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Sowing the wind and reaping the whirlwind? The effect of wind turbines on residential well-being

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Sowing the Wind and Reaping the Whirlwind?

The Effect of Wind Turbines on Residential Well-Being

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Abstract

We investigate the effect of the physical presence of wind turbines on residential well-being in Germany, using panel data from the German Socio-Economic Panel (SOEP) and a unique novel panel data set on more than 20,000 wind turbines for the time period between 2000 and 2012. Using a Geographical Information System (GIS), we calculate the *proximity* between households and the nearest wind turbine as the most important determinant of their disamenities, e.g. visual interference into landscape aesthetics. Our unique novel panel data set on wind turbines, which was collected at the regional level, includes their exact geographical coordinates and construction dates. This allows estimating the causal effect of the physical presence of wind turbines on residential well-being, using a difference-in-differences design. To ensure comparability of the treatment and control group, we apply propensity-score and novel spatial matching techniques based on exogenous weather data and geographical locations of residence, respectively. We show that the construction of a wind turbine within a treatment radius of 4,000 metres around households has a significantly negative effect on life satisfaction. For larger treatment radii, no negative externalities can be detected. Moreover, the effect is transi-

tory, vanishing after five years at the latest. As wind turbines are addressed at avoiding negative externalities of local pollutant and global greenhouse gas emissions, they fulfil an important role in the de-carbonization of electricity systems world-wide. Comparing the imposed spatially and temporally limited externalities with the avoided externalities from emissions, the positive impact of wind turbines is by several magnitudes higher than the negative.

Keywords:

Life Satisfaction, Social Acceptance,
Wind Power, Wind Turbines, Renewables, Externalities,
SOEP, GIS, Spatial Analysis

JEL:

C23, Q42, Q51, R20

1. Introduction

Over the past decades, there has been a world-wide trend towards renewable resources for electricity generation. In OECD countries, the share of renewables in electricity supply, excluding hydro power, quadrupled from 1.8% to 7.2% between 1990 and 2012 (IEA, 2013).¹ Wind power has been a major driver of this development: in the same time period, installed net electricity generation capacity and gross production grew by more than 20% annually (IEA, 2013). In Germany, for example, more than 20,000 wind turbines contributed 7% to total electricity consumption in 2012 (Fraunhofer IWES, 2013).² Also in non-OECD countries, wind power plays an ever increasing role, with substantial progress in installed capacity, for example, in Asia, largely driven by India and China, being the world's biggest market today (WWEA, 2013).

The basic economic rationale behind this trend towards renewables is to avoid negative environmental externalities common to conventional electricity generation technologies.³ The most obvious are noxious local emissions from burning fossil fuels—comprising particulate matter, sulphur dioxides, and others—which are, for example, the largest contributor to the notorious air pollution within China's capital region (Guan et al., 2014). Beyond local emissions, carbon dioxide emissions from fossil fuel combustion are responsible for global climate change. Nuclear power, on the other hand, is subject to unclear long-term storage of nuclear waste and low-probability but high-impact accidents.

Wind power is largely free of emissions, waste, and risks. Although public support is consistently found to be high throughout the world—see, for example, Eltham et al. (2008) for the United Kingdom, Koundouri et al. (2009) for Greece, Forsa (2010) for Germany, Ladenburg et al. (2013) for Denmark, or Ek and Persson (2014) for Sweden—it also entails

¹The figures include wind, solar, geothermal, tidal, waste, and biomass power. As hydro power can be regarded a mature technology before 1990, figures excluding hydro power are more indicative of the dynamics of renewables deployment.

²Due to its variability, in some hours with especially favourable wind conditions more than half of total electricity consumption was provided by wind power (own calculations based on EEX (2014) and ENTSO-E (2014)).

³Beyond negative environmental externalities, independence from fuel imports or idiosyncratically low electricity generation costs, as, for example, with geothermal power where geologically feasible, are major drivers.

externalities, which, for a balanced cost-benefit analysis, have to be taken into account. Thereby, it is important to distinguish between the externalities of *wind power* and the externalities of *wind turbines*. Wind power, that is, electricity generated by wind turbines, might require changes within the electricity system, including the need to build more flexible backup capacities or to expand the transmission grid.⁴ Wind turbines, in contrast to large centralised conventional power plants which tend to foster out-of-sight-out-of-mind attitudes, have to be constructed in large numbers for wind power to play an effective role in electricity generation. This renders them more spatially dispersed and, therefore, in greater proximity to consumers than conventional power plants, increasing the salience of energy supply (Pasqualetti, 2000; Wüstenhagen et al., 2007). In fact, for residents who live close to them, wind turbines have been found to have unpleasant noise emissions (see, for example, Knopper and Ollson (2011) or Shepherd et al. (2011)) and, most importantly, negative impacts on landscape aesthetics (see, for example, Devine-Wright (2005), Jobert et al. (2007), or Wolsink (2007)). Moreover, they have been shown to have negative impacts on biodiversity (see, for example, Lehnert et al. (2014)). Just as other electricity generation technologies, thus, wind turbines do not come without negative externalities, which, in general, do not have market prices and, therefore, are typically valued monetarily using stated preference approaches (see, for example, Groothuis et al. (2008), Jones and Eiser (2010), or Meyerhoff et al. (2010)) or revealed preference approaches (see, for example, Dröes and Koster (2014), Gibbons (2014), or Sunak and Madlener (2014)).

So far, the effect of the physical presence of wind turbines on residential well-being has not been investigated. We attempt to fill this gap. We investigate the effect of the physical presence of wind turbines on residential well-being in Germany, using panel data from the German Socio-Economic Panel (SOEP) and a unique novel panel data set on more than 20,000 wind turbines for the time period between 2000 and 2012. In doing so, we value the negative externalities caused by the physical presence of wind turbines monetarily using the life satisfaction approach (see, for example, Welsch (2007)), which trades off the decrease in life satisfaction caused by the physical presence of wind turbines against

⁴See Hirth (2015) for a more detailed overview.

the increase in life satisfaction caused by income.⁵ As the life satisfaction approach has already been applied to valuing other environmental externalities monetarily, including air pollution (see, for example, Welsch (2002, 2006, 2007), Rehdanz and Maddison (2008), Ambrey and Fleming (2011), Menz (2011), Ferreira et al. (2013), Kopmann and Rehdanz (2013), or Ambrey et al. (2014)) or noise pollution (see, for example, van Praag and Baarsma (2005) or Rehdanz and Maddison (2008)), we contribute to a steadily growing stream of literature.

We apply a treatment effect analysis to investigate the effect of the physical presence of wind turbines on residential well-being, allocating residents to the treatment group in case that a wind turbine is constructed within a pre-defined treatment radius around their households, and to the control group otherwise. Using a difference-in-differences design, which exploits the exact geographical coordinates and interview dates of households on the one hand and the exact geographical coordinates and construction dates of wind turbines on the other, we establish the causality of the effect. To ensure comparability of the treatment and control group, we apply propensity-score and novel spatial matching techniques based on socio-demographic characteristics, including exogenous weather data, and geographical locations of residence, respectively. We show that the construction of a wind turbine within a treatment radius of 4,000 metres around households has a significantly negative effect on life satisfaction. The size of the effect is economically significant, accounting for up to a fourth of the size of the effect of being unemployed on life satisfaction, and is strongest for residents who are house owners and residents who are not very concerned about the environment or climate change. For larger treatment radii, no negative externalities can be detected. Moreover, the effect is transitory, vanishing after five years at the latest, and does not additionally intensify with proximity to or cumulation of wind turbines. Contrasting the monetary valuation of these spatially and temporally limited negative externalities caused by the physical presence of wind turbines with the damage

⁵German law prescribes compensation measures for landscape intrusions caused, for example, by wind turbines. However, these are directed at an ecological or aesthetical amelioration of the natural region, which does not necessarily comprise the narrow geographical scope of wind turbines. Moreover, direct payments to residents or other highly salient compensation measures are not provided. See BMUB (2013) for a draft law which summarizes the regulations in place.

through CO₂ emissions avoided by them, wind power is a favourable technology. In fact, the monetary valuation of the avoided damage exceeds that of the negative externalities by several magnitudes.

We contribute to the literature in several ways. Firstly, we investigate the effect of the physical presence of wind turbines on residential well-being for the first time in the literature. In doing so, we use panel data on residential well-being and a unique novel panel data set on more than 20,000 wind turbines in Germany. Secondly, we use a difference-in-differences design in combination with propensity-score and novel spatial matching techniques, which ensure comparability of the treatment and control group, to establish the causality of the effect. Thirdly, we add to the ongoing debate on the political economy of renewable energy by providing figures on the negative externalities caused by the physical presence of wind turbines, which can be contrasted with those of conventional electricity generation technologies. Finally, we provide an assessment of these negative externalities from a macro perspective as the presented results are not site-specific, compared to most previous research.

The rest of this paper is organised as follows. Section 2 provides a literature review on the negative externalities caused by the physical presence of wind turbines and the different methodological approaches to value them monetarily. Section 3 describes the data. Section 4 introduces the empirical model, whereas the results are presented in Section 5. Section 6 puts the results into perspective. Section 7 concludes and outlines avenues for future research.

2. Literature Review

A plethora of studies address the negative externalities caused by the physical presence of wind turbines. Most of them apply stated preference approaches, such as contingent valuation or discrete choice experiments, or revealed preference approaches, such as hedonic pricing. We will first review the most important findings from both classes and then discuss how they relate to our approach. Before we begin, however, we will briefly elaborate on the potential transmission mechanisms through which these negative externalities might actually materialise.

2.1. Environmental Psychology: Rationales for Rejecting Wind Turbines

The physical presence of wind turbines may be undesirable to residents in their immediate surroundings. As, in general, no market price exists, it constitutes in economic terms a negative externality. Concerns about landscape aesthetics, in particular visual intrusions into the landscape, constitute a dominant motive for rejecting wind turbines. Deeper explanations for the underlying rationales can be found in the environmental psychology literature.

Zoellner et al. (2008) suggest a preference for untouched landscapes, which have higher recreational values. Specifically, Kirchhoff (2014) argues that the subjective evaluation of landscapes is based on objective ideals, that is, culturally determined patterns of perception. In Germany, these ideals are predominantly conservative, triggering a preference for traditional idiosyncrasies, in particular a pastoral appeal or an idealised picture of romantic untouched wilderness. Both patterns contradict an industrialised appeal due to uniform technological structures, such as wind turbines.

In a similar vein, the environmental psychological theory of place attachment posits a positive emotional bond between people and places which develops over time, generating meaning and belonging (Vorkinn and Riese, 2001; Cass and Walker, 2009). As place attachment has a strong temporal component and is related to personal or local tradition, it fosters a taste for continuity (Devine-Wright, 2005; Pasqualetti, 2011). By disrupting this continuity, the construction of wind turbines can cause negative emotions, evoke oppositional attitudes, and reduce subjective well-being (Cass and Walker, 2009). In a case study, Devine-Wright and Howes (2010) apply this theory to the proposed construction of an offshore wind park. The authors identify the conflict between an industrialised appeal in case that wind turbines are constructed and a natural scenic beauty in case that the landscape remains untouched as source of disrupted place-bound identities.

Another psychological argument is brought forward by Pedersen et al. (2007): applying grounded theory to in-depth qualitative interviews, they designate the physical presence of wind turbines as an intrusion into the privacy of residents in their immediate surroundings, triggering discomfort through feelings of lack of control.

Taken together, a preference for untouched landscapes, a positive emotional bond be-

tween persons and places, and an intrusion into privacy represent the potential transmission mechanisms through which the negative externalities caused by the physical presence of wind turbines might actually materialise.

2.2. Stated Preference Approaches: Contingent Valuation or Discrete Choice Experiments

Most studies using stated preference approaches examine the siting process, shedding light on the question which factors drive opposition to particular wind turbine projects. As such, they focus on what shapes perceptions rather than valuing the negative externalities caused by the physical presence of wind turbines monetarily. Nevertheless, there are several findings from these studies which are relevant in the context of this study.

Firstly, it is important to distinguish between the general support of *wind power* and the specific support of *particular wind turbine projects*. In fact, global support alongside local opposition is a widespread narrative in the siting debate. To describe this phenomenon, the term NIMBY—short for “not in my back yard”—is common. The academic literature, however, has come to abandon the NIMBY concept as a sole explanation for opposition to particular wind turbine projects as it has been deemed too superficial to capture the complexity of the phenomenon.⁶ As we aim at valuing negative externalities at an aggregate level, we do not investigate such potentially ambivalent attitudes within subjects. Nevertheless, evidence suggests not to interpret findings from a pure NIMBY perspective.⁷

Secondly, throughout these studies, landscape externalities in form of visual disamenities are found to be a crucial trigger of opposition to particular wind turbine projects (Ek, 2007; Wolsink, 2007; Groothuis et al., 2008; Jones and Eiser, 2010; Meyerhoff et al., 2010, and others). Thereby, opposition is shaped by two potentially opposing forces: proximity and habituation.

⁶Wolsink (2012) subsumes more than a decade of research on the acceptance of wind turbines and stresses the inadequate and harmful character of the NIMBY concept. Normatively, it is a self-fulfilling prophecy and destroys the important resource of trust among stakeholders. Positively, it could not be confirmed in most empirical research (see, for example, Krohn and Damborg (1999), Ek (2007), Rygg (2012), or Bidwell (2013)).

⁷The literature rather identifies process-related aspects, such as transparency, procedural fairness, and political and economic participation as the main drivers of the acceptance of particular wind turbine projects (see, for example, Devine-Wright (2005), Hall et al. (2013), or Ek and Persson (2014)).

Concerning proximity, Meyerhoff et al. (2010), in a discrete choice experiment, find a significant willingness-to-pay of residents to locate planned wind turbines further away from their places of residence. Ladenburg and Dubgaard (2007) show a similar result for offshore wind parks, and Jones and Eiser (2010) identify this effect to be especially pronounced for residents who are very concerned about landscape intrusions. Drechsler et al. (2011) and Molnarova et al. (2012) report analogous findings, whereas Devine-Wright (2005) and Ladenburg et al. (2013) also review studies presenting no or a reverse relationship. Taken together, however, the literature suggests that proximity between households and wind turbines negatively affects attitudes towards installations.

Concerning habituation, Ladenburg et al. (2013) find that more frequent exposure to wind turbines negatively affects attitudes towards them in case that residents have installations within their view-sheds. In the same vein, frequent recreational coast visitors exhibit a significantly more negative perception of offshore wind parks than others (Ladenburg, 2010). Comparing attitudes before and after the construction of a wind park, Eltham et al. (2008) cannot isolate changes in attitudes, whereas a U-shaped pattern in acceptance over time is detected by Krohn and Damborg (1999), Warren et al. (2005), and Wolsink (2007).⁸ Taken together, the literature is still mixed on whether habituation affects attitudes towards installations.

Although some studies using stated preference approaches explicitly calculate a willingness-to-pay of residents to locate planned wind turbines further away from their places of residence, all assessments are based on hypothetical scenarios and subject to several caveats, which we will discuss in more detail in Sub-Section 2.4. Moreover, most studies are site-specific, rendering external validity difficult. In contrast, we aim to deliver an assessment from a macro perspective which allows drawing more general conclusions.

⁸Notably, the perception of wind turbines is hypothesised to be influenced by the type of landscape they are placed in. Taken together, the findings on this hypothesis in studies using stated preference approaches are mixed (Devine-Wright, 2005; van der Horst, 2007; Molnarova et al., 2012).

2.3. Revealed Preference Approach: Hedonic Pricing

As a revealed preference approach, the hedonic pricing method infers a monetary valuation of externalities from a change in real estate prices. On this note, several studies econometrically assess the effect of the physical presence of wind turbines on the real estate prices of properties in their immediate surroundings. The findings are somewhat mixed, although more recent studies detect significantly negative effects.

Evidence for significantly negative externalities caused by the physical presence of wind turbines comes from 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%.⁹

The potential transmission mechanisms through which the construction of wind turbines depresses real estate prices include noise and, most importantly, visual pollution. To this end, different measures of visibility are employed, using either varying proximity radii as a proxy (Heintzelmann and Tuttle, 2012; Dröes and Koster, 2014), specific visibility indices drawing upon terrain elevation (Gibbons, 2014; Sunak and Madlener, 2014), or view-shed analyses (Jensen et al., 2013). In all studies, negative externalities through visual pollution are found to significantly materialise in property prices. The study by Jensen et al. (2013) additionally disentangles these negative externalities into a noise pollution component accounting for up to over 6% lower average marginal willingness-to-pay, depending on the decibel level.

Other studies do not detect significant effects (Sims and Dent, 2007; Sims et al., 2008; Hoen et al., 2011; Lang et al., 2014). Nevertheless, there is evidence that the physical presence of wind turbines depresses real estate prices of properties in their immediate surroundings, whereby proximity serves as feasible and solid proxy absorbing noise and, most importantly, visual pollution. The hedonic pricing method, however, is also subject to several caveats, which we will discuss in more detail in Sub-Section 2.4.

⁹The most extreme cases are detected by Heintzelmann and Tuttle (2012), depending on the proximity between households and the nearest wind turbine. The other studies find values in between.

2.4. *Life Satisfaction Approach*

Contrary to stated preference approaches, such as contingent valuation or discrete choice experiments, or revealed preference approaches, such as hedonic pricing, the life satisfaction approach uses data on self-reported subjective well-being to value environmental disamenities. Assuming that the self-reported life satisfaction of residents constitutes a valid approximation of their welfare, this approach specifies a microeconomic life satisfaction function which relates the self-reported life satisfaction of residents to the environmental disamenity to be valued, along with income and other variables which affect life satisfaction. Estimating this function yields the parameter estimates of the environmental disamenity and income, which are then used to calculate the implicit marginal rate of substitution between both—or, in other words, the amount of income which the resident is willing to pay in order to decrease the provision of the environmental disamenity by one unit (Frey et al., 2004). Compared to stated or revealed preference approaches, the life satisfaction approach has a number of advantages.

Compared to stated preference approaches, the life satisfaction approach avoids bias resulting from the expression of attitudes or the complexity of the valuation of the environmental disamenity, which leads to symbolic or superficial valuation. Regardless of contingent valuation or discrete choice experiments, stated preference approaches are subject to symbolic valuation: it is unclear what is actually measured in the spectrum of public responses. For wind turbines, Batel et al. (2014) point at subtle differences in the wording of questionnaires which drive results. For example, the expression *acceptance* has been found to transport a normative top-down perspective, which, in turn, has been found to be more likely to trigger opposition against wind turbines. It is thus intrinsic attitudes rather than extrinsic preferences which are measured—not mirroring the willingness-to-pay, while being 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, which leads to superficial valuation, the life satisfaction approach, does not rely on the ability of residents to consider all relevant consequences of a decrease in the provision of the environmental disamenity. It thus reduces the cognitive burden which is associated with stated preference approaches. Moreover, it does not reveal to

residents the relationship between life satisfaction and the environmental disamenity, reducing the incentive to answer in a strategic or socially desirable way (Kahneman and Sugden, 2005; van der Horst, 2007). It thus avoids bias resulting from a wedge between statements and intrinsic attitudes, as well as from the fact that attitudes do not necessarily coincide with the willingness-to-pay and, therefore, cannot conveniently be monetised.

Compared to revealed preference approaches, the life satisfaction approach avoids bias resulting from the assumption that the market for the private good taken to be the 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. Rather than assuming that the valuation of the environmental disamenity is reflected in market transitions, the life satisfaction approach requires only that the self-reported life satisfaction of residents constitutes a valid approximation of their welfare. Moreover, it does not involve future risk expectations, which are common to all market transactions, reducing distorted future risk perceptions due to the complexity of the environmental disamenity (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 life satisfaction approach is not entirely free of methodological issues itself. For example, for data on the self-reported life satisfaction of residents to constitute a valid approximation of their welfare, they have to be at least ordinal in character. Moreover, the micro-econometric life satisfaction function which relates the self-reported life satisfaction of residents to the environmental disamenity to be valued has to be correctly specified. These requirements, however, are typically met in practice.¹⁰

So far, the life satisfaction approach has been applied to a variety of contexts (see, for example, Welsch (2002, 2006, 2007), Rehdanz and Maddison (2008), Menz (2011), Ferreira et al. (2013), or Ambrey et al. (2014) for the context of air pollution; Israel and Levinson (2003) for the context of water pollution; Frijters and van Praag (1998), Rehdanz and Maddison (2005), and Maddison and Rehdanz (2011) for the context of climate; Carroll

¹⁰See Welsch and Kühling (2009a) for a more detailed review.

et al. (2009) and Lüchinger and Raschky (2009) for the context of natural disasters; or Ferrer-i-Carbonell and Gowdy (2007) for the context of environmental degradation more generally).

Specifically, the studies which are most closely related to this study are van Praag and Baarsma (2005) and Rehdanz and Maddison (2008) for the context of noise pollution and Ambrey and Fleming (2011) and Kopmann and Rehdanz (2013) for the context of visual pollution. van Praag and Baarsma (2005) investigate the effect of noise pollution on residential well-being in case of the Amsterdam Schiphol International Airport, using a postal survey of the population which lives within a 50 kilometres radius around the airport. The authors demonstrate that households without noise insulation and with a monthly net household income of 1,500 Euro would have to be compensated with 34 Euro monthly for a noise increase by 10 Kosten units and with 57 Euro monthly for a noise increase by 20 Kosten units.¹¹ Similarly, Rehdanz and Maddison (2008) investigate the effect of noise pollution on residential well-being in case of Germany, using self-reported noise pollution in the German Socio-Economic Panel (SOEP) in 1994, 1999, and 2004. The authors show that individuals would have to be compensated with 390 Euro monthly for a noise increase by one category on a five-point single-item Likert scale. Using the Household, Income, and Labour Dynamics Survey in Australia (HILDA) and the SEQ Regional Scenic Amenity Study in 2005, Ambrey and Fleming (2011) provide evidence that individuals are willing to pay 823 Euro monthly for a one category increase in scenic amenity on a ten-point single-item Likert scale.¹² Using the European Quality of Life Survey (EQLS) in 2007 and the Coordination of Information on the Environment (CORINE) Land Cover Data in 2006, Kopmann and Rehdanz (2013) find that the willingness to pay for artificial land covers, such as minding, dumping, and construction sites, is negative.

Taken together, the life satisfaction approach has a number of advantages compared to stated or revealed preference approaches and provides a suitable means to evaluate negative externalities through noise and, most importantly, visual pollution, which wind

¹¹Notably, Kosten units are a measure of aircraft noise which was developed in the Netherlands in 1967, based on aircraft noise in decibels, the flight frequency, and a correcting factor for day and night air traffic.

¹²Converted with an exchange rate of 1,4194 EUR/AUD.

turbines are prone to evoke.

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. It provides information on all household members, including Germans living in the old and new federal states, foreigners, and recent immigrants (Wagner et al., 2007, 2008). Most importantly, it provides information on the geographical locations of the places of residence of individuals, allowing to merge data on residential well-being with data on wind turbines through geographical coordinates.¹³ As such, the SOEP is not only representative of individuals living in Germany today, but also provides the necessary geographical points of reference for our analysis.¹⁴

To investigate the effect of the physical presence of wind turbines on residential well-being, we select a dependent variable which covers the most important area of residential well-being. Specifically, we select *satisfaction with life* as an indicator of life satisfaction in general. The indicator is obtained from an eleven-point single-item Likert scale which asks “How satisfied are you with your life, all things considered?”.¹⁵

3.2. Data on Wind Turbines

At the heart of our empirical analysis lies a unique novel panel data set 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 no freely accessible data

¹³The SOEP provides geographical coordinates of the places of residence of individuals at street-block level.

¹⁴The SOEP is subject to rigorous data protection legislation. It is never possible to derive the household data from the coordinates since they are never visible to the researcher at the same time. For more information, see Göbel and Pauer (2014).

¹⁵Conceptually, life satisfaction, which is equivalent to subjective well-being (Welsch and Kühling, 2009b) or experienced utility (Kahnemann et al., 1997), is defined as the cognitive evaluation of the circumstances of life (Diener et al., 1999).

were available, we contacted the subordinate body in charge for accounting permissions in each federal state separately and filed a request for data disclosure. See Appendix D 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 the exact geographical coordinates, the construction dates, and some indicator for the size of the installation, such as hub height or nameplate capacity. The distinctly novel feature of our data is the information on the exact geographical coordinates of wind turbines, not just their zip codes or postal addresses, as recorded in the public transparency platform on renewable energy installations in Germany.¹⁶ The temporal restrictions are motivated by the aim to fully exploit the temporal dimension of our data, that is, the interview dates of households in the SOEP. Conversely, when not knowing the construction dates, it would be opaque whether the construction of a wind turbine took place before or after an interview. Combining the exact geographical coordinates and interview dates of households in the SOEP with the exact geographical coordinates and construction dates of wind turbines in our data set, we can conduct a much more accurate analysis than previous studies and isolate the causal effect of the physical presence of wind turbines on residential well-being on a highly resolved spatial and temporal scale.

Out of the more than 20,000 wind turbines with exact geographical coordinates, a total of 12,842 wind turbines fulfil the minimum requirements on construction dates and some information on size. As not all relevant or desirable attributes are recorded for each wind turbine, we adopt a conservative approach and reduce the total number further such as to arrive at an *included group* of wind turbines on which inference can reliably be based.

In doing so, we focus only on wind turbines which were constructed after 2000—the exact geographical coordinates of households in the SOEP are only available from 2000 onwards—and exceed a certain size threshold. The choice of a size threshold is made to exclude wind turbines which are very small as they are less likely to interfere with

¹⁶The public transparency platform on renewable energy installations in Germany provides the so-called *Anlagenstammdaten* (renewables installations master data). It can be accessed under <http://www.netztransparenz.de/de/Anlagenstammdaten.htm> (in German), accessed June 1, 2015.

landscape aesthetics.¹⁷ 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 which have a hub height of less than 50 metres or an installed capacity of less than 0.5 megawatts. This conservative approach leaves us with a set of 10,083 wind turbines, which constitutes the *included group*. The descriptive statistics of the wind turbines in the *included group* are given in Table A.1.

Table A.1 about here

3.3. Merge

We merge the data on residential well-being with the data on wind turbines in two steps. Firstly, we convert the geographical coordinates of the places of residence of individuals in the SOEP and the geographical coordinates of the wind turbines in our data set into a common coordinate system. Secondly, we merge the data on residential well-being with the data on wind turbines, having calculated the distances between households and the nearest wind turbine using a Geographical Information System (GIS). 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.¹⁸ The controls at the micro level include demographic characteristics, human capital characteristics, and economic conditions at the individual level, as well as household characteristics and housing conditions at the household level. The controls at the macro level include macroeconomic conditions and neighbourhood characteristics at the county (*Landkreis*) level.

So far, we have a set of 10,083 wind turbines, which constitutes the *included group*, in the final sample. We are, however, aware that the excluded wind turbines cannot be

¹⁷A further rationale for the choice of a size threshold comes from the ownership structure of wind turbines in Germany: for smaller units, it is more likely that they are owned by residents in immediate proximity to the site. We could therefore measure an effect different than a negative externality. See Sub-Section 4.1 for a more detailed discussion.

¹⁸See Frey (2010) for a review of the relevant controls.

neglected. Otherwise, that is, in case an individual lives in close proximity to a wind turbine which was, for example, constructed before 2000, this observation would blur the results if—in our treatment effect analysis—it is fully attributed to the control group although in fact it belongs to the treatment group. For any definition of the treatment group, thus, some observations have to be dropped. These are all individuals living *close* to wind turbines for which at least one of the following data shortcomings is true: unknown construction date, constructed before 2000, unknown size or size below threshold, or inactive.¹⁹ In total, 10,554 wind turbines are prone to these data shortcomings and, therefore, constitute the *excluded group*.

As only wind turbines of the *included group* are relevant for our empirical analysis, those of the *excluded group* have to be subtracted from the final sample. To do so, initially, 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. We subsequently check for each individual and year whether a wind turbine of the *included* or *excluded group* is located within this treatment radius at the interview date. There are four potential cases. Consider Figure 1 for a graphical illustration.

Firstly, there is a wind turbine of the *included*, but none of the *excluded group* present. In this case, the individual is allocated to the treatment group (lower left panel). Secondly, there is no wind turbine of either the *included* or the *excluded group* present. Accordingly, the individual is allocated to the control group (lower right panel). Thirdly, there is no wind turbine of the *included*, but one of the *excluded group* present. In this case, the individual is dropped (upper right panel). Fourthly, if wind turbines of both the *included* and the *excluded group* are present, then it depends on the earliest construction date: in case that the first wind turbine of the *included group* was constructed before the first wind turbine of the *excluded group*, the individual is allocated to the treatment group, and discarded otherwise (upper left panel).

Finally, we discard all observations for which the currentness of the data on wind

¹⁹For the definition of the treatment group, we specify different treatment radii. See Sub-Section 4.1 for a more detailed overview.

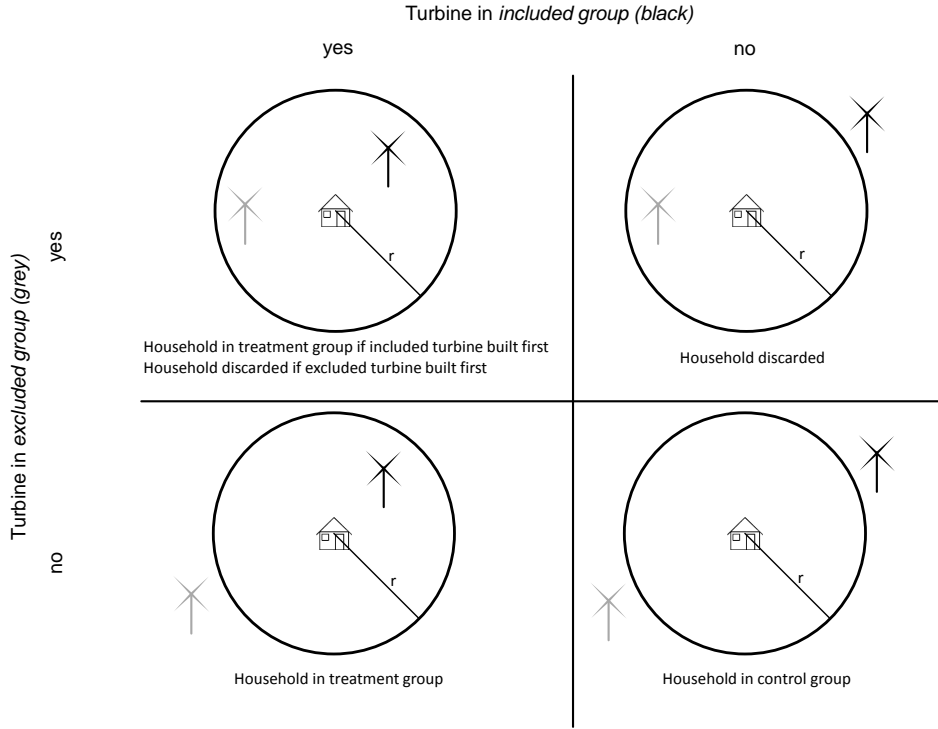


Figure 1: Households around which a wind turbine of the *excluded group* is constructed first are discarded, the others are allocated to either the treatment or control group

turbines is older than the interview date in a specific year as we cannot be sure whether no new wind turbines were added in case of these. For the federal state of Mecklenburg-Vorpommern, all years up to 2010 are included, for Saxony all years up to 2011, and for all other federal states all years up to 2012. Moreover, we neglect all individuals for which the interview date is given with insufficient accuracy in the year in which the first wind turbine was constructed in their surroundings as we cannot be sure whether these individuals should be allocated to the treatment or control group in this specific year. Finally, we discard all individuals who “start” in the treatment group in a specific year, for example, all individuals in households which 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 respective size of the treatment and control group depends on the respective choice of the treatment radius.

The descriptive statistics of the final sample are given in Table A.2.

Table A.2 about here

4. Empirical Model

4.1. Identification Strategy

We employ a difference-in-differences design to investigate the effect of the physical presence of wind turbines on residential well-being. Thereby, residents are allocated to the treatment group in case that a wind turbine is constructed within a pre-defined treatment radius around their households at any point in time during the observation period, and to the control group otherwise. We choose 4,000 metres as the default treatment radius.²⁰ Moreover, we choose 8,000 metres as an additional treatment radius for sensitivity analyses.²¹ To achieve a clear-cut distinction between the treatment and control group, we omit residents who experience the construction of a wind turbine within a pre-defined ban radius around their households at any point in time during the observation period. We choose 8,000 metres as the default ban radius.²²

We have to make three identifying assumptions to establish causality of the effect of the physical presence of wind turbines on residential well-being. Firstly, the construction of a wind turbine within a pre-defined treatment radius around households is exogenous. We make sure that this identifying assumption holds by omitting wind turbines which

²⁰Notably, the default treatment radius of 4,000 metres is motivated by both a theoretical and a practical consideration. As a theoretical consideration, a treatment radius of 4,000 metres around households is still close enough for residents to be considered as treated. As a practical consideration, a treatment radius of 4,000 metres around households allows for a sufficient sample size to estimate the effect of the physical presence of wind turbines on residential well-being not only for the entire population, but also for different population sub-groups when stratifying the final sample. In fact, although we cover an entire country for a time period of thirteen years, the construction of a wind turbine in the immediate surroundings of households is still a rather rare event, both in itself and even more so in the SOEP, as this data set over-samples urban rather than rural areas.

²¹In Germany, the evaluation of intrusions into the environment is based on the so-called *impact radius*. However, there is considerable heterogeneity in the legislation which prescribes the impact radius across federal states, yielding, for example, impact radii between 1,500 and 6,000 metres for a wind turbine of a hub height of 100 metres. See <http://www.wind-ist-kraft.de/grundlagenanalyse/landschaftsbildbewertungsverfahren> (in German), accessed June 1, 2015, for more information.

²²See Sub-Section 4.3 for a graphical illustration.

are very small as they are more likely to be run by residents who are private operators.²³ Moreover, we omit residents who are farmers as they are more likely to let farm land to commercial operators.²⁴ Finally, we add a set of established controls at the micro and at the macro level, as well as fixed effects at the individual level to account for systematic differences between treatment and control group at any point in time. Secondly, the treatment and control group follow a common time trend. We make sure that this identifying assumption holds by controlling for confounders which could cause differences in time trends between the treatment and control group. Moreover, we apply propensity-score and novel spatial matching techniques based on socio-demographic characteristics, including exogenous weather data, and geographical locations of residence, respectively, in order to arrive at a control group which is similar to the treatment group.²⁵ Thirdly, the interview date is random and unrelated to the construction date of a wind turbine. We make sure that this identifying assumption holds by checking the distribution of interview dates around the construction dates of wind turbines, and it seems that the distribution of interview dates is indeed random and unrelated.

4.2. Mitigating Endogenous Residential Sorting

In the given context, there might be two types of endogeneity, both of which resulting from self-selection of residents into particular rural areas, commonly referred to as *endogenous residential sorting*, and leading to reverse causality and therewith biased and inconsistent parameter estimates as the regressors are correlated with the error terms.²⁶

In the first type of endogeneity, residents who have lower preferences for wind turbines might have moved to particular rural areas with higher distance to them, et vice versa, which has made them better off prior to the observation period. In other words, residents might have moved from the treatment to the control group, et vice versa. We can account

²³Notably, with a hub height of less than 50 metres or an installed capacity of less than 0.5 megawatts are considered as small and attributed to the *excluded group*.

²⁴The obtained results are robust to the inclusion of residents who are farmers.

²⁵See Sub-Section 4.3 for a detailed description.

²⁶Notably, in case of endogenous residential sorting, residents might leave the treatment or control group and enter either the treatment or control group. Especially problematic is a change of groups in either way, commonly referred to as *endogenous assignment* into the treatment or control group.

for this type of endogeneity, commonly referred to as *unobserved heterogeneity*, given that the data on residential well-being are panel data, including more than one observation for each individual over time. As such, we can account for unobserved heterogeneity of residents by including individual fixed effects. However, this comes at the cost that discrete models, which assume ordinality, are not easily applicable to panel data, so that continuous linear models, which assume cardinality, are preferred in practice. In fact, this introduces measurement error as *satisfaction with life* is a discrete variable, which is censored from above and from below. However, the bias resulting from this measurement error has been found to be minor in practice (see, for example, Ferrer-i-Carbonell and Frijters (2004) for panel data and Brereton et al. (2008) and Ferreira and Moro (2010) for repeated cross-section data).

In the second type of endogeneity, residents who have lower preferences for wind turbines might still move to particular rural areas with higher distance to them, et vice versa, which makes them better off, during the observation period. In other words, residents might still move from the treatment to the control group, et vice versa. We can account for this type of endogeneity, commonly referred to as *simultaneity*, given that the data on residential well-being include the moving dates of residents. As such, we can account for simultaneity by excluding residents who move. However, this comes at the cost that the parameter estimates might be biased due to the fact that residents who move might be systematically different from residents who do not. In fact, the parameter estimates might be biased in both directions; that is, they might be upward biased in case that residents move away from wind turbines or they might be downward biased in case that residents move towards wind turbines. However, when trading off this bias against the bias resulting from simultaneity, the distortions from the exclusion of residents who move are likely to be considerably smaller than the distortions from the endogenous assignment of residents into the treatment or control group.²⁷ Moreover, when hypothesizing that wind turbines have a negative effect on residential well-being, the distortions from the exclusion of resi-

²⁷Traditionally, (inter-generational) geographical mobility is very low in Germany. In a given year, only about 1% of respondents move.

dents who move are likely to result in parameter estimates which are attenuated towards zero as residents who are most adversely affected by wind turbines are most likely to move away from them. As such, our parameter estimates might be interpreted as lower bounds. More generally, we obtain lower bounds, given that we proxy the effect of the physical presence of wind turbines on residential well-being by proximity, implicitly assuming that every wind turbine is visible to every resident.

4.3. Matching Treatment and Control Group

Up to now, the treatment group is relatively small when compared to the control group. Intuitively, the treatment group is concentrated in particular rural areas, whereas the control group is dispersed over the entire country. As such, they are not necessarily comparable to each other. Thus, the question arises whether the control group is credible and, following from this question, whether the treatment and control group follow a common time trend. To make residents in the treatment group as comparable as possible to residents in the control group and strengthen the identifying assumption of a common time trend between them, we focus only on residents who live in rural areas. Residents who live in city states or in counties with a population density in the two top deciles of counties ranked according to their population density are excluded.²⁸ 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 to match residents on macro controls, including the unemployment rate, average household income, and population density at the county level, as well as whether they live in the same federal state and whether they live in an area with a similar mean expected annual energy yield of a wind turbine.²⁹ The mean expected annual energy yield of a wind turbine captures wind power adequacy at a local

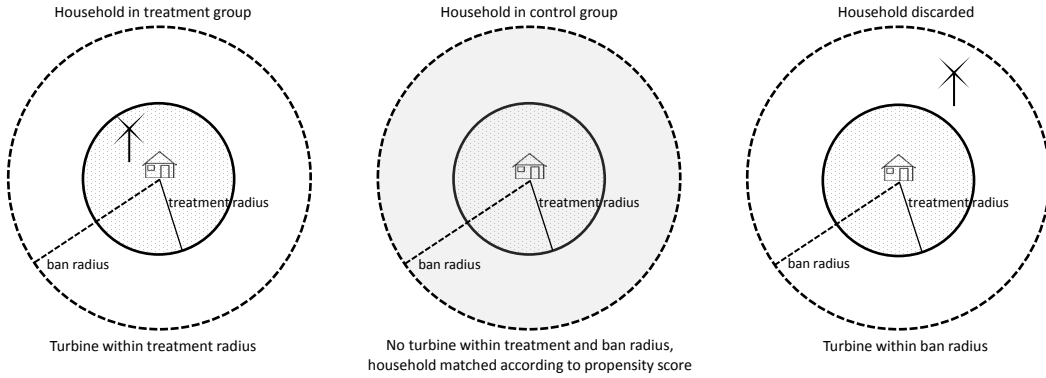
²⁸The obtained results are robust to the inclusion of residents who live in urban areas.

²⁹Notably, we match residents on time-invariant variables which are generated by taking the means of these variables over the entire observation period. Strictly speaking, it would be cleaner to use the pre-treatment values of these variables only. However, using the pre-treatment values 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 variables.

level, taking into account a multitude of climatical and geographical factors.³⁰ In doing so, we make residents in the treatment group as comparable as possible to residents in the control group in terms of socio-demographic characteristics, including exogenous weather data, and strengthen the identifying assumption of a common time trend between them.³¹

The propensity-score matching is illustrated in Figure 2:

Figure 2: Empirical Model - Difference-in-Differences Design (Propensity-Score Matching)



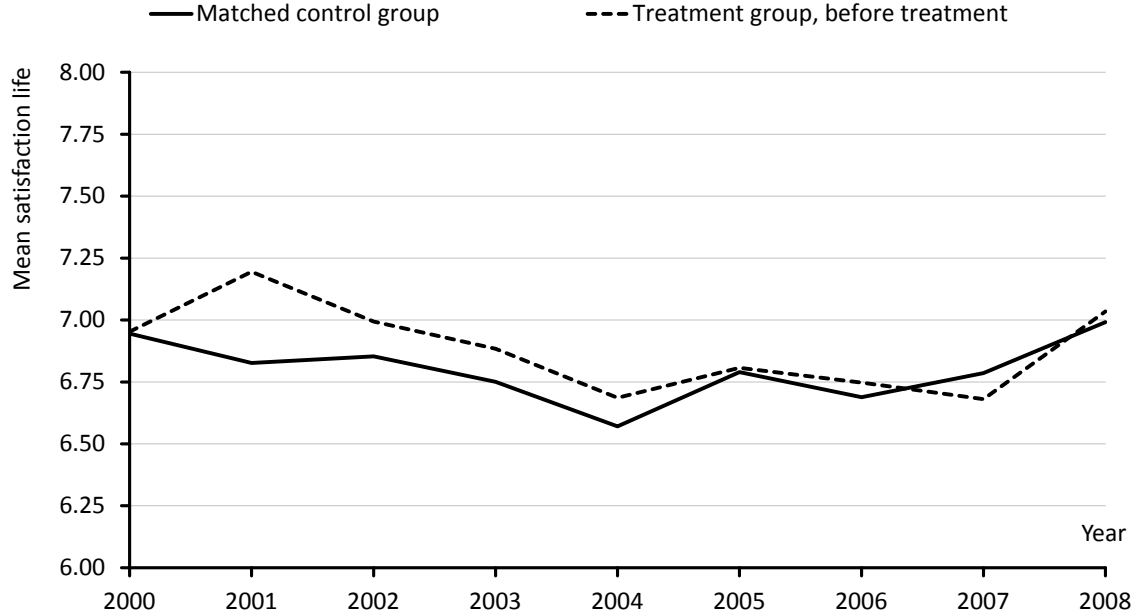
In the left panel, a wind turbine is constructed within the treatment radius, but none is constructed within the ban radius. Accordingly, the individual is allocated to the treatment group. In the middle panel, no wind turbine is constructed, neither within the treatment nor within the ban radius. Accordingly, the individual is allocated to the control group if this individual is matched to another individual in the treatment group, using propensity-score matching. In the right panel, no wind turbine is constructed within the treatment radius, but one is constructed within the ban radius. Accordingly, the individual

³⁰We use data from the German Meteorological Service for the time period between 1981 and 2000. The German Meteorological Service is the official service for information on weather and climate in Germany. Most importantly, it provides information on the expected annual energy yield of a wind turbine in kilowatt hours per square metre of rotor area (German Meteorological Service (DWD), 2014). The expected annual energy yield indicates how many kilowatt hours per year an average wind turbine would have generated per square metre of rotor area on average during the time period between 1981 and 2000. 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. The German Meteorological Service provides information on the expected annual energy yield of a wind turbine on the basis of 1 kilometre \times 1 kilometre tiles which are distributed over the entire country. Using a Geographical Information System (GIS), we match households with the nearest tile, calculating the mean expected annual energy yield of a wind turbine from the 25 tiles surrounding it. See Figure B.6 for a graphical illustration.

³¹The obtained results are robust to different propensity-score matching specifications.

is discarded.

Figure 3: Common Time Trend (Propensity-Score Matching)



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

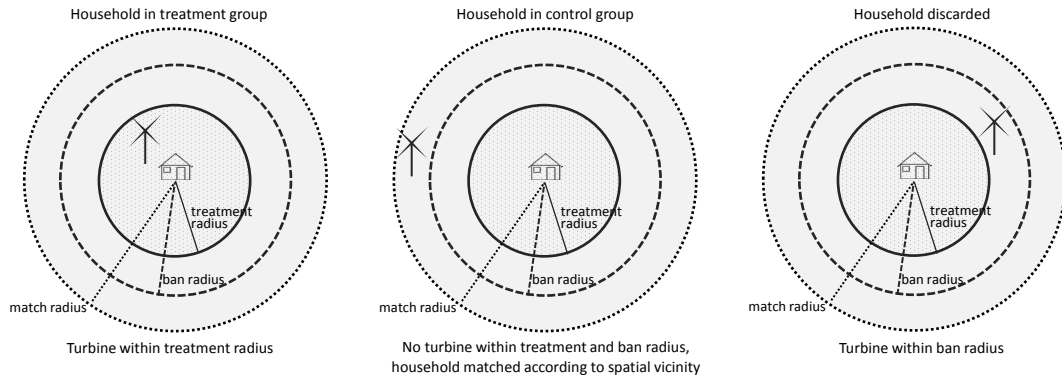
Figure 3 visualises how the dependent variable, *satisfaction with life*, evolves over time. The annual mean life satisfaction is shown for the matched control group (solid line) and the treatment group before treatment (dashed line).³² All figures control for confounders. As can be seen, the matched control and pre-treatment group co-move in a similar pattern over time, and there is no evidence for a divergent time trend.

The second type of matching is a novel type of matching called *spatial matching*. Specifically, we use a matching radius to match residents who experience the construction of a wind turbine within a pre-defined treatment radius around their households with those who experience the construction of a wind turbine outside the treatment radius, but inside the matching radius. In other words, we match residents who live close to a wind turbine

³²The horizontal axis is restricted to the time period between 2000 and 2008. Thereafter, the pre-treatment group mean is based only on very few observations and delivers hardly insightful information.

and close enough to be treated with those who live close to a wind turbine, but not close enough to be treated. We choose 15,000 metres as the default matching radius. Moreover, we choose 10,000 metres as an additional matching radius for sensitivity analyses. In doing so, we again make residents in the treatment group as comparable as possible to residents in the control group in terms of geographical locations of residence and strengthen the identifying assumption of a common time trend between them. The spatial matching is illustrated in Figure 4:

Figure 4: Empirical Model - Difference-in-Differences Design (Spatial Matching)



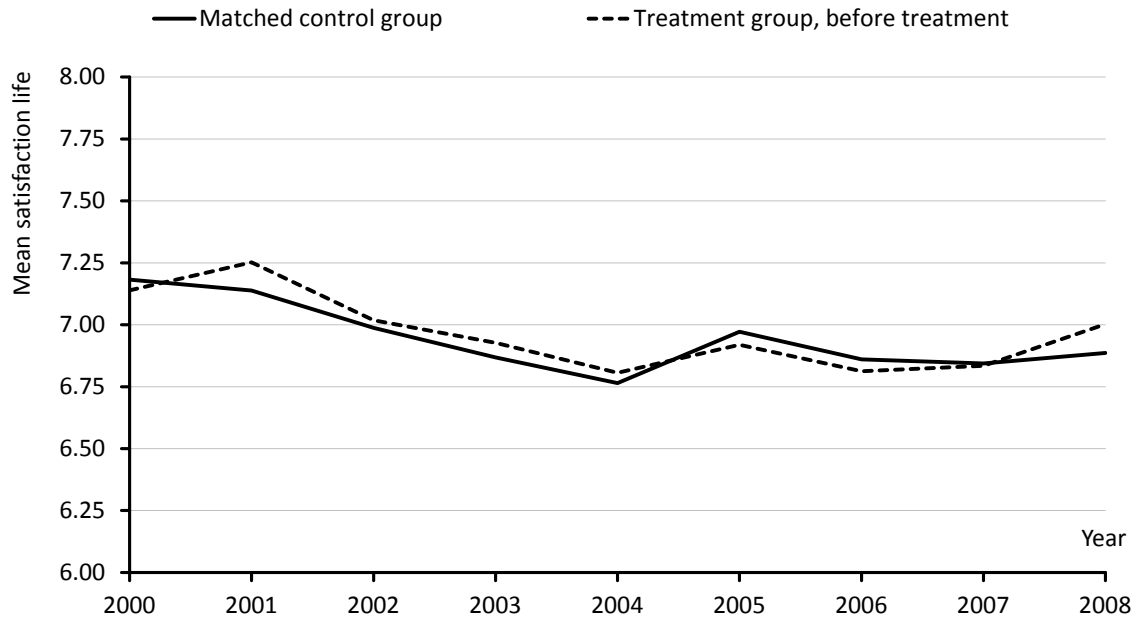
In the left panel, a wind turbine is constructed within the treatment radius, but none is constructed within the ban radius. Accordingly, the individual is allocated to the treatment group. In the middle panel, no wind turbine is constructed, neither within the treatment nor within the ban radius. However, a turbine is located within the matching radius. Accordingly, the individual is allocated to the control group. In the right panel, no wind turbine is constructed within the treatment radius, but one is constructed within the ban radius. Accordingly, the individual is discarded.

Using spatial matching, the scope of the analysis is narrowed down to residents who are comparable in terms of local living conditions. In fact, it is reasonable to assume that residents who live close to a wind turbine, be it within 4,000 or 15,000 metres distance, are sufficiently similar in terms of local socio-demographic characteristics. On the same note, potential positive effects of wind turbines, in particular local economic benefits, can be mitigated: both the treatment and control group could profit to a certain extent from

a wind turbine; however, only the treatment group within its 4,000 metres distance is likely to be negatively affected by its physical presence. Thus, by reducing the scope of the analysis to localities with wind turbines, we create a credible control group.

Figure 5 is constructed analogously to Figure 3, using the default matching radius of 15,000 metres. Again, there is no evidence for a divergent time trend between matched control and pre-treatment group.³³

Figure 5: Common Time Trend (Spatial Matching)



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

4.4. Regression Equation

We employ a linear regression model estimated by generalised least squares (GLS) with fixed effects and robust standard errors which are clustered at the federal state level. We test whether fixed or random effects are present, using the simple specification test by Wu (1973) and Hausman (1978), which tests whether the differences in parameter estimates

³³ A similar picture arises for the additional matching radius of 10,000 metres.

between two auxiliary regressions that are estimated by fixed effects and random effects, respectively, are significant. We cannot reject the presence of fixed effects, using not only this simple specification test, but also the robust version of this test by Wooldridge (2002), which does not assume that random effects are fully efficient and which works better with robust standard errors.³⁴

We employ three regression equations to investigate the effect of the physical presence of wind turbines on residential well-being.

Regression Equation (1) estimates the overall treatment effect. It includes $Construction_{it,r}$ as the regressor of interest, which is a dummy variable that is equal to one in the time period t in which the first wind turbine is constructed within the treatment radius r around the household, if the individual i was interviewed after the construction of this wind turbine, and zero else, while being equal to one in all time periods t thereafter. Thus, Regression Equation (1) captures the overall effect of the physical presence of wind turbines on residential well-being.

Regression Equation (2) estimates the treatment effect intensity. It includes $Construction_{it,r} \times Intensity_{it,r}$ as the regressor of interest, which is a numerical variable that is equal to different measures of treatment effect intensity in the time period t in which the first wind turbine is constructed within the treatment radius r around the household, if the individual i was interviewed after the construction of this wind turbine, and zero else, while being equal to the respective measure of treatment effect intensity in all time periods t thereafter. The different measures of treatment effect intensity include $InverseDistance_{it,r}$, $ReverseDistance_{it,r}$, and $Cumulative_{it,r}$. $InverseDistance_{it,r}$ is generated by dividing one by the Euclidean distance in kilometres between the household and the nearest wind turbine within the treatment radius r . $ReverseDistance_{it,r}$ is generated by subtracting

³⁴We can reject the null hypothesis that the differences in parameter estimates between two auxiliary regressions which are estimated by fixed effects and random effects, respectively, are not systematic at the 1% level, using the simple specification test by Wu (1973) and Hausman (1978) and the robust version of this test by Wooldridge (2002). In fact, the empirical values of the test statistic, 204.20 and 220.38 under propensity-score matching and 211.12 and 243.20 under spatial matching, exceed by far the critical value 56.06 of the χ^2 -distribution with 34 degrees of freedom. As such, we cannot reject that the regressors are correlated with the error terms. Thus, the estimation with fixed effects is strictly preferable to the estimation with random effects.

the Euclidean distance in kilometres between the household and the nearest wind turbine from the treatment radius r . Both $InverseDistance_{it,r}$ and $ReverseDistance_{it,r}$ make parametric assumptions and take on higher values for higher treatment effect intensities. $Cumulative_{it,r}$ is generated by counting the number of wind turbines within the treatment radius r . As more or more closely located wind turbines can be constructed during the observation period, the different measures of treatment effect intensity can change over time. Thus, Regression Equation (2) captures the degree to which the effect of the physical presence of wind turbines on residential well-being depends on treatment effect intensity.

Regression Equation (3) estimates the treatment effect transitoriness. It includes $TransitionPeriod_{it-\tau,r}$ as the regressor of interest, which is a dummy variable that is equal to one in the time period t which is τ time periods after the first wind turbine was constructed within the treatment radius r around the household, while being equal to zero in all time periods t thereafter. Thus, Regression Equation (3) captures the degree to which the effect of the physical presence of wind turbines on residential well-being persists over time.

$$\begin{aligned}
y_{it} = & \beta_0 + \mathbf{MIC}'_{it}\beta_1 + \mathbf{MAC}'_{it}\beta_2 + \\
& + \delta_1 \mathit{Construction}_{it,r} + \sum_{n=1}^{12} \gamma_n \mathit{Year}_{2000+n} + \\
& + \mu_i + \epsilon_{it}
\end{aligned} \tag{1}$$

$$\begin{aligned}
y_{it} = & \beta_0 + \mathbf{MIC}'_{it}\beta_1 + \mathbf{MAC}'_{it}\beta_2 + \\
& + \delta_1 \mathit{Construction}_{it,r} \times \mathit{Intensity}_{it,r} + \sum_{n=1}^{12} \gamma_n \mathit{Year}_{2000+n} + \\
& + \mu_i + \epsilon_{it}
\end{aligned} \tag{2}$$

$$\begin{aligned}
y_{it} = & \beta_0 + \mathbf{MIC}'_{it}\beta_1 + \mathbf{MAC}'_{it}\beta_2 + \\
& + \sum_{\tau=1}^9 \delta_\tau \mathit{TransitionPeriod}_{it-\tau,r} + \sum_{n=1}^{12} \gamma_n \mathit{Year}_{2000+n} + \\
& + \mu_i + \epsilon_{it}
\end{aligned} \tag{3}$$

where y_{it} is *satisfaction with life* as the regressand, β_0 is the constant, β_1 , β_2 , δ_1 , δ_τ , and γ_n are the coefficients, **MIC** and **MAC** are the vectors of controls at the micro level and macro level, respectively, μ_i is time-invariant unobserved heterogeneity or the fixed effect at the individual level, and ϵ_{it} is the idiosyncratic disturbance of resident i in time period t . Index r captures the treatment radius, and $\mathit{Construction}_{it,r}$, $\mathit{Construction}_{it,r} \times \mathit{Intensity}_{it,r}$, and $\mathit{TransitionPeriod}_{it-\tau,r}$ are the regressors of interest, with δ_1 and δ_τ as the respective average treatment effects on the treated (ATOT).³⁵

³⁵Notably, in a difference-in-differences design with treatment at a single point in time, the average treatment effect on the treated (ATOT) is given by the interaction between a time-variant dummy variable which differentiates pre-treatment from post-treatment observations and a time-invariant dummy variable which differentiates treated from control individuals, both of which have to be included in the regression equation. We employ a difference-in-differences design with treatment at multiple points in time, whereby the year dummy variables replace the time-variant dummy variable and the fixed effects at the individual

5. Results

We begin by presenting the results of the difference-in-differences design without matching the treatment and control group in Sub-Section 5.1. For our baseline specifications in Sub-Sections 5.2 and 5.3, we then present the results of the difference-in-differences design with propensity-score and spatial matching, respectively. Finally, heterogeneous effects are presented in Sub-Section 5.4.

5.1. *No Matching*

Table C.1 presents the results of the difference-in-differences design without matching the treatment and control group. The first two columns are estimated by pooled ordinary least squares (OLS) estimators, whereas the last two columns are estimated by fixed effects (FE) estimators, with and without controls, respectively. Thereby, comparing the first with the second column and the third with the fourth column sheds light on the importance of controlling for observables, whereas comparing the first with the third column and the second with the fourth column sheds light on the importance of controlling for unobservables. As can be seen, controlling for both observables and unobservables is important when it comes to the size and significance of the effect of the physical presence of wind turbines on life satisfaction. As such, the fixed-effects model with controls, as stated in Regression Equation (1), is our baseline model to estimate the overall treatment effect.³⁶

Table C.1 about here

As can be seen, already without matching the treatment and control group, there is evidence that the construction of a wind turbine within the default treatment radius of 4,000 metres around households has a negative effect on life satisfaction. In fact, the

level replace the time-invariant dummy variable.

³⁶As reported elsewhere (see, for example, (Clark and Oswald, 2004; Blanchflower, 2008)), having very good health has a significantly positive effect, whereas having very bad health and being unemployed has a significantly negative effect on life satisfaction at the 1% level.

coefficient estimate of δ_1 is negative in all models, and marginally significant at the 10% level in our baseline model.

There are, however, only 506 individuals in the treatment group, compared to 7,611 individuals in the control group. As discussed, the question arises whether the control group is credible and, thus, whether the treatment and control group follow a common time trend. To make residents in the treatment group as comparable as possible to residents in the control group and strengthen the identifying assumption of a common time trend between them, we use propensity-score and spatial matching, which are our two baseline specifications.

5.2. Propensity-Score Matching

Table C.2 presents the results of our first baseline specification—the difference-in-differences design with propensity-score matching. The treatment and matched control group are equal in size, with 1,000 individuals in total.³⁷ Again, controlling for both observables and unobservables is important when it comes to the size and significance of the effect of the physical presence of wind turbines on life satisfaction. As such, the fixed-effects model with controls, as stated in Regression Equation (1), is our baseline model to estimate the overall treatment effect.

Table C.2 about here

As can be seen, with propensity-score matching, the construction of a wind turbine within the default treatment radius of 4,000 metres around households has a significantly negative effect on life satisfaction at the 1% level in our baseline model. The size of this effect is economically significant. That is, the construction of a wind turbine within the default treatment radius of 4,000 metres around households decreases life satisfaction by 8% of a standard deviation, compared to a 26% drop in life satisfaction when becoming

³⁷During the estimation of the models with controls, some individuals are lost due to missing-at-random data on observables. As such, the regressions are run on 498 treated and 488 matched control individuals. We deem this a minor disturbance, not causing the coefficient estimates to be biased.

unemployed. As such, our first baseline specification—the difference-in-differences design with propensity-score matching—shows a significantly negative average treatment effect on the treated (ATOT). Thus, it provides evidence for significantly negative local externalities triggered by the physical presence of wind turbines.

Table C.3 about here

What happens if we increase the treatment radius? Table C.3 shows the coefficient estimates in case of treatment radii of 8,000, 10,000, and 15,000 metres.³⁸ The coefficient estimates in case of treatment radii of 8,000 and 10,000 metres are negative, but considerably smaller in size and insignificant at any conventional level. Moreover, no effect can be detected in case of a treatment radius of 15,000 metres. Taken together, these findings corroborate that we indeed pick up negative local externalities triggered by the physical presence of wind turbines—closer proximity to them appears to be a good proxy for such negative externalities, whereas a larger distance to them appears not to pick up such negative externalities anymore. Put differently, these findings point towards that we indeed systematically pick up negative local externalities triggered by wind turbines rather than local peculiarities.

Table C.4 about here

We explore the treatment effect intensity next. Thereby, the inverse and reverse distance and the number of wind turbines within the default treatment radius of 4,000 metres around households are used as different measures of treatment effect intensity, as stated in Regression Equation (2). Table C.4 presents the results. All coefficient estimates have the expected sign, but none of them is significant at any conventional level. As such, although

³⁸Intuitively, the group sizes of the treatment and control group change: within a treatment radius of 8,000 metres, there are 684 treated and 673 matched control individuals; within a treatment radius of 10,000 metres, there are 474 treated and 465 matched control individuals; and within a treatment radius of 15,000 metres, there are 212 treated and 211 matched control individuals. The lower numbers arise as more individuals are excluded with increasing treatment radii. For the larger treatment radii, we apply no ban radius.

distance and cumulation effects play some role, they are not the main drivers of the overall effect. Thus, the mere presence of wind turbines matters primarily, whereas distance to or cumulation of wind turbines does not matter much additionally.³⁹

Table C.5 about here

Intuitively, the question arises whether the negative effect of the physical presence of wind turbines on life satisfaction is not only spatially limited, but also temporally or, put differently, whether residents adapt to the presence of wind turbines in their immediate surroundings. To explore the treatment effect transitoriness, we employ a set of dummy variables which count up to nine time periods after the construction of a wind turbine within the default treatment radius of 4,000 metres around households, as stated in Regression Equation (3). Table C.5 presents the results. We focus on the default treatment radius only, given that the negative effect of the physical presence of wind turbines on life satisfaction has been shown to be strongest in the immediate surroundings of households. As can be seen, the negative effect of the physical presence of wind turbines on life satisfaction is not only spatially, but also temporally limited. In fact, 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.⁴⁰ As such, the results provide evidence that, although there is an initially negative effect of the physical presence of wind turbines on life satisfaction, residents adapt to their presence. Thus, exposure to wind turbines does not prove to be a permanent burden.

³⁹As we have no indication on view-sheds or concrete visibility, we cannot disentangle whether the non-significance arises from the non-visibility of wind turbines or the non-relevance of distance and cumulation effects.

⁴⁰Notably, it is not surprising that there is no significant effect in time period one, that is, the year of the construction of a wind turbine. Throughout all specifications, we use the construction date. In reality, however, a wind turbine is not constructed within a single day, and it is not stated explicitly whether the construction date marks the beginning or the end of the construction process. Therefore, there may be some blur, which is picked up by the coefficient estimate of the first time period. 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.

5.3. Spatial Matching

Tables C.6, C.7, and C.8 presents the results of our second baseline specification—the difference-in-differences design with spatial matching. While the group size of the treatment group remains the same throughout all specifications, the group size of the control group changes: in total, there are 506 treated individuals, and 2,080 and 811 matched control individuals in case of the matching radius of 15,000 metres and the matching radius of 10,000 metres, respectively.

Table C.6 about here

As can be seen in Table C.6, when it comes to the overall treatment effect, the results obtained using spatial matching corroborate the results obtained using propensity-score matching: the construction of a wind turbine within the default treatment radius of 4,000 metres around households has a significantly negative effect on life satisfaction at the 5% level in case of the matching radius of 15,000 metres and at the 1% level in case of the matching radius of 10,000 metres. Moreover, the sizes of the coefficient estimates are close to those obtained previously. Finally, for a treatment radius of 8,000 metres, the coefficient estimates are negative but insignificant, as shown before.⁴¹

Moreover, as can be seen in Table C.7, when it comes to the treatment effect intensity, the results obtained using spatial matching also corroborate the results obtained using propensity-score matching: there is only weak evidence for distance and cumulation effects. Throughout all specifications, the default matching radius of 15,000 metres is used.⁴²

Table C.7 about here

Finally, as can be seen in Table C.8, when it comes to the treatment effect transitoriness, the results obtained using spatial matching again corroborate the results obtained

⁴¹Notably, for a treatment radius of 8,000 metres, there are 698 treated individuals, as well as 1,495 and 543 matched control individuals in case of the matching radius of 15,000 metres and the matching radius of 10,000 metres, respectively.

⁴²The results are robust to using the additional matching radius of 10,000 metres.

using propensity-score matching: for both matching radii, the coefficient estimates are significantly negative for time periods two, three, and four after the construction of a wind turbine, at the 1% and 5% level, respectively— the only exception is time period four in case of the matching radius of 15,000 metres, which is marginally significant at the 10% level only. As such, the negative effect of the construction of a wind turbine on life satisfaction fades away five years after construction, at the latest. Thus, together with the results on treatment effect transitoriness obtained previously, we provide evidence for habituation towards wind turbines.

Table C.8 about here

5.4. *Heterogeneity Analysis*

Up to now, we have investigated the effect of the physical presence of wind turbines on life satisfaction for the entire population. To gain a more detailed picture, we apply our treatment effect analysis to different population sub-groups. Table C.9 presents the results for residents who are house owners versus residents who are not, residents who are very concerned about the environment versus residents who are not, and residents who are very concerned about climate change versus residents who are not.⁴³ Throughout all specifications, we use the difference-in-differences design with spatial matching and the default matching radius of 15,000 metres.⁴⁴

Table C.9 about here

⁴³Specifically, being very concerned about the environment and being very concerned about climate change are obtained from single-item three-point Likert scales which ask respondents to rate how concerned they are about “environmental protection” and “climate change”, respectively. We collapse these items into binary indicators which are equal to one for the highest category of concerns, and zero otherwise.

⁴⁴Notably, we do not use the difference-in-differences design with propensity-score matching as each stratification would require a separate propensity-score matching for each population sub-group. Moreover, we prefer to base the results on a larger control group. The results are robust to using the additional matching radius of 10,000 metres.

When it comes to residents who are house owners versus residents who are not, the coefficient estimate for house owners shows a significantly negative effect (first column, $\delta_1 = -0.1261^{**}$), which is not the case for non-house owners (second column, $\delta_1 = -0.0937$). 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 due to a decrease in real estate prices.⁴⁵ Relating this result to the literature on hedonic pricing—the most recent studies mostly found significantly negative effects of the physical presence of wind turbines on real estate prices—it is both in line with classical economic theory and the critique of the hedonic pricing method: if the negative externality was already completely priced into real estate values, there would be no scope for an additional effect. If, however, slow adjustment of prices, incomplete information, transaction costs, and a low variety of private goods, as is the case for wind turbines, preclude a full internalisation of their negative externalities, then other methods can detect complementary effects.⁴⁶

When stratifying the final sample into residents who are very concerned about the environment versus residents who are not, the coefficient estimate for non-concerned individuals shows a significantly negative effect (fourth column, $\delta_1 = -0.1356^{**}$), which is not the case for concerned individuals (third column, $\delta_1 = -0.0711$). A similar picture arises for residents who are very concerned about climate change (fifth column, $\delta_1 = 0.0634$) versus residents who are not (sixth column, $\delta_1 = -0.2127^{***}$). Again, the sizes of these coefficient estimates are stronger 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 eco-friendly, and our findings for residents who are environmentally aware are in line with that interpretation. Likewise, less green individuals may have a lower preference for emission-free electricity production and, thus, be more sensitive towards intrusions into their surroundings.

⁴⁵Notably, sensitivity analyses including land price at the county level as an additional control at the macro level leave the results for both the entire population and the different population sub-groups unchanged.

⁴⁶Luechinger (2009) provides a discussion of this complementarity in the context of air pollutant emissions from fossil fuelled power plants.

Taken together, the heterogeneity analysis suggests that the negative effect of the physical presence of wind turbines at the aggregate level is stronger for specific population sub-groups, most notably residents who are property owners and residents who are generally less environmentally aware.

6. Discussion

The results provide empirical evidence that the physical presence of wind turbines is not free of negative externalities, although they are both spatially and temporally limited. This insight can be an ingredient for an analysis when it comes to evaluating the transition towards renewables for electricity generation, which features high on the policy agenda of many countries throughout the world. Beyond the effect of the physical presence of wind turbines on residential well-being, a complete assessment of wind power would have to take into account changes within the electricity system, macro-economic impacts, such as job creation, and geo-political repercussions, such as resource dependency. On the other hand, the same picture would have to be drawn for competing resources for electricity generation, such as coal, gas, or solar power. This complete assessment is beyond the scope of this study.

Nevertheless, we want to put our findings into context and draw some modest comparisons between the negative local externalities caused by the physical presence of wind turbines and the negative externalities which wind power is targeted to mitigate, in particular greenhouse gas emissions. Moreover, we want to mirror our findings with those for other electricity generation technologies using the same methodological approach. We thus contextualise our findings in two directions. All assessments, however, remain somewhat crude “back-of-the-envelope” calculations. Notwithstanding, we think that this is an important exercise to put some intuition to our findings.

To begin with, we want to value the identified negative externalities monetarily. As an important caveat, the monetisation of results of life satisfaction studies is not free of issues. For example, regression coefficients capture marginal effects of both the externality to be valued and income on life satisfaction. The changes to be valued are however in any case greater than marginal. Likewise, the impact of income on life satisfaction may

be more subtle, comprising aspects like relative comparison 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 supposed to be indicative and should not be taken at face value. Rather they serve as an informed point of reference for comparisons on a macro level with the externalities avoided by the deployment of wind turbines.

As the negative effect of the physical presence of wind turbines on residential well-being, as measured in terms of life satisfaction, is found to be transitory, we draw on the results obtained using our second baseline specification—the difference-in-differences design with spatial matching in Table C.9:⁴⁷ only the coefficient estimates for transition period two, three, four are significantly negative, at the 5% and 10% level, respectively, whereas the coefficient estimate of household income is significantly positive at the 1% level. On the other end of our findings, we may assume that the effect is non-transitory and take the significant coefficient estimate which is highest in absolute value from our first baseline specification—the difference-in-differences design with propensity-score matching in Table C.2. Intuitively, the monetary valuation of the identified negative externalities applies only to affected residents. In the final sample, there are 20,637 wind turbines and 4,150 affected residents—note that, in this exercise, we can ignore incomplete data on wind turbines or residents who move. Assuming that the distribution of wind turbines and residents in the final sample can be scaled up to the entire German population, each wind turbine affects approximately 0.20 residents.⁴⁸ 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 impact of an average wind turbine, the average monetised negative externalities thus amount to 181 Euro per wind turbine in total, 49 Euro for the second year, 58 for the third and 74 for the fourth; or, assuming a lifetime of a wind turbine of 20 years and for simplicity no discounting, 9 Euro per wind turbine

⁴⁷The implications are qualitatively the same when drawing on the results obtained using our first baseline specification—the difference-in-differences design with propensity-score matching—in Table C.6.

⁴⁸As wind turbines are concentrated in rural rather than urban areas, the actual ratio is likely to be lower.

and year. On the other end of our findings, supposing a permanent effect, these average monetised negative externalities amount to 59 Euro per wind turbine and year.

To put these figures into context, we assess how much damage through CO₂ emissions which would have otherwise accrued is avoided by a single wind turbine. To this end, we draw on the literature in energy economics which attempts to quantify the CO₂ savings from wind power. The methodological approach consists in the numerical simulation of a counterfactual electricity generation system without wind power. To be clear, these numerical simulations, by their very nature, depend in part on assumptions to which extent conventional electricity generation technologies are replaced by renewables. Nevertheless, the literature delivers a quite narrow corridor of results: Weigt et al. (2013) set up a numerical simulation model for Germany for the time period between 2006 and 2010, arriving at estimates which range between roughly 22.5 and 31.5 million tons of CO₂ per year avoided through the deployment of wind power, or 650 and 790 grams of CO₂ per kilowatt hour of wind power.⁴⁹ For the year 2013, Memmler et al. (2014) arrive at roughly comparable figures of 37 million tons of CO₂ per year, corresponding to 720 grams per kilowatt hour of wind power.

Damage through CO₂ emissions is world-wide and quantified by large integrated assessment models, which is an highly intricate task and for which a large literature exists (see, for example, Foley et al. (2013)). We assume a medium value of 50 $\frac{\text{Euro}}{\text{ton}}$ to value the damage through CO₂ emissions monetarily. A modern wind turbine with an average capacity of 2.5 megawatts (Memmler et al., 2014) and an average operating time of roughly 1,600 full-load hours per year (BMWi (2014)) produces approximately 4 gigawatt hours of electrical energy per year. With 700 grams of CO₂ displaced per kilowatt hour produced, a total of 2,800 tons of CO₂ is avoided. In other words, there is a total monetised *avoided negative externality* in terms of CO₂ emissions by a single wind turbine of 140,000 Euro per year. Even under very conservative assumptions, that is, a wind turbine with capacity of 1 megawatt, an operating time of 1,500 full-load hours, 650 grams of CO₂ displaced

⁴⁹For more information on the underlying assumptions of this numerical simulation, see the corresponding discussion paper by Weigt et al. (2012).

per kilowatt hour, and social costs of carbon of 20 Euro per ton, there is a total monetised *avoided negative externality* of 19,500 Euro per year.

Analogously, we can assess how much damage through other air pollutants arising from burning fossil fuels which would have otherwise accrued is avoided by a single wind turbine. Beyond CO₂ emissions, conventional power plants, such as coal and gas stations, emit SO₂, causing so-called “acid rain”. Using the life satisfaction approach for 13 European countries, Luechinger (2010) estimates an annual marginal willingness to pay to reduce SO₂ emissions by one micro-gram per cubic metre annual mean air pollution of 312\$ for the time period between 1979 and 1994, which corresponds to 1.1% of average household income. Luechinger (2009) carried out an analogous analysis for Germany, based on subjective well-being data from the SOEP, which we also use. The author identified an annual marginal willingness to pay for SO₂ concentration reductions of 313 Euro per micro-gram per cubic metre annual mean air pollution, which corresponds to 1.5% of average household income. These estimations can provide the basis for comparing the negative externalities of different resources for electricity generation “within the same methodological approach” of their monetary valuation.

The evidence on the negative externalities of SO₂ and, especially, CO₂ is, admittedly, not easy to compare to that of wind turbines. Nevertheless, the figures indicate that the negative externalities caused by the physical presence of wind turbines are rather marginal when compared to those of conventional electricity generation technologies. Taking their monetised valuation between 9 and 59 Euro per wind turbine and year at face value, the annual benefits from avoiding the damage through CO₂ emissions of up to over 100,000 Euro per year are disproportionately high. With this rough sketch of a cost-benefit analysis in mind, wind power, despite negative local externalities, is a favourable technology. Both comparisons, naturally, remain somewhat crude back-of-the-envelope calculations. Nevertheless, they illustrate that the *avoided negative externalities* in terms of CO₂ emissions by wind turbines by far outweigh their *imposed negative local externalities*.

Compared to the negative environmental externalities common to conventional electricity generation technologies, in particular noxious local and carbon dioxide emissions in case of fossil fuel combustion, as well as nuclear waste which emits radiation for millions

of years and low-probability but high-impact accidents which do not only have negative local effects, but also significant tangible and intangible spillovers on other countries (see, for example, Goebel et al. (2015)) in case of nuclear fission, the local negative externalities caused by the physical presence of wind turbines are small. Let alone the damage caused by CO₂ emissions, wind turbines saved between 1.1 and 3.7 billion Euro in Germany in 2013, as opposed to 1.2 million Euro in monetised negative externalities. Moreover, our findings indicate that these are both spatially and temporally limited: for distances greater than 4,000 metres and after five years at the latest, no negative externalities can be detected. A major implication for policy is to communicate these findings. Beyond that, the damage caused by CO₂ emissions is of global and the damage caused by SO₂ emissions is of regional nature, whereas the negative externalities caused by the physical presence of wind turbines are highly local. It is thus mostly 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 basic economic rationale behind this trend is to avoid negative environmental externalities common to conventional electricity generation 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 in electricity generation, however, wind turbines have to be constructed in large numbers, which renders them more spatially dispersed and, therefore, in greater proximity to consumers than conventional power plants, increasing the salience of energy supply. In fact, this greater proximity of wind turbines to consumers has been found to have negative externalities itself, notably unpleasant noise emissions and, most importantly, negative impacts on landscape aesthetics.

Against this background, we investigated the effect of the physical presence of wind turbines on residential well-being in Germany, using panel data from the German Socio-Economic Panel (SOEP) and a unique novel panel data set on more than 20,000 wind turbines, of which over 10,000 include the exact geographical coordinates and construction dates, for the time period between 2000 and 2012. In doing so, we valued the negative

externalities caused by the physical presence of wind turbines using the life satisfaction approach.

Using a difference-in-differences design, which exploits the exact geographical coordinates and interview dates of households on the one hand and the exact geographical coordinates and construction dates of wind turbines on the other, we established causality. To ensure comparability of the treatment and control group, we applied propensity-score and novel spatial matching techniques based on socio-demographic characteristics, including exogenous weather data, and geographical locations of residence, respectively. We showed that the construction of a wind turbine in the immediate surroundings of households has a negative effect on life satisfaction. Importantly, the effect is both spatially and temporally limited. The results are robust to using different baseline and model specifications.

We arrive at a monetary valuation of the negative externalities caused by the physical presence of an average wind turbine between 9 and 59 Euro per wind turbine and year. Although non-negligible, this amount is substantially lower—by a factor of up to a thousand—than the damage caused by CO₂ emissions, which would be caused by conventional power plants that are displaced due to the deployment of wind turbines. In this respect, an average wind turbine *avoids* negative externalities of over 100,000 Euro per year under standard assumptions or 19,500 Euro per year under very conservative assumptions. Contrasting the monetary valuation of these spatially and temporally limited negative externalities caused by the physical presence of wind turbines with the damage through CO₂ emissions avoided by them, wind power is a favourable technology.

From a policy perspective, opposition against wind turbines cannot be neglected. We found that the construction of a wind turbine in the immediate surroundings around households has a negative effect on residential well-being. Our evidence, however, suggests that it is much smaller than possibly expected. It remains the task of policy-makers to communicate and moderate decision-making processes, also concerning the distributional implications, and to arrange potential compensation measures.

There are several limitations and open points which provide room for further research. Firstly, we do not have data on view-sheds or concrete visibility of wind turbines from the places of residence, as could be provided by digital surface models. Secondly, for

convenience we exclude residents who move from our analysis. Thirdly, we do not have data on the ownership structure of wind turbines—a point that refers to potential positive monetary effects 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. If there are such tendencies, we will, if anything, underestimate the negative effect of the physical presence of wind turbines on residential well-being. Beyond that, avenues for future research lie in the transfer of the empirical strategy applied in this study to other energy infrastructure, such as biomass plants or transmission towers.

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Appendix A. Data

	[Number]	Capacity [kW]			Total height [m]			Share
		min	max	average	min	max	average	
Germany	10083	200	7500	1571	51	239	123	48.9 %
Baden-Württemberg	309	500	3000	1425	66	186	124	77.3 %
Bavaria	434	500	3370	1705				68.4 %
Berlin	1			2000			138	100 %
Brandenburg	2401	500	7500	1683	83	239	133	71.1 %
Bremen	2	2000	2500	2250	118	143	131	2.7 %
Hamburg	7	270	6000	3096	66	198	156	11.7 %
Hesse	343	500	3000	1616	85	186	138	51.4 %
Lower Saxony	631	300	2500	1674	67	170	118	33.5 %
Mecklenburg-Vorpommern	726	500	2500	1005				59.0 %
North Rhine-Westphalia	956	500	2500	1358				33.3 %
Rhineland-Palatinate								0 %
Saarland	2	2300	2300	2300	145	145	145	1.2 %
Saxony	491	299	3158	1528	51	186	116	59.1 %
Saxony-Anhalt	2029	300	7500	1683	56	199	126	77.0 %
Schleswig-Holstein	1489				63	183	106	55.4 %
Thuringia	262	600	3075	1741				40.9 %

Note: capacity and total height rounded to integers. Shares rounded to one decimal place. Blanks if no information available. The share describes the percentage of turbines with full data (*included group*) within each federal state of Germany.

Source: see Appendix D

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

Table A.2: Descriptive Statistics

Variables	Mean	Standard Deviation	Minimum	Maximum	Number of Observations
<i>Dependent Variable</i>					
Satisfaction With Life	6.9798	1.7679	0	10	40,398
<i>Independent Variables of Interest</i>					
$Construction_{i,4000}$	0.0556	0.2292	0	1	40,398
$Construction_{i,4000} \times InverseDistance$	0.0213	0.0943	0	1.0965	40,398
$Construction_{i,4000} \times ReverseDistance$	0.0614	0.3175	0	3.088	40,398
$Construction_{i,4000} \times Cumul$	0.1786	0.9407	0	10	40,398
<i>Other Independent Variables - Micro Level</i>					
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
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
<i>Other Independent Variables - Macro Level</i>					
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

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Variables	Mean	Standard Deviation	Minimum	Maximum	Number of Observations
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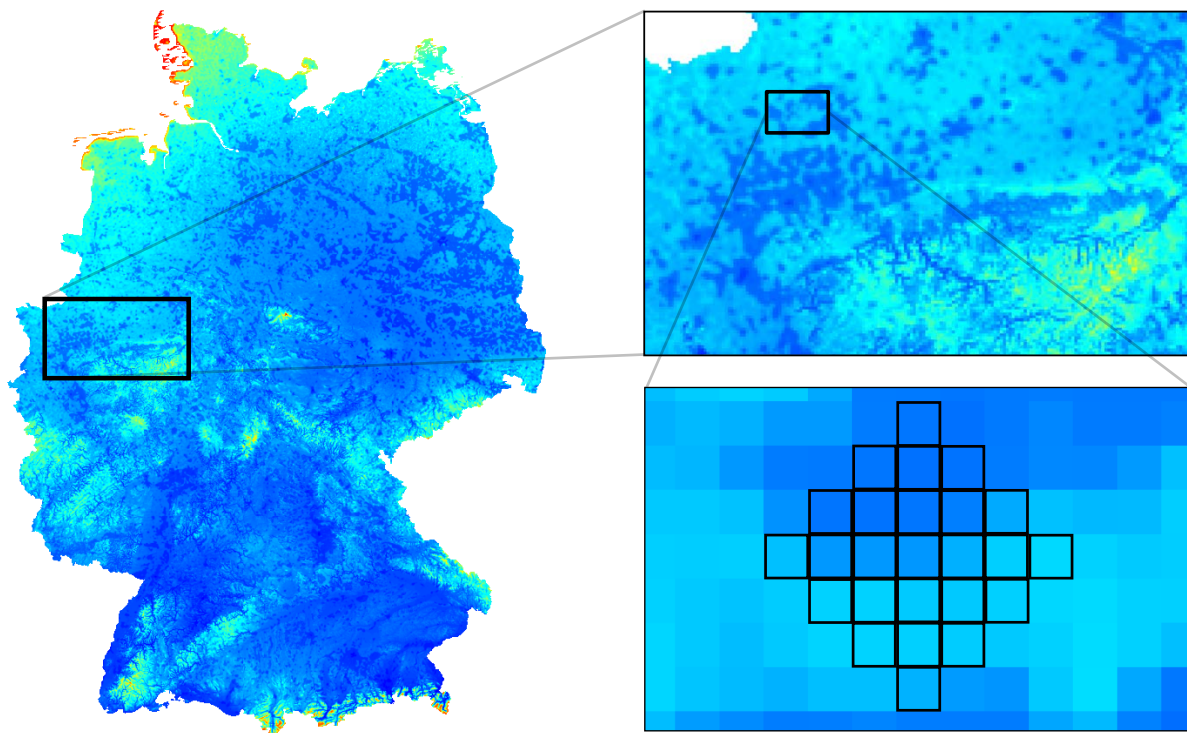
^a Annually in Euro/Inflation-Adjusted (Base Year 2000), ^c Detached, Semi-Detached, or Terraced

Note: All figures are rounded to four decimal places.

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

Appendix B. Empirical Model

Figure B.6: 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)

Appendix C. Results

Table C.1: Results - Satisfaction With Life, OLS/FE Models, Full Sample
Construction_{t,4000}

Dependent Variable: Satisfaction With Life

Regressors	OLS	OLS	FE	FE
Construction _{t,4000}	-0.1304 (0.1302)	-0.0641 (0.0949)	-0.0400 (0.0477)	-0.0759* (0.0347)
Age		-0.0275** (0.0098)		-0.0535** (0.0174)
Age Squared		0.0003*** (0.0001)		0.0001 (0.0001)
Is Female		0.0551 (0.0352)		
Is Married		0.1809* (0.0921)		0.3250 (0.2155)
Is Divorced		-0.0220 (0.0785)		0.2574* (0.1366)
Is Widowed		-0.0882 (0.0924)		-0.1907 (0.2807)
Has Very Good Health		1.0605*** (0.0429)		0.3939*** (0.0235)
Has Very Bad Health		-2.3525*** (0.0731)		-1.2404*** (0.0660)
Is Disabled		-0.4632*** (0.0420)		-0.2765*** (0.0334)
Has Migration Background		0.0078 (0.0388)		
Has Tertiary Degree		0.0398 (0.0337)		-0.0629 (0.0636)
Has Lower Than Secondary Degree		-0.1016* (0.0475)		0.1474 (0.1226)
Is in Education		0.0327 (0.0879)		0.2004 (0.1281)
Is Full-Time Employed		-0.2946*** (0.0478)		0.0386 (0.0358)
Is Part-Time Employed		-0.1395*** (0.0286)		-0.0871*** (0.0212)
Is on Parental Leave		0.1897*** (0.0593)		0.1287** (0.0520)
Is Unemployed		-0.9319*** (0.0730)		-0.4501*** (0.0852)
Individual Income ^a		0.1319*** (0.0228)		0.0440** (0.0185)
Has Child in Household		0.0024 (0.0573)		0.0248 (0.0252)
Household Income ^b		0.4028*** (0.0332)		0.1992*** (0.0287)
Lives in House ^c		0.0255 (0.0199)		0.0054 (0.0261)
Lives in Small Apartment Building		0.0020 (0.0279)		0.0031 (0.0206)
Lives in Large Apartment Building		0.0107 (0.0298)		0.0047 (0.0242)
Lives in High Rise		0.0650 (0.1645)		0.0362 (0.1078)
Number of Rooms per Individual		0.1164*** (0.0172)		0.0232 (0.0160)
Unemployment Rate		-0.0240*** (0.0054)		-0.0194 (0.0099)
Average Household Income ^a		0.0002 (0.0001)		-0.0004 (0.0003)

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Dependent Variable: Satisfaction With Life

Regressors	OLS	OLS	FE	FE
Constant	7.1460*** (0.0743)	2.4487*** (0.4137)	7.3602*** (0.0238)	7.8811*** (0.6398)
Number of Observations	48,785	40,398	48,785	40,398
Number of Individuals	8,791	8,117	8,791	8,117
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: 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 D, own calculations

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

Dependent Variable: Satisfaction With Life

Regressors	OLS	OLS	FE	FE
Construction _{t,4000}	-0.0741 (0.1757)	-0.0094 (0.1333)	-0.1702*** (0.0494)	-0.1405*** (0.0399)
Age		-0.0021 (0.0192)		-0.0689 (0.0425)
Age Squared		0.0001 (0.0002)		0.0001 (0.0004)
Is Female		0.0663 (0.0779)		
Is Married		0.1390 (0.3131)		0.0903 (0.1449)
Is Divorced		-0.0337 (0.2856)		0.2802 (0.4173)
Is Widowed		-0.0526 (0.2434)		-0.1891 (0.2035)
Has Very Good Health		1.1136*** (0.1296)		0.2967*** (0.0693)
Has Very Bad Health		-2.5500*** (0.1685)		-1.3187*** (0.1184)
Is Disabled		-0.4028** (0.1522)		-0.0137 (0.1113)
Has Migration Background		-0.0953 (0.1292)		
Has Tertiary Degree		-0.0630 (0.1124)		-0.0087 (0.1926)
Has Lower Than Secondary Degree		-0.3026** (0.1336)		-0.0008 (0.3042)
Is in Education		0.2165 (0.2107)		0.3740 (0.4008)
Is Full-Time Employed		-0.4358*** (0.0983)		0.0001 (0.1182)
Is Part-Time Employed		-0.1081 (0.1304)		-0.1220 (0.1056)
Is on Parental Leave		0.1233 (0.3778)		0.0709 (0.2157)
Is Unemployed		-0.9275*** (0.2068)		-0.5000*** (0.1233)
Individual Income ^a		0.1313** (0.0516)		0.0538 (0.0539)
Has Child in Household		0.1446 (0.1437)		0.1555* (0.0741)
Household Income ^b		0.4225*** (0.0868)		0.1738 (0.1173)
Lives in House ^c		0.0029 (0.0887)		-0.0135 (0.0954)
Lives in Small Apartment Building		0.0335 (0.0923)		0.0051 (0.0935)
Lives in Large Apartment Building		-0.0196 (0.0718)		-0.0262 (0.0765)
Lives in High Rise		0.0929 (0.2198)		0.1176 (0.2136)
Number of Rooms per Individual		0.1725** (0.0670)		0.0011 (0.0416)
Unemployment Rate		-0.0339*** (0.0099)		-0.0199 (0.0133)
Average Household Income ^a		0.0002 (0.0003)		0.0008 (0.0006)
Constant	6.9566*** (0.1155)	1.7537* (0.8362)	7.0849*** (0.0449)	7.2583*** (0.8130)

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Dependent Variable: Satisfaction With Life

Regressors	OLS	OLS	FE	FE
Number of Observations	7,818	6,637	7,818	6,637
Number of Individuals	1,000	1,000	1,000	986
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: 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 D, own calculations

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

Dependent Variable: Satisfaction With Life

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

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Dependent Variable: Satisfaction With Life

Regressors	FE	FE	FE
	(0.0006)	(0.0008)	(0.0009)
Constant	7.7639*** (0.7048)	7.2524*** (0.7316)	9.7895*** (1.1269)
Number of Observations	9,389	6,254	2,767
Number of Individuals	1,357	939	423
F-Statistic	5,951.5600	7,431.9500	1,373.6400
R ²	0.0698	0.0816	0.0798
Adjusted R ²	0.0665	0.0766	0.0683

^a 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: 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 D, own calculations

Table C.4: Results - Treatment Intensities, Satisfaction With Life, FE Model, Propensity Score Matching
 $Construction_{t,4000} \times InverseDistance$, $Construction_{t,4000} \times ReverseDistance$, $Construction_{t,4000} \times Cumul$

Dependent Variable: Satisfaction With Life

Regressors	FE	FE	FE
$Construction_{t,4000} \times InverseDistance$	-0.2090 (0.1605)		
$Construction_{t,4000} \times ReverseDistance$		-0.0128 (0.0550)	
$Construction_{t,4000} \times Cumul$			-0.0178 (0.1556)
Age	-0.0738 (0.0438)	-0.0790 (0.0446)	-0.0738 (0.0444)
Age Squared	0.0001 (0.0004)	-0.0001 (0.0004)	0.0001 (0.0004)
Is Female			
Is Married	-0.0946 (0.1456)	0.1056 (0.1451)	0.1116 (0.1399)
Is Divorced	0.2825 (0.4115)	0.2913 (0.4110)	0.3020 (0.4142)
Is Widowed	-0.1842 (0.2078)	-0.1696 (0.2079)	-0.1615 (0.2026)
Has Very Good Health	0.2967*** (0.0694)	0.2955*** (0.0698)	0.2963*** (0.0696)
Has Very Bad Health	-1.3164*** (0.1189)	-1.3166*** (0.1201)	-1.3222*** (0.1197)
Is Disabled	0.0149 (0.1101)	0.0137 (0.1103)	0.0128 (0.1099)
Has Migration Background			
Has Tertiary Degree	-0.0016 (0.1923)	0.0038 (0.1920)	0.0035 (0.1915)
Has Lower Than Secondary Degree	0.0029 (0.3066)	0.0032 (0.3092)	-0.0021 (0.3069)
Is in Education	0.3658 (0.4006)	0.3658 (0.4004)	0.3670 (0.4029)
Is Full-Time Employed	-0.0022 (0.1181)	-0.0024 (0.1180)	-0.0046 (0.1178)
Is Part-Time Employed	-0.0154 (0.1052)	-0.0156 (0.1059)	-0.0148 (0.1064)
Is on Parental Leave	0.0743 (0.2203)	0.0768 (0.2242)	0.0784 (0.2201)
Is Unemployed	-0.5049*** (0.1224)	-0.5080*** (0.1208)	-0.5075*** (0.1209)
Individual Income ^a	0.0540 (0.0536)	0.0541 (0.0532)	0.0539 (0.0533)
Has Child in Household	0.1509 (0.0742)	0.1491* (0.0753)	0.1479* (.0743)
Household Income ^b	0.1720 (0.1181)	0.1726 (0.1170)	0.1760 (0.1178)
Lives in House ^c	-0.0134 (0.0957)	-0.0144 (0.0958)	-0.0134 (0.0958)
Lives in Small Apartment Building	0.0043 (0.0945)	0.0028 (0.0960)	0.0041 (0.0954)
Lives in Large Apartment Building	-0.0260 (0.0769)	-0.0264 (0.0774)	-0.0255 (0.0770)
Lives in High Rise	0.1176 (0.2107)	0.1180 (0.0774)	0.1181 (0.2103)
Number of Rooms per Individual	0.0007 (0.0415)	0.0002 (0.0411)	0.0006 (0.0413)
Unemployment Rate	-0.0222 (0.0142)	-0.0241 (0.0146)	-0.0237 (0.0148)
Average Household Income ^a	0.0008	0.0008	0.0007

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Dependent Variable: Satisfaction With Life

Regressors	FE	FE	FE
	(0.0007)	(0.0007)	(0.0007)
Constant	7.5459*** (0.8708)	7.8139*** (0.8644)	7.6105*** (0.8269)
Number of Observations	6,637	6,637	6,637
Number of Individuals	986	986	986
F-Statistic	3,052.8700	2,800.3000	2,605.9000
R ²	0.0698	0.0694	0.0697
Adjusted R ²	0.0650	0.0646	0.0649

^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: 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 D, own calculations

Table C.5: Results - Transitory Effects, Satisfaction With Life, FE Model, Propensity Score Matching
 $Construction_{t,4000} \times TransitionPeriod_{1/2/3/4/5/6/7/8/9}$

Dependent Variable: Satisfaction With Life

Regressors	FE
$Construction_{t,4000} \times TransitionPeriod_1$	-0.0546 (0.0642)
$Construction_{t,4000} \times TransitionPeriod_2$	-0.1616** (0.0697)
$Construction_{t,4000} \times TransitionPeriod_3$	-0.1912** (0.0609)
$Construction_{t,4000} \times TransitionPeriod_4$	-0.2242** (0.0917)
$Construction_{t,4000} \times TransitionPeriod_5$	-0.2253** (0.0924)
$Construction_{t,4000} \times TransitionPeriod_6$	-0.2637 (0.1495)
$Construction_{t,4000} \times TransitionPeriod_7$	-0.2215 (0.1271)
$Construction_{t,4000} \times TransitionPeriod_8$	0.0305 (0.1846)
$Construction_{t,4000} \times TransitionPeriod_9$	-0.0679 (0.2816)
Age	-0.0672 (0.0413)
Age Squared	0.0010 (0.0004)
Is Female	
Is Married	0.0986 (0.1530)
Is Divorced	0.3110 (0.4034)
Is Widowed	-0.1833 (0.2078)
Has Very Good Health	0.2971*** (0.0694)
Has Very Bad Health	-1.3280*** (0.1135)
Is Disabled	0.0212 (0.1132)
Has Migration Background	
Has Tertiary Degree	-0.0284 (0.1914)
Has Lower Than Secondary Degree	-0.0131 (0.3061)
Is in Education	0.3770 (0.3998)
Is Full-Time Employed	0.0022 (0.1120)
Is Part-Time Employed	-0.0113 (0.1056)
Is on Parental Leave	0.0727 (0.2144)
Is Unemployed	-0.5013*** (0.1241)
Individual Income ^a	0.0532 (0.0552)
Has Child in Household	0.1546* (0.0791)
Household Income ^b	0.1744 (0.1184)
Lives in House ^c	-0.0136

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Dependent Variable: Satisfaction With Life

Regressors	FE
	(0.0954)
Lives in Small Apartment Building	0.0046
	(0.0927)
Lives in Large Apartment Building	-0.0272
	(0.0761)
Lives in High Rise	0.1120
	(0.2111)
Number of Rooms per Individual	0.0008
	(0.0421)
Unemployment Rate	-0.0159
	(0.0127)
Average Household Income ^a	0.0009
	(0.0007)
Constant	7.0489***
	(0.9185)
Number of Observations	6,637
Number of Individuals	986
F-Statistic	38,865.0800
R ²	0.0718
Adjusted R ²	0.0659

^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: 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 D, own calculations

Table C.6: Results - Satisfaction With Life, FE Models, Spatial Matching (10,000m, 15,000m)
Construction_{t,4000/8000}

Dependent Variable: Satisfaction With Life

Regressors	(1)	(2)	(3)	(4)
Construction _{t,4000}	-0.1088*** (0.0222)	-0.1138** (0.0366)		
Construction _{t,8000}			-0.0642 (0.0372)	-0.0452 (0.0447)
Age	-0.0792*** (0.0197)	-0.0142 (0.0199)	-0.0242 (0.0266)	-0.0030 (0.0248)
Age Squared	0.0002 (0.0002)	-0.0001 (0.0002)	-0.0001 (0.0002)	-0.0001 (0.0002)
Is Female				
Is Married	-0.1502 (0.1856)	0.1175 (0.2095)	-0.4424 (0.5476)	-0.0844 (0.4607)
Is Divorced	-0.0721 (0.0945)	0.1241 (0.2315)	-0.0619 (0.4789)	0.0909 (0.5164)
Is Widowed	-0.7490** (0.3319)	-0.2608 (0.2513)	-0.8117 (0.5315)	-0.4189 (0.4720)
Has Very Good Health	0.2833*** (0.0536)	0.3674*** (0.0424)	0.3484*** (0.0741)	0.3920*** (0.0518)
Has Very Bad Health	-1.2854*** (0.0887)	-1.2141*** (0.1000)	-1.3571*** (0.1412)	-1.2564*** (0.1378)
Is Disabled	-0.0101 (0.0881)	-0.2080** (0.0691)	-0.0327 (0.1207)	-0.1994** (0.0831)
Has Migration Background				
Has Tertiary Degree	-0.0303 (0.2628)	-0.1976 (0.1660)	-0.1510 (0.1510)	-0.2413 (0.2108)
Has Lower Than Secondary Degree	0.1677 (0.2073)	0.2274 (0.2062)	0.1362 (0.1975)	0.2324 (0.1761)
Is in Education	0.1739 (0.2544)	0.3345 (0.2033)	-0.0400 (0.2082)	0.2268 (0.1824)
Is Full-Time Employed	0.0213 (0.0780)	0.0841 (0.0655)	0.1017 (0.0831)	0.1417 (0.0779)
Is Part-Time Employed	-0.0534 (0.0904)	-0.0426 (0.0644)	0.0588 (0.0783)	0.0545 (0.0597)
Is on Parental Leave	-0.0308 (0.2097)	0.1516 (0.1289)	-0.0244 (0.1257)	0.0714 (0.0862)
Is Unemployed	-0.4325*** (0.0864)	-0.4542*** (0.0772)	-0.4511*** (0.0998)	-0.4796*** (0.0747)
Individual Income ^a	0.0523 (0.0436)	0.0385 (0.0282)	0.0188 (0.0373)	0.0056 (0.0395)
Has Child in Household	0.1997*** (0.0521)	0.0897** (0.0374)	0.2174** (0.0760)	0.0976 (0.0568)
Household Income ^b	0.2503*** (0.0695)	0.2003*** (0.0537)	0.2354** (0.0793)	0.1812*** (0.0453)
Lives in House ^c	0.0057 (0.0484)	0.0086 (0.0414)	0.0098 (0.0230)	0.0172 (0.0413)
Lives in Small Apartment Building	0.0234 (0.0575)	0.0159 (0.0395)	0.0534 (0.0539)	0.0102 (0.0432)
Lives in Large Apartment Building	-0.0060 (0.0421)	0.0144 (0.0298)	-0.0571 (0.0368)	-0.0008 (0.0580)
Lives in High Rise	0.0925 (0.2107)	0.0720 (0.1805)	0.1087 (0.0820)	0.0110 (0.1546)
Number of Rooms per Individual	-0.0157 (0.0402)	0.0136 (0.0210)	0.0095 (0.0210)	0.0230 (0.0185)
Unemployment Rate	-0.0353*** (0.0102)	-0.0081 (0.0105)	-0.0445*** (0.0080)	-0.0230** (0.0070)
Average Household Income ^a	0.0004 (0.0008)	-0.0006 (0.0005)	-0.0005 (0.0007)	-0.0010* (0.0005)
Constant	7.7061***	6.7254***	7.4786***	7.4268***

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Dependent Variable: Satisfaction With Life

Regressors	(1)	(2)	(3)	(4)
	(0.6694)	(0.8511)	(0.9088)	(0.8225)
Number of Observations	8,609	16,378	12,847	14,485
Number of Individuals	1,317	2,586	1,946	2,193
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: 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 D, own calculations

Table C.7: Results - Treatment Intensities, Satisfaction With Life, FE Model, Spatial Matching (15,000m)
 $Construction_{t,4000} \times InverseDistance$, $Construction_{t,4000} \times ReverseDistance$, $Construction_{t,4000} \times Cumul$

Dependent Variable: Satisfaction With Life

Regressors	FE	FE	FE
$Construction_{t,4000} \times InverseDistance$	-0.1862* (0.0940)		
$Construction_{t,4000} \times ReverseDistance$		-0.0181 (0.0338)	
$Construction_{t,4000} \times Cumul$			-0.0174 (0.0106)
Age	-0.0158 (0.0204)	-0.0176 (0.0207)	-0.0156 (0.0202)
Age Squared	-0.0001 (0.0002)	-0.0001 (0.0002)	-0.0001 (0.0002)
Is Female			
Is Married	0.1184 (0.2084)	0.1217 (0.2069)	0.1231 (0.2088)
Is Divorced	0.1241 (0.2309)	0.1262 (0.2069)	0.1298 (0.2305)
Is Widowed	-0.2560 (0.2503)	-0.2547 (0.2486)	-0.2532 (0.2498)
Has Very Good Health	0.3675*** (0.0426)	0.3673*** (0.0428)	0.3675*** (0.0425)
Has Very Bad Health	-1.2137*** (0.1001)	-1.2141*** (0.1002)	-1.2161*** (0.1001)
Is Disabled	-0.2078** (0.0687)	-0.2083** (0.0686)	-0.2086** (0.0687)
Has Migration Background			
Has Tertiary Degree	-0.1954 (0.1668)	-0.1934 (0.1674)	-0.1934 (0.1673)
Has Lower Than Secondary Degree	0.2284 (0.2061)	0.2286 (0.2062)	0.2266 (0.2061)
Is in Education	0.3323 (0.2027)	0.3327 (0.2025)	0.3327 (0.2036)
Is Full-Time Employed	0.0833 (0.0656)	0.0830 (0.0657)	0.0822 (0.0659)
Is Part-Time Employed	-0.0434 (0.0642)	-0.0434 (0.0643)	-0.0431 (0.0647)
Is on Parental Leave	0.1517 (0.1291)	0.1514 (0.1293)	0.1525 (0.1294)
Is Unemployed	-0.4554*** (0.0774)	-0.4562*** (0.0773)	-0.4565*** (0.0774)
Individual Income ^a	0.0386 (0.0281)	0.0388 (0.0281)	0.0386 (0.0282)
Has Child in Household	0.0881** (0.0373)	0.0875** (0.0374)	0.0868** (0.0371)
Household Income ^b	0.2002*** (0.0541)	0.2009*** (0.0539)	0.2021*** (0.0540)
Lives in House ^c	0.0086 (0.0415)	0.0083 (0.0417)	0.0087 (0.0417)
Lives in Small Apartment Building	0.0157 (0.0397)	0.0153 (0.0398)	0.0158 (0.0396)
Lives in Large Apartment Building	0.0144 (0.0301)	0.0141 (0.0304)	0.0146 (0.0302)
Lives in High Rise	0.0715 (0.1780)	0.0710 (0.1795)	0.0716 (0.1798)
Number of Rooms per Individual	0.0135 (0.0210)	0.0133 (0.0211)	0.0134 (0.0211)
Unemployment Rate	-0.0083 (0.0100)	-0.0082 (0.0098)	-0.0089 (0.0098)
Average Household Income ^a	-0.0006	-0.0006	-0.0006

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Dependent Variable: Satisfaction With Life

Regressors	FE	FE	FE
	(0.0005)	(0.0005)	(0.0005)
Constant	6.7883***	6.8483***	6.7995***
	(0.8429)	(0.8313)	(0.8319)
Number of Observations	16,378	16,378	16,378
Number of Individuals	2,586	2,586	2,586
F-Statistic	4,299.3200	4,088.2000	5,747.9200
R ²	0.0650	0.0650	0.0649
Adjusted R ²	0.0630	0.0629	0.0630

^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: All regression equations include dummy variables for years. All figures are rounded to four decimal places. Spatial matching with 15,000m matching radius.

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

Table C.8: Results - Transitory Effects, Satisfaction With Life, FE Models, Spatial Matching (15,000m)
 $Construction_{t,4000} \times TransitionPeriod_{1/2/3/4/5/6/7/8/9}$

Dependent Variable: Satisfaction With Life

Regressors	(1)	(2)
$Construction_{t,4000} \times TransitionPeriod_1$	-0.0401 (0.0657)	-0.0392 (0.0590)
$Construction_{t,4000} \times TransitionPeriod_2$	-0.1212** (0.0482)	-0.1262** (0.0546)
$Construction_{t,4000} \times TransitionPeriod_3$	-0.1381*** (0.0411)	-0.1506** (0.0550)
$Construction_{t,4000} \times TransitionPeriod_4$	-0.1808** (0.0687)	-0.1902* (0.0911)
$Construction_{t,4000} \times TransitionPeriod_5$	-0.1311 (0.0837)	-0.1472 (0.0885)
$Construction_{t,4000} \times TransitionPeriod_6$	-0.1664 (0.1264)	-0.1519 (0.1441)
$Construction_{t,4000} \times TransitionPeriod_7$	-0.0963 (0.0941)	-0.0744 (0.1009)
$Construction_{t,4000} \times TransitionPeriod_8$	0.1847 (0.1483)	0.2104 (0.1576)
$Construction_{t,4000} \times TransitionPeriod_9$	0.0378 (0.2452)	0.0778 (0.2460)
Age	-0.0793*** (0.0199)	-0.0146 (0.0193)
Age Squared	0.0002 (0.0002)	-0.0001 (0.0002)
Is Female		
Is Married	-0.1467 (0.1967)	0.1194 (0.2104)
Is Divorced	-0.0546 (0.0970)	0.1356 (0.2302)
Is Widowed	-0.7428* (0.3372)	-0.2566 (0.2524)
Has Very Good Health	0.2834*** (0.0539)	0.3673*** (0.0423)
Has Very Bad Health	-1.2900*** (0.0862)	-1.216*** (0.0991)
Is Disabled	-0.0037 (0.0911)	-0.2042** (0.0715)
Has Migration Background		
Has Tertiary Degree	-0.0495 (0.2641)	-0.2098 (0.1681)
Has Lower Than Secondary Degree	0.1619 (0.2104)	0.2234 (0.2076)
Is in Education	0.1811 (0.2554)	0.3395 (0.2021)
Is Full-Time Employed	0.0273 (0.0803)	0.0873 (0.0650)
Is Part-Time Employed	-0.0492 (0.0919)	-0.0408 (0.0640)
Is on Parental Leave	-0.0315 (0.2087)	0.1525 (0.1299)
Is Unemployed	-0.4321*** (0.0882)	-0.4542*** (0.0766)
Individual Income ^a	0.0519 (0.0441)	0.0383 (0.0280)
Has Child in Household	0.1957*** (0.0551)	0.0867** (0.0381)
Household Income ^b	0.2491*** (0.0709)	0.1994*** (0.0538)
Lives in House ^c	0.0052	0.0083

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Dependent Variable: Satisfaction With Life

Regressors	(1)	(2)
	(0.0481)	(0.0412)
Lives in Small Apartment Building	0.0224	0.0153
	(0.0569)	(0.0394)
Lives in Large Apartment Building	-0.0066	0.0140
	(0.0420)	(0.0297)
Lives in High Rise	0.0947	0.0732
	(0.2103)	(0.1808)
Number of Rooms per Individual	-0.0156	0.0138
	(0.0401)	(0.0211)
Unemployment Rate	-0.0323**	-0.0059
	(0.0113)	(0.0112)
Average Household Income ^a	0.0004	-0.0006
	(0.0008)	(0.0005)
Constant	7.7148***	6.7459***
	(0.6749)	(0.8462)
Number of Observations	8,609	16,378
Number of Individuals	1,317	2,586
F-Statistic	10,774.6900	8,860.9700
R ²	0.0725	0.0659
Adjusted R ²	0.0680	0.0635

^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) Radius matching 10,000m , (2) , Radius matching 15,000m

Robust standard errors in parentheses

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

Note: All regression equations include dummy variables for years. All figures are rounded to four decimal places. Spatial matching with 15,000m matching radius.

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

Table C.9: Results - Sub-Samples, Satisfaction With Life, FE Models, Spatial Matching (15, 000m)
Construction_{t-4,000}

Dependent Variable: Satisfaction With Life						
Regressors	(1)	(2)	(3)	(4)	(5)	(6)
Construction _{t,4000}	-0.1261** (0.0488)	-0.0937 (0.1132)	-0.0711 (0.0686)	-0.1356** (0.0436)	0.0634 (0.0499)	-0.2127*** (0.0605)
Age	-0.0188 (0.0166)	0.0025 (0.0446)	-0.1069** (0.0410)	0.0043 (0.0259)	-0.0388 (0.0270)	-0.0004 (0.0332)
Age Squared	-0.0001 (0.0002)	0.0001 (0.0003)	0.0006** (0.0002)	-0.0003 (0.0003)	0.0002 (0.0003)	-0.0003 (0.0003)
Is Female						
Is Married	0.0589 (0.0946)	0.3851 (0.7317)	-0.0522 (0.1953)	0.0620 (0.1471)	0.3197 (0.4429)	-0.0734 (0.1527)
Is Divorced	0.0391 (0.2112)	0.4838 (0.6903)	-0.5064 (0.8270)	0.1950 (0.3434)	-0.0679 (0.4314)	0.2127 (0.2987)
Is Widowed	-0.5247* (0.2652)	0.0895 (0.7342)	-0.9141 (0.7701)	-0.2729 (0.1820)	-0.4955 (0.8712)	-0.3157 (0.2506)
Has Very Good Health	0.3674*** (0.0503)	0.3737** (0.1615)	0.4583*** (0.1345)	0.3490*** (0.0449)	0.3639*** (0.0636)	0.3686*** (0.0658)
Has Very Bad Health	-1.3017*** (0.1269)	-1.0011*** (0.1538)	-1.1366*** (0.2749)	-1.2267*** (0.1051)	-1.3264*** (0.1891)	-1.1695*** (0.0952)
Is Disabled	-0.1545 (0.0934)	-0.3634* (0.1811)	-0.3932 (0.2154)	-0.1647 (0.1039)	-0.3259*** (0.0691)	-0.1430 (0.1332)
Has Migration Background						
Has Tertiary Degree	-0.2054 (0.1951)	-0.3403 (0.2783)	-0.4993* (0.2485)	-0.0646 (0.1469)	-0.2762 (0.3597)	-0.1930 (0.1417)
Has Lower Than Secondary Degree	0.3635* (0.1882)	-0.3660 (0.3417)	0.6399 (1.0752)	0.2814 (0.1900)	-0.1533 (0.3664)	0.4471* (0.2403)
Is in Education	0.1265 (0.1735)	1.0588** (0.3595)	0.6272 (0.5650)	0.3490* (0.1690)	0.3120 (0.2717)	0.3212 (0.2403)
Is Full-Time Employed	-0.0462 (0.0871)	0.6159*** (0.0913)	0.1730 (0.1622)	0.1174* (0.0620)	0.0846 (0.1230)	0.0753 (0.0699)
Is Part-Time Employed	-0.0561 (0.0602)	0.0547 (0.1327)	-0.0196 (0.1663)	-0.0034 (0.0853)	-0.1111 (0.1104)	0.0057 (0.0932)
Is on Parental Leave	0.1815 (0.1016)	0.2686 (0.4238)	0.1355 (0.2755)	0.1546 (0.1321)	0.0187 (0.2173)	0.2277* (0.1239)
Is Unemployed	-0.4953*** (0.1131)	-0.2808* (0.1304)	-0.3720 (0.2070)	-0.4486*** (0.0720)	-0.4415** (0.1523)	-0.4850*** (0.1133)
Individual Income ^a	0.0693 (0.0399)	-0.0393 (0.0767)	0.0789 (0.0890)	0.0094 (0.0331)	0.0771 (0.0541)	0.0149 (0.0380)
Has Child in Household	0.1105* (0.0555)	-0.0186 (0.1371)	0.1073 (0.1434)	0.1133** (0.0477)	0.0124 (0.0738)	0.1367** (0.0509)
Household Income ^b	0.2405*** (0.0645)	0.1759 (0.1271)	0.0596 (0.0938)	0.2240*** (0.0599)	0.3090*** (0.0905)	0.1357** (0.0439)
Lives in House ^c	-0.0099 (0.0679)	0.0679 (0.0679)	-0.0006 (0.0679)	0.0145 (0.0679)	-0.0116 (0.0679)	0.0175 (0.0679)

Continued on next page

Dependent Variable: Satisfaction With Life

Regressors	(1)	(2)	(3)	(4)	(5)	(6)
Lives in Small Apartment Building	(0.0455) -0.0011 (0.0521)	(0.0678) 0.0506 (0.0871)	(0.0807) -0.0312 (0.0898)	(0.0594) 0.0232 (0.0522)	(0.0497) 0.0047 (0.0741)	(0.0602) 0.0204 (0.0518)
Lives in Large Apartment Building	-0.0091 (0.0310)	0.0335 (0.0816)	-0.0251 (0.0873)	0.0277 (0.0460)	-0.0076 (0.0682)	0.0262 (0.0515)
Lives in High Rise	0.0597 (0.1908)	0.1164 (0.3136)	0.2536 (0.3930)	0.0279 (0.1849)	0.0481 (0.3097)	0.0819 (0.1575)
Number of Rooms per Individual	0.0216 (0.0229)	0.0104 (0.0493)	-0.0228 (0.0697)	0.0132 (0.0231)	-0.0330 (0.0505)	0.0302 (0.0333)
Unemployment Rate	-0.0081 (0.00149)	-0.0178 (0.0155)	-0.0259 (0.0360)	-0.0102 (0.0155)	-0.0113 (0.0163)	-0.0037 (0.0104)
Average Household Income ^a	-0.0003 (0.0005)	-0.0019 (0.0012)	-0.0004 (0.0012)	-0.0007 (0.0006)	-0.0011** (0.0004)	-0.0002 (0.0007)
Constant	6.2501*** (0.9662)	7.2812*** (1.6959)	10.7316*** (1.1070)	6.1764*** (0.9447)	6.6104*** (1.5696)	6.7511*** (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
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: All regression equations include dummy variables for years. All figures are rounded to four decimal places.
Spatial matching with 15,000m matching radius.

SOEP, v29 (2013), 2000-2012, individuals aged 17 or above, sources in Appendix D, own calculations

Appendix D. 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 Länderinformationssystem 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*

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