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Do wind turbines have adverse health impacts?

Christian Krekel
Johannes Rode
Alexander Roth

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

UKRI Economic and Social Research Council

Abstract
Wind power is considered key in the transition towards net zero, but there are concerns about adverse health impacts on local residents. Based on precise geographical coordinates, we link representative longitudinal household data to all wind turbines in Germany and exploit their staggered rollout over two decades for identification in a spatial difference-in-differences design. We also consider exogenous wind directions. We find little evidence of negative effects on mental and physical health in the 12-Item Short Form Survey (SF-12), and on self-assessed health and doctor visits. Finally, we detect no impacts on suicides, as an extreme outcome of mental distress.

Keywords: wind turbines, externalities, health, renewable energy, difference-in-differences, event study
JEL Codes: D62; I10; Q20; Q42; R10

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Christian Krekel, Centre for Economic Performance (CEP), London School of Economics (LSE); Department of Psychological and Behavioural Science, LSE. Johannes Rode, TU Darmstadt, International Economics. Alexander Roth, German Institute for Economic Research (DIW Berlin and; Technische Universität Berlin.

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1 Introduction

Wind power is considered key in the transition towards net zero. About 100 gigawatts of onshore capacity – roughly 500,000 wind turbines – were built in Europe between 2011 and 2020 alone, satisfying about 7% of Europe's electricity demand as of 2020 (WindEurope, 2021). By 2050, wind power is expected to contribute large shares to the electricity supply in Europe (Child et al., 2019) and worldwide (IEA, 2021), making it the most important renewable energy after solar.

Yet, wind power is not without controversy. Although its importance is generally acknowledged, local residents often oppose new wind turbines near their homes. In fact, negative impacts on house prices and the subjective wellbeing of nearby residents have been documented (Heintzelman and Tuttle, 2012; Gibbons, 2015; Dröes and Koster, 2016; Möllendorff and Welsch, 2017; Krekel and Zerrahn, 2017; C. Andersen and Hener, 2023; Quentel, 2023), though these tend to be small and diminishing with distance and over time (Guo, Lenz, and Auffhammer, 2024). Importantly, residents often cite concerns about adverse health impacts. Baxter, Morzaria, and Hirsch (2013) find that such concerns are the single most important predictor of resistance. What is more, there is a considerable amount of misinformation surrounding wind power, with over a quarter of respondents in nationally representative samples in the United States, United Kingdom, and Australia agreeing with contrarian claims such that noise from wind turbines can cause health problems yet that this information is withheld from them by governments and scientists (Winter et al., 2024). Systematic, causal evidence on potential health externalities, however, is scarce, and credible evidence is ever more important for the public acceptance of wind power and renewables more generally.

We ask: do wind turbines have negative causal effects on the health of local residents? If so, which health dimensions are affected, and by how much? And are effects, if any, spatially or temporally limited? To answer these questions, we use quasi-experimental methods and representative longitudinal household data from Germany – a country with a fast expansion of wind power in recent decades and hence a suitable case study – linked to a nationwide dataset on wind turbines based on precise geographical coordinates, covering the universe of about 30,000 installations built in Germany through 2022. We exploit additional exogenous wind direction data to capture the direction of potential impacts. Finally, we look at suicides at the county level as an extreme outcome of mental distress, taken from official statistics.

In theory, adverse health impacts may be driven by several factors.[1] First, and most important, there are concerns about noise pollution from both audible and non-audible (low-frequency) sound, as well as visual pollution from both shadow flicker and anti-aircraft lights. Whether feared or actually present, these may lead to worry, anxiety, or sleep disturbances, resulting in mental or physical health issues (cf. Bolin et al., 2011; Onakpoya et al., 2014; Freiberg et al., 2019). Besides technologi-

[1] For reviews of wind turbine externalities, see Mattmann, Logar, and Brouwer (2016) or Zerrahn (2017).

cal concerns, residents may also feel overwhelmed or annoyed by not having been involved in local decision-making processes, aspects of fairness and procedural utility (cf. Pohl, Gabriel, and Hübner, 2018; van Kamp and van den Berg, 2021; Ki et al., 2022). Finally, once installations have been built, psychological theory suggests that residents may be disturbed by violations of their landscape preferences or their attachment to their places of residence (cf. Devine-Wright, 2005; Jobert, Laborgne, and Mimler, 2007; Wolsink, 2007; Waldo, 2012). Each of these factors may provoke negative emotional reactions and stress, resulting in adverse health impacts, if sufficiently strong.[2]

To provide systematic, causal evidence on potential health externalities, we link the health outcomes of household members to the nearest wind turbine based on precise geographical coordinates of both households and installations. We measure general, mental, and physical health using the 12-Item Short Form Survey (SF-12) (RAND, 2022), a routine instrument for monitoring health in the general population. In addition, we measure self-assessed health and the number of doctor visits as a retrospective behavioural outcome to capture potential impacts beyond self-assessment, as well as the frequency of experiencing negative emotions, sleep satisfaction, and the number of hours of sleep as often cited mechanisms. To estimate causal effects, we exploit the staggered rollout of installations over a two-decade period in a spatial difference-in-differences design, using two-way fixed-effects estimators and, in addition, the robust estimator by Sun and Abraham (2021) to account for potential treatment effect heterogeneity over time (cf. Goodman-Bacon, 2021).

We are the first to study the health effects of wind turbines using quasi-experimental methods and nationwide data while explicitly accounting for potential treatment effect heterogeneity due to changing technology over time. We find no systematic evidence of negative effects on either general, mental, or physical health in the SF-12, neither on aggregate nor on any of the different mental or physical health sub-scales. We do not detect consistent impacts on self-assessed health and the number of doctor visits either. An exception appears to be a temporary increase in doctor visits some years after treatment, which seems to be driven by individuals in the early years of the rollout (when technology was newer), in close distance to installations (within 2,000 metres), and between two and five installations in their surroundings. Beyond that, there is no evidence for dynamic effects over time, for cumulative effects, or for individuals living downwind of installations. When looking at mechanisms, we find no consistent evidence that residents living closer to installations experience more negative emotions, are less satisfied with their sleep, or sleep fewer hours. In our baseline specification, we use a treatment group within 4,000 metres and a control group between 4,000 and

[2] Some studies point towards salience, personality, and individual differences to explain these findings. For example, Crichton and Petrie (2015) show that concerns created by the media may trigger symptom reporting, while Taylor et al. (2013) detect perceived symptoms only amongst residents who score high in terms of neuroticism, negative affect, and frustration intolerance. Jalali et al. (2016) find sleep disturbances only amongst residents who have negative attitudes towards wind turbines, concerns about property devaluations, and who can see installations from their homes. A similar argument has been made for lower environmental attitudes (Hobman and Ashworth, 2013), less experience in and knowledge of renewables (Aitken, 2010), or conservative political attitudes (Eltham, Harrison, and Allen, 2008; Karlstrom and Ryghaug, 2014).

8,000 metres to the nearest installation.[3] Our results are robust to different treatment and control radii, different bins around plants, different plant sizes, and to accounting for residential sorting.

Suicide has previously been used as an objective measure of adverse mental health impacts of environmental stressors, for example air pollution in the US (Molitor, Mullins, and White, 2023) or high temperatures in Mexico and the US (Burke et al., 2018). The paper most closely related to ours is Zou (2020), who studies the impact of wind turbines on suicides using administrative data on 800 new wind farms and suicide rates at the county level in the US from 2001 to 2013. The author uses spatial difference-in-differences and two-way fixed-effects estimators, finding significant increases in suicides in counties closer to wind farms. However, impacts tend to be small and detectable only for individuals between 15 and 19 of age and for those over 80 years. Leveraging additional survey data, the author shows that increases are likely driven by sleep insufficiency.[4] Exploiting administrative data on suicide rates at the county level in Germany and replicating our previous analysis, we do not detect any impacts. Taken together, our findings cast doubt on health externalities of wind turbines on local residents, which has important implications for the public and academic debate around wind power.

We contribute to a literature that is – despite a clear, theoretical causal chain from environmental stressor to health – inconclusive and that relies mostly on cross-sectional and local case studies.[5] Most studies find that being located close to a wind turbine is associated with increases in noise annoyance (Bakker et al., 2012; Michaud et al., 2016; Pohl, Gabriel, and Hübner, 2018; Radun et al., 2022), health concerns (especially when installations are visible) (Michaud et al., 2016), sleep disturbances (Bakker et al., 2012; Turunen et al., 2021; van Kamp and van den Berg, 2021), and psychological distress (Bakker et al., 2012), with similar patterns across countries (Hübner et al., 2019). Besides issues of causality, a common concern is that studies are often framed as or are seemingly related to wind turbines, which may elicit attitude expression rather than the reporting of genuine impacts. Given the quality of the evidence, meta-analyses are inconclusive (Bolin et al., 2011; Knopper and Olson, 2011; Onakpoya et al., 2014; Freiberg et al., 2019). In a systematic review, Schmidt and Klokker (2014) find that exposure to wind turbines increases the risk of annoyance and sleep disturbance, yet find no conclusive evidence of other claimed health effects, noting that "selection bias and information bias of differing magnitudes were found to be present in all current

[3] Individuals within 4,000 metres have previously been shown to experience negative externalities on their subjective wellbeing (cf. Krekel and Zerrahn, 2017).

[4] In a study not related to health, Brunner, Hoen, and Hyman (2022) use a spatial difference-in-differences design that exploits the nationwide rollout of wind turbines in the US between 1995 and 2016. The authors estimate the effects of wind turbines on test scores, high-school completion, and long-run outcomes of local students, finding precisely estimated zero effects. Like us, the authors use both two-way fixed-effects estimators and the robust estimator by Sun and Abraham (2021).

[5] There is also a proliferating grey and pseudo-scientific literature suggesting that proximity to wind turbines is causing a wide range of health issues, from autism to cancer or outright death. We limit ourselves to peer-reviewed articles.

studies." The World Health Organization, in its *Environmental Noise Guidelines*, takes a cautionary stance and recommends "reducing noise levels produced by wind turbines below 45 dB L_{den} [decibel day-evening-night-weighted sound pressure level], as wind turbine noise above this level is associated with adverse health effects", and that "policy-makers implement suitable measures to reduce noise exposure [...] above the guideline values". However, it also acknowledges that the quality of evidence is "low" or even entirely missing (World Health Organization, 2018).

More generally, we contribute to the literature in health, environmental, and public economics that looks at the external effects of infrastructure, either directly on health and health-related quality of life, such as freeways and associated congestion (Currie and Walker, 2011; Brinkman and Lin, 2022) or shale gas development and fracking (Hill, 2018), or indirectly via noise pollution, such as airports or neighbourhood structure (Bilger and Carrieri, 2012; Boes, Nüesch, and Stillman, 2013); via air pollution such as industrial facilities, power plants, or heating and agricultural systems (Agarwal, Banternghansa, and Bui, 2010; Luechinger, 2014; Currie, Davis, et al., 2015; Sheldon and Sankaran, 2017; Fan, He, and Zhou, 2020), or the impacts of air quality on health and societal welfare in general (Currie, Neidell, and Schmieder, 2009; Muller, Mendelsohn, and Nordhaus, 2011; Coneus and C. K. Spiess, 2012; Tanaka, 2015; Deryugina et al., 2019; Anderson, 2020; Giaccerini, Kopinska, and Palma, 2021), and specifically, the societal benefits and costs of wind power (Cullen, 2013; Novan, 2015). Our paper adds a particular type of infrastructure – renewable energy facilities, specifically wind turbines – that is being deployed in many countries at fast pace.

2 Data

2.1 Health

Our health data come from the German Socio-Economic Panel (SOEP), a representative panel of private households in Germany (SOEP, 2023). It has been conducted annually since 1984 and includes more than 30,000 individuals living in almost 20,000 households in its most recent 2021 wave. Importantly, the panel provides, besides interview dates, the geographical coordinates of every household in every year since 2000, allowing us to merge the health outcomes of individuals living in a representative sample of German households with data on wind turbines based on precise geographical information and timing (Goebel, Grabka, et al., 2019).[6] Neither surveys nor questions are framed as being related to wind turbines, so priming of respondents is of no concern.

Our main outcomes come from the 12-Item Short Form Survey (SF-12) (RAND, 2022), which is part of the SOEP every other year (i.e. 2000, 2002, 2004, etc.). It includes summary scales for *general*

[6] The SOEP is subject to rigorous data protection: it is not possible to derive household data from geographical coordinates as both are not visible to the researcher at the same time. See Goebel and Pauer (2014) for details.

health, *mental health*, and *physical health*, alongside respective sub-scales.[7] The SF-12 is a standard instrument on health-related quality of life. It is widely used in health economics for monitoring and assessing health outcomes in both general and clinical populations (Ware, Kosinski, and Keller, 1995). All scales are normalised between zero and 100, with a mean of 50 and a standard deviation of 10 (H. H. Andersen, Mühlbacher, and Nübling, 2007).

Moreover, we obtain data on subjective *self-assessed health* and, as a retrospective behavioural outcome, the reported *number of doctor visits* in the year prior to their interview, both of which are asked every year.[8] Finally, we obtain data on the frequency of experiencing certain emotions (happiness, sadness, anxiety, and anger), sleep satisfaction, and the number of hours of sleep on a normal weekday and on a normal weekend day to look at often cited mechanisms through claimed health effects of wind turbines are thought to come about (cf. Bolin et al., 2011; Onakpoya et al., 2014; Freiberg et al., 2019).[9]

We select a wide range of demographic and socio-economic characteristics as covariates, including marital status, employment status, log annual net household income, the ownership status of the dwelling and its log annual rent, as well as the number of adults and children in the household.[10].

Appendix Table A.I shows summary statistics for outcomes and covariates for our baseline specification, which uses a treatment group within 4,000 metres and a control group between 4,000 and 8,000 metres to the nearest installation.[11] Individuals in our estimation sample are typical of the German urban population: they are, on average, 54 years old, 70% married, 35% full-time and 13% part-time employed (with a median annual net household income of about €32,000), 4% unemployed, 68% owning their dwelling and 32% renting, and have, on average, slightly less than three individuals in their household. They also tend to be healthy, on balance: for our main outcomes,

[7] For mental health, these are *role-emotional* and *social functioning*, which are defined as the extent to which individuals are capable of mastering work or other daily and social activities without being affected by emotional problems, as well as *general mental health* and *vitality*, which are defined as the absence of mental disorder and fatigue. For physical health, these are *role-physical* and *physical functioning* as well as *bodily pain*. Each sub-scale is obtained from a five-point Likert scale, whereby the respective summary scale combines these with equal weights.

[8] The former is obtained from a five-point Likert scale question that asks "How would you describe your current health?", with answers ranging from five ("Very good") to one ("Bad"). The latter is obtained from a question that asks "Have you gone to a doctor within the last year? If yes, please state how often."

[9] The frequency of experiencing certain emotions is obtained from a five-point Likert scale question that asks "Please indicate for each feeling how often or rarely you experienced this feeling in the last four weeks: angry, worried, happy, and sad", with answers including one ("Very rarely"), two ("Rarely"), three ("Occasionally"), four ("Often"), and five ("Very often"). Moreover, sleep satisfaction is obtained from an eleven-point Likert scale question that asks "How satisfied are you with your sleep?", with answers ranging from zero ("Completely dissatisfied") to ten ("Completely satisfied"). Finally, the number of hours of sleep is obtained from free-text questions that ask "How many hours do you sleep on average on a normal day during the working week? How many hours on a normal weekend day?".

[10] The SOEP asks renters to report their actual and owners to report their *estimated* rent in the hypothetical case in which they would not own their dwelling. We combine both in one variable.

[11] The table refers to our estimation sample with self-assessed health as the outcome.

individuals have median mental and physical health scores of around 50, and they themselves assess their health as good (though not very good). The median number of doctor visits in the last year was four.

2.2 Wind Turbines

Our data on wind turbines come from Unnewehr et al. (2021) and Marktstammdatenregister (2023), and include all 30,000 onshore wind turbines connected to the grid in Germany until the end of 2022.[12] They contain information on the exact location of each installation in form of precise geographical coordinates, the starting date of operation, and further details such as power capacity, hub height, and rotor diameter.

The exact location of each installation is essential for our analysis, and we carried out extensive plausibility checks to ensure high data quality. In particular, we drew a 10% random sample of wind turbines and then personally verified the location of each randomly drawn installation based on satellite imagery from Google Earth. We found that about 95% of installations had the correct geographical coordinates.[13] Our data on wind turbines are, therefore, of high quality. Based on our data, Figure 1 shows the diffusion of onshore wind turbines in Germany until 2022.

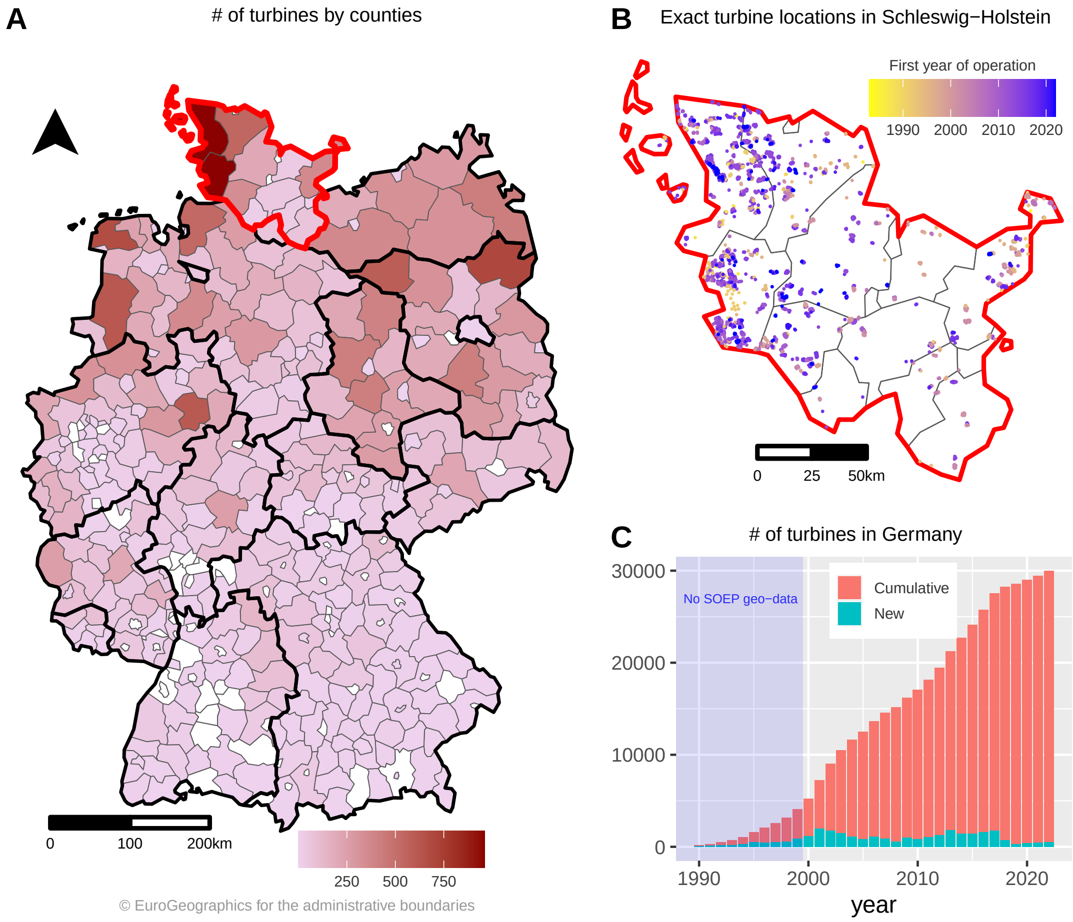
Panel A shows the geographical distribution of wind turbines at the level of counties (NUTS-3 areas), whereby counties coloured in darker shades of red exhibit more installations. We observe that 330 out of 401 counties had installations by the end of 2022. Most can be found in the north of Germany, near the sea where wind intensity tends to be highest.

Panel B shows, as an example, the exact location of each wind turbine in the federal state of *Schleswig-Holstein*, whereby older installations are coloured in yellow and newer ones in blue. In total, there were 3,601 installations at the end of 2022.[14] Finally, Panel C plots the annual number of cumulative and new installations in Germany since 1990. While new builds steadily increased in the 1990s, their number peaked in 2002, two years after the *Renewable Energy Sources Act* established an attractive feed-in-tariff system for electricity generated from wind power. After fewer new builds in 2008 and an increase in the following years, the number of new builds per year remained roughly stable at around 1,500 between 2013 and 2017. Since then, we observe fewer new builds again. Our

[12] The data by Unnewehr et al. (2021) contain all wind turbines that started operation until the end of 2017, the data by Marktstammdatenregister (2023) all that started operation between beginning of 2018 and end of 2022.

[13] More specifically, for the data by Unnewehr et al. (2021), 93.9% of the random 10% draw had exactly the same geographical coordinates as in Google Earth. For 1.4%, the geographical coordinates were almost the same. For the rest, we found that 2.8% no longer existed, while 1.6% could not be found, 0.1% were under construction, and 0.25% came with similar geographical coordinates as another installation nearby. For the data by Marktstammdatenregister (2023), 93.4% of the random 10% draw had exactly the same geographical coordinates as in Google Earth. For 2.1%, the geographical coordinates were almost the same. 4.5% were under construction and could not be checked. Due to the high accuracy of the rest of the data, we expect that those under construction are also correct.

[14] Appendix Figure A.I shows the exact locations of all 30,000 onshore wind turbines connected to the grid in Germany through the end of 2022.



Panel A shows the geographical distribution of wind turbines across counties (NUTS-3 areas: *Landkreise und Kreisfreie Städte*) in Germany in 2022. The thick black lines indicate the borders of federal states (NUTS-1 regions), whereas the red thick line indicates the border of the federal state of *Schleswig-Holstein*, the most northern German state. *Panel B* is a close-up of *Schleswig-Holstein* and shows, as an example, the exact location of each installation in that federal state, whereby each dot indicates one installation, coloured by the first year of operation. *Panel C* plots the annual number of cumulative and new installations in Germany since 1990.

Figure 1: Diffusion of Onshore Wind Turbines in Germany until 2022.

analysis focuses on the period between 2000 and 2021, for which the SOEP provides the precise geographical coordinates of every household in every year.

Appendix Table A.II shows summary statistics for our baseline specification (treatment group within 4,000 metres, control group between 4,000 and 8,000 metres). Installations in our estimation sample have a power capacity of, on average, 2 megawatts (standard deviation of 1.2), a hub height of 95.7 metres (standard deviation of 32.1), and a rotor diameter of 85.9 metres (standard deviation of 30). Appendix Table A.III shows how these have evolved during our observation period: at mean, capacity has almost tripled, from 1.4 megawatts in 2002 to 3.6 in 2020, and there have been substantial increases in hub height (from 80.2 metres in 2002 to 132.6 in 2020) and rotor diameter (from 65.1 metres to 123.9).

2.3 Wind

To capture the direction of potential health impacts, we obtain exogenous wind direction data from the German Meteorological office (Deutscher Wetterdienst, 2024). In particular, we obtain the dominant local wind direction for each of the 272 weather stations in Germany. We then match each wind turbine to its closest weather station.[15] Finally, we calculate the angle α between the location of each individual and its closest wind turbine. This procedure allows us to determine whether an individual lives in an up- or downwind location to the nearest wind turbine.

3 Empirical Strategy

3.1 Model

Our empirical strategy rests on a spatial difference-in-differences design. We estimate the following model:

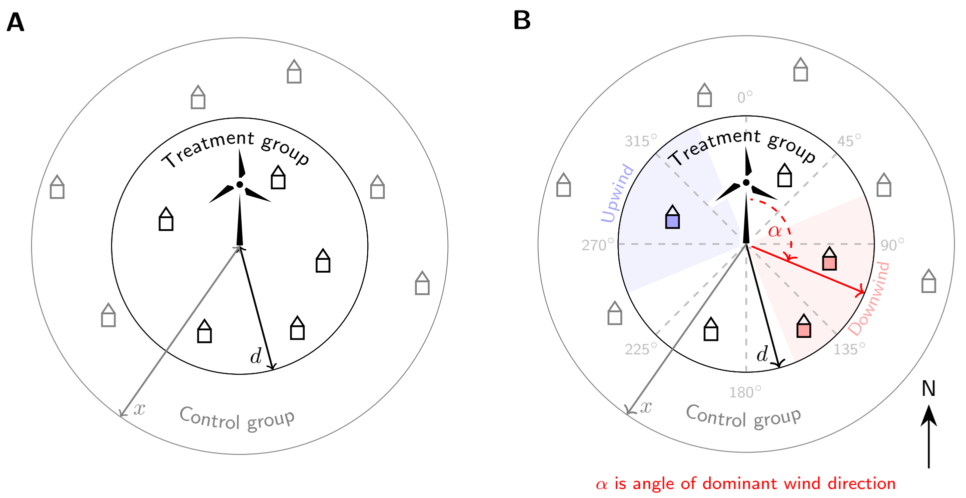
$$\begin{aligned} Y_{ijd,t} = \beta_0 + \beta_1(1\{Near\}_{ijd} \times 1\{Operating\}_{ij,t}) + \beta_2 1\{Near\}_{ijd} + \beta_3 1\{Operating\}_{ij,t} \\ + \beta_4' X_{ijd,t} + r + s + t + s \times t + u_i + \epsilon_{ijd,t} \end{aligned} \tag{1}$$

where $Y_{ijd,t}$ is the health outcome of individual i in year t, given the nearest installation j and its distance d to the household of the individual. The indicator $1\{Near\}_{ijd}$ is a time-invariant dummy that is one if the household is located within distance band $[0; d]$ metres (our treatment group), and zero if located within distance band $(d; x]$ metres (our control group, whereby $x > d$). That is, individuals in our control group are located close to an installation but not close enough to be treated. Figure 2 Panel A illustrates this setup. Panel B shows different positions of treated households relative to a wind turbine given the dominant local wind direction and angle α. The indicator $1\{Operating\}_{ij,t}$ is a time-varying dummy that is one if the installation is operational in a given year, and zero else.[16] The vector $X_{ijd,t}$ are time-varying covariates, including demographic

[15] We assume that the dominant local wind direction at the weather station and at the wind turbine are the same.

[16] We use the starting date of operation, as adverse health impacts are mostly attributed to operation rather than construction. Note that the construction of a wind turbine is fast: for example, it only takes about two months to build a smaller, ten megawatts wind farm and about six months for a larger, 50 megawatts farm, each comprising several wind turbines (European Wind Energy Association, 2023). As Figure 3 shows, we find no evidence of anticipation effects, which could be attributed to construction.

and socio-economic characteristics. The variables r, s, and t are county, federal state, and year fixed effects,[17] whereas u_i is an individual fixed effect. Together, r, s, t, and u_i net out time-invariant unobserved heterogeneity at the county, federal state, year, and individual level. We also include interactions between federal state and year fixed effects to flexibly account for trends in health across federal states over time. As plants determine treatment, we cluster robust standard errors at the plant level.



In *both panels*, the midpoint indicates the wind turbine location. Households in black are in the treatment group as they are within distance d to the wind turbine. Households in grey are in the control group as they are between distance d and x to the wind turbine. In *Panel B*, treated households in light red are downwind given the dominant wind direction α and treated households in light blue upwind. Treated households that are not coloured are neither downwind nor upwind.

Figure 2: Illustration of treatment and control group due to household locations (Panel A) and illustration of different positions of treated households relative to wind turbine and dominant wind direction (Panel B).

Equation 1 implements our spatial difference-in-differences design as a two-way fixed-effects estimator.[18] Equation 1 can be rewritten as:

$$Y_{ijd,t} = \beta_0 + \beta_1 D_{ijd,t} + \beta_2' X_{ijd,t} + r + s + t + s \times t + u_i + \epsilon_{ijd,t} \tag{2}$$

As we are also interested in whether individuals adapt to nearby installations or whether continued exposure potentially aggravates adverse health impacts, we also estimate this model as an event

[17] In Germany, there are 401 counties (NUTS-3 areas) and 16 federal states (NUTS-1 regions).

[18] This closely resembles the model by Currie, Davis, et al. (2015) for estimating the causal effect of toxic plant closings on health, the main difference being that our model takes the level of analysis from the aggregate to the individual level.

study:

$$Y_{ijd,t} = \beta_0 + \sum_{l} \beta_1^l D_{ijd,t}^l + \beta_2' X_{ijd,t} + r + s + t + s \times t + u_i + \epsilon_{ijd,t} \quad (3)$$

where $D_{ijd,t}^l$ is a set of dummies that are one for the l^{th} lead before (from $l = -6$ to $l = -1$) or lag after construction (from $l = 0$ to $l = 8$), and zero otherwise.[19]

We are interested in β_1 in Equation 2 and β_1^l in Equation 3, which can be interpreted as the average causal effects on health from being located within distance band $[0; d]$ metres to the nearest wind turbine if our identifying assumptions in Section 3.2 hold.

3.1.1 Treatment Effect Heterogeneity

Chaisemartin and D'Haultfœuille (2020), Callaway and Sant'Anna (2021), Goodman-Bacon (2021), Sun and Abraham (2021), Athey and Imbens (2022), and Borusyak, Jaravel, and J. Spiess (2023) show that Equations 2 and 3 yield unbiased estimates of β_1 and β_1^l only if treatment effects are homogeneous over time.[20] This may not be true in our case: we exploit the staggered rollout of installations over a two-decade period during which technology may have changed. In fact, Appendix Table A.III shows that power capacity, as well as hub height and rotor diameter, has increased substantially between 2002 and 2015.

To eliminate potential bias, we adopt the robust estimator by Sun and Abraham (2021). This approach has several advantages in our case: first, it allows us to show an unbiased common trend between treated and controlled pre-treatment, by looking at leads, as well as an unbiased trajectory of adaptation to nearby installations post-treatment, by looking at lags. We can then aggregate lags into a single parameter to obtain an unbiased average effect. Second, it allows us to elicit the extent of bias arising from treatment effect heterogeneity, by directly comparing estimates from our two-way fixed-effects estimator in Equation 3 with those from Sun and Abraham (2021).

Sun and Abraham (2021) use cohort-specific average treatment effects on the treated as building blocks, which in our case can be defined as $CATT_{e,l} = E[Y_{ijd,e+l}^1 - Y_{ijd,e+l}^0 | E_{ijd} = e]$, where $E_{ijd} = min\{t : D_{ijd,t} = 1\}$ is the year of first treatment, individuals in cohort $e \in \{1, 2, ...T, \infty\}$ are first treated in year $\{i : E_{ijd} = e\}$ (with ∞ denoting cohorts that are never treated), and $Y_{ijd,e+l}^1$ and $Y_{ijd,e+l}^0$ are potential outcomes of treatment and control group, respectively.[21] Hence, $CATT_{e,l}$ is the average treatment effect l periods relative to the year of first treatment for the cohort

[19] We normalise the year of first treatment as $t = 0$ and use the pre-treatment year $t = -1$ as the reference category. Note that, due to small sample sizewe trim observations before the sixth lead and after the eighth lag.

[20] See also Chaisemartin and D'Haultfœuille (2022) and Roth et al. (2023) for recent reviews of this issue.

[21] The data structure of our event study can be described as *hybrid* (Miller, 2022), considering that treatment occurs at multiple points in time and that it includes both individuals who are later treated and individuals who are never treated.

of individuals who are first treated in year e. The authors show that, for a non-empty cohort e, some pre-periods $s < e$, and some set of non-empty control cohorts $C \subseteq \{c : e + l < c \leq T\}$, an estimate $\hat{\delta}_{e,l}$ of $CATT_{e,l}$ can be obtained from:

$$\hat{\delta}_{e,l} = \frac{\frac{1}{N}\sum_{i=1}^{N}(Y_{ijd,e+l} - Y_{ijd,s}) \times 1\{E_{ijd} = e\}}{\frac{1}{N}\sum_{i=1}^{N} 1\{E_{ijd} = e\}} - \frac{\frac{1}{N}\sum_{i=1}^{N}(Y_{ijd,e+l} - Y_{ijd,s}) \times 1\{E_{ijd} \in C\}}{\frac{1}{N}\sum_{i=1}^{N} 1\{E_{ijd} \in C\}} \tag{4}$$

Then, estimates of the l^{th} lead before or lag after construction, $\hat{\beta}_1^l$, can be calculated as weighted averages of $\hat{\delta}_{e,l}$ using estimated weights $\hat{PR}\{E_{ijd} = e | E_{ijd} \in [-l, T - l]\}$, which are obtained from sample shares of each cohort in relevant periods l:

$$\hat{\beta}_1^l = \sum_l \sum_e \hat{\delta}_{e,l} \hat{PR}\{E_{ijd} = e | E_{ijd} \in [-l, T - l]\} \tag{5}$$

Finally, an overall estimate, $\hat{\beta}_1$, can be calculated as the average across all lags after construction. Sun and Abraham (2021) show that, if our identifying assumptions in Section 3.2 are satisfied, $\hat{\delta}_{e,l}$ is a consistent estimate of $CATT_{e,l}$ and sample shares $\hat{PR}\{E_{ijd} = e | E_{ijd} \in [-l, T - l]\}$ are consistent estimates of population shares, implying that $\hat{\beta}_1^l$ and $\hat{\beta}_1$ are consistent estimates even if treatment effects are heterogeneous over time. Note that, regardless of our estimator, we assume that treatment is an absorbing state, i.e. once a wind turbine becomes operational, it remains so until the end of our observation period.[22]

3.2 Identification

We choose our control group to be close enough to installation j to capture highly localised area conditions such as local demography, deprivation, or health clusters, yet far enough not to be treated.

As there exists no uniform legislation in Germany that can serve as a point of reference (e.g. a mandated setback distance), we use different treatment radii, i.e. $d = \{2000, 3000, 4000, 5000, 6000\}$, as well as different control radii, i.e. $x = \{4500, 5000, 5500, 6000, 8000, 10000\}$. A treatment radius of $d = 4000$ and a control radius of $x = 8000$ are our default, as individuals within 4,000 metres have previously been shown to experience negative externalities of wind turbines on

[22] Our data on wind turbines do not include the date of decommissioning, if applicable. However, the average lifespan of a wind turbine is 20 years (Environmental Protection Agency, 2013). Decommission is, therefore, likely to be a minor issue during our observation period. In any case, it would bind our treatment effects from below. The same is true if wind turbines are taken off-grid for maintenance or repair (which usually takes only very short time).

their subjective wellbeing (cf. Krekel and Zerrahn, 2017). This is a common approach in the literature (cf. Gibbons, 2015; Krekel and Zerrahn, 2017) if a treatment radius cannot be endogenously determined, for example by estimating how far a pollutant travels (cf. Currie, Davis, et al., 2015). It also allows us to test for spatial decay of potential externalities.

Our empirical strategy rests on two identifying assumptions:

1. ***Exogeneity of Treatment.*** Whether an individual is allocated to our treatment or control group is as good as random, conditional on time-varying covariates $X_{ijd,t}$, county and federal state fixed effects r and s, year fixed effects t, and individual fixed effects u_i. That is, $D_{ijd,t} \perp 0, 1 | X_{ijd,t}, r, s, t, u_i$. This also implies no anticipatory behaviour prior to treatment.

2. ***Common Trend.*** In a hypothetical absence of treatment, our treatment group would have followed the same trend in health outcomes as our control group, conditional on time-varying covariates $X_{ijd,t}$, county and federal state fixed effects r and s, year fixed effects t, and individual fixed effects u_i. That is, $E[Y_{ijd,t} - Y_{ijd,t-1} | X_{ijd,t}, r, s, t, u_i, D_{ijd,t} = 1] = E[Y_{ijd,t} - Y_{ijd,t-1} | X_{ijd,t}, r, s, t, u_i, D_{ijd,t} = 0]$.

Regarding exogeneity of treatment, Appendix Table A.IV shows means and variances of our covariates separately for our default treatment and control group, including scale-free normalised differences. According to Imbens and Wooldridge (2009), a normalised difference greater than 0.25 suggests covariate imbalance. As seen, none of our covariates exceeds this value. In a robustness check below, we will show that *not* controlling for time-varying covariates, county and federal state fixed effects, year fixed effects, and individual fixed effects does not change our results. This suggests exogeneity of treatment, even unconditionally. As Figure 3 below shows, we find no evidence of anticipatory behaviour prior to treatment.

Regarding common trend, we will plot leads before the year of first treatment in our event studies, for our two-way fixed-effects estimator and for the robust estimator by Sun and Abraham (2021). As will be seen, none of these leads turns out significantly different from zero in our baseline specification, suggesting common trend behaviour.

A threat to identification may come from *endogenous sorting*: some individuals may be more likely to move away from installations, for example because they are concerned about adverse health impacts or are experiencing them. Others, however, may move towards installations, where rental prices may be lower, potentially mispredicting adverse health impacts or even deliberately taking them into account. The direction of resulting bias is not *ex-ante* clear. Thus, in our baseline specification, we omit movers.[23] Note that mobility in Germany is rather low: in the SOEP, only about 5% of individuals move every year.

[23]We will include movers in a robustness check below.

Another threat to identification may come from *endogenous construction*: some individuals may be more likely to have installations constructed nearby, while others may even construct installations themselves. For example, wind turbines may be more likely to be placed in deprived areas, where local resistance may be lower. On the other hand, private persons may be generating income from wind turbines, for example farmers who build a wind farm on their land or who lease their land to utility companies. To the extent that endogenous construction is correlated with health, as is found for deprivation and income (cf. Frijters, Haisken-DeNew, and Shields, 2005; Lindahl, 2005; Jones and Wildman, 2008), it may bias our estimates, the direction of which is again not *ex-ante* clear.

We deal with endogenous construction in three ways. First, recall that our control group is located within distance band $(d; x]$ metres to the nearest installation, hence far enough not to be treated but close enough to capture highly localised area conditions such as deprivation and income. Second, we use different treatment and control radii d and x to capture different aspects of these conditions. Additionally, we control for county fixed effects r to capture localised area conditions such as local attitudes (as well as federal state fixed effects s and their interaction with years to capture regional socio-political conditions and their trends over time). Finally, we exclude farmers and urban counties, so that our estimation sample is restricted to a relatively homogeneous group of individuals living in rural areas.[24]

3.3 Estimation Sample

Our estimation sample consists of all individuals who are interviewed from 2000 through 2021, who have at least one pre-treatment and one post-treatment observation, and who have no missings on either outcomes or covariates. The number of observations depends on the availability of outcomes in a given year and on our treatment and control radii.

In our baseline specification, which uses a treatment group within 4,000 metres and a control group between 4,000 and 8,000 metres to the nearest installation, we have 740 individuals in our treatment and 8,638 individuals in our control group for our main outcomes based on the SF-12, being treated by 250 wind turbines. For self-assessed health (number of doctor visits), this amounts to 1,558 (1,557) individuals in our treatment and 11,479 (10,703) in our control group, being treated by 417 (414) wind turbines. For a treatment group within 6,000 metres, we have 952 treated and 6,297 controlled for our main outcomes, being treated by 270 wind turbines. For self-assessed health and the number of doctor visits, there are 1,994 treated and 8,546 controlled, being treated by 475 wind turbines.

To assess whether our study is sufficiently powered to detect a small effect size, we conduct an *ex-post* power calculation. We assume a small effect size of $d = 0.2$, an error probability of $\alpha = 0.05$, and a power of $1 - \beta = 0.95$. This yields a required sample size of 1,084 individuals,

[24] We will include urban counties in a robustness check below.

with 542 individuals each in treatment and control. As our group sizes exceed this threshold for each of our outcomes, our study is sufficiently powered to detect even a small effect size, if present.

Appendix Figure A.II Panel A shows the number of individuals treated by year in our estimation sample, Panel B the number of individuals never treated, exemplary for our outcome *self-assessed health*, which is available in every year. Appendix Figure A.III replicates this figure for *general health* from the SF-12, which is available in every other year. As seen, in both cases, the number of individuals treated is almost constant during our observation period, except for a slight increase in 2016 and a much stronger increase around 2002, when the feed-in-tariff system for electricity generated from wind power was established in Germany. In line with this, Panel C shows the cumulative density of individuals treated by year, with a much steeper increase during the first years of our observation period. Finally, Appendix Figure A.IV shows the share of individuals treated by one, two, or more newly built wind turbines. Most are treated by one wind turbine or wind farms with less than five installations.

4 Results

We first look at average treatment effects. Table 1 presents the results from our baseline specification. Panel A shows the estimates from our two-way fixed-effects estimator, Panel B those from the robust estimator by Sun and Abraham (2021). For comparability, we standardised outcomes to have a mean of zero and a standard deviation of one (z-scores).

We find no statistically significant effect on either the mental or physical health summary scale (Columns 2 and 3 in each panel), our main outcomes from the SF-12. If anything, we detect a *positive* effect on general health as an overall measure of health (Column 1). However, it is small and significant at the 5% level only. Considering that we are testing five hypotheses, a Bonferroni correction suggests a critical value of $(0.10/5) = 0.02$ for a 10% level of statistical significance, which is clearly lower than our empirical P value (about 0.4, for each estimator). Going on, we find no statistically significant effect on self-assessed health (Column 4) nor on the number of doctor visits (Column 5). Estimates from our two-way fixed-effects estimator generally resemble those from the estimator by Sun and Abraham (2021).[25]

Next, we look at treatment effects over time. Figure 3 shows the estimates from our baseline specification implemented as an event study. Panels A to E plot leads and lags for each of our outcomes in Table 1. A visual inspection of the leads indicates no difference in time trends between our treatment and control group in any of the panels, suggesting common trend behaviour.

Again, we find no statistically significant effects on either the mental or physical health summary scales from the SF-12. We find no effects on self-assessed health nor on the number of doctor visits

[25]Appendix Tables A.V and A.VI disentangle the mental and physical health summary scales from the SF-12 into their respective sub-scales. In line with our previous results, we find no statistically significant effect on any of them.

Table 1: Average Treatment Effects.

(a) Two-Way Fixed-Effects Estimator.

	SF-12 Health Survey			Other Health Outcomes	
Dependent Variable:	General Health (1)	Mental Health Summary Scale (2)	Physical Health Summary Scale (3)	Self-Assessed Health (4)	Doctor Visits (5)
Variable					
Treated 0-4 km	0.06**	0.01	-0.007	0.02	0.02
	(0.03)	(0.03)	(0.03)	(0.01)	(0.02)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
Individual	Yes	Yes	Yes	Yes	Yes
County	Yes	Yes	Yes	Yes	Yes
State-Year	Yes	Yes	Yes	Yes	Yes
Statistics					
Adjusted R^2	0.591	0.468	0.665	0.600	0.344
Obs.	29,236	29,236	29,236	72,962	71,118
N treated	740	740	740	1,558	1,557
N never treated	8,638	8,638	8,638	11,479	10,703

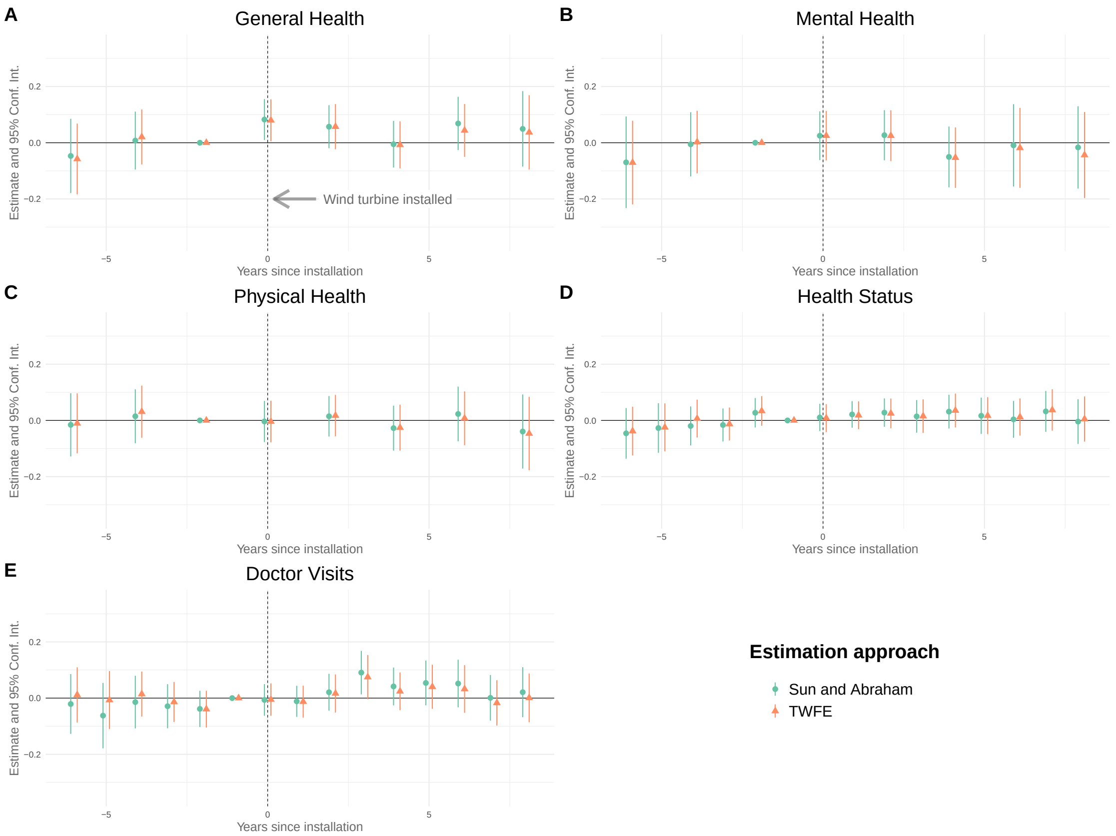
(b) Robust Estimator by Sun and Abraham (2021).

	SF-12 Health Survey			Other Health Outcomes	
Dependent Variable:	General Health (1)	Mental Health Summary Scale (2)	Physical Health Summary Scale (3)	Self-Assessed Health (4)	Doctor Visits (5)
Variable					
Treated 0-4 km	0.05*	0.0007	-0.004	0.02	0.03
	(0.03)	(0.04)	(0.03)	(0.02)	(0.02)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
Individual	Yes	Yes	Yes	Yes	Yes
County	Yes	Yes	Yes	Yes	Yes
State-Year	Yes	Yes	Yes	Yes	Yes
Statistics					
Adjusted R^2	0.591	0.468	0.665	0.601	0.344
Obs.	29,236	29,236	29,236	72,962	71,118
N treated	740	740	740	1,558	1,557
N never treated	8,638	8,638	8,638	11,479	10,703

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; clustered (plant) standard-errors in parentheses; treatment group 0-4 km; control group 4-8 km.
Outcomes in z-scores; more indicates better health (but for doctoral visits more indicates worse).

either, with the exception of the third lag for doctor visits, which is positive and just about significant for the estimator by Sun and Abraham (2021). We observe that the small, positive effect on general health is only significant in the year in which a new wind turbine is built (P value of about 0.02, for each estimator). Considering that we are testing 15 hypotheses (six leads and eight lags), a Bonferroni correction suggests a critical value of $(0.10/15) = 0.007$ for a 10% level of statistical significance, which is again lower than our empirical P value. A similar argument can be made for doctor visits in $t = 3$. Estimates from our two-way fixed-effects estimator once more resemble those from the estimator by Sun and Abraham (2021).

It could be that potential effects only emerge from more than one wind turbine. To capture potential cumulative impacts, for example by wind farms, Appendix Figure A.V replicates Figure 3



Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 metres) and individuals living further away (i.e. between 4,000 and 8,000 metres). Outcomes are in z-scores. Higher values indicate better health (but for doctor visits higher indicates worse). The vertical bars represent the 95% confidence intervals.

Figure 3: Dynamic treatment effects for two-way fixed-effects estimator and robust estimator by Sun and Abraham (2021).

for different treatment intensities, i.e. being treated by one, two to five, or more than five wind turbines, using Sun and Abraham, 2021's estimator. As before, we find no consistent effects. There is only some indication for a temporal effect on doctor visits from two to five wind turbines, but in this case the common trend assumption does not seem to hold.

It could also be that potential effects only emerge for individuals living downwind of installations. To capture the direction of potential impacts, we further refine our treatment group, by only including individuals living downwind of installations in a 90 degrees centigrade cone, given the dominant wind direction α within our default treatment radius of 4,000 metres. We also run a model that includes individuals living both downwind *and* upwind of installations, given that literature in acoustics has found noise emissions, in particular of low-frequency sound, to be present in both directions (Hubbard and Shepherd, 1990; Oerlemans and Schepers, 2009). Appendix Table A.VIII shows average treatment effects, Figure A.VI dynamic treatment effects over time, each based on Sun and Abraham (2021). As before, we find little evidence of negative effects on health outcomes for individuals living downwind as well as both downwind and upwind of installations.

Perhaps effects manifest themselves for different age groups. Appendix Figure A.VII replicates Figure 3 for different age groups, defined as younger (between 18 and 40 years of age), middle-aged (between 41 and 59), and older (from 60 onwards), based on Sun and Abraham, 2021's estimator. Again, we do not detect impacts on any age group for any of our outcomes.

Although we find little evidence of negative effects on health outcomes, there may still be externalities, though perhaps not strong enough to manifest themselves in adverse health impacts. Because noise annoyances and sleep disturbances are often cited as mechanisms through which adverse health impacts may come about, we also look at the frequency of experiencing certain emotions as well as sleep satisfaction and the number of hours of sleep as additional outcomes. Appendix Figure A.VIII replicates Figure 3 for these additional outcomes. As seen, we find no statistically significant effects on either happiness, sadness, anxiety, or anger, nor on the number of hours respondents report to sleep or their sleep satisfaction within a distance of 4,000 metres.[26]

5 Robustness

We conduct several robustness checks. If not stated otherwise, estimates are based on our baseline specification and the estimator by Sun and Abraham, 2021.[27] We conduct each robustness check for each of our health outcomes.

We first look at our standard errors, which, in our baseline specification, are clustered at the plant level, where randomisation takes place. Appendix Table A.VII Column 1 shows that clustering at the household level, i.e. at a lower and hence less conservative level, does not change our results. Clustering at the plant times year level does not change our results either (Appendix Figure A.X). Next, we look at endogenous sorting. We omitted movers in our baseline specification as movers may move away from or towards installations, depending on preferences. Movers may also bias our estimates because moving itself may have health effects. Appendix Table A.VII Column 2, however, shows that including movers leaves our results unchanged. We trimmed observations before the sixth lead and after the eighth lag as these are only identified by few observations. We now include these observations in Column 3, thereby capturing potential effects that may occur many years after a new wind turbine was built. As shown, there is no evidence for such effects. Finally, in Columns

[26] See upper part of Table A.IX for the corresponding average treatment effects.

[27] We also implemented the two-stage difference-in-differences framework by Gardner (2022) and Gardner and Butts (2022) as an alternative to Sun and Abraham (2021). This framework identifies group and period effects in a first stage from the sample of untreated observations and, in a second stage, identifies treatment effects by comparing treated and untreated outcomes after removing these group and period effects. We obtain qualitatively similar results using this framework (Appendix Figure A.IX).

4 and 5, we split our estimation sample into the years before and after 2010, i.e. the years in which wind power was still relatively novel and later years, whereas in Columns 6 and 7, we differentiate small from large plants, i.e. plants with a hub height below 100 metres from those with a hub height above. Especially for the latter, a potential concern could be that plants with a higher hub height may affect our control group, thereby reducing our treatment effect. Focusing on smaller plants should mitigate this concern.[28] As shown, there are no statistically significant effects (at the 5% level) across Columns 4 to 7.

Splitting Sample by Decade. Appendix Figure A.XI shows dynamic treatment effects over time when splitting our estimation sample into the years before and after 2010. Again, we find no consistent evidence of adverse health impacts. Once more, doctor visits are an exception, which temporarily increase in lags three and five after a new wind turbine was built, though only for the years before 2010 (when technology was newer).[29]

Modifying Control Group. Next, we look at whether modifying our control group changes our results. What if individuals in our control group living close to an installation (but just outside our treatment radius) are also, though slightly, affected by its presence? To answer this question, in Appendix Figure A.XII, we narrow down our control group to individuals living in 500-metre bins between 4,000 and 6,000 metres to the nearest newly built wind turbine. Again, we find little evidence of adverse health impacts across bins. As an alternative, we further modify our control group, by selectively including individuals living further away because it is even less likely that they are slightly affected by a turbine. Figure A.XIII shows little evidence of such impacts. Insignificant impacts are also obtained regardless of whether we include or exclude urban counties (Appendix Figure A.XIV).

Modifying Treatment Group. Next, we vary our treatment radius in Figure A.XV. As seen, we find no evidence of adverse health impacts within 3,000 or 6,000 metres either. An exception appears to be 2,000 metres, where we detect a higher number of doctor visits for lags two, three, and four post-treatment, yielding a small average effect below 10% of a standard deviation (Table A.VII Column 8). We similarly observe negative, temporary impacts on general health and self-assessed health at $t = 4$. There also seems to be a slight deterioration of mental health, though we observe a violation of the common trend assumption here.

As we find suggestive evidence for temporal, negative impacts on some health outcomes within a distance of 2,000 metres, we also look at our secondary outcomes as often cited mechanisms. Appendix Figure A.VIII shows that we find no consistent effects on either happiness, sadness, anxiety, or anger, nor on the number of hours respondents report to sleep or their sleep satisfaction within a distance of 2,000 metres.[30]

[28] In another robustness check, we additionally controlled for hub height, which left our results unchanged (Appendix Figure A.XVII). They also remained unchanged when controlling for distance to the nearest installation or for the size of a wind park, if there are several installations.

[29] Here, we also see a temporal effect for physical health at $t = 4$ for the years since 2010.

[30] See lower part of Table A.IX for the corresponding average treatment effects.

Controls. Finally, Appendix Figure A.XVI shows that excluding and including various fixed effects (i.e. county, federal state, year, federal state times year, and individual fixed effects) does not change our results. Our results also do not change with the inclusion of fixed effects for different distance bins around newly built wind turbines (e.g. a fixed effect for all households that are located within 1,000 metres to the nearest installation, another for all households that are located within 1,000-2,000 metres, and so on). Appendix Figure A.XVII shows that including no controls at all yields, likewise, no consistent negative impacts.

6 Additional Analysis: Suicides

We move on to an alternative approach for measuring potential adverse health impacts. In particular, we use suicide rates as an extreme outcome of mental distress, as has been used for air pollution in the US (Molitor, Mullins, and White, 2023) or high temperatures in the US and Mexico (Burke et al., 2018). The advantage of information on suicides is that it relies on administrative records as opposed to self-reports and that it is consistently measured across a population over time. In doing so, we follow Zou (2020), who exploits administrative data on 800 wind farms and suicides at the county level in the US from 2001 to 2013 in a spatial difference-in-differences design with two-way fixed-effects estimators. The author finds significant increases in suicide rates in counties closer to wind farms. In what follows, we replicate our analysis for annual suicides per million population in the 401 counties of Germany. The Statistical Offices of the German federal states provided us with the data.

We control for covariates shown in Appendix Table B.I. These include unemployment per capita, GDP per capita, and the average age, which are obtained from INKAR (2023).[31] We further include county and federal state times year fixed effects.[32]

Table 2 Column 1 presents our results using the robust estimator by Sun and Abraham (2021). It shows differences in suicides per million population between treated counties (those with at least one newly built wind turbine) *versus* non-treated counties (those with no wind turbines).[33] In our

[31] Appendix Table B.II shows normalised differences between treated and never-treated counties. We are not particularly concerned about differences greater than 0.25 for GDP per capita (which Imbens and Wooldridge, 2009 suggest as a threshold for covariate imbalance) as our county fixed effects account for GDP imbalances which should mainly be time-invariant. We also control for the log-transformed level of suicides, lagged by 10 years. This allows us to compare counties that had similar suicide levels in the past. As we trim our data to observations with six leads before and eight lags after a new wind turbine was built, this only includes lagged suicide information before treatment.

[32] County fixed effects capture time-invariant county-specific determinants of suicides, whereas federal state times year fixed effects capture characteristics that vary on the federal state level and change over time, for example changes in the healthcare system.

[33] Appendix Figure B.I Panel A illustrates that there are many counties with at least one wind turbine in 2000, i.e. always treated counties. In our estimations, we focus on counties without a wind turbine in 2000 as only these allow for inference. Appendix Figure B.I Panel C gives a first indication that the average number of suicides per million between counties with and without installations in 2000 follows a similar trend. Figure B.II Panel A shows the number of counties that are treated

baseline specification, we focus on non-urban counties as wind turbines are mainly installed there.[34] We find no statistically significant differences in suicides between treated and non-treated counties.

Table 2: Wind turbines on suicides.

Treatment	At least one turbine	Ten or more turbines	0.1 or more turbines per sqkm
Dependent Variable:		Suicides per million population	
	(1)	(2)	(3)
Variable			
ATT	0.37	-0.20	-0.01
	(1.2)	(1.2)	(1.2)
Controls	Yes	Yes	Yes
Fixed-effects			
County	Yes	Yes	Yes
State-Year	Yes	Yes	Yes
Statistics			
Adjusted R^2	0.959	0.929	0.937
Observations	1,310	4,016	7,207
N treated	74	132	74
N never treated	18	129	317

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; clustered (county) standard-errors in parentheses;
Estimates based on Sun and Abraham (2021)
Controls are GDP per capita, unemployment rate, average age and the log of number of suicides lagged by 10 years.
In column (1), we focus on non-urban areas only and neglect counties with a turbine installed in 2000.
In column (2), we neglect observations with between 4 and 9 turbines and those with 10 or more turbines in 2000.
In column (3), we neglect counties with more than 0.1 turbines per sqkm in 2000.
In column (3), we also neglect observations between 0.075 and 0.1 turbines per sqkm.

Next, we look at treatment effects over time. Appendix Figure B.III Panel A shows the estimates from our baseline specification implemented as an event study, with six leads before and eight lags after the first wind turbine is built. As before, the period in which an installation is built is normalised to zero. A visual inspection of the leads indicates no difference in time trends between our treatment and control group, which suggests common trend behaviour.[35]

Suicides are extreme events. It could be that potential effects only emerge from more than one installation. We thus increase the threshold which we regard as treatment. Table 2 Columns 2 and 3 reveal no effect, neither for ten or more installations nor for counties that reach an installation density of 0.1 or more per square kilometre.[36] The threshold of 0.1 installations per square kilometre

by year, Panel B the number of counties that are never treated. We observe that the number of counties that are treated is largest at the beginning of our observation period. In line with this observation, Panel C shows the cumulative density of counties that are treated by year, with a much steeper increase during the first years. This is in line with Figure A.II and Figure A.III, which show the frequencies and cumulative densities for our analyses of self-reported health outcomes.

[34]Concentrating on non-urban counties allows us to analyse a homogeneous group of counties. Nevertheless, we include urban counties in a robustness check below.

[35]Appendix Figure B.III also indicates a common trend before treatment based on our two-way fixed effects estimator.

[36]We drop observations close to thresholds. In Column 2, we neglect observations with between three and nine installations and counties with an installation in 2000. In Column 3, we drop counties with more than 0.1 installations per square kilometre in 2000 and observations with between 0.075 and 0.1 installations per square kilometre. In Table 1

indicates a high turbine density. The value is very close to the 90th percentile of 0.098 installations per square kilometre (for the pooled dataset of counties between 2000 and 2020). A visual inspection of the corresponding event studies in Appendix Figure B.III, Panels B and C, reveals no difference in time trends between our treatment and control group, neither before nor after treatment, for both alternative treatment thresholds.

Table B.III shows that our results are robust in various dimensions. We take the treatment threshold of at least one wind turbine as our baseline specification. In Column 1, we find no evidence for effects using the log-transformed level of suicides as an outcome. This approach allows for directly capturing potentially heterogeneous effects for counties with different suicide levels. In Columns 2 and 3, we focus on suicides per million population again, controlling for the number and the log-transformed number of wind turbines, respectively. Still, we find no evidence for effects. In Column 4, we include urban areas. Again, there is no evidence for an increase in suicides after wind turbine construction. In Column 5, we only focus on the years between 2000 and 2009 (when wind turbines were smaller), and in Column 6, the years between 2010 and 2020 (when they were larger). There is no evidence of effects in either period. In Column 7, we also look at wind turbines close to a county (within 4,000 metres) as treatment.[37] Again, this alternative definition of treatment does not reveal any effects. Finally, in Column 8, we also include counties with a wind turbine in 2000, i.e. always-treated counties. This approach only reveals a correlation but allows for including counties in the north of Germany, where installations are common due to more favourable wind conditions near the North Sea. If there is an effect of wind turbines on suicides, we would still expect significant effects. Again, we find no difference in suicides per population between counties with and without wind turbines.

7 Discussion and Conclusion

Our findings cast doubt on systematic, negative causal effects of wind turbines on local residents. To arrive at these, we used a representative panel linked to nationwide data on wind turbines based on precise geographical coordinates and a spatial difference-in-differences design that exploited the staggered rollout of installations. We also took advantage of exogenous wind direction data. We used both two-way fixed-effects estimators and the robust estimator by Sun and Abraham (2021). To our knowledge, we are the first to do so.

However, our study has several limitations. For one, while reliance on secondary data and quasi-experimental methods avoids priming respondents and ensures external validity, our inference is

Columns 2 and 3, we include urban counties in order to have a large enough control group.

[37] Appendix Figure B.I Panel B is a close-up of the federal state of *Schleswig-Holstein*. For example, blue dots indicate a wind turbine relevant for *Pinneberg* county (in yellow). In Table B.III Column 7, we consider not only blue dots within the county but also those within 4,000 metres distance to the county border.

limited when it comes to residents who live in very close proximity to installations. Similarly, our sample size requires us, in most cases, to estimate average effects. Although these are most relevant for policy, they may cast potentially important heterogeneities. For example, evidence in psychology shows that some individuals are more sensitive to their environment than others (Pluess et al., 2023). Unfortunately, we have no data on such individual differences. Finally, the context of Germany, where residents are aware of climate change and generally favourably disposed toward renewables, may impose limitations when it comes to transferability of findings to other countries.

Although we find little evidence of adverse health impacts, this does not preclude that other externalities do not exist, such as on house prices (cf. Gibbons, 2015; Quentel, 2023) or subjective wellbeing (cf. Möllendorff and Welsch, 2017; Krekel and Zerrahn, 2017). Furthermore, concern or fear of potential negative health consequences is a real phenomenon (cf. Michaud et al., 2016), with actual consequences, including local protests or voting outcomes (Financial Times, 2021). However, recent studies suggest that residents develop more favourable attitudes towards the technology *after* having been exposed to it (Bayulgen et al., 2021; Urpelainen and Zhang, 2022), suggesting learning about one's preferences or rationalisation *ex-post*. In fact, Baxter, Morzaria, and Hirsch (2013) find that residents in communities without wind turbines are *more* concerned about the technology and show *lower* support than residents in communities with installations. Finally, wind turbines can also have positive externalities, for example on local fiscal outcomes or air pollution (Kahn, 2013).

Local resistance may slow the transition to renewable energy and risks missing climate goals, which is why concerns must be taken seriously and addressed by policy, for example by actively involving resident communities in local planning and decision-making processes and disseminating targeted, factual information grounded in scientific evidence. Promising avenues for future research include how to achieve fairness and procedural utility during new build projects, as well as distributional equity in sharing the burden of external effects amongst the general population.

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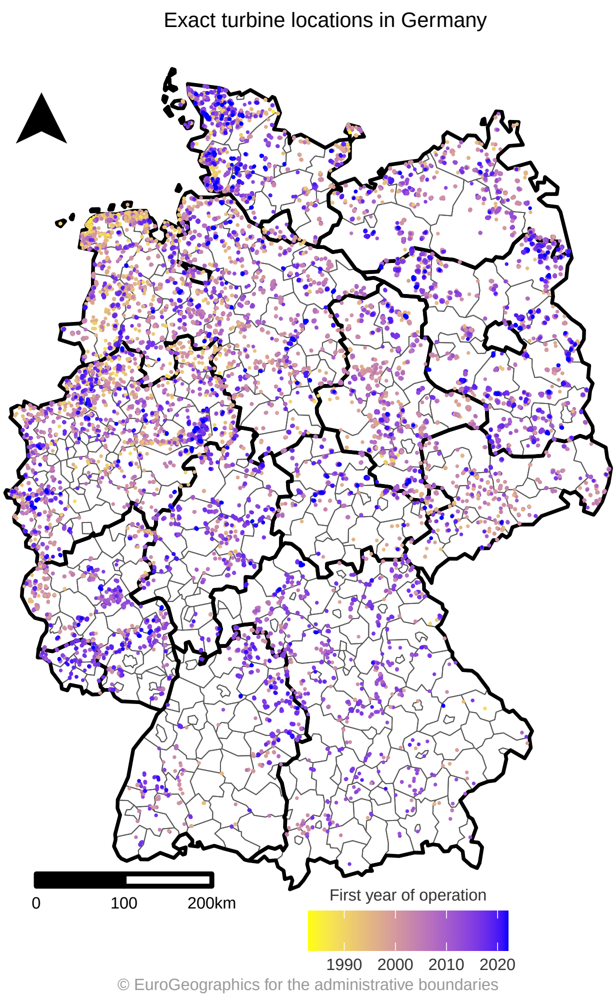
Appendix

Contents

A Health

A.1 Illustrations



Each dot indicates a turbine coloured by the first year of operation. Thick black lines indicate the borders of federal states.

Figure A.I: Exact locations of on-shore wind turbines in Germany until 2022.

A.2 Descriptives

Table A.I: Summary statistics.

Variable	Mean	Median	SD	Minimum	Maximum	Observations
Outcomes						
General Health	49.11	45.61	9.86	24.85	66.37	29236
Mental Health: Summary Scale	51.19	52.95	9.84	3.11	79.33	29236
... General	51.13	50.26	9.76	19.73	68.58	29236
... Role-Emotional Functioning	50.39	58.08	10.02	13.34	58.08	29236
... Social Functioning	50.18	57.12	10.05	14.69	57.12	29236
... Vitality	49.67	48.71	9.94	26.82	70.60	29236
Physical Health: Summary Scale	48.21	49.91	10.21	9.21	75.46	29236
... Role-Physical Functioning	49.05	50.27	10.42	21.92	59.72	29236
... Physical Functioning	48.47	50.58	10.36	27.25	58.35	29236
... Bodily Pain	49.17	50.64	10.31	23.00	59.85	29236
Self-Assessed Health	3.34	3.00	0.95	1.00	5.00	29236
Doctor Visits	9.56	4.00	15.23	0.00	360.00	28744
Covariates						
Age	53.57	54.00	16.68	16.00	99.00	29236
Gender [1: male, 2: female]	1.51	2.00	0.50	1.00	2.00	29235
Is Married	0.70	1.00	0.46	0.00	1.00	29236
Is in Civil Partnership	0.00	0.00	0.03	0.00	1.00	29236
Is Divorced	0.07	0.00	0.25	0.00	1.00	29236
Is Widowed	0.07	0.00	0.26	0.00	1.00	29236
Is Unemployed	0.04	0.00	0.20	0.00	1.00	29236
Is on Parental Leave	0.01	0.00	0.09	0.00	1.00	29236
Is in Training	0.02	0.00	0.13	0.00	1.00	29236
Is Part-Time Employed	0.13	0.00	0.33	0.00	1.00	29236
Is Full-Time Employed (baseline)	0.35	0.00	0.48	0.00	1.00	29236
Number of Individuals in Household	2.78	2.00	1.30	1.00	13.00	29236
Number of Children in Household	0.51	0.00	0.94	0.00	8.00	29236
Is Owner	0.68	1.00	0.47	0.00	1.00	29236
Is Renter (baseline)	0.32	0.00	0.47	0.00	1.00	29236
Annual Rent (in 1000)	4.01	0.00	5.71	0.00	119.99	29236
Annual Net Household Income (in 1000)	37.88	32.40	31.57	0.12	1199.99	29236

Summary statistics for outcomes are before standardising.

Table A.II: Wind power plants: summary statistics.

Variable	mean	md	sd	min	max
Power capacity [MW]	2.02	2	1.21	0	9.0
Hub height [m]	95.67	98	32.12	2	197.5
Rotor diameter [m]	85.86	82	30.03	0	180.0

Summary statistics for baseline regression.

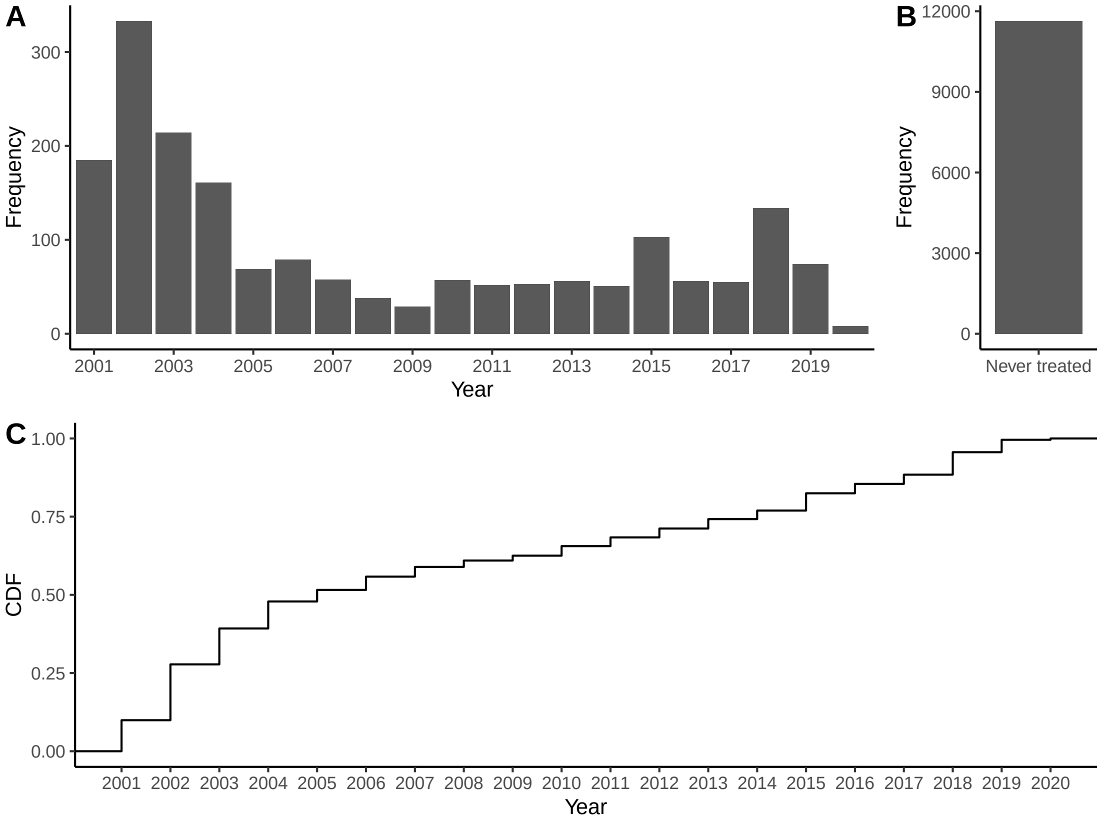
Table A.III: Wind power plants: summary statistics per year.

Variable	year	mean	md	sd	min	max
Power capacity [MW]	2002	1.37	1.50	0.52	0.01	3.45
	2010	1.87	2.00	0.74	0.01	7.58
	2015	2.67	2.97	0.61	0.01	3.50
	2020	3.64	3.45	1.16	0.80	7.35
Hub height [m]	2002	80.20	78.00	16.29	10.00	184.00
	2010	91.80	98.00	24.60	10.00	142.00
	2015	118.33	128.00	25.99	6.00	156.00
	2020	132.61	137.00	24.10	58.91	169.00
Rotor diameter [m]	2002	65.07	70.00	14.03	3.30	150.00
	2010	77.90	82.00	15.50	29.70	127.00
	2015	102.92	112.00	17.49	5.00	131.00
	2020	123.92	126.00	21.74	52.90	158.00

Summary statistics for baseline regression.

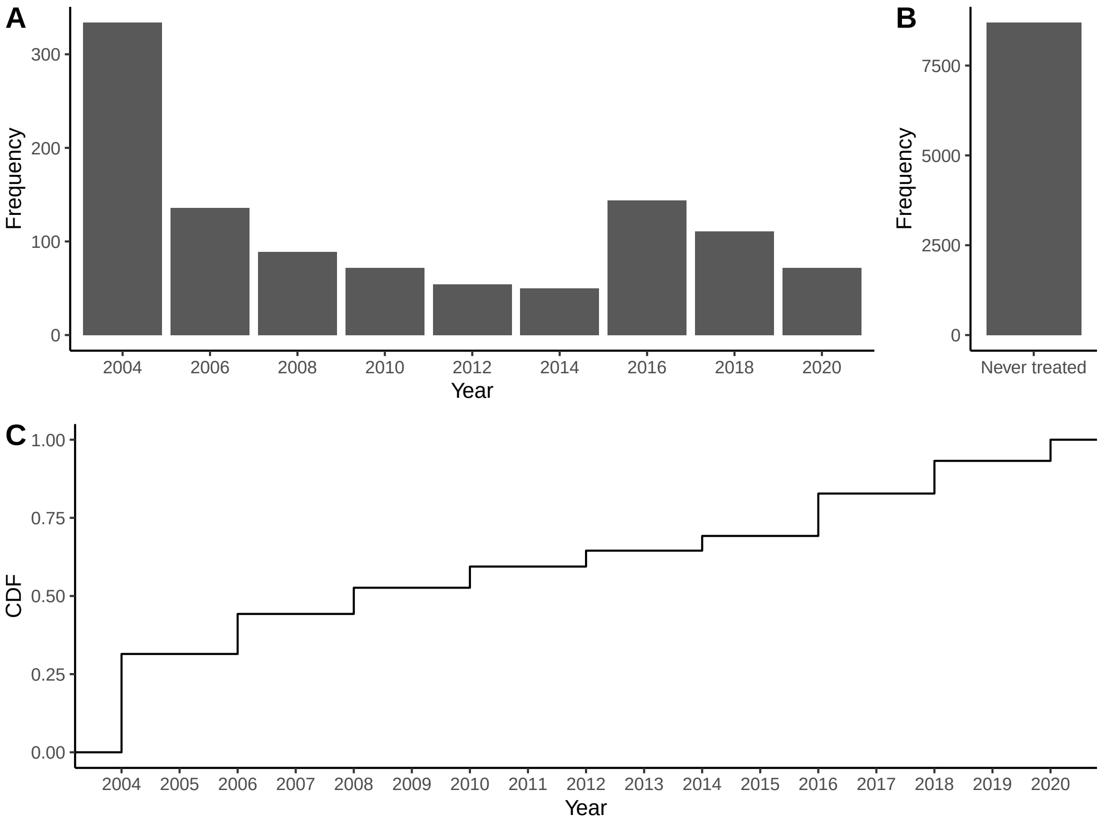
Table A.IV: Normalised differences between treatment (4 km) and control (4-8 km) group.

	Mean		Variance		
Variable	Treatment	Control	Treatment	Control	Normalised Difference
Age	55.2	52.93	250.56	289.38	0.1
Gender [1: male, 2: female]	1.5	1.51	0.25	0.25	0.02
Is Married	0.74	0.69	0.19	0.21	0.08
Is in Civil Partnership	0	0	0	0	0.01
Is Divorced	0.06	0.06	0.05	0.06	0.02
Is Widowed	0.07	0.07	0.07	0.07	0.01
Is Unemployed	0.04	0.04	0.04	0.04	0.02
Is on Parental Leave	0	0.01	0	0.01	0.04
Is in Training	0.02	0.02	0.02	0.02	0.02
Is Part-Time Employed	0.11	0.13	0.1	0.11	0.03
Is Full-Time Employed (baseline)	0.35	0.35	0.23	0.23	0.01
Number of Individuals in Household	2.71	2.81	1.48	1.75	0.05
Number of Children in Household	0.42	0.53	0.73	0.9	0.09
Is Owner	0.76	0.66	0.18	0.22	0.16
Is Renter (baseline)	0.24	0.33	0.18	0.22	0.15
Annual Rent (in 1000)	4.1	3.87	29	32.14	0.03
Annual Net Household Income (in 1000)	36.15	38.08	450.96	1085.21	0.05
Observations	8178	23217			



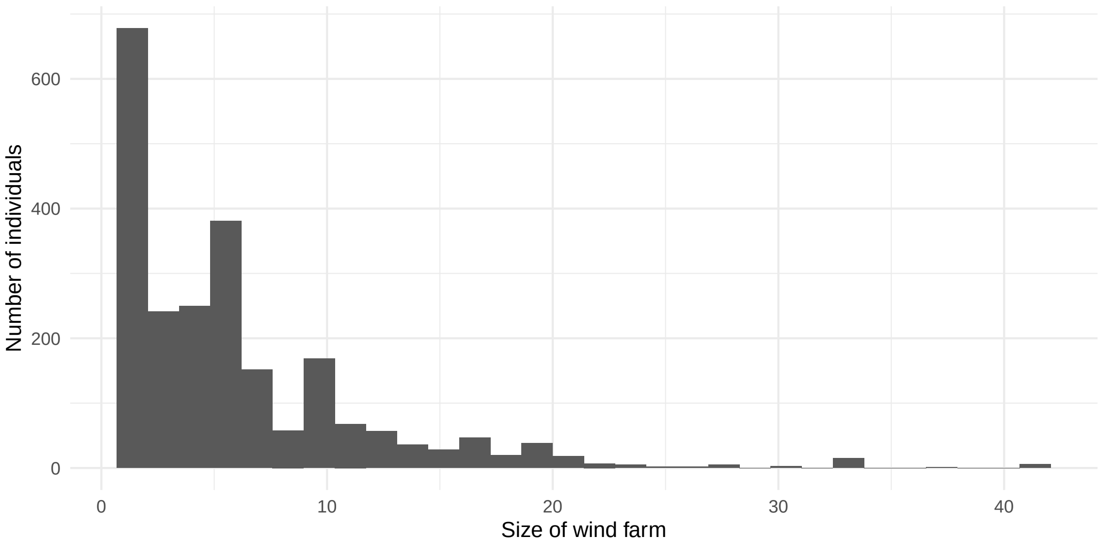
The figure relates to our baseline specification (0-4 km treatment group, 4-8 km control group, outcome: self-assessed health (Table 1 Column 4)). In *Panel A*, we show the frequency of firstly treated individuals (new wind turbine installed nearby individual by year). In *Panel B*, we show the frequency of never-treated individuals. *Panel C*, the cumulative density function of individuals from Panel A.

Figure A.II: Frequency (Panel A) and cumulative density (Panel B) of treated individuals by year and frequency of never treated individuals (Panel C) for outcome self-assessed health.



The figure relates to our baseline specification (0-4 km treatment group, 4-8 km control group, outcome: general health (Table 1 Column 1)). In *Panel A*, we show the frequency of firstly treated individuals (new wind turbine installed nearby individual by year). In *Panel B*, we show the frequency of never treated individuals. *Panel C*, the cumulative density function of individuals from Panel A.

Figure A.III: Frequency (Panel A) and cumulative density (Panel B) of treated individuals by year and frequency of never treated individuals (Panel C) for outcome general health.



The figure depicts the number of treated individuals by the size of the wind park. As seen, most individuals are treated by single wind turbines or by wind farms consisting of less than five wind turbines.

Figure A.IV: Treatment intensity.

A.3 Results

A.3.1 Static – Alternative Outcomes

Table A.V: Average Treatment Effects: Mental Health.

	SF-12 Health Survey: Mental Health			
Dependent Variable:	General (1)	Role-Emotional Functioning (2)	Social Functioning (3)	Vitality (4)
Variable				
Treated 0-4 km	0.02	-0.03	0.010	-0.01
	(0.04)	(0.04)	(0.04)	(0.04)
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Individual	Yes	Yes	Yes	Yes
county_code_reconstructed	Yes	Yes	Yes	Yes
State-Year	Yes	Yes	Yes	Yes
Statistics				
Adjusted R^2	0.480	0.456	0.413	0.446
Obs.	29,236	29,236	29,236	29,236
N treated	740	740	740	740
N never treated	8,638	8,638	8,638	8,638

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; clustered (plant) standard-errors in parentheses; treatment group 0-4 km; control group 4-8 km. Outcomes in z-scores; more indicates better health; estimates based on Sun and Abraham (2021).*

Table A.VI: Average Treatment Effects: Physical Health.

	SF-12 Health Survey: Physical Health		
Dependent Variable:	Role-Emotional Functioning (1)	Physical Functioning (2)	Bodily Pain (3)
Variable			
Treated 0-4 km	-0.007	-0.007	-0.04
	(0.03)	(0.03)	(0.04)
Controls	Yes	Yes	Yes
Fixed-effects			
Individual	Yes	Yes	Yes
County	Yes	Yes	Yes
State-Year	Yes	Yes	Yes
Statistics			
Adjusted R^2	0.536	0.652	0.519
Obs.	29,236	29,236	29,236
N treated	740	740	740
N never treated	8,638	8,638	8,638

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; clustered (plant) standard-errors in parentheses; treatment group 0-4 km; control group 4-8 km. Outcomes in z-scores; more indicates better health (but for bodily pain more indicates worse); estimates based on Sun and Abraham (2021).*

A.3.2 Static – Robustness

Table A.VII: Robustness Checks.

	SF-12 Health Survey: General Health Summary Scale							
	SE Clust. at household	Incl. movers	Incl. all leads and lags	Years < 2010	Years $\geq$ 2010	Small plants only (< 100m hub height)	Large plants only ($\geq$ 100m)	Treatment radius 2 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Treated	0.05	0.05*	0.04	0.06	0.02	0.07*	0.02	-0.05
	(0.04)	(0.03)	(0.03)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
Fixed-effects								
Individual, County and State-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Adjusted R^2	0.591	0.584	0.587	0.614	0.590	0.593	0.590	0.592
Obs.	29,236	46,214	30,247	10,577	16,986	27,455	27,065	27,114
N treated	740	1,015	741	371	253	408	329	340
N never treated	8,638	14,085	8,638	3,454	6,640	8,638	8,638	8,638

	SF-12 Health Survey: Mental Health Summary Scale							
	SE Clust. at household	Incl. movers	Incl. all leads and lags	Years < 2010	Years $\geq$ 2010	Small plants only (< 100m hub height)	Large plants only ($\geq$ 100m)	Treatment radius 2 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Treated	0.0007	0.02	-0.007	0.04	-0.008	0.01	-0.02	-0.12**
	(0.04)	(0.03)	(0.04)	(0.05)	(0.07)	(0.05)	(0.05)	(0.06)
Fixed-effects								
Individual, County and State-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Adjusted R^2	0.468	0.468	0.467	0.509	0.458	0.463	0.465	0.461
Obs.	29,236	46,214	30,247	10,577	16,986	27,455	27,065	27,114
N treated	740	1,015	741	371	253	408	329	340
N never treated	8,638	14,085	8,638	3,454	6,640	8,638	8,638	8,638

	SF-12 Health Survey: Physical Health Summary Scale							
	SE Clust. at household	Incl. movers	Incl. all leads and lags	Years < 2010	Years $\geq$ 2010	Small plants only (< 100m hub height)	Large plants only ($\geq$ 100m)	Treatment radius 2 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Treated	-0.004	-0.004	-0.008	0.005	-0.07	0.009	-0.02	0.007
	(0.04)	(0.03)	(0.03)	(0.05)	(0.06)	(0.04)	(0.04)	(0.04)
Fixed-effects								
Individual, County and State-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Adjusted R^2	0.665	0.657	0.660	0.685	0.666	0.667	0.668	0.666
Obs.	29,236	46,214	30,247	10,577	16,986	27,455	27,065	27,114
N treated	740	1,015	741	371	253	408	329	340
N never treated	8,638	14,085	8,638	3,454	6,640	8,638	8,638	8,638

	Self-Assessed Health							
	SE Clust. at household	Incl. movers	Incl. all leads and lags	Years < 2010	Years $\geq$ 2010	Small plants only (< 100m hub height)	Large plants only ($\geq$ 100m)	Treatment radius 2 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Treated	0.02	0.006	0.01	0.04*	0.005	0.03	-0.007	-0.03
	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)
Fixed-effects								
Individual, County and State-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Adjusted R^2	0.601	0.589	0.595	0.621	0.598	0.603	0.600	0.602
Obs.	72,962	111,985	77,020	32,094	37,762	67,895	63,658	64,396
N treated	1,558	2,154	1,561	1,038	451	1,019	535	611
N never treated	11,479	17,942	11,479	4,655	8,632	11,479	11,479	11,479

	Doctor Visits							
	SE Clust. at household	Incl. movers	Incl. all leads and lags	Years < 2010	Years $\geq$ 2010	Small plants only (< 100m hub height)	Large plants only ($\geq$ 100m)	Treatment radius 2 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Treated	0.03	0.02	0.03	0.05*	-0.02	0.05	-0.02	0.07**
	(0.03)	(0.02)	(0.03)	(0.03)	(0.05)	(0.03)	(0.04)	(0.03)
Fixed-effects								
Individual, County and State-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Adjusted R^2	0.344	0.328	0.333	0.370	0.332	0.344	0.332	0.325
Obs.	71,118	108,832	75,180	32,051	35,971	66,069	61,839	62,585
N treated	1,557	2,151	1,560	1,040	448	1,018	534	609
N never treated	10,703	16,741	10,703	4,652	7,858	10,703	10,703	10,703

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; clustered (plant, unless differently) standard-errors in parentheses;*
treatment group 0-4 km (except for column (8)); control group 4-8 km; estimates based on Sun and Abraham (2021)

A.3.3 Static – Wind Directions

Table A.VIII: Wind Directions.

	SF-12 Health Survey: General Health Summary Scale			
	All	Downwind	Upwind	Down- and upwind
	(1)	(2)	(3)	(4)
Variables				
Treated 0-4 km	0.05*	0.04	0.06	0.05
	(0.03)	(0.06)	(0.05)	(0.04)
Fixed-effects				
Individual, County and State-Year	Yes	Yes	Yes	Yes
Fit statistics				
Adjusted R^2	0.591	0.592	0.595	0.595
Obs.	29,236	26,227	26,108	27,043
N treated	740	173	157	330
N never treated	8,638	8,638	8,638	8,638

	SF-12 Health Survey: Mental Health Summary Scale			
	All	Downwind	Upwind	Down- and upwind
	(1)	(2)	(3)	(4)
Variables				
Treated 0-4 km	0.0007	0.15**	0.01	0.09
	(0.04)	(0.07)	(0.07)	(0.06)
Fixed-effects				
Individual, County and State-Year	Yes	Yes	Yes	Yes
Fit statistics				
Adjusted R^2	0.468	0.459	0.464	0.465
Obs.	29,236	26,227	26,108	27,043
N treated	740	173	157	330
N never treated	8,638	8,638	8,638	8,638

	SF-12 Health Survey: Physical Health Summary Scale			
	All	Downwind	Upwind	Down- and upwind
	(1)	(2)	(3)	(4)
Variables				
Treated 0-4 km	-0.004	-0.11**	0.0009	-0.06
	(0.03)	(0.05)	(0.05)	(0.04)
Fixed-effects				
Individual, County and State-Year	Yes	Yes	Yes	Yes
Fit statistics				
Adjusted R^2	0.665	0.669	0.672	0.670
Obs.	29,236	26,227	26,108	27,043
N treated	740	173	157	330
N never treated	8,638	8,638	8,638	8,638

	Self-Assessed Health			
	All	Downwind	Upwind	Down- and upwind
	(1)	(2)	(3)	(4)
Variables				
Treated 0-4 km	0.02	0.06	0.02	0.04
	(0.02)	(0.04)	(40.6)	(0.03)
Fixed-effects				
Individual, County and State-Year	Yes	Yes	Yes	Yes
Fit statistics				
Adjusted R^2	0.601	0.601	0.604	0.602
Obs.	72,962	62,092	61,970	65,454
N treated	1,558	375	377	752
N never treated	11,479	11,479	11,479	11,479

	Doctor Visits			
	All	Downwind	Upwind	Down- and upwind
	(1)	(2)	(3)	(4)
Variables				
Treated 0-4 km	0.03	0.003	0.02	0.010
	(0.02)	(0.06)	(42.8)	(0.04)
Fixed-effects				
Individual, County and State-Year	Yes	Yes	Yes	Yes
Fit statistics				
Adjusted R^2	0.344	0.341	0.331	0.340
Obs.	71,118	60,269	60,164	63,624
N treated	1,557	373	377	750
N never treated	10,703	10,703	10,703	10,703

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; clustered (plant, unless differently state) standard-errors in parentheses; treatment group 0-4 km; control group 4-8 km; estimates based on Sun and Abraham (2021)*

A.3.4 Static – Alternative Outcomes

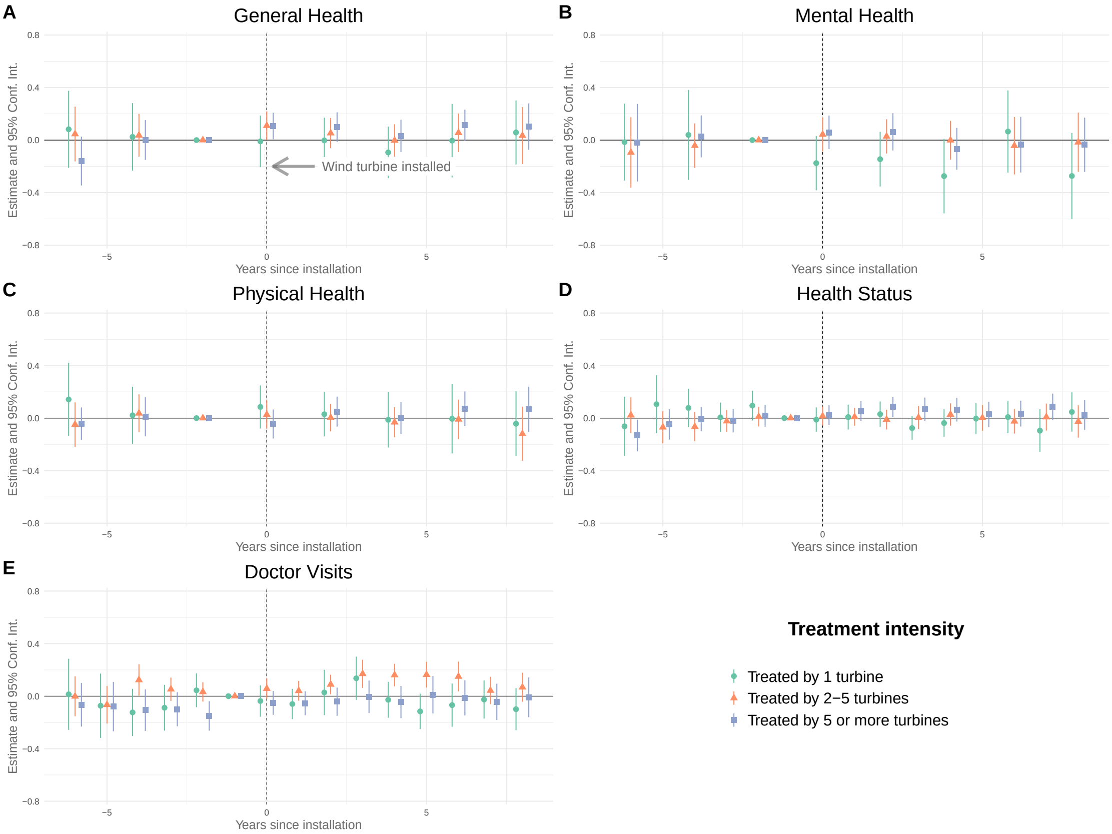
Table A.IX: Alternative Outcomes.

	Treatment 0-4 km						
	Satisfaction with Sleep (1)	Hours of Sleep on Weekday (2)	Hours of Sleep on Weekend (3)	Frequency: Happy (4)	Frequency: Sad (5)	Frequency: Anxious (6)	Frequency: Angry (7)
Variables							
Treated	0.03	-0.02	0.04	0.01	-0.08*	-0.006	0.002
	(0.04)	(0.09)	(0.08)	(0.04)	(0.04)	(0.04)	(0.04)
Fixed-effects							
Individual, County and State-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Adjusted R^2	0.566	0.571	0.578	0.462	0.397	0.432	0.405
Obs.	40,254	17,802	17,741	39,742	39,750	39,726	39,760
N treated	509	151	151	496	495	495	496
N never treated	8,234	5,548	5,548	7,965	7,966	7,966	7,964

	Treatment 0-2 km						
	Satisfaction with Sleep (1)	Hours of Sleep on Weekday (2)	Hours of Sleep on Weekend (3)	Frequency: Happy (4)	Frequency: Sad (5)	Frequency: Anxious (6)	Frequency: Angry (7)
Variables							
Treated	0.03	0.07	0.006	-0.03	0.0005	-0.01	0.007
	(0.04)	(0.13)	(0.10)	(0.06)	(0.06)	(0.05)	(0.06)
Fixed-effects							
Individual, County and State-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Adjusted R^2	0.562	0.572	0.579	0.463	0.397	0.433	0.407
Obs.	38,213	17,411	17,342	37,942	37,953	37,932	37,961
N treated	258	68	67	269	269	269	269
N never treated	8,234	5,548	5,548	7,965	7,966	7,966	7,964

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; clustered (plant, unless differently) standard-errors in parentheses;*
treatment group 0-4 km (except for column (8)); control group 4-8 km; estimates based on Sun and Abraham (2021)

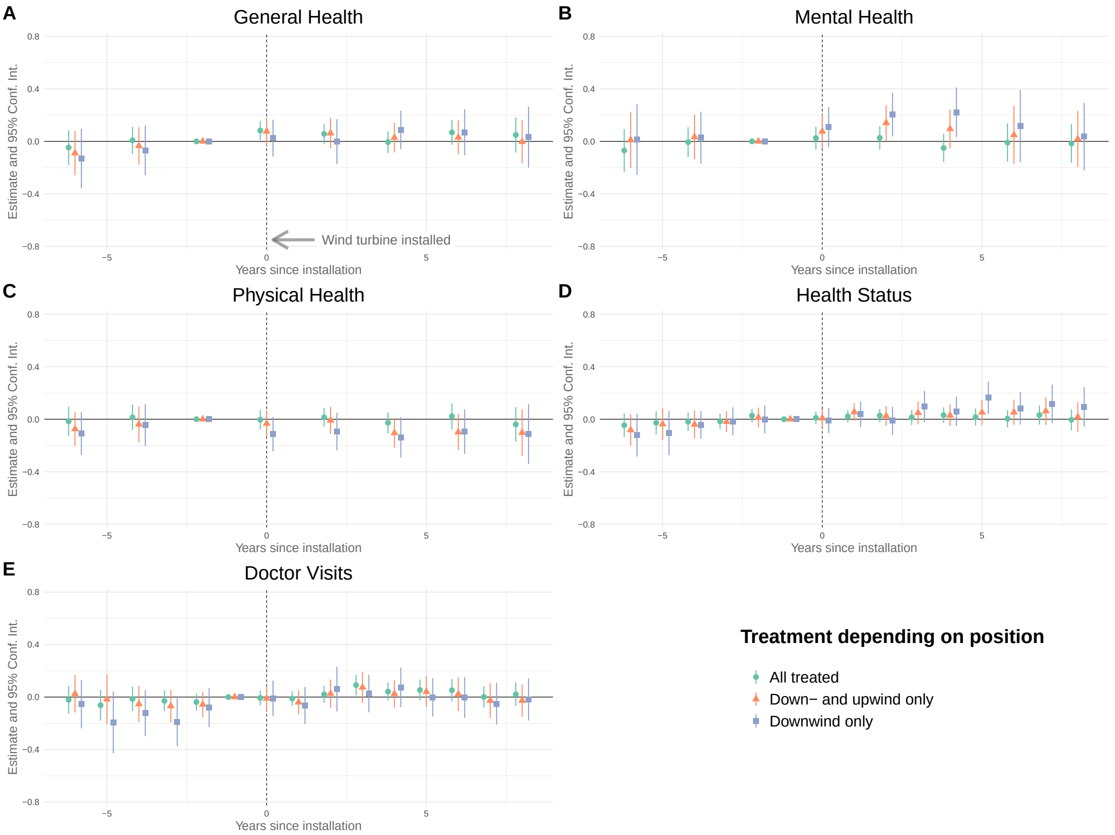
A.3.5 Dynamic – Treatment Intensity



Difference in health outcomes between individuals living nearby one or several newly built wind turbines (i.e. within 4,000 metres) and individuals further away (i.e. between 4,000 and 8,000 metres). Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse). Estimates based on Sun and Abraham (2021). The vertical bars represent the 95% confidence intervals.

Figure A.V: Treatment intensities.

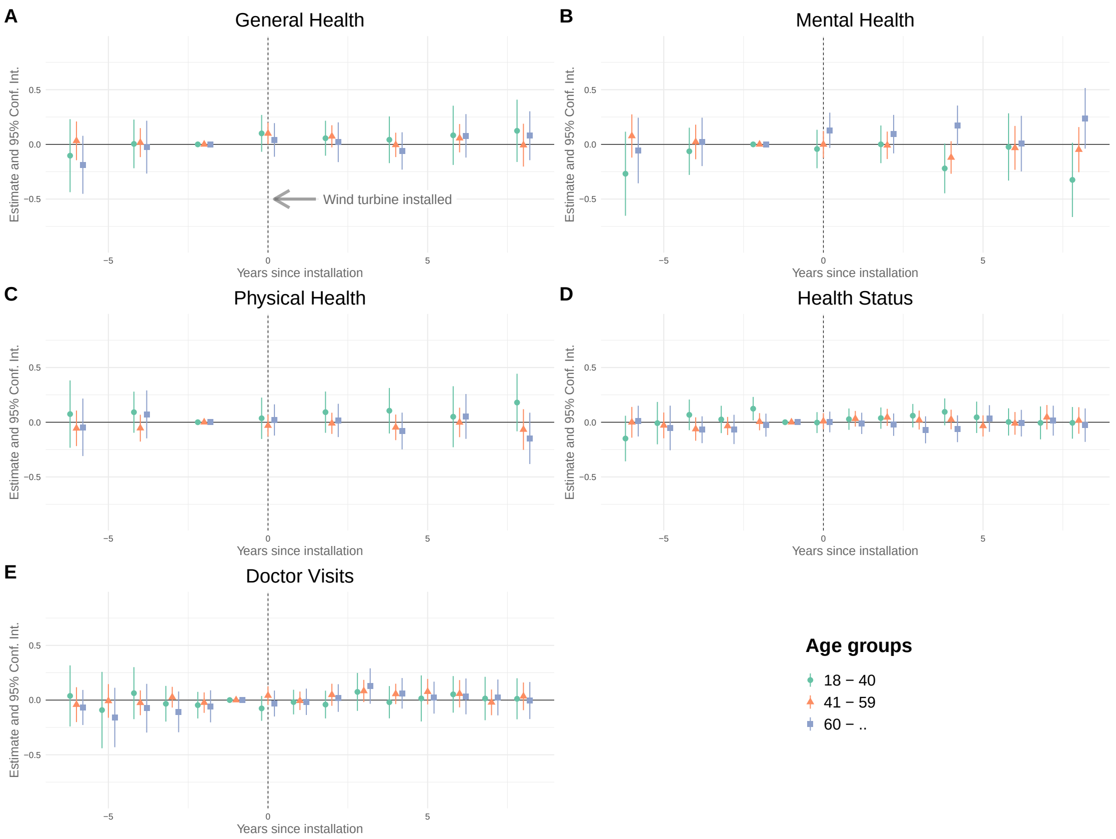
A.3.6 Dynamic – Wind Directions



Difference in health outcomes between individuals living nearby a newly built wind turbine (within 4,000 metres) and individuals further away (between 4,000 and 8,000 metres). Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse). Estimates based on Sun and Abraham (2021). The vertical bars represent the 95% confidence intervals.

Figure A.VI: Dynamic effects for different positions of treated households relative to the power plants and the dominant wind direction.

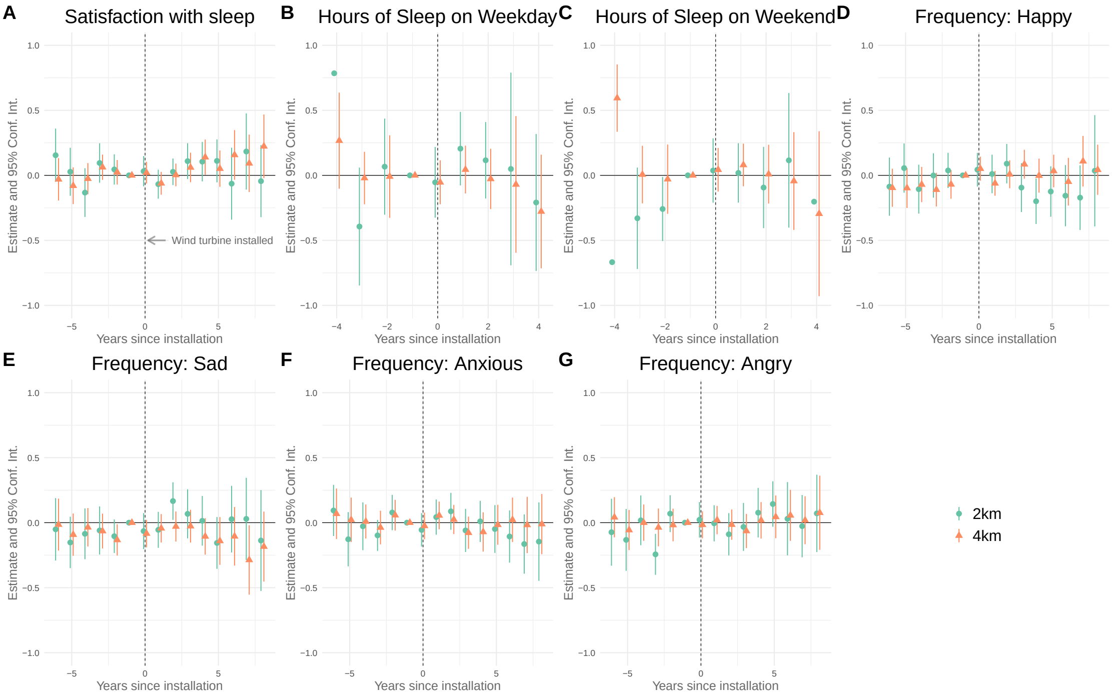
A.3.7 Dynamic – Different Age Groups



Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 metres) and individuals further away (i.e. between 4,000 and 8,000 metres). Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse). Estimates based on Sun and Abraham (2021). The vertical bars represent the 95% confidence intervals.

Figure A.VII: Dynamic effects for different age groups.

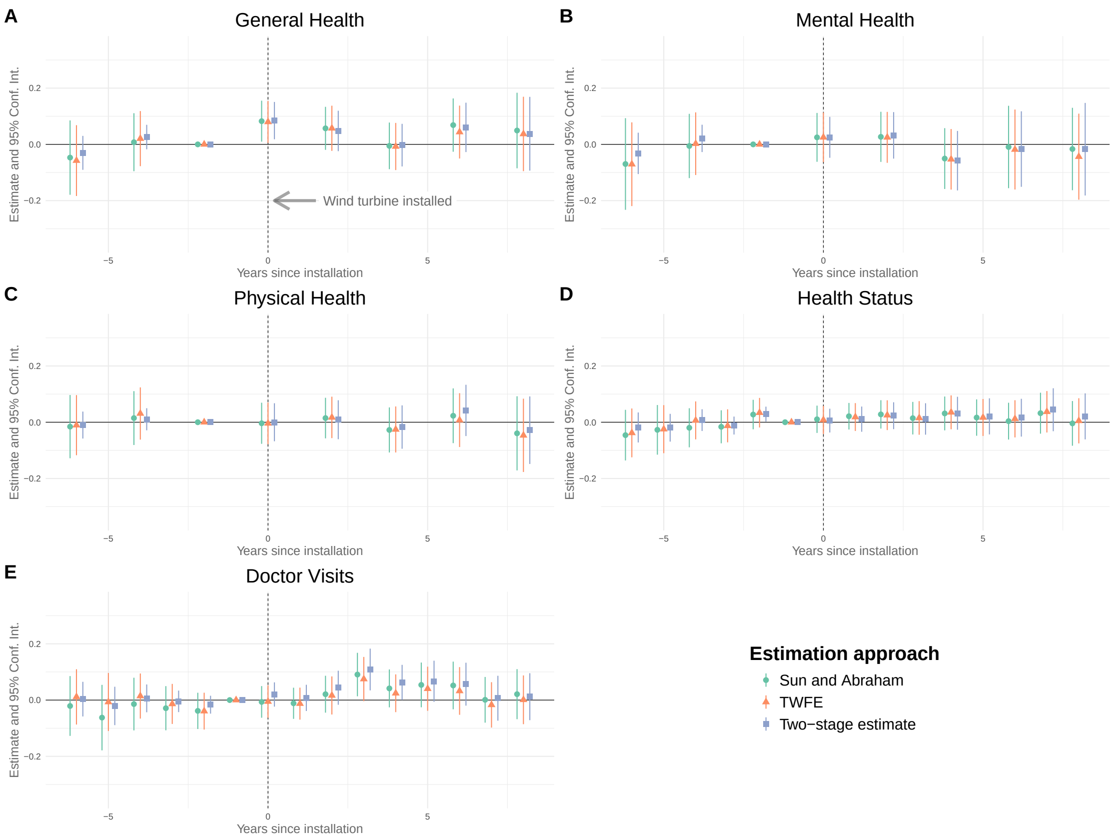
A.3.8 Dynamic – Alternative Outcomes



Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 2,000/4,000 metres) and individuals further away (i.e. between 4,000 and 8,000 metres). Panels A-C as of 2008 (until 2013 for B and C), Panels D-G as of 2007. Outcomes are in z-scores. More indicates better health (but for panels E, F, G more indicates worse). Estimates based on Sun and Abraham (2021). The vertical bars represent the 95% confidence intervals.

Figure A.VIII: Dynamic effects for alternative outcomes.

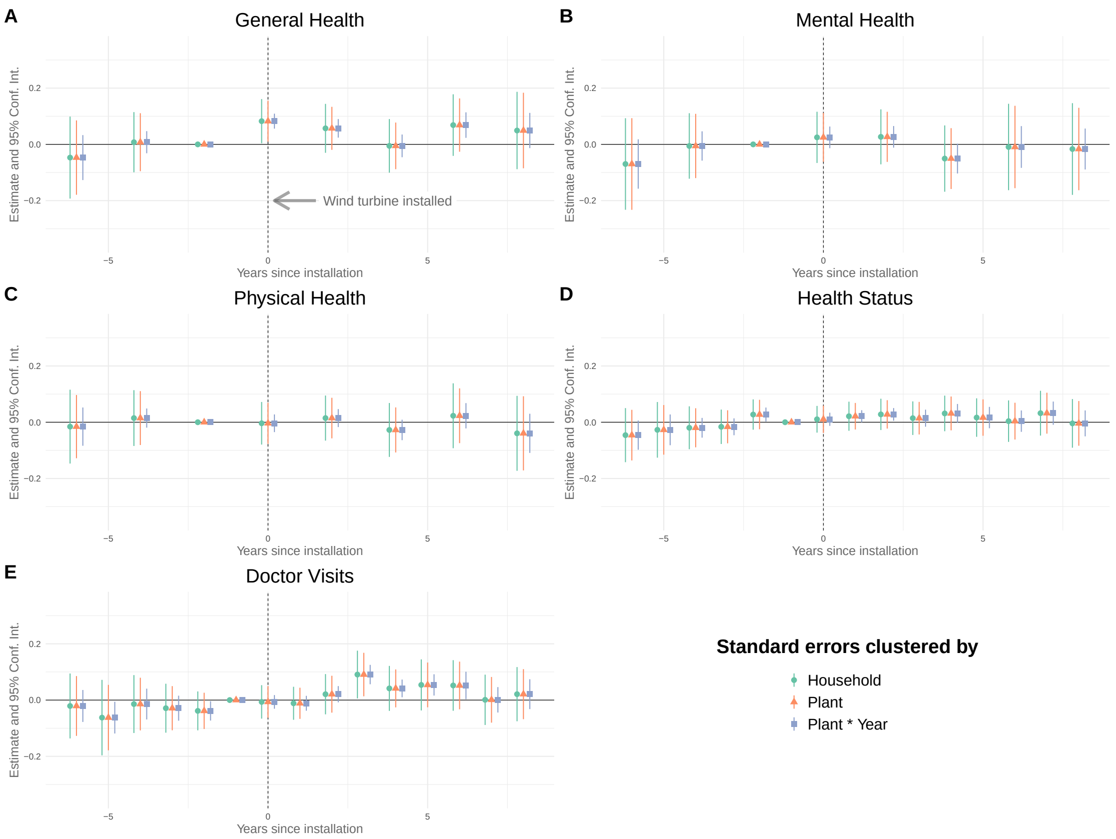
A.3.9 Dynamic – Alternative Estimators



Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 metres) and individuals further away (i.e. between 4,000 and 8,000 metres). Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse). The vertical bars represent the 95% confidence intervals.

Figure A.IX: Dynamic effects for different estimators.

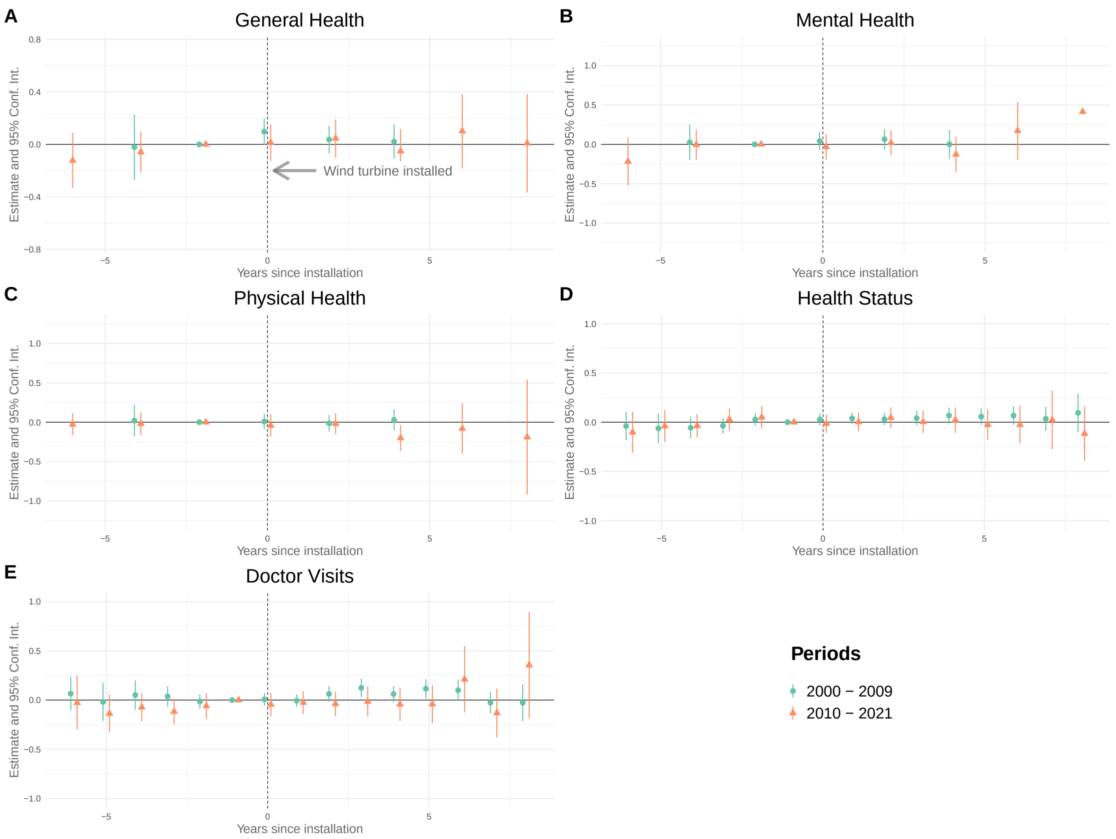
A.3.10 Dynamic – Alternative Standard Errors



Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 metres) and individuals further away (i.e. between 4,000 and 8,000 metres). Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse). Estimates based on Sun and Abraham (2021). The vertical bars represent the 95% confidence intervals.

Figure A.X: Dynamic effects for different clustering of standard errors.

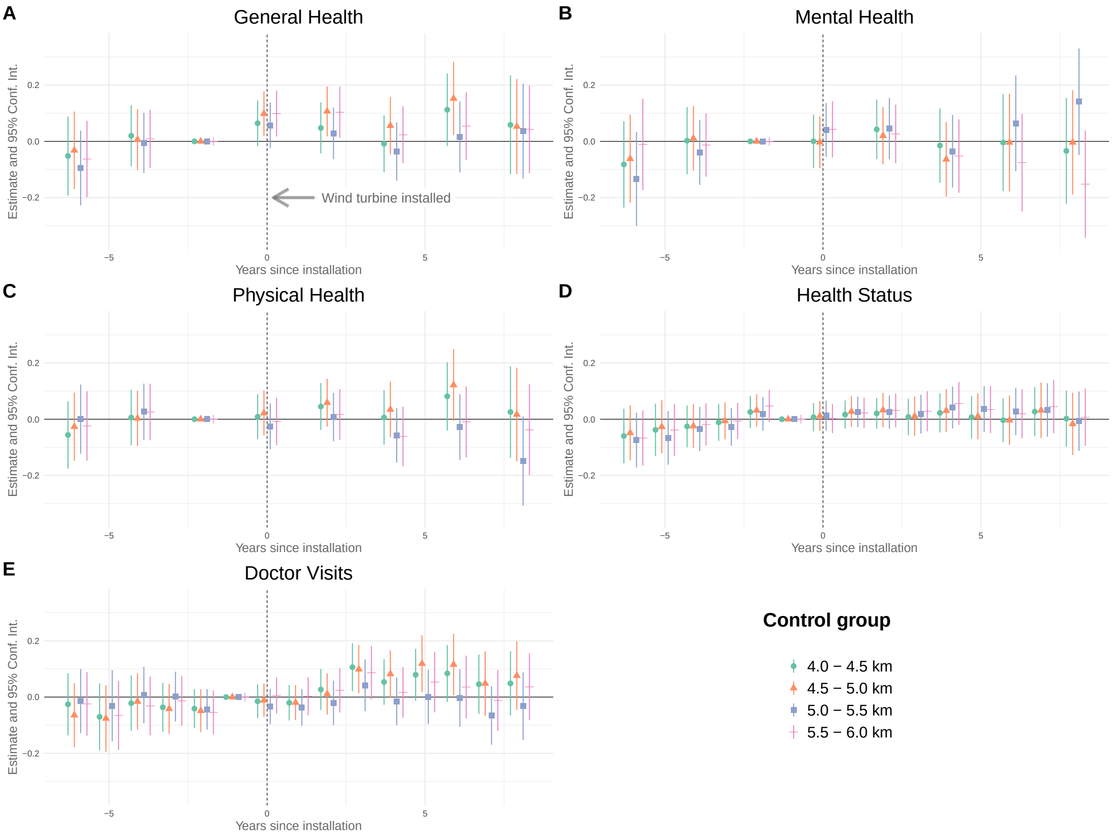
A.3.11 Dynamic – Early and Late Sample



Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 metres) and individuals further away (i.e. between 4,000 and 8,000 metres). Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse). Estimates based on Sun and Abraham (2021). The vertical bars represent the 95% confidence intervals.

Figure A.XI: Dynamic effects for different sample periods.

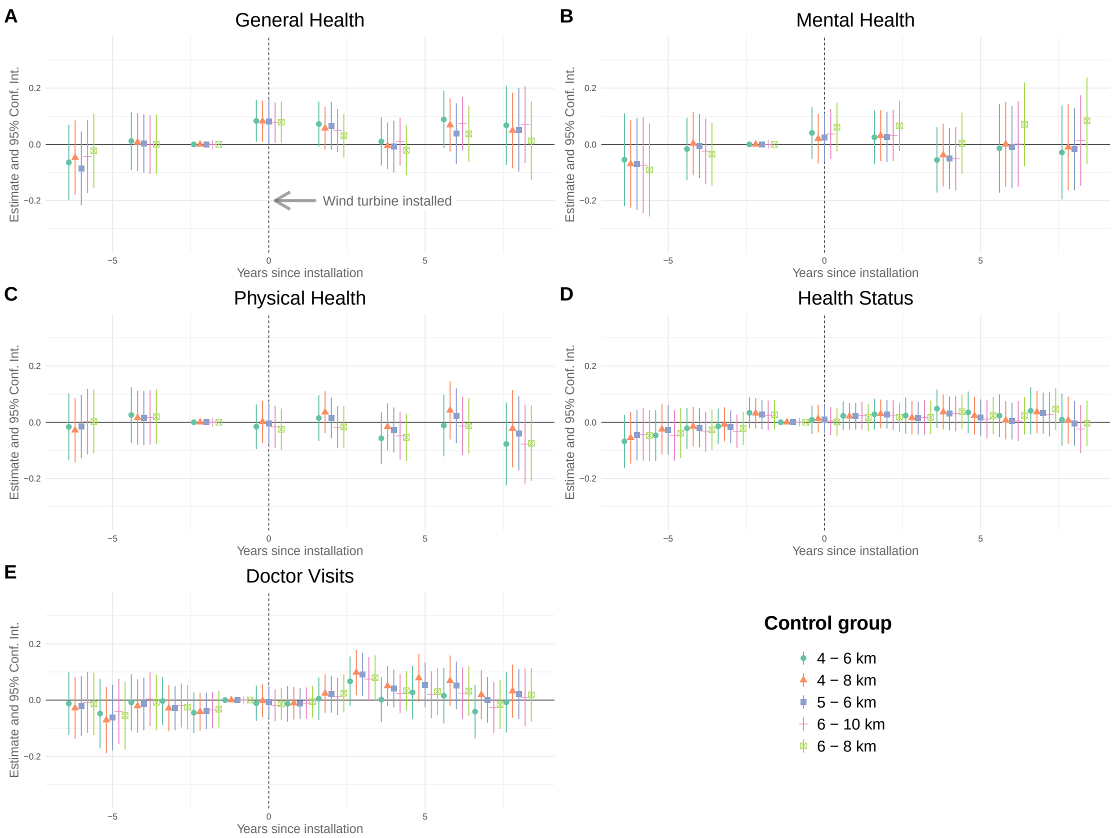
A.3.12 Dynamic – Alternative Control Groups Nearby



Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 metres) and individuals further away (i.e. between 4,000 and 4,500 metres, within 4,000 and 5,000 metres, within 4,500 and 5,000 metres, within 5,000 and 5,500 metres, or within 5,500 and 6,000 metres). Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse). Estimates based on Sun and Abraham (2021). The vertical bars represent the 95% confidence intervals.

Figure A.XII: Dynamic effects for different control groups.

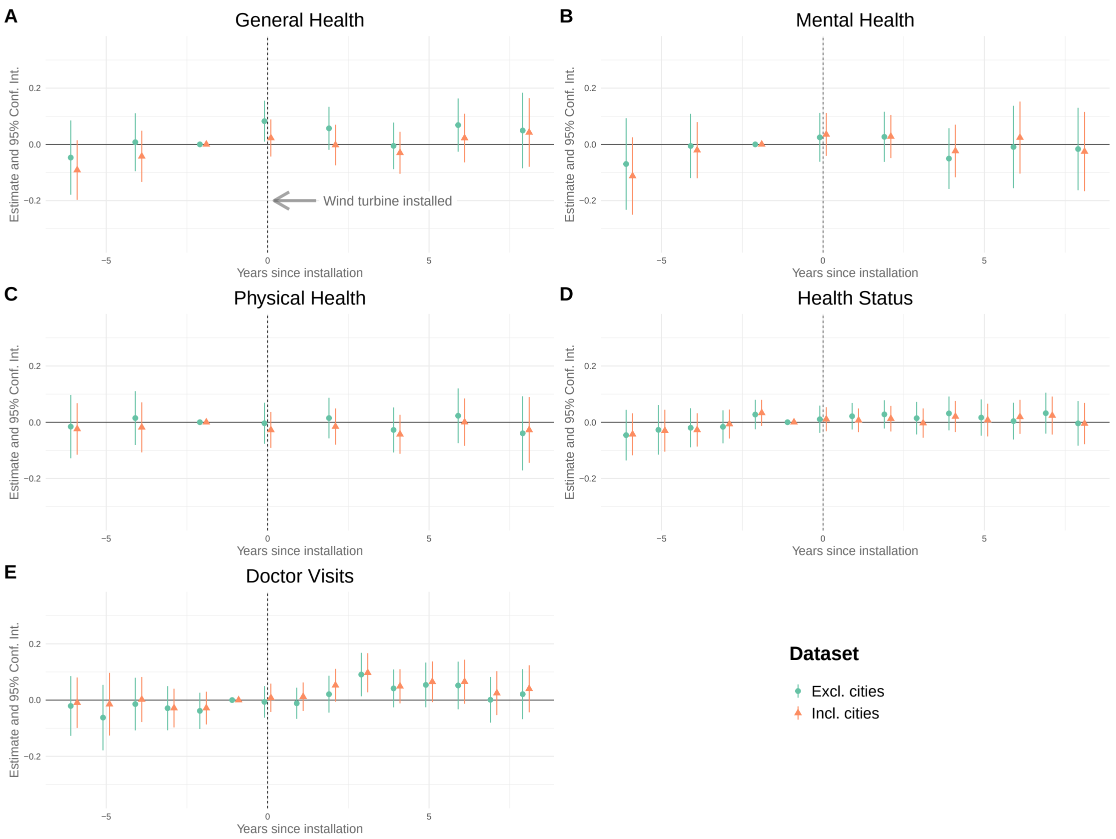
A.3.13 Dynamic – Alternative Control Groups Further Away



Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 metres) and individuals further away (i.e. between 4,000 and 6,000 metres, within 4,000 and 8,000 metres, or within 6,000 and 10,000 metres). Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse). Estimates based on Sun and Abraham (2021). The vertical bars represent the 95% confidence intervals.

Figure A.XIII: Dynamic effects for different control groups.

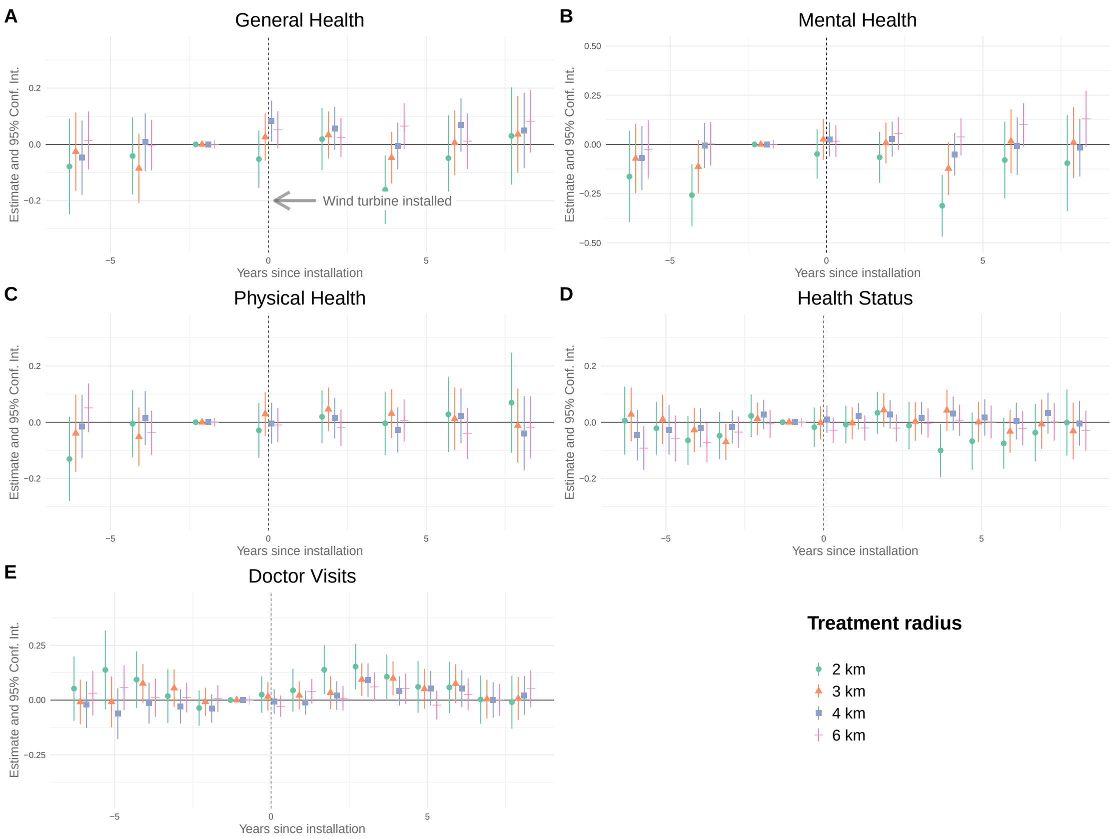
A.3.14 Dynamic – With and Without Cities



Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 metres) and individuals further away (i.e. between 4,000 and 8,000 metres). Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse). Estimates based on Sun and Abraham (2021). The vertical bars represent the 95% confidence intervals.

Figure A.XIV: Dynamic effects for different samples, excl. and incl. cities.

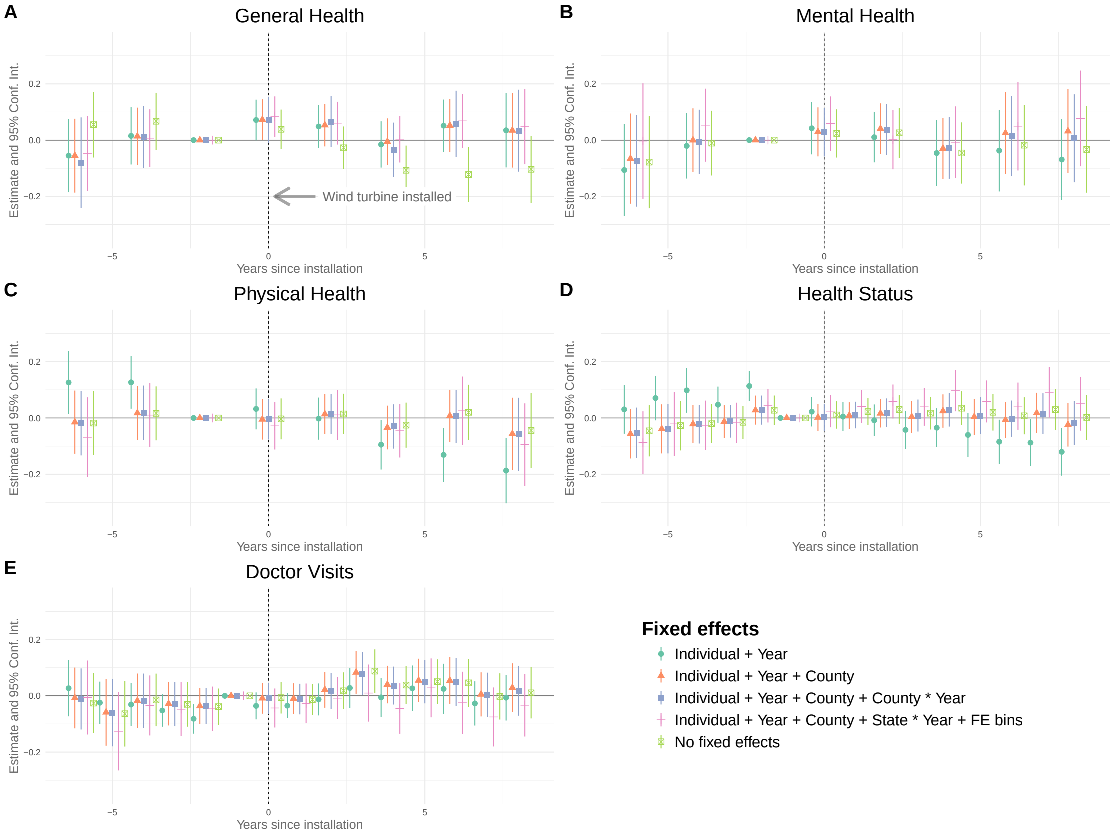
A.3.15 Dynamic – Alternative Treatment Radii



Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 2,000 metres, within 3,000 metres or within 4,000 metres) and individuals further away (i.e. between 4,000 and 8,000 metres). For treatment of 6,000 metres, the control group is 6,000-10,000 metres. Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse). Estimates based on Sun and Abraham (2021). The vertical bars represent the 95% confidence intervals.

Figure A.XV: Dynamic effects for different treatment radii.

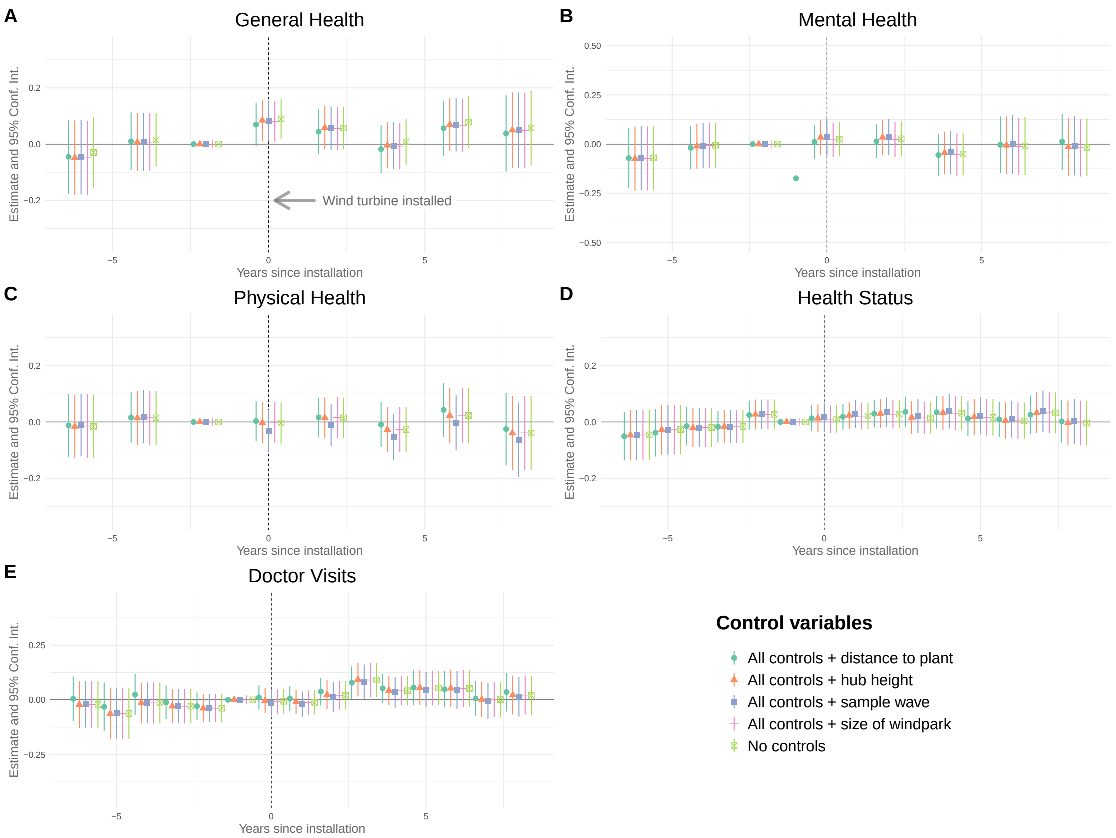
A.3.16 Dynamic – Alternative Fixed Effects



Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 metres) and individuals further away (i.e. between 4,000 and 8,000 metres). Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse). Estimates based on Sun and Abraham (2021). The vertical bars represent the 95% confidence intervals.

Figure A.XVI: Dynamic effects for different fixed effects.

A.3.17 Dynamic – Alternative Control Variables

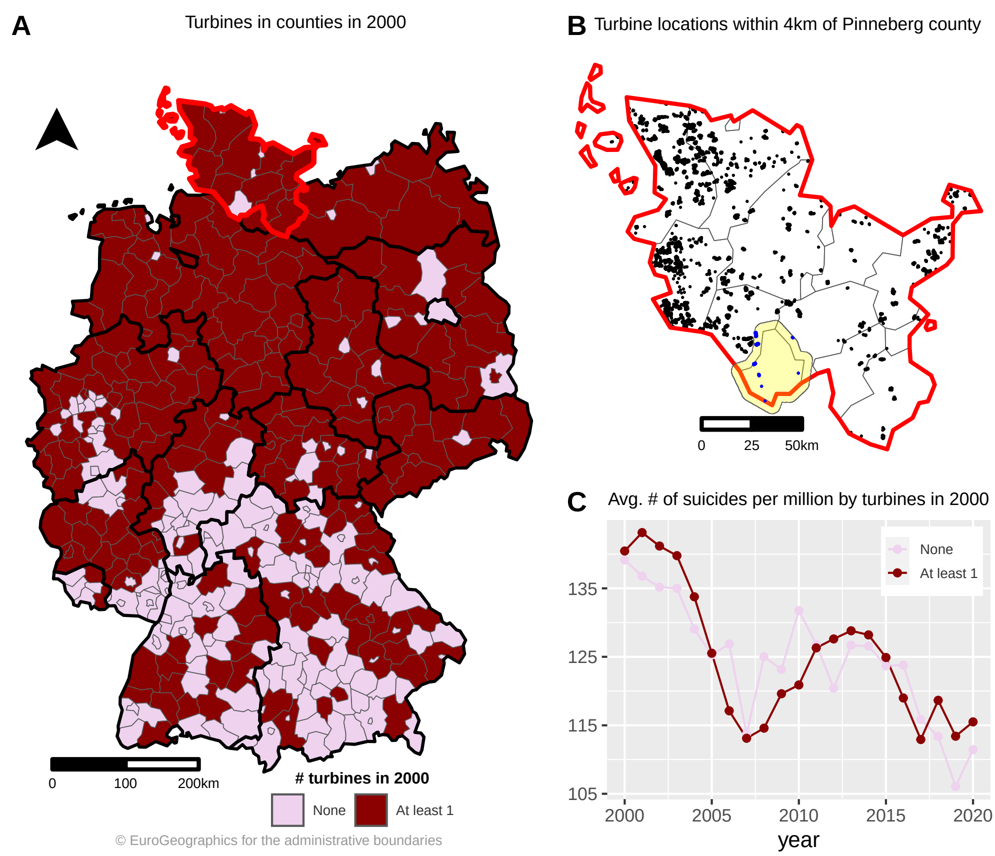


Difference in health outcomes between individuals living nearby a newly built wind turbine (i.e. within 4,000 metres) and individuals further away (i.e. between 4,000 and 8,000 metres). Outcomes are in z-scores. More indicates better health (but for doctor visits more indicates worse). Estimates based on Sun and Abraham (2021). The vertical bars represent the 95% confidence intervals.

Figure A.XVII: Dynamic effects for different control variables.

B Suicides

B.1 Illustrations



Panel A shows counties with and without wind turbines in Germany in 2000. The thick black lines indicate the borders of federal states (NUTS-1 regions), whereas the red thick line indicates the border of the federal state of *Schleswig-Holstein*, the most northern German state. *Panel B* is a close-up of *Schleswig-Holstein* and shows, as an example, the exact location of each installation in that federal state, where each dot indicates one installation. Blue dots highlight turbine locations within 4 km of *Pinneberg* county. *Panel C* plots the average number of suicides per million population by year for counties with and without turbines as of 2000.

Figure B.I: Counties with and without wind turbines in 2000, illustration of turbines nearby a county and average suicides by population over time for counties with and without turbines.

B.2 Descriptives

Table B.I: Summary statistics suicides

Variable	Mean	Median	SD	Minimum	Maximum	Observations
Outcomes						
Suicides per million population	127.50	124.40	34.42	22.70	273.98	1310
Covariates						
Unemployed per capita	0.03	0.02	0.01	0.01	0.11	1310
GDP per capita [in thousand EUR]	29.43	26.89	12.17	11.01	115.65	1310
Average age	42.44	42.50	1.81	37.36	49.15	1310

Table B.II: Normalised differences between treated and not treated counties

	Mean		Variance		
Variable	Treatment	Control	Treatment	Control	Normalised Difference
Unemployed per capita	0.03	0.03	0	0	0.04
GDP per capita [in thousand EUR]	31.4	27.19	207.34	71.52	0.25
Average age	42.2	42.72	3.4	3.01	0.21
Observations	613	697			

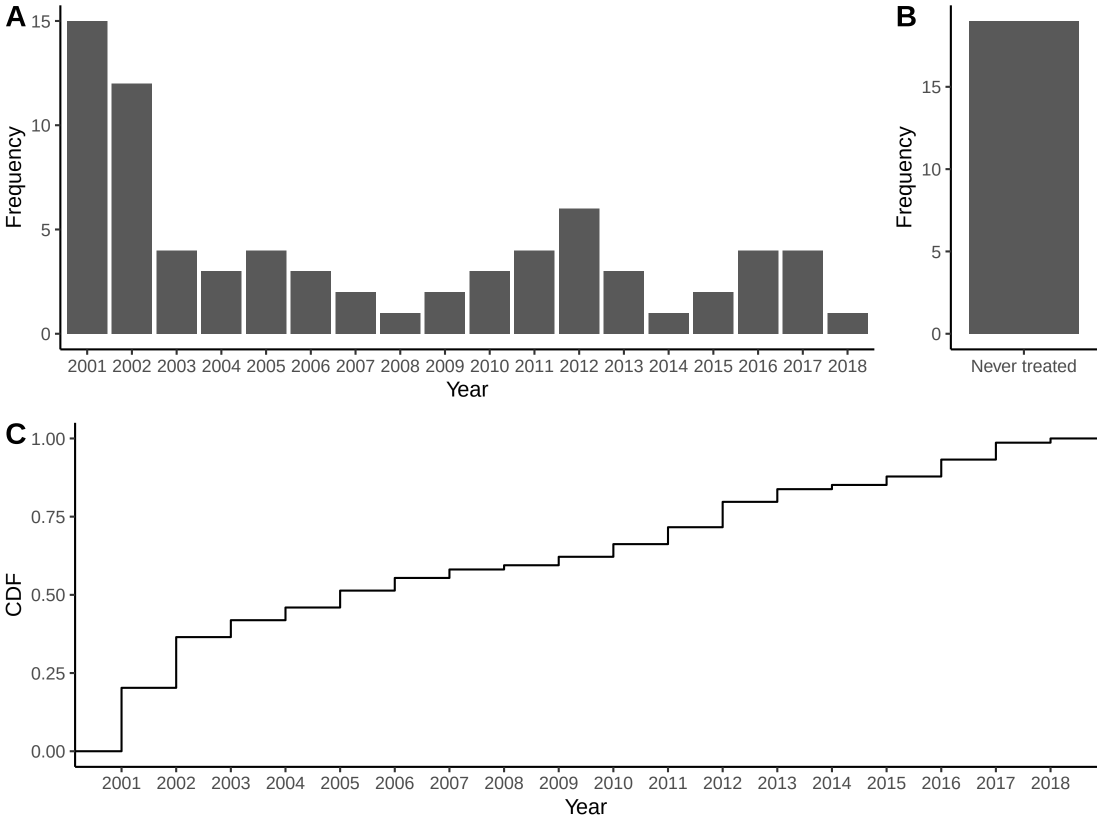


Figure B.II: Frequency (Panel A) and cumulative density (Panel B) of treated counties by year and frequency of never treated counties (Panel C).

B.3 Results

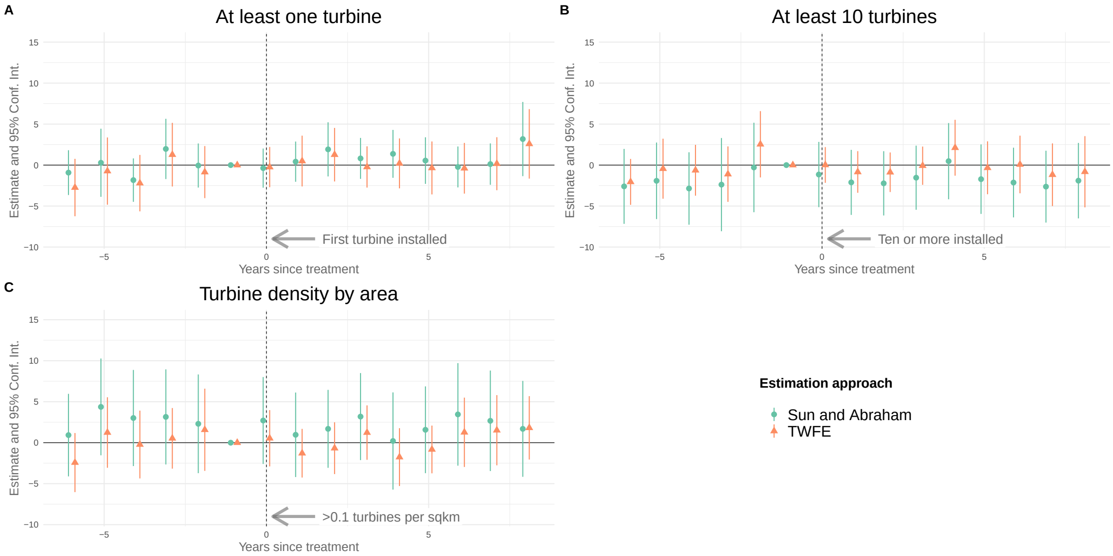
B.3.1 Static

Table B.III: Robustness of wind turbines on suicides.

Description	Other dependent variable	Controlling for intensity		With urban counties	Years 2000-2009	Years 2010-2020	Considering turbines within 4km	With counties with turbine in 2000
Dependent Variables:	ln(Suicides)	Suicides per million population						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable								
ATT	7.7×10^{-17}	-0.25	-0.72	-2.0*	1.0	-2.7	-0.21	-0.84
	(8.2×10^{-17})	(1.4)	(2.2)	(1.2)	(1.3)	(3.1)	(1.4)	(1.0)
# Turbines		0.08						
		(0.08)						
$\ln(1 + \#\text{Turbines})$			0.67					
			(0.94)					
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects								
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Statistics								
Adjusted R^2	1	0.959	0.959	0.917	0.963	0.967	0.965	0.947
Observations	1,310	1,310	1,310	2,774	714	534	884	5,417
N treated	74	74	74	104	46	31	55	273
N never treated	18	18	18	71	38	19	10	18

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; clustered (county) standard-errors in parentheses; estimates based on Sun and Abraham (2021)
Controls are GDP per capita, unemployment rate, average age and the log of number of suicides lagged by 10 years.
In columns (1-3, 5-8), we focus on non-urban areas only. In columns (1-7), we neglect counties with a turbine installed in 2000.

B.3.2 Dynamic



Standard errors at 95% are clustered at the county level. We control for GDP per capita, the unemployment rate and average age. In *Panel A*, we focus on non-urban areas only and also control for the log of number of suicides lagged by 10 years. We neglect counties that had a turbine already installed in 2000. In *Panel B*, we neglect observations with between 3 and 9 turbines installed and counties that had 10 or more turbines already installed in 2000. In *Panel C*, we neglect regions with more than 0.1 turbines per sqkm in 2000. We also drop observations with between 0.075 and 0.1 turbines per sqkm. Table 2 contains further details on the underlying estimations.

Figure B.III: Dynamic effects for wind turbines on suicides per 1,000,000 population for two estimation approaches. Difference between counties with a (new) wind turbine (Panel A), counties with at least 10 turbines (Panel B) or counties with at least 0.1 turbines per sqkm (Panel C) and counties without turbines.