wind turbines with a hub height of less than 50 metres or a capacity of less than 0.5 megawatts. Out of more than 20,000, this conservative approach leaves us with a set of 10,083 wind turbines relevant for our analysis. These constitute the *included group* (see Table A.1 for descriptive statistics). The other 10,554 turbines constitute the *excluded group*.

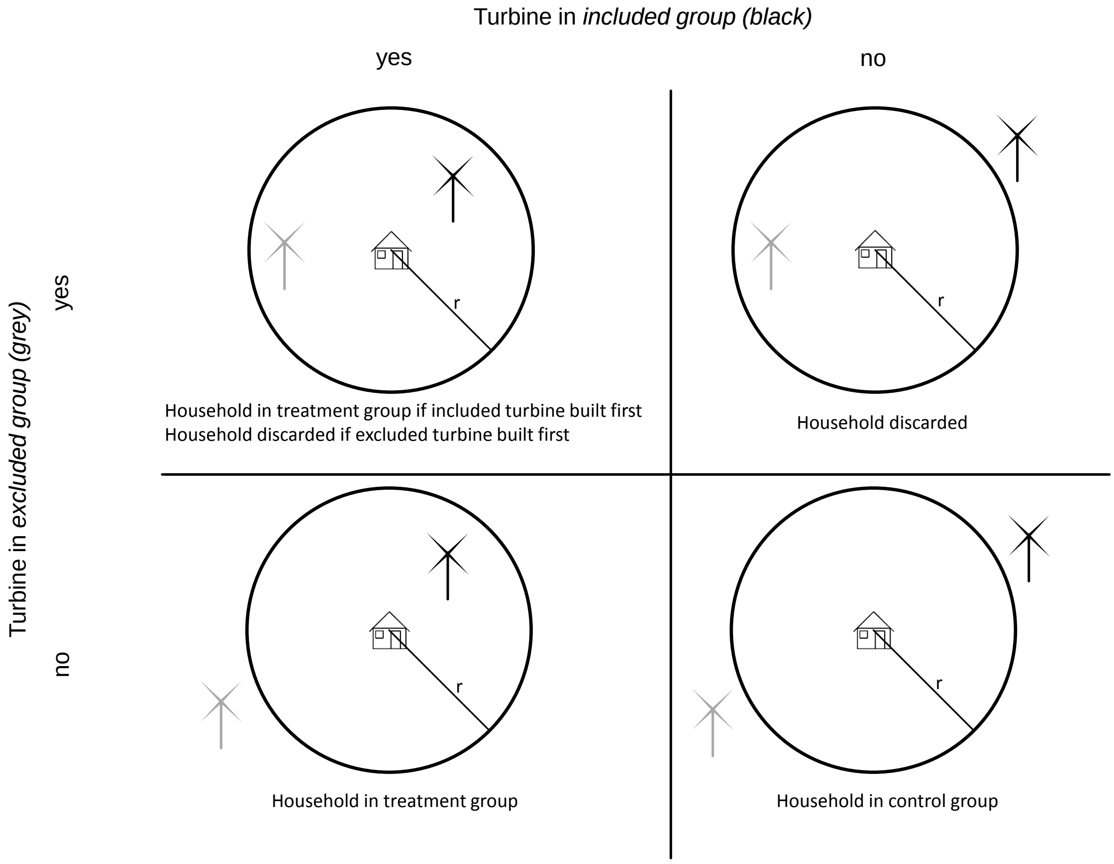
[2]See `http://www.netztransparenz.de/de/Anlagenstammdaten.htm` (in German), accessed June 1, 2015.

3.3. Merge

We merge the data on residential well-being with the data on wind turbines by calculating the distance between the place of residence of an individual and the nearest installations in a Geographical Information System (GIS). 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 there is no such turbine within the treatment radius, the individual is allocated to the control group. 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 must be dropped from the analysis. Otherwise, for example, if an individual lives close to a wind turbine which was constructed before 2000, this observation would blur the results if it is fully attributed to the control group although it in fact belongs to the treatment group. If both a turbine from the *included* and *excluded group* are present, then the individual is allocated to the treatment group in case the first turbine built is from the *included group*, and discarded otherwise. Consider Figure 1 for a graphical illustration.

Some further data adjustments must be made. Due to currentness of data, only years up to 2010 are included for the federal state of Mecklenburg-Vorpommern, up to 2011 for Saxony, and all years up to 2012 for all other states. Moreover, we discard individuals for which the interview date is given with insufficient accuracy in the year the first wind turbine was constructed in their surroundings. For those individuals, we cannot be sure whether they are allocated to the treatment or control group in this specific year. We also discard individuals who "start" in the treatment group, for example, if they enter the SOEP 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 respective choice of the treatment radius.

Figure 1: 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



Finally, we add controls at the micro level, originating from the SOEP, and at the macro level, originating from the Federal Statistical Office, all of which have been shown to affect the dependent variable in the literature (see Frey (2010) for a review). 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. Macro controls include macroeconomic conditions and neighbourhood characteristics at the county (*Landkreis*) level. The descriptive statistics of the final sample are given in Table A.2.

4. Empirical Model

4.1. Choice of Treatment Radius

As default treatment radius, we choose 4,000 metres, motived by three considerations. First, we consider this radius close enough for turbines to unfold a negative impact. Second, this radius allows for a sufficient sample size not only for the entire population, but also for different population sub-groups when stratifying the final sample. Third, there is no uniform legislation in Germany that could serve as reference. Across time and federal 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 sensitivity analyses with other radii.

Moreover, for 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 omitted.

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 of a wind turbine. In other words, residents should not strategically postpone interviews due to construction. We make sure that this identifying assumption holds by checking the distribution of interview dates around construction, and it seems that their distribution is indeed random and unrelated. Second, treatment and control group follow a common time trend in the absence of treatment. We make sure that this identifying assumption holds by controlling for confounders that could cause differences in time trends. Moreover, we apply propensity-score and novel spatial matching techniques, as described in Section 4.3. Third, the construction of a wind turbine within the treatment radius is exogenous.

In our setting, endogeneity may arise through two channels: endogenous construction of turbines or endogenous residential sorting. In other words, for certain residents it could be systematically more likely that either a new wind turbine is constructed in their surroundings, or that they move away from or towards existing turbines. In both cases, estimates would be biased if such endogenous assignment into the treatment or control group is based on an omitted or the outcome variable. We argue that both channels are mitigated.

Concerning endogenous construction of turbines, we omit small installations and individuals in their surroundings as they are more likely to be installed by nearby residents as private operators, and focus on large installations instead. Moreover, we omit residents who are farmers: these are more likely to let land to commercial operators.[3] Finally, a set of established controls at the micro and macro level, as well as fixed effects at the individual level, account for systematic differences between treatment and control group over time and at any point in time.

In case of endogenous residential sorting, residents with lower (higher) preference for wind turbines self-select into areas with greater (smaller) distance to them, whereby the preference is 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*. We work around simultaneity by excluding residents who move. However, this comes at the cost that the parameter estimates might be biased as residents who move might be systematically different from residents who do not. In fact, this bias might run in both directions, that is, an upward bias in case residents move away from wind turbines or a downward bias in case residents move towards wind turbines (and vice versa when hypothesizing a positive effect of wind turbines on

[3]Results are robust to the inclusion of farmers.

residential well-being). However, when trading off this bias against the bias resulting from simultaneity, distortions from the exclusion of movers are likely to be considerably smaller than distortions from the endogenous assignment of treatment status. Besides, traditionally, geographical mobility in Germany is low: in a given year, only about 1% of respondents move. Moreover, hypothesizing that wind turbines exert a negative effect on residential well-being, distortions from the exclusion of movers will result in attenuated estimates as most adversely affected individuals are most likely to move away from wind turbines. As such, parameter estimates can be interpreted as lower bounds.

This lower-bound interpretation is also in line 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.

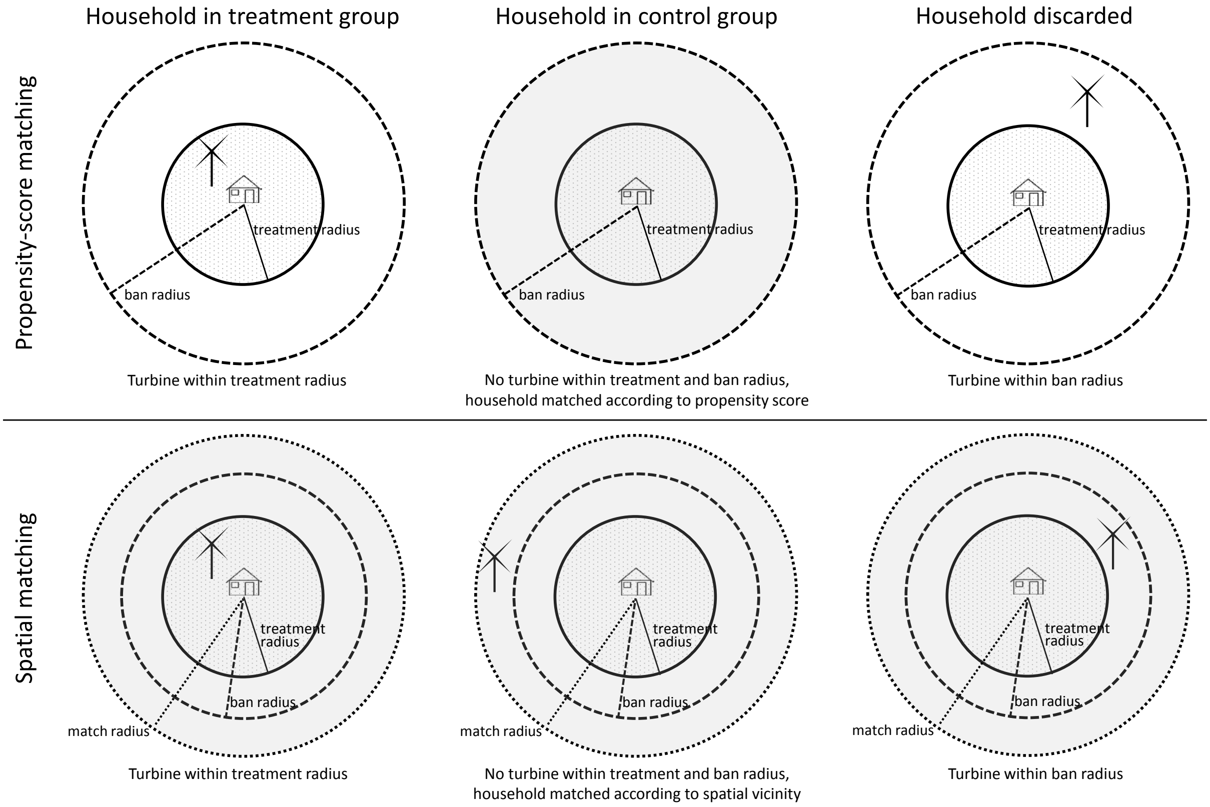
4.3. Matching Treatment and Control Group

Under the basic definition, the treatment group is relatively small and concentrated in particular rural areas, whereas the 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 focus only on residents in rural areas, excluding individuals living in city counties (*kreisfreie Städte*) and counties ranked in the top two deciles according to population density.[4] Moreover, we use two types of matching.

The first type of matching is *propensity-score matching*. Specifically, we use one-to-one nearest-neighbour matching on macro controls, that is, the unemployment rate, average household income, population density at county level, and a federal state dummy. See the upper panel of Figure 2 for an illustration. Notably, we match residents on time-invariant

[4] Results are robust to the inclusion of residents living in urban areas.

Figure 2: Empirical Model - Matching Strategy

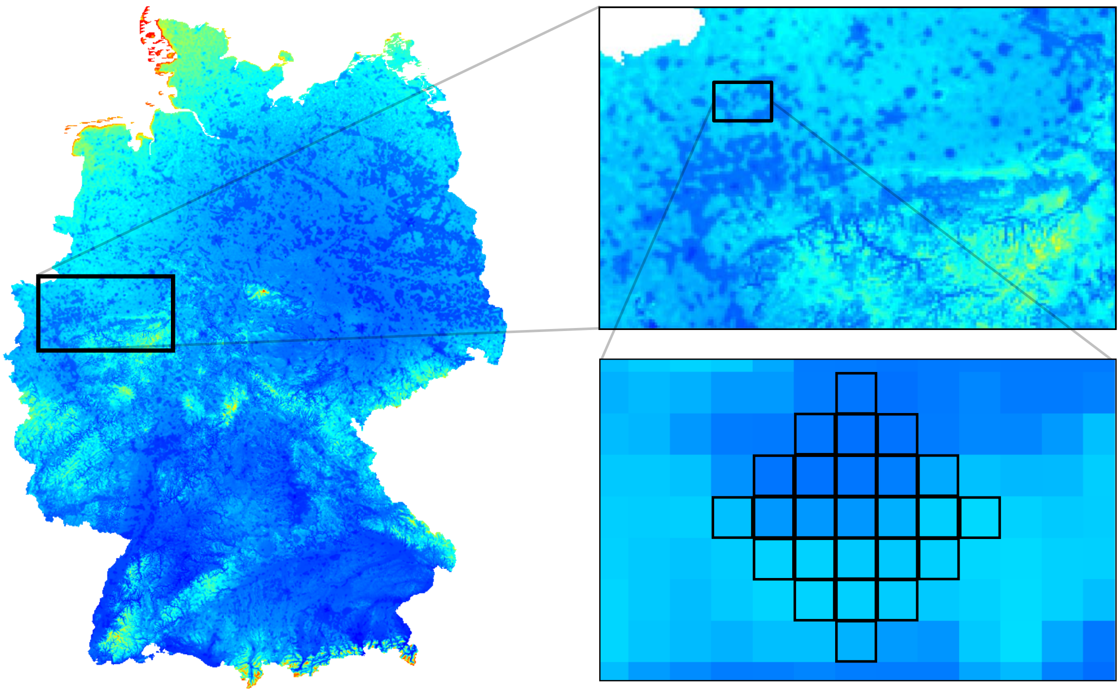


variables, which are generated by taking the means over the entire observation period. Strictly speaking, it would be cleaner to use pre-treatment values of these variables only. This, however, is computationally complicated as we employ a difference-in-differences design with treatment at multiple points in time. Moreover, using the means is conceptually uncomplicated as treatment is unlikely to affect these aggregate variables.[5] 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,

[5]In a comprehensive study for Germany, May and Nilsen (2015) could not find any significant effects of wind power deployment on local GDP.

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 × 1 kilometre tiles, distributed over the entire country. Using a GIS, 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 3 for a graphical illustration.

Figure 3: 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. Colour coding ranging from dark . blue (lowest expected annual wind yield) to red (highest expected annual wind yield)

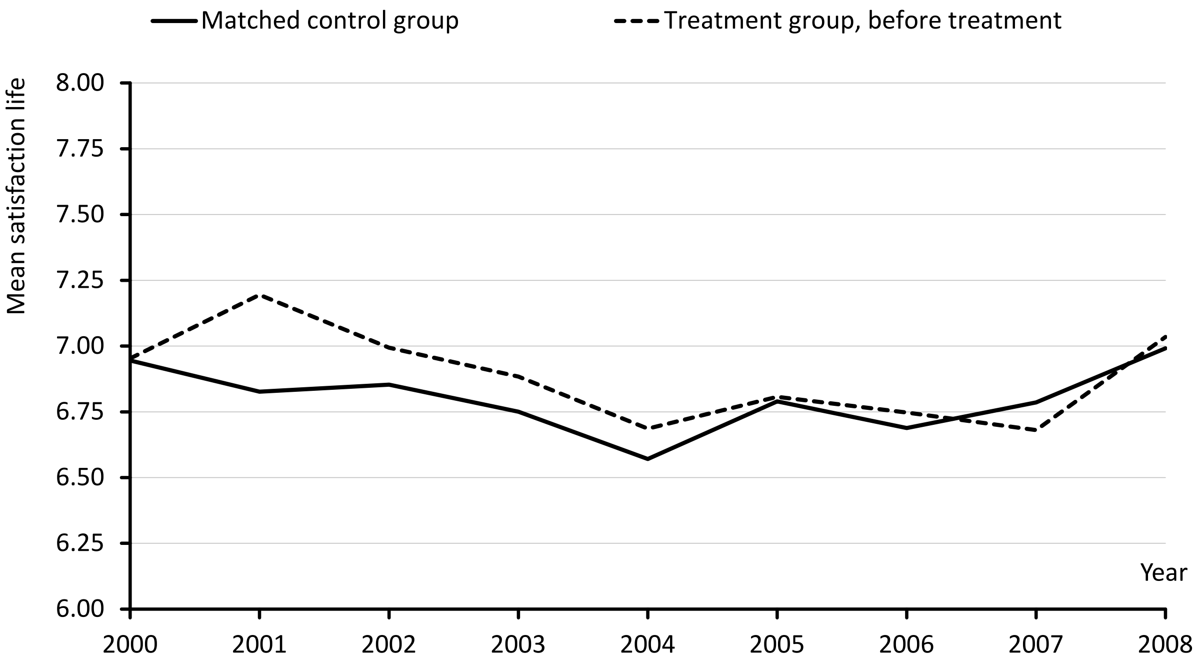
Source: German Meteorological Service (DWD) (2014))

Figure 4 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 before treatment (dashed line).[6] All graphs control for

[6]The horizontal axis is restricted to the time period between 2000 and 2008. Thereafter, the pre-

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

Figure 4: Common Time Trend (Propensity-Score Matching)



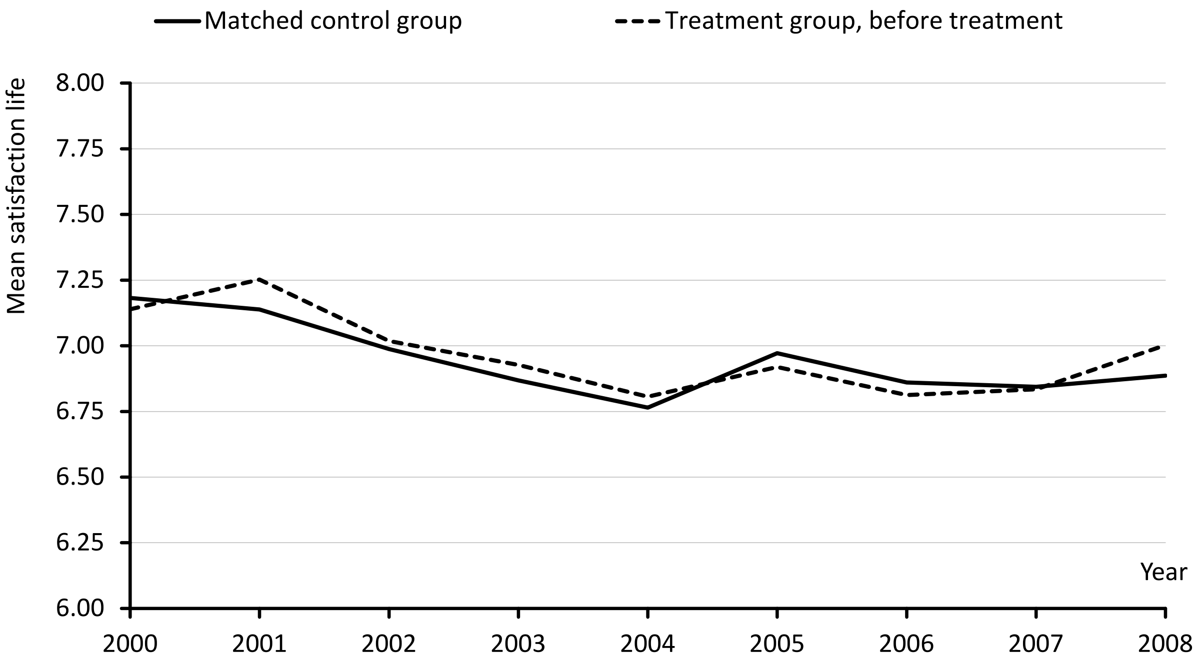
Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, own calculations

The second type of matching is called *spatial matching*. It is a novel type of matching, 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. Specifically, we define a matching radius around each place of residence. Individuals who are neither treated nor discarded, but experience construction of a turbine within the matching radius, constitute the control group. In other words, we match residents who live close to a wind turbine 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, where the latter serves

treatment group mean is based only on very few observations and hardly delivers insightful information.

as default. See the lower panel of Figure 2 for an illustration. 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 5: Common Time Trend (Spatial Matching, 15,000 metres)



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

Figure 5 is constructed analogously to Figure 4, 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.

4.4. Regression Equation

We employ a linear model estimated by the fixed-effects (FE) within estimator and robust standard errors clustered at the federal state level.[7] The specification test by Wu (1973) and Hausman (1978), as well as the robust version by Wooldridge (2002) indicate that a FE model is strictly preferable. Specifically, all tests reject the null of identical coefficients between a fixed and a random effects specification at the 1% significance level.[8]

Regression Equation (1) estimates the overall treatment effect, with $Construction_{itr}$ as the regressor of interest. $Construction_{itr}$ is a dummy variable equal to one in time period t if a wind turbine is present within the treatment radius r around the household of individual i, and zero else. Regression Equation (2) estimates the treatment effect intensity, with the interaction $Construction_{itr} \times Intensity_{itr}$ as the regressor of interest. $Intensity_{itr}$ is a placeholder for different measures of treatment intensity, either $InvDist_{itr}$ as the inverse of the distance to the nearest turbine in kilometres, $RevDist_{itr}$ as the treatment radius minus the distance to the nearest turbine, and $Cumul_{itr}$ as the number of turbines 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, while the two distance measures make different parametric assumptions. Regression Equation (3) estimates the treatment effect persistence. The regressor of interest, $Trans_{i(t-\tau)r}$, is a dummy variable equal to one in time period t, which is τ periods after

[7] This *preference heterogeneity* is mitigated by including individual fixed effects. However, discrete models for ordinal variables are not easily applicable to panel data and fixed effects. In practice, continuous linear models assuming cardinality are preferred. In fact, this introduces measurement error as *satisfaction with life* is a discrete variable, which is censored from above and below. The bias resulting from this measurement error, however, has been found to be minor in practice (see for example Brereton et al., 2008; Ferreira and Moro, 2010; Ferrer-i-Carbonell and Frijters, 2004).

[8] 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. As such, we cannot reject that regressors are correlated with the error terms.

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

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

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

$$y_{it} = \beta_0 + \mathbf{MIC'_{it}}\boldsymbol{\beta}_1 + \mathbf{MAC'_{it}}\boldsymbol{\beta}_2 + \sum_{\tau=1}^{9} \delta_\tau Trans_{i(t-\tau)r} + \\ + \sum_{n=1}^{12} \gamma_n Year_{2000+n} + \mu_i + \epsilon_{it} \tag{3}$$

where y_{it} as *satisfaction with life* is the regressand, β_0 the constant, $\beta_{\mathbf{1}}$, $\beta_{\mathbf{2}}$, δ_1, δ_τ, and γ_n the coefficients, $\mathbf{MIC}_{it}$ and $\mathbf{MAC}_{it}$ vectors of controls at the micro and macro level, respectively, and $Year_{2000+n}$ are yearly dummy variables. The fixed effect μ_i captures time-invariant unobserved heterogeneity at the individual level, and ϵ_{it} is the idiosyncratic disturbance. The respective average treatment effects on the treated (ATOT) are captured by coefficients δ_1 and δ_τ.

5. Results

5.1. Propensity-Score Matching

Table 5.1 shows the results of the difference-in-differences specification with propensity-score matching. For convenience, we only report results on our treatment variables here; detailed tables reporting all covariates can be found in Appendix B. The treatment and matched control group are equal in size, with 1,000 individuals in total.[9] The first two

[9]During estimation, some individuals are lost due to missing-at-random data on observables. As such, regressions are run on 498 treated and 488 control individuals.

columns are estimated by pooled ordinary least squares (OLS), the last two columns are estimated by fixed-effects (FE) within estimators, with and without controls, respectively. Comparing coefficients across models, size and significance of the ATOT vary starkly, pointing toward the importance of controlling for both observables and time-invariant unobservables. As such, the FE model with controls is our baseline model.

Table 5.1: Results - Satisfaction With Life, OLS/FE Models, Propensity-Score Matching *$Construction_{t,4000}$*

Dependent Variable: Satisfaction With Life

Regressors	OLS	OLS	FE	FE
$\text{Construction}_{t,4000}$	-0.0741	-0.0094	-0.1702***	-0.1405***
	(0.1757)	(0.1333)	(0.0494)	(0.0399)
Micro Controls	yes	yes	yes	yes
Macro Controls	yes	yes	yes	yes
Constant	6.9566***	1.7537*	7.0849***	7.2583***
	(0.1155)	(0.8362)	(0.0449)	(0.8130)
Number of Observations	7,818	6,637	7,818	6,637
Number of Individuals	1,000	986	1,000	986
of which in treatment group	500	498	500	498
of which in control group	500	488	500	488
F-Statistic		2,018.1800	372.3400	2,462.52000
R^2	0.0048	0.2206	0.0220	0.0704
Adjusted R^2	0.0031	0.2162	0.0203	0.0657

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{t,4000}$ is a dummy variable equal to one if a wind turbine is present within a treatment radius of 4,000 metres in year t, and zero else. All regression equations include dummy variables for years. All figures are rounded to four decimal places.

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

The last column contains our main result: 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% level. The size of this effect is also economically significant: life satisfaction decreases by 8% of a standard deviation, compared to a 26% drop when becoming unemployed. The baseline specification thus provides evidence for significant negative local externalities.[10]

Table 5.2: Results - Satisfaction With Life, FE Model, Propensity-Score Matching
$Construction_{t,8000/10000/15000}$

Dependent Variable: Satisfaction With Life

Regressors	r=8000	r=10000	r=15000
$\text{Construction}_{\text{t,r}}$	-0.0348	-0.0074	0.1303
	(0.0508)	(0.0645)	(0.1858)
Micro Controls	yes	yes	yes
Macro Controls	yes	yes	yes
Constant	7.7639***	7.2524***	9.7895***
	(0.7048)	(0.7316)	(1.1269)
Number of Observations	9,389	6,254	2,767
Number of Individuals	1,357	939	423
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

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{\text{t,r}}$ is a dummy variable equal to one if a wind turbine is present within a treatment radius of r metres in year t, and zero else. All regression equations include dummy variables for years. All figures are rounded to four decimal places.

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

What happens if we increase the treatment radius? For 8,000 and 10,000 metres, coefficient estimates are negative, but considerably smaller in size and insignificant at any conventional level (see Table 5.2). Likewise, no effect can be detected in case of a 15,000 metres treatment radius.[11] 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 good proxy for an undesired impact,

[10] Also without any matching strategy, results point into that direction. The coefficient estimate of $\delta_1 = -0.0759$ is negative and marginally significant at the 10% level in the baseline model. See Table B.1 in Appendix B.

[11] For larger treatment radii, we apply no ban radius.

for larger distances such an effect cannot be detected any more.

We explore treatment effect intensity next. For inverse distance, reverse distance, and cumulation, coefficient estimates have the expected sign, but none of them is significant at any conventional level (see Table 5.3). It seems that the presence a wind turbine itself is sufficient for negative externalities to arise, and specific intensity measures do not matter in addition.

Intuitively, the question arises whether residents adapt to the presence of wind turbines in their surroundings. Table 5.3 also presents results on habituation, 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 is not only spatially, but also temporally limited. It is significant at the 5% level from transition period two, that is, one year after the construction of a wind turbine, to transition period five. The size of the effect in each time period is somewhat larger than the size of the combined effect. Note that it is not surprising that there is no significant effect in transition period one. 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 coefficient estimate of the first period: 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.

Table 5.3: Results - Satisfaction With Life, FE Model, Propensity-Score Matching
$Construction_{t,4000}$ × Intensity, $Trans_{t\text{-}\tau,4000}$

Dependent Variable: Satisfaction With Life

	Intensity			Transition	
Regressors	$\text{InvDist}_{t,4000}$	$\text{RevDist}_{t,4000}$	$\text{Cumul}_{t,4000}$	$\text{Trans}_{t-\tau,4000}$	# treated
$\text{Construction}_{t,4000}$ × Intensity	-0.2090	-0.0128	-0.0178		
	(0.1605)	(0.0550)	(0.1556)		
$\text{Trans}_{t-1,4000}$				-0.0546	498
				(0.0642)	
$\text{Trans}_{t-2,4000}$				-0.1616**	444
				(0.0697)	
$\text{Trans}_{t-3,4000}$				-0.192**	424
				(0.0609)	
$\text{Trans}_{t-4,4000}$				-0.2242**	376
				(0.0917)	
$\text{Trans}_{t-5,4000}$				-0.2253**	335
				(0.0924)	
$\text{Trans}_{t-6,4000}$				-0.2637	288
				(0.1495)	
$\text{Trans}_{t-7,4000}$				-0.2215	240
				(0.1271)	
$\text{Trans}_{t-8,4000}$				0.0305	204
				(0.1846)	
$\text{Trans}_{t-9,4000}$				-0.0679	167
				(0.2816)	
Micro Controls	yes	yes	yes	yes	
Macro Controls	yes	yes	yes	yes	
Constant	7.5459***	7.8139***	7.6105***	7.0489***	
	(0.8708)	(0.8644)	(0.8269)	(0.9185)	
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	

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{t,4000}$ is a dummy variable equal to one if a wind turbine is present within a treatment radius of 4,000 metres in year t, and zero else. $\text{InvDist}_{t,4000}$ is the inverse distance, $\text{RevDist}_{t,4000}$ is equal to 4 minus the distance to the next wind turbine in kilometres, $\text{Cumul}_{t,4000}$ is equal to the number of wind turbines within a 4,000 metres treatment radius, all in year t. $\text{Trans}_{t-\tau,4000}$ is a dummy variable equal to one if a wind turbine is present within a 4,000 metres treatment radius in year $t-\tau$, and zero else. All regression equations include dummy variables for years. All figures are rounded to four decimal places.
Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Appendix C, own calculations.

Results thus suggest that residents adapt to wind turbines in their surroundings, and their presence does not prove to be a permanent burden. As a caveat, however, one should note that 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. Non-significance may thus arise as a statistical artefact. Likewise, heavily affected residents might be excluded as they move away. Both indications are, however, consistent with a lower-bound interpretation.

Table 5.4: Results - Satisfaction With Life, FE Model, Spatial Matching (10,000m, 15,000m) $Construction_{t,4000/8000}$

Dependent Variable: Satisfaction With Life

Regressors	(1)	(2)	(3)	(4)
$\text{Construction}_{t,4000}$	-0.1088***	-0.1138**		
	(0.0222)	(0.0366)		
$\text{Construction}_{t,8000}$			-0.0642	-0.0452
			(0.0372)	(0.0447)
Micro Controls	yes	yes	yes	yes
Macro Controls	yes	yes	yes	yes
Constant	7.7061***	6.7254***	7.4786***	7.4268***
	(0.6694)	(0.8511)	(0.9088)	(0.8225)
Number of Observations	8,609	16,378	8,643	14,485
Number of Individuals	1,317	2,586	1,241	2,193
of which in treatment group	506	506	698	698
of which in control group	811	2,080	543	1,495
F-Statistic	9,891.2100	5,251.8600	26,893.1900	14,555.3300
R^2	0.0715	0.0652	0.0740	0.0676
Adjusted R^2	0.0678	0.0632	0.0704	0.0654

[a] Monthly in Euro/Inflation-Adjusted (Base Year 2000), [b] Annually in Euro/Inflation-Adjusted (Base Year 2000)
[c] Detached, Semi-Detached, or Terraced

(1) Spatial matching $10,000m$, (2) Spatial matching $15,000m$,
(3) Spatial matching $10,000m$, (4) Spatial matching $15,000m$

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{t,4000}$ ($\text{Construction}_{t,8000}$) is a dummy variable equal to one if a wind turbine is present within a treatment radius of 4,000 metres (8,000 metres) in year t, and zero else. All regression equations include dummy variables for years. All figures are rounded to four decimal places.

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

5.2. Spatial Matching

Tables 5.4 and 5.5 show the results of the difference-in-differences specification with spatial matching. For the overall treatment effect results corroborate the previous findings: 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% level for the 10,000 metres matching radius, and at the 5% level for the 15,000 metres matching radius, respectively. Moreover, the sizes of the coefficient estimates are close to those obtained under propensity-score matching. Likewise, for a higher treatment radius of 8,000 metres, no significant effect is found, as is the case for the various treatment intensity measures. Finally, results on transitoriness also suggest habituation: significant negative effects at the 1% and 5% level are estimated for transition periods two, three, and four after construction, except for period four under the 15,000 metres matching radius, with marginal significance at the 10% level only.

We now 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. Moreover, we analyse different distance bands around treated individuals. For example, 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, as well as two larger bands for robustness checks. Table 5.6 shows the results for the 15,000 metres matching radius; findings are analogous for the 10,000 metres matching radius. For all smaller distances, no significant effects are detected, as is for the $[2,000; 3,000]$ band. For larger distance bands, however, coefficient estimates are significant negative at the 5% level and large in size.

Table 5.5: Results - Satisfaction With Life, FE Model, Spatial Matching (10,000m, 15,000m)
$Construction_{t,4000}$ × Intensity, $Trans_{t\text{-}\tau,4000}$

Dependent Variable: Satisfaction With Life

	Matching radius 10,000 metres				Matching radius 15,000 metres				
Regressors	$InvDist_{t,4000}$	$RevDist_{t,4000}$	$Cumul_{t,4000}$	$Trans_{t-\tau,4000}$	$InvDist_{t,4000}$	$RevDist_{t,4000}$	$Cumul_{t,4000}$	$Trans_{t-\tau,4000}$	# treated
$Construction_{t,4000}$ × Intensity	-0.1604	-0.0078	-0.01423		-0.1862*	-0.0181	-0.0174		
	(0.1038)	(0.0411)	(0.0113)		(0.0940)	(0.0338)	(0.0106)		
$Trans_{t-1,4000}$				-0.0401				-0.0392	506
				(0.0657)				(0.0642)	
$Trans_{t-2,4000}$				-0.1212**				-0.1262**	450
				(0.0482)				(0.0697)	
$Trans_{t-3,4000}$				-0.1381***				-0.1506**	430
				(0.0411)				(0.0609)	
$Trans_{t-4,4000}$				-0.1808**				-0.1902*	382
				(0.0687)				(0.0917)	
$Trans_{t-5,4000}$				-0.1311				-0.1472	341
				(0.0837)				(0.0924)	
$Trans_{t-6,4000}$				-0.1664				-0.1519	291
				(0.1264)				(0.1495)	
$Trans_{t-7,4000}$				-0.0963				-0.0744	243
				(0.0941)				(0.1271)	
$Trans_{t-8,4000}$				0.1847				0.2104	207
				(0.1483)				(0.1846)	
$Trans_{t-9,4000}$				0.0378				-0.0778	170
				(0.2452)				(0.2816)	
Micro Controls	yes	yes	yes	yes	yes	yes	yes	yes	
Macro Controls	yes	yes	yes	yes	yes	yes	yes	yes	
Constant	7.8501***	7.9803***	7.8766***	7.7148***	6.7883***	6.8483***	6.7995***	6.7459***	
	(0.6745)	(0.6731)	(0.6554)	(0.6749)	(0.8429)	(0.8313)	(0.8319)	(0.8462)	
Number of Observations	8,609	8,609	8,609	8,609	16,378	16,378	16,378	16,378	
Number of Individuals	1,317	1,317	1,317	1,317	2,586	2,586	2,586	2,586	
of which in treatment group	506	506	506		506	506	506		
of which in control group	811	811	811	811	2,080	2,080	2,080	2,080	
F-Statistic	10,029.0400	9,702.5400	9,832.3100	10,774.6900	4,299.3200	4,088.2000	5,747.9200	8,860.9700	
R^2	0.0711	0.0709	0.0711	0.0725	0.0650	0.0650	0.0649	0.0659	
Adjusted R^2	0.0704	0.0672	0.0674	0.0680	0.0630	0.0629	0.0630	0.0635	

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Continued on next page

Regressors	Matching radius 10,000 metres				Matching radius 15,000 metres				# treated
	$\text{InvDist}_{t,4000}$	$\text{RevDist}_{t,4000}$	$\text{Cumul}_{t,4000}$	$\text{Trans}_{t-\tau,4000}$	$\text{InvDist}_{t,4000}$	$\text{RevDist}_{t,4000}$	$\text{Cumul}_{t,4000}$	$\text{Trans}_{t-\tau,4000}$	

Note: $\text{Construction}_{\text{t,4000}}$ is a dummy variable equal to one if a wind turbine is present within a treatment radius of 4,000 metres in year t, and zero else. $\text{InvDist}_{t,4000}$ is the inverse distance, $\text{RevDist}_{t,4000}$ is equal to 4 minus the distance to the next wind turbine in kilometres, $\text{Cumul}_{t,4000}$ is equal to the number of wind turbines within a 4,000 metres treatment radius, all in year t. $\text{Trans}_{t-\tau,4000}$ is a dummy variable equal to one if a wind turbine is present within a 4,000 metres treatment radius in year $t-\tau$, and zero else. All regression equations include dummy variables for years. All figures are rounded to four decimal places.

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

Table 5.6: Coefficient estimates for closer proximity and distance bands, Spatial Matching 15,000m $Construction_{t,4000}$

Dependent Variable: Satisfaction With Life

Treatment radius	$\text{Construction}_{t,r}$	treatment group size
2,000	0.0232	183
	(0.1107)	
2,500	-0.0169	274
	(0.0613)	
3,000	-0.0442	356
	(0.0589)	
4,000	-0.1138**	506
	(0.0366)	
$[2,000; 3,000]$	-0.0827	243
	(0.0614)	
$[2,000; 4,000]$	-0.1749**	411
	(0.0551)	
$[2,500; 4,000]$	-0.1869**	329
	(0.0754)	
$[3,000; 4,000]$	-0.1799*	232
	(0.0842)	
$[3,000; 5,000]$	-0.0798	348
	(0.0462)	
$[4,000; 5,000]$	0.0473	223
	(0.0988)	

Robust standard errors in parentheses

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

Note: $\text{Construction}_{\text{t,r}}$ is a dummy variable equal to one if a wind turbine is present within a treatment radius of r metres in year t, and zero else. All regression equations include micro controls, macro controls, and dummy variables for years. Coefficient estimates are rounded to four decimal places, p-values are rounded to three decimal places.

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

We put forward several explanations for this finding. 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 profit from installations, for instance, by directed compensation measures, as anecdotal evidence for electricity transmission towers suggests. Alternatively, individuals in particularly close distance could also actively erect turbines in their surroundings, and profit monetarily. Although we discarded small turbines that are unlikely to be built by utilities from our analysis, we cannot fully exclude this case. Both explanations, however, are in line with the finding that the effect within the $[2,000; 4,000]$ band is much stronger than that of the mere treatment radius of 4,000 metres. Unfortunately, we do not have information on the ownership structure of installations.

In any case, the overall significant negative effect within 4,000 metres remains a robust finding, and insignificant parameter estimates for closer distances, whatever the reason, are in line with a lower-bound interpretation. For the larger bands between 3,000 or 4,000 and 5,000 metres, no effects are found. Likewise, insignificant parameter estimates for the different intensity measures can be explained by the non-significance of effects for smaller distances: if coefficients are insignificant for individuals living closer to wind turbines, then treatment intensity increasing in proximity is obsolete.

5.3. Heterogeneity Analysis

To gain a more diverse picture, we now apply our treatment effect analysis to different population sub-groups. Table 5.7 presents the results for residents who are house owners versus residents who are not, as well as 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" and "climate change", respectively. We collapse these items into binary indicators equal to one for the highest category of concerns, and zero otherwise. Throughout all models, we use the difference-in-differences specification with spatial matching and the 15,000 metres matching radius; results are robust to using the 10,000 metres matching radius.

Table 5.7: Results - Sub-Samples, Satisfaction With Life, FE Model, Spatial Matching (15,000m)
Construction$_{t,4000}$

Dependent Variable: Satisfaction With Life

Regressors	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Construction}_{t,4000}$	-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
Constant	6.2501***	7.2812***	10.7316***	6.1764***	6.6104***	6.7511***
	(0.9662)	(1.6959)	(1.1070)	(0.9447)	(1.5696)	(1.1183)
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] Monthly in Euro/Inflation-Adjusted (Base Year 2000), [b] Annually in Euro/Inflation-Adjusted (Base Year 2000)
[c] 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 inn parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{t,4000}$ is a dummy variable equal to one if a wind turbine is present within a treatment radius of 4,000 metres in year t, and zero else. All regression equations include dummy variables for years. All figures are rounded to four decimal places.

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

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. This result is intuitive as house owners, beyond negative local externalities due to a decrease in landscape aesthetics, may 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 for both the entire population and the different population 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.[12]

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.

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

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 5.5, 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 (Table 5.1). Here, the average monetised negative externality amounts to 59 Euro per wind turbine and year.[13]

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 medium 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, 2014) 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 of 20 Euro per ton, the total

[13] 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 (2014) 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.

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 novel 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. Third, 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.

Acknowledgements

The authors would like to thank seminar participants at the 30th Annual Congress of the European Economic Association, the 11th World Congress of the Econometric Society, the 20th Spring Meeting of Young Economists, the 2015 Annual Conference of the Scottish Economic Society, and the 14th European Conference of the International Association for Energy Economics. Moreover, we would like to thank Sarah Dahmann, Claudia Kemfert, Michael Neumann, Philipp M. Richter, Aleksandar Zaklan, and Nicolas R. Ziebarth for valuable comments. We are grateful to Jan Goebel at DIW Berlin for continuous support with the SOEP.

For the kind provision of data on wind turbines in the respective areas, the authors would like to thank the State Office for the Environment, Land Surveying, and Nature Conservation Baden-Württemberg (LUBW), the Bavarian State Office for the Environment (LFU Bayern), the Brandenburg State Office for the Environment, Public Health, and Consumer Protection, the Bremen Senator for the Environment, Construction and Transportation, the Hamburg Office for Urban Development and the Environment, the

Hessian Ministry for the Environment, Energy, Agriculture, and Consumer Protection, the Construction Office of the district of Ammerland, the Office for Construction and Nature Conservation of the district of Aurich, the Administration Union Greater Braunschweig, the district of Oldenburg, the Office for Environmental Protection and Construction of the city of Oldenburg, the district of Cloppenburg, the municipal utilities of the city of Delmenhorst, the Administrative Department for District and Business Development of the district of Harburg, the district of Holzminden, the Office for Construction, Immission Control, and Monument Preservation of the district of Lüchow-Dannenberg, the district of Oldenburg, the Office for the Environment and Climate Protection of the city of Osnabrück, the Construction Office of the district of Osterholz, the district of Osterode, the district of Peine, the Office for Construction and Immission Control of the district of Stade, the Office for Planning, the Environment, and Construction of the district of Vechta, the Construction Office of the city of Wilhelmshaven, the State Office for the Environment, Nature Conservation, and Geology Mecklenburg-Vorpommern, the State Office for Nature Conservation, the Environment, and Consumer Protection North Rhine-Westphalia, the Ministry for Economic Affairs, Climate Protection, Energy, and State Planning Rhineland-Palatinate, the Saarland State Office for Land Surveying, Geographical Information, and Regional Development, the Saxon Energy Agency SAENA, the State Administration Office Saxony-Anhalt, the State Office for Agriculture, the Environment and Rural Areas Schleswig-Holstein, and the Thuringian State Administration Office.

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 infrastrucures: 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.

Federal Ministry for Economic Affairs and Energy (BMWi), "Zeitreihen zur Entwicklung der erneuerbaren Energien in Deutschland," (2014).

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 (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 (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, "Combining spatial modeling and choice experiments for the optimal spatial allocation of wind turbines," *Energy Policy* 39 (2011), 3845–3854.

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

Eltham, D., G. Harrison, and S. Allen, "Change in public attitude towards a Cornish wind farm: Implications for planning," *Energy Policy* 36 (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* 6(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., A. Rezai, and L. Taylor, "The social cost of carbon emissions: Seven propositions," *Economics Letters* 121 (2013), 90–97.

Frey, B., S. Lüchinger, and A. Stutzer, "Valuing Public Goods: The Life Satisfaction Approach," *University of Zurich Institute for Empirical Research in Economics Working Paper Series* 184 (2004).

Frey, B. 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 Impact 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* forthcoming (2015).

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

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

Heintzelmann, M. and C. Tuttle, "Values in the Wind: A Hedonic Analysis of Wind Power Facilities," *Land Economics* 88(3) (2012), 561–588.

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 (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 (2007), 2751–2760.

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

Kahneman, D. and R. Sugden, "Exprienced Utility as a Standard of Policy Evaluation," *Environmental & Resource Economics* 32 (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 (2008), 1833–1845.

Ladenburg, J., "Attitude towards offshore wind farms – The role of beach visits on attitude and attitude and demographic relations," *Energy Policy* 38 (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 (2013), 45–54.

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

Lehnert, L., S. Kramer-Schadt, S. Schönborn, O. Lindecke, I. Niermann, and C. Voigt, "Wind Farm Facilities in Germany Kill Noctule Bats from Near and Far," *PLOS ONE* 9(8) (2014), 1–8.

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

Luechinger, S., "Valuing air quality using the life satisfaction approach," *The Economic Journal* 119(536) (2009), 482–515.

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

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

May, N.G., and O.A. Nilsen, "The Local Economic Impact of Wind Power Deployment," *IZA Discussion Papers* 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 and Environmental Medicine* 56(11) (2014), 108–130.

Memmler, M., L. Schrempf, S. Hermann, S. Schneider, J. Pabst, and M. D. (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 (2010), 82–92.

Molnarova, K., P. Sklenicka, J. Stirobek, 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., "Morality, Space, and the Power of Wind-Energy Landscapes," *Geographical Review* 90(3) (2000), 381–394.

Pasqualetti, M., "Opposing Wind Energy Landscapes: A Search for Common Causes," *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 (2012), 386–394.

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

Rehdanz, K. and D. Maddison, "Local Environmental Quality and Life Satisfaction in Germany," *Ecological Economics* 64(4) (2008), 787–797.

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

Socio-Economic Panel (SOEP), "Data for years 1984-2012, version 29," *SOEP* (2013).

Sunak, Y. and R. Madlener, "The Impact of Wind Farms on Property Values: A Geographically Weighted Hedonic Pricing Model," *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 (2007), 2705–2714.

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

von Moellendorff, C. and H. Welsch, "Measuring Renewable Energy Externalities: Evidence from Subjective Well-Being Data," *Oldenburg Discussion Papers in Economics* V-373-14 (2014).

Vorkinn, M. and H. Riese, "Environmental Concern in a Local Context: The Significance of Place Attachement," *Environment and Behavior* 33 (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), 139–169.

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., C. Lumsden, S. O'Down, and R. 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 aabatement from renewables in the German electricity sector: Does a CO_2 price help?," *Energy Economics* 40 (2013), 149–158.

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 (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. Bürer, "Social acceptance of renewable energy innovation: An introduction to the concept," *Energy Policy* 35 (2007), 2683–2691.

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

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

Appendix A. Descriptive Statistics

Table A.1: Descriptive statistics for wind turbines in the *included group*

	[Number]	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 Appendix C

Table A.2: Descriptive statistics for the final sample

Variables	Mean	Standard Deviation	Minimum	Maximum	Number of Observations
Dependent Variable					
Satisfaction With Life	6.9798	1.7679	0	10	40,398
Independent Variables of Interest					
$Construction_{t,4000}$	0.0556	0.2292	0	1	40,398
$Construction_{t,4000} \times InvDist$	0.0213	0.0943	0	1.0965	40,398
$Construction_{t,4000} \times RevDist$	0.0614	0.3175	0	3.088	40,398
$Construction_{t,4000} \times Cumul$	0.1786	0.9407	0	10	40,398
Other Independent Variables - Micro Level					
Age	53.2430	15.9781	16	99	40,398
Is Female	0.5145	0.4998	0	1	40,398
Is Married	0.7409	0.4382	0	1	40,398
Is Divorced	0.0476	0.2130	0	1	40,398
Is Widowed	0.0765	0.2657	0	1	40,398
Has Very Good Health	0.0684	0.2525	0	1	40,398
Has Very Bad Health	0.0427	0.2023	0	1	40,398
Is Disabled	0.1430	0.3501	0	1	40,398
Has Migration Background	0.1361	0.3429	0	1	40,398
Has Tertiary Degree	0.2592	0.4382	0	1	40,398
Has Lower Than Secondary Degree	0.1965	0.3974	0	1	40,398
Is in Education	0.0154	0.1233	0	1	40,398
Is Full-Time Employed	0.3613	0.4804	0	1	40,398
Is Part-Time Employed	0.1072	0.3094	0	1	40,398
Is on Parental Leave	0.0118	0.1075	0	1	40,398
Is Unemployed	0.0502	0.2184	0	1	40,398
Individual Income[a]	1,633.3140	1,339.8170	4	25,000.0000	21,448
Has Child in Household	0.2612	0.4393	0	1	40,398
Household Income[b]	39,592.4300	27,569.4600	25	743,830.0000	40,394
Lives in House[c]	0.7991	0.4007	0	1	4,585
Lives in Small Apartment Building	0.0663	0.2488	0	1	4,585
Lives in Large Apartment Building	0.0515	0.2210	0	1	4,585

Continued on next page

Continued from previous page

Variables	Mean	Standard Deviation	Minimum	Maximum	Number of Observations
Lives in High Rise	0.0037	0.0608	0	1	4,585
Number of Rooms per Individual	1.9279	0.9969	0	12.5000	46,071
Other Independent Variables - Macro Level					
Unemployment Rate	8.5123	4.8383	1.6000	29.3000	40,398
Average Household Income[a]	1,468.7570	220.7825	988.0000	2,533.0000	40,398

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

Note: All figures are rounded to four decimal places.

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

Appendix B. Detailed Results

Table B.1: Results - Satisfaction With Life, OLS/FE Models, No Matching
Construction$_{t,4000}$

Dependent Variable: Satisfaction With Life

Regressors	OLS	OLS	FE	FE
Construction$_{t,4000}$	-0.1304	-0.0641	-0.0400	-0.0759*
	(0.1302)	(0.0949)	(0.0477)	(0.0347)
Age		-0.0275**		-0.0535**
		(0.0098)		(0.0174)
Age Squared		0.0003***		0.0001
		(0.0001)		(0.0001)
Is Female		0.0551		
		(0.0352)		
Is Married		0.1809*		0.3250
		(0.0921)		(0.2155)
Is Divorced		-0.0220		0.2574*
		(0.0785)		(0.1366)
Is Widowed		-0.0882		-0.1907
		(0.0924)		(0.2807)
Has Very Good Health		1.0605***		0.3939***
		(0.0429)		(0.0235)
Has Very Bad Health		-2.3525***		-1.2404***
		(0.0731)		(0.0660)
Is Disabled		-0.4632***		-0.2765***
		(0.0420)		(0.0334)
Has Migration Background		0.0078		
		(0.0388)		
Has Tertiary Degree		0.0398		-0.0629
		(0.0337)		(0.0636)
Has Lower Than Secondary Degree		-0.1016*		0.1474
		(0.0475)		(0.1226)
Is in Education		0.0327		0.2004
		(0.0879)		(0.1281)
Is Full-Time Employed		-0.2946***		0.0386
		(0.0478)		(0.0358)
Is Part-Time Employed		-0.1395***		-0.0871***
		(0.0286)		(0.0212)
Is on Parental Leave		0.1897***		0.1287**
		(0.0593)		(0.0520)
Is Unemployed		-0.9319***		-0.4501***
		(0.0730)		(0.0852)
Individual Income[a]		0.1319***		0.0440**
		(0.0228)		(0.0185)
Has Child in Household		0.0024		0.0248
		(0.0573)		(0.0252)
Household Income[b]		0.4028***		0.1992***
		(0.0332)		(0.0287)

Continued on next page

Continued from previous page

Dependent Variable: Satisfaction With Life

Regressors	OLS	OLS	FE	FE
Lives in House[c]		0.0255		0.0054
		(0.0199)		(0.0261)
Lives in Small Apartment Building		0.0020		0.0031
		(0.0279)		(0.0206)
Lives in Large Apartment Building		0.0107		0.0047
		(0.0298)		(0.0242)
Lives in High Rise		0.0650		0.0362
		(0.1645)		(0.1078)
Number of Rooms per Individual		0.1164***		0.0232
		(0.0172)		(0.0160)
Unemployment Rate		-0.0240***		-0.0194
		(0.0054)		(0.0099)
Average Household Income[a]		0.0002		-0.0004
		(0.0001)		(0.0003)
Constant	7.1460***	2.4487***	7.3602***	7.8811***
	(0.0743)	(0.4137)	(0.0238)	(0.6398)
Number of Observations	48,785	40,398	48,785	40,398
Number of Individuals	8,971	8,117	8,971	8,117
of which in treatment group	510	506	510	506
of which in control group	8,461	7,611	8,461	8,711
F-Statistic		86,753.0500	930.8400	113,933.1500
R^2	0.0031	0.2058	0.0233	0.0699
Adjusted R^2		0.2050	0.0231	0.0691

[a] Monthly in Euro/Inflation-Adjusted (Base Year 2000), [b] Annually in Euro/Inflation-Adjusted (Base Year 2000)
[c] Detached, Semi-Detached, or Terraced

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{t,4000}$ is a dummy variable equal to one if a wind turbine is present within a treatment radius of 4,000 metres in year t, and zero else. All regression equations include dummy variables for years. All figures are rounded to four decimal places.

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

Table B.2: Results - Satisfaction With Life, OLS/FE Models, Propensity-Score Matching
$Construction_{t,4000}$

Dependent Variable: Satisfaction With Life

Regressors	OLS	OLS	FE	FE
$\text{Construction}_{t,4000}$	-0.0741	-0.0094	-0.1702***	-0.1405***
	(0.1757)	(0.1333)	(0.0494)	(0.0399)
Age		-0.0021		-0.0689
		(0.0192)		(0.0425)
Age Squared		0.0001		0.0001
		(0.0002)		(0.0004)
Is Female		0.0663		
		(0.0779)		
Is Married		0.1390		0.0903
		(0.3131)		(0.1449)
Is Divorced		-0.0337		0.2802
		(0.2856)		(0.4173)
Is Widowed		-0.0526		-0.1891
		(0.2434)		(0.2035)
Has Very Good Health		1.1136***		0.2967***
		(0.1296)		(0.0693)
Has Very Bad Health		-2.5500***		-1.3187***
		(0.1685)		(0.1184)
Is Disabled		-0.4028**		-0.0137
		(0.1522)		(0.1113)
Has Migration Background		-0.0953		
		(0.1292)		
Has Tertiary Degree		-0.0630		-0.0087
		(0.1124)		(0.1926)
Has Lower Than Secondary Degree		-0.3026**		-0.0008
		(0.1336)		(0.3042)
Is in Education		0.2165		0.3740
		(0.2107)		(0.4008)
Is Full-Time Employed		-0.4358***		0.0001
		(0.0983)		(0.1182)
Is Part-Time Employed		-0.1081		-0.1220
		(0.1304)		(0.1056)
Is on Parental Leave		0.1233		0.0709
		(0.3778)		(0.2157)
Is Unemployed		-0.9275***		-0.5000***
		(0.2068)		(0.1233)
Individual Income[a]		0.1313**		0.0538
		(0.0516)		(0.0539)
Has Child in Household		0.1446		0.1555*
		(0.1437)		(0.0741)
Household Income[b]		0.4225***		0.1738
		(0.0868)		(0.1173)
Lives in House[c]		0.0029		-0.0135
		(0.0887)		(0.0954)
Lives in Small Apartment Building		0.0335		0.0051

Continued on next page

Continued from previous page

Dependent Variable: Satisfaction With Life

Regressors	OLS	OLS	FE	FE
		(0.0923)		(0.0935)
Lives in Large Apartment Building		-0.0196		-0.0262
		(0.0718)		(0.0765)
Lives in High Rise		0.0929		0.1176
		(0.2198)		(0.2136)
Number of Rooms per Individual		0.1725**		0.0011
		(0.0670)		(0.0416)
Unemployment Rate		-0.0339***		-0.0199
		(0.0099)		(0.0133)
Average Household Income[a]		0.0002		0.0008
		(0.0003)		(0.0006)
Constant	6.9566***	1.7537*	7.0849***	7.2583***
	(0.1155)	(0.8362)	(0.0449)	(0.8130)
Number of Observations	7,818	6,637	7,818	6,637
Number of Individuals	1,000	986	1,000	986
of which in treatment group	500	498	500	498
of which in control group	055	488	500	488
F-Statistic		2,018.1800	372.3400	2,462.52000
R^2	0.0048	0.2206	0.0220	0.0704
Adjusted R^2	0.0031	0.2162	0.0203	0.0657

[a] Monthly in Euro/Inflation-Adjusted (Base Year 2000), [b] Annually in Euro/Inflation-Adjusted (Base Year 2000)
[c] Detached, Semi-Detached, or Terraced

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{t,4000}$ is a dummy variable equal to one if a wind turbine is present within a treatment radius of 4,000 metres in year t, and zero else. All regression equations include dummy variables for years. All figures are rounded to four decimal places.

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

Table B.3: Results - Satisfaction With Life, FE Model, Propensity-Score Matching
$Construction_{t,8000/10000/15000}$

Dependent Variable: Satisfaction With Life

Regressors	r=8000	r=10000	r=15000
$\text{Construction}_{t,r}$	-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)
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)
Household Income[b]	0.2628***	0.2074**	0.1571
	(0.0482)	(0.0736)	(0.1164)
Lives in House[c]	0.0011	-0.0209	0.0106
	(0.0617)	(0.0469)	(0.1294)
Lives in Small Apartment Building	0.0152	-0.0098	0.0156

Continued on next page

Continued from previous page

Dependent Variable: Satisfaction With Life

Regressors	r=8000	r=10000	r=15000
	(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 Household Income[a]	-0.0012*	-0.0009	0.0006
	(0.0006)	(0.0008)	(0.0009)
Constant	7.7639***	7.2524***	9.7895***
	(0.7048)	(0.7316)	(1.1269)
Number of Observations	9,389	6,254	2,767
Number of Individuals	1,357	939	423
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

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{t,r}$ is a dummy variable equal to one if a wind turbine is present within a treatment radius of *r* metres in year *t*, and zero else. All regression equations include dummy variables for years. All figures are rounded to four decimal places.

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

Table B.4: Results - Satisfaction With Life, FE Model, Propensity-Score Matching
Construction$_{t,4000}$ × *Intensity, Trans*$_{t\text{-}\tau,4000}$

Dependent Variable: Satisfaction With Life

	Intensity			Transition	
Regressors	InvDist$_{t,4000}$	RevDist$_{t,4000}$	Cumul$_{t,4000}$	Trans$_{t-\tau,4000}$	# treated
Construction$_{t,4000}$ × Intensity	-0.2090	-0.0128	-0.0178		
	(0.1605)	(0.0550)	(0.1556)		
Transition$_1$				-0.0546	498
				(0.0642)	
Trans$_{t-1,4000}$				-0.0546	498
				(0.0642)	
Trans$_{t-2,4000}$				-0.1616**	444
				(0.0697)	
Trans$_{t-3,4000}$				-0.192**	424
				(0.0609)	
Trans$_{t-4,4000}$				-0.2242**	376
				(0.0917)	
Trans$_{t-5,4000}$				-0.2253**	335
				(0.0924)	
Trans$_{t-6,4000}$				-0.2637	288
				(0.1495)	
Trans$_{t-7,4000}$				-0.2215	240
				(0.1271)	
Trans$_{t-8,4000}$				0.0305	204
				(0.1846)	
Trans$_{t-9,4000}$				-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)	
Individual Income[a]	0.0540	0.0541	0.0539	0.0532	

Continued on next page

	Intensity			Transition	
Regressors	$\text{InvDist}_{t,4000}$	$\text{RevDist}_{t,4000}$	$\text{Cumul}_{t,4000}$	$\text{Trans}_{t-\tau,4000}$	# treated
	(0.0536)	(0.0532)	(0.0533)	(0.0552)	
Has Child in Household	0.1509	0.1491*	0.1479*	0.1546*	
	(0.0742)	(0.0753)	(.0743)	(0.0791)	
Household Income[b]	0.1720	0.1726	0.1760	0.1744	
	(0.1181)	(0.1170)	(0.1178)	(0.1184)	
Lives in House[c]	-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 Household Income[a]	0.0008	0.0008	0.0007	0.0009	
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	
Constant	7.5459***	7.8139***	7.6105***	7.0489***	
	(0.8708)	(0.8644)	(0.8269)	(0.9185)	
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	

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{t,4000}$ is a dummy variable equal to one if a wind turbine is present within a treatment radius of 4,000 metres in year t, and zero else. $\text{InvDist}_{t,4000}$ is the inverse distance, $\text{RevDist}_{t,4000}$ is equal to 4 minus the distance to the next wind turbine in kilometres, $\text{Cumul}_{t,4000}$ is equal to the number of wind turbines within a 4,000 metres treatment radius, all in year t. $\text{Trans}_{t-\tau,4000}$ is a dummy variable equal to one if a wind turbine is present within a 4,000 metres treatment radius in year $t - \tau$, and zero else. All regression equations include dummy variables for years. All figures are rounded to four decimal places.
Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Appendix C, own calculations.

Table B.5: Results - Satisfaction With Life, FE Model, Spatial Matching (10,000m, 15,000m) $Construction_{t,4000/8000}$

Dependent Variable: Satisfaction With Life

Regressors	(1)	(2)	(3)	(4)
$\text{Construction}_{t,4000}$	-0.1088***	-0.1138**		
	(0.0222)	(0.0366)		
$\text{Construction}_{t,8000}$			-0.0642	-0.0452
			(0.0372)	(0.0447)
Age	-0.0792***	-0.0142	-0.0242	-0.0030
	(0.0197)	(0.0199)	(0.0266)	(0.0248)
Age Squared	0.0002	-0.0001	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Is Female				
Is Married	-0.1502	0.1175	-0.4424	-0.0844
	(0.1856)	(0.2095)	(0.5476)	(0.4607)
Is Divorced	-0.0721	0.1241	-0.0619	0.0909
	(0.0945)	(0.2315)	(0.4789)	(0.5164)
Is Widowed	-0.7490**	-0.2608	-0.8117	-0.4189
	(0.3319)	(0.2513)	(0.5315)	(0.4720)
Has Very Good Health	0.2833***	0.3674***	0.3484***	0.3920***
	(0.0536)	(0.0424)	(0.0741)	(0.0518)
Has Very Bad Health	-1.2854***	-1.2141***	-1.3571***	-1.2564***
	(0.0887)	(0.1000)	(0.1412)	(0.1378)
Is Disabled	-0.0101	-0.2080**	-0.0327	-0.1994**
	(0.0881)	(0.0691)	(0.1207)	(0.0831)
Has Migration Background				
Has Tertiary Degree	-0.0303	-0.1976	-0.1510	-0.2413
	(0.2628)	(0.1660)	(0.1510)	(0.2108)
Has Lower Than Secondary Degree	0.1677	0.2274	0.1362	0.2324
	(0.2073)	(0.2062)	(0.1975)	(0.1761)
Is in Education	0.1739	0.3345	-0.0400	0.2268
	(0.2544)	(0.2033)	(0.2082)	(0.1824)
Is Full-Time Employed	0.0213	0.0841	0.1017	0.1417
	(0.0780)	(0.0655)	(0.0831)	(0.0779)
Is Part-Time Employed	-0.0534	-0.0426	0.0588	0.0545
	(0.0904)	(0.0644)	(0.0783)	(0.0597)
Is on Parental Leave	-0.0308	0.1516	-0.0244	0.0714
	(0.2097)	(0.1289)	(0.1257)	(0.0862)
Is Unemployed	-0.4325***	-0.4542***	-0.4511***	-0.4796***
	(0.0864)	(0.0772)	(0.0998)	(0.0747)
Individual Income[a]	0.0523	0.0385	0.0188	0.0056
	(0.0436)	(0.0282)	(0.0373)	(0.0395)
Has Child in Household	0.1997***	0.0897**	0.2174**	0.0976
	(0.0521)	(0.0374)	(0.0760)	(0.0568)
Household Income[b]	0.2503***	0.2003***	0.2354**	0.1812***
	(0.0695)	(0.0537)	(0.0793)	(0.0453)
Lives in House[c]	0.0057	0.0086	0.0098	0.0172

Continued on next page

Continued from previous page

Dependent Variable: Satisfaction With Life

Regressors	(1)	(2)	(3)	(4)
	(0.0484)	(0.0414)	(0.0230)	(0.0413)
Lives in Small Apartment Building	0.0234	0.0159	0.0534	0.0102
	(0.0575)	(0.0395)	(0.0539)	(0.0432)
Lives in Large Apartment Building	-0.0060	0.0144	-0.0571	-0.0008
	(0.0421)	(0.0298)	(0.0368)	(0.0580)
Lives in High Rise	0.0925	0.0720	0.1087	0.0110
	(0.2107)	(0.1805)	(0.0820)	(0.1546)
Number of Rooms per Individual	-0.0157	0.0136	0.0095	0.0230
	(0.0402)	(0.0210)	(0.0210)	(0.0185)
Unemployment Rate	-0.0353***	-0.0081	-0.0445***	-0.0230**
	(0.0102)	(0.0105)	(0.0080)	(0.0070)
Average Household Income[a]	0.0004	-0.0006	-0.0005	-0.0010*
	(0.0008)	(0.0005)	(0.0007)	(0.0005)
Constant	7.7061***	6.7254***	7.4786***	7.4268***
	(0.6694)	(0.8511)	(0.9088)	(0.8225)
Number of Observations	8,609	16,378	8,643	14,485
Number of Individuals	1,317	2,586	1,241	2,193
of which in treatment group	506	506	698	698
of which in control group	811	2,080	543	1,495
F-Statistic	9,891.2100	5,251.8600	26,893.1900	14,555.3300
R^2	0.0715	0.0652	0.0740	0.0676
Adjusted R^2	0.0678	0.0632	0.0704	0.0654

[a] Monthly in Euro/Inflation-Adjusted (Base Year 2000), [b] Annually in Euro/Inflation-Adjusted (Base Year 2000)
[c] Detached, Semi-Detached, or Terraced

(1) Spatial matching $10,000m$, (2) Spatial matching $15,000m$,
(3) Spatial matching $10,000m$, (4) Spatial matching $15,000m$

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{t,4000}$ ($\text{Construction}_{t,8000}$) is a dummy variable equal to one if a wind turbine is present within a treatment radius of 4,000 metres (8,000 metres) in year t, and zero else. All regression equations include dummy variables for years. All figures are rounded to four decimal places.

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

Table B.6: Results - Satisfaction With Life, FE Model, Spatial Matching (10,000m)
$Construction_{t,4000} \times Intensity,\ Trans_{t\text{-}\tau,4000}$

Dependent Variable: Satisfaction With Life

Regressors	$\text{InvDist}_{t,4000}$	$\text{RevDist}_{t,4000}$	$\text{Cumul}_{t,4000}$	$\text{Trans}_{t-\tau,4000}$	# treated
$\text{Construction}_{t,4000}$ × Intensity	-0.1604	-0.0078	-0.0142		
	(0.1038)	(0.0411)	(0.0113)		
$\text{Trans}_{t-1,4000}$				-0.0401	506
				(0.0657)	
$\text{Trans}_{t-2,4000}$				-0.1212**	450
				(0.0482)	
$\text{Trans}_{t-3,4000}$				-0.1381***	430
				(0.0411)	
$\text{Trans}_{t-4,4000}$				-0.1808**	382
				(0.0689)	
$\text{Trans}_{t-5,4000}$				-0.1311	341
				(0.0837)	
$\text{Trans}_{t-6,4000}$				-0.1644	291
				(0.1264)	
$\text{Trans}_{t-7,4000}$				-0.0963	243
				(0.0941)	
$\text{Trans}_{t-8,4000}$				0.1847	207
				(0.1483)	
$\text{Trans}_{t-9,4000}$				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)	
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***	
	(0.0525)	(0.0525)	(0.0519)	(0.0551)	

Continued on next page

Regressors	$InvDist_{t,4000}$	$RevDist_{t,4000}$	$Cumul_{t,4000}$	$Trans_{t-\tau,4000}$
Household Income[b]	0.2497***	0.2506***	0.2523***	0.2492***
	(0.0702)	(0.0698)	(0.0700)	(0.0709)
Lives in House[c]	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 Household Income[a]	0.0004	0.0004	0.0004	0.0004
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Constant	7.8502***	7.9808***	7.8766***	7.7148***
	(0.6744)	(0.6731)	(0.6554)	(0.6749)
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

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\mathrm{Construction}_{\mathrm{t,4000}}$ is a dummy variable equal to one if a wind turbine is present within a treatment radius of 4,000 metres in year t, and zero else. $InvDist_{t,4000}$ is the inverse distance, $RevDist_{t,4000}$ is equal to 4 minus the distance to the next wind turbine in kilometres, $Cumul_{t,4000}$ is equal to the number of wind turbines within a 4,000 metres treatment radius, all in year t. $Trans_{t-\tau,4000}$ is a dummy variable equal to one if a wind turbine is present within a 4,000 metres treatment radius in year $t-\tau$, and zero else. All regression equations include dummy variables for years. All figures are rounded to four decimal places.
Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Appendix C, own calculations.

Table B.7: Results - Satisfaction With Life, FE Model, Spatial Matching (15,000m)
$Construction_{t,4000}$ × Intensity, $Trans_{t\text{-}\tau,4000}$

Dependent Variable: Satisfaction With Life

Regressors	$\text{InvDist}_{t,4000}$	$\text{RevDist}_{t,4000}$	$\text{Cumul}_{t,4000}$	$\text{Trans}_{t-\tau,4000}$	# treated
$\text{Construction}_{t,4000}$ × Intensity	-0.1862*	-0.0181	-0.0174		
	(0.0940)	(0.0338)	(0.0106)		
$\text{Transition}_{t-1,4000}$				-0.0392	506
				(0.0642)	
$\text{Transition}_{t-2,4000}$				-0.1262**	450
				(0.0697)	
$\text{Transition}_{t-3,4000}$				-0.1506**	430
				(0.0609)	
$\text{Transition}_{t-4,4000}$				-0.1902*	382
				(0.0917)	
$\text{Transition}_{t-5,4000}$				-0.1472	341
				(0.0924)	
$\text{Transition}_{t-6,4000}$				-0.1519	291
				(0.1495)	
$\text{Transition}_{t-7,4000}$				-0.0744	243
				(0.1271)	
$\text{Transition}_{t-8,4000}$				0.2104	207
				(0.1846)	
$\text{Transition}_{t-9,4000}$				-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)	
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**	
	(0.0373)	(0.0374)	(0.0371)	(0.0381)	

Continued on next page

Regressors	$\text{InvDist}_{t,4000}$	$\text{RevDist}_{t,4000}$	$\text{Cumul}_{t,4000}$	$\text{Trans}_{t-\tau,4000}$
Household Income[b]	0.2002***	0.2009***	0.2021***	0.1994***
	(0.0541)	(0.0539)	(0.0540)	(0.0538)
Lives in House[c]	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 Household Income[a]	-0.0006	-0.0006	-0.0006	-0.0006
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Constant	6.7883***	6.8483***	6.7995***	6.7459***
	(0.8429)	(0.8313)	(0.8319)	(0.8462)
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

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{t,4000}$ is a dummy variable equal to one if a wind turbine is present within a treatment radius of 4,000 metres in year t, and zero else. $\text{InvDist}_{t,4000}$ is the inverse distance, $\text{RevDist}_{t,4000}$ is equal to 4 minus the distance to the next wind turbine in kilometres, $\text{Cumul}_{t,4000}$ is equal to the number of wind turbines within a 4,000 metres treatment radius, all in year t. $\text{Trans}_{t-\tau,4000}$ is a dummy variable equal to one if a wind turbine is present within a 4,000 metres treatment radius in year $t-\tau$, and zero else. All regression equations include dummy variables for years. All figures are rounded to four decimal places.
Source: SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Appendix C, own calculations.

Table B.8: Results - Sub-Samples, Satisfaction With Life, FE Models, Spatial Matching ($15,000m$)
$Construction_{t,4000}$

Dependent Variable: Satisfaction With Life

Regressors	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Construction}_{t,4000}$	-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)
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**

Continued on next page

Continued from previous page

Dependent Variable: Satisfaction With Life

Regressors	(1)	(2)	(3)	(4)	(5)	(6)
	(0.0555)	(0.1371)	(0.1434)	(0.0477)	(0.0738)	(0.0509)
Household Income[b]	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 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)
Constant	6.2501***	7.2812***	10.7316***	6.1764***	6.6104***	6.7511***
	(0.9662)	(1.6959)	(1.1070)	(0.9447)	(1.5696)	(1.1183)
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] Monthly in Euro/Inflation-Adjusted (Base Year 2000), [b] Annually in Euro/Inflation-Adjusted (Base Year 2000)
[c] 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 in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $\text{Construction}_{t,4000}$ is a dummy variable equal to one if a wind turbine is present within a treatment radius of 4,000 metres in year t, and zero else. All regression equations include dummy variables for years. All figures are rounded to four decimal places.

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

Appendix C. 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.

Bavaria:
Data source: Bavarian State Office for the Environment (Datenquelle: Bayerisches Landesamt für Umwelt)
`http://www.lfu.bayern.de/index.htm` (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.