Wind Turbine Syndrome:
The Impact of Wind Farms on Suicide[1]

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Abstract

Current technology uses wind turbines' blade aerodynamics to convert wind energy to electricity. This process generates significant low-frequency noise that reportedly produces annoyance symptoms and disrupts the sleep of nearby residents. However, the existence and the importance of wind farms' health effects on a population scale remain unknown. Exploiting over 800 utility-scale wind farm installation events in the United States from 2001 to 2013, I show robust evidence that wind farms lead to significant increases in suicide. I explore indirect tests of the role of low-frequency noise exposure that support the connection. The suicide effect rises with the number of days that people experience greater exposure to low-frequency noise radiation as the result of the direction of prevailing winds. Data from a large-scale health survey suggest that sleep insufficiency increased as new wind farms began operating. The suicide increase is most pronounced among two age groups: those in the 15-19 age group and those over than age 80. I estimate that the suicide cost of wind farms is not trivial in magnitude compared to the environmental and health benefits of wind energy.

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1. Introduction

The rising use of large machinery in industrial operations brings about significant noise pollution. A common feature of machinery noise is that it contains significant amounts of energy in the low-frequency (< 100 Hz) range. With a low pitch, these sounds are less attenuated by barriers, travel longer distances, and their "rumbling" nature appears to be particularly annoying to many.[2] Over the past decade, the rapid growth of the wind energy industry has triggered an increase in the public and academic interest of the health risks of low-frequency noise. By current technology, energy in wind flow is captured using large wind turbines that, with three giant and properly curved blades, convert air motion to rotational energy, which is in turn used to generate electricity. As a byproduct of blade aerodynamics, wind turbines emit substantial low-frequency sound. Around the world, communities near some wind farms have complained, and, on occasion, have filed lawsuits, about health effects reportedly due to wind farms' low-frequency noise (e.g., Butler, 2009; Pierpont, 2009). Complainants contend that the noise causes headache, nausea, dizziness, and, most predominantly, sleep disruptions.

The phenomenon, usually referred to as "wind turbine syndrome" (Pierpont, 2009), has generated great academic and policy controversy. The debate can be summarized into three pairs of conflicting facts and views. First, industry groups deny the relevance of wind farms' noise beyond certain distances, usually 500 meters. In contrast, independent measurements from the physics literature show that wind farms' low-frequency noise can be measured in homes kilometers away from the source (e.g., Willshire, 1985; Willshire and Zorumski, 1987; van den Berg, 2004; Moller and Pedersen, 2011; Ambrose, Rand, and Krogh, 2012). Second, wind turbines' noise contains a significant component at extremely low frequencies (< 20 Hz). Sound in this frequency region ("infrasound") is typically inaudible to humans, and so, in theory, it should have no health effects through auditory channels (Basner et al., 2014). However, recent though not yet conclusive medical research suggests that exposure to infrasound can cause non-auditory responses, such as the excitement of neural pathways responsible for attention and alerting, which might contribute to sleep loss (Salt, Lichtenhan, Gill, and Hartsock, 2013; Kugler, et al., 2014). Finally, while anecdotal evidence of wind turbine syndrome exists in almost every country that has wind farms, the epidemiology literature, which predominantly focuses on survey reports of various annoyance symptoms, has reached little consensus regarding the existence and the importance of wind farms' health impacts on a population scale (Bakker et al., 2012; McCunney et al, 2014; Schmidt and Klokker, 2014). Against this backdrop of

[2] Atmospheric attenuation of sound energy increases at the rate of the square of the sound's frequency. Barriers' ability to absorb sound also decreases at lower frequencies. As a consequence, low-frequency noise exposure may appear stronger in indoor environments where walls block higher-frequency sounds (Ambrose, Rand, and Krogh, 2012; Moller and Pedersen, 2011). For a review, see Leventhall (2004). See more about wind turbine acoustics basics in Appendix A.

uncertainty over whether and how wind turbines may affect health, the use of wind energy is growing. Better understanding of any potential health risks associated with wind farms is crucial in informing future policies that relate to a growing source of electricity generation.

This paper presents a new step toward greater understanding of wind turbine syndrome. There are two main innovations. First, to characterize wind turbine syndrome and to learn about its external costs, I study wind farms' impact on suicide, which can be consistently measured across the population using death records data. While suicide is an extreme act, taken by individuals who have reached the depths of despair (Case and Deaton, 2017), it is likely to be an all-encompassing measure of the many, disparate annoyance symptoms associated with wind turbine syndrome. In particular, suicide is closely related to sleep loss – the signature symptom among wind turbine syndrome sufferers – which has long been understood as a significant risk factor for suicidal ideation (Choquet and Menke, 1990; Roberts, Roberts, and Chen, 2001), suicide attempts (Tishler, McKenry, and Morgan, 1981), and deaths by suicide (Farberow and MacKinnon, 1974; Fawcett, et al., 1990; Rod et al., 2011). Suicide also merits study because of its high social costs, especially given the fact that suicides often occur as a result of impulsive behavior, sometimes independent of any accompanying medical conditions (e.g., Simon et al., 2001); thus, it cuts short lives of people who might otherwise have been expected to reach normal life expectancies. While the analysis focuses on suicide, I also use the death records data to consider potential responses of other major causes of death, as I describe in more detail below.

The second innovation of this paper is the use of a quasi-experimental estimation framework that delivers causal estimates on wind farms' adverse health effects. The basis of my research design draws on over 800 events of utility-scale wind farm installations across the United States from 2001 to 2013, including both openings of new wind farms as well as major additions of turbines to existing farms. These events allow me to explore quasi-experimental variations in exposure to wind farms along three dimensions: (1) the abrupt change in exposure before and after the new turbines began operation, (2) the geographic variation in residents' exposure by their proximity to the wind farms, and (3) the year-to-year variation in whether installation events occur during a given time of year. Each of these variations, alone *and* in combination, produce effect estimates that are based on alternative natural comparison groups. Taken together, these analyses rule out a range of potential confounding factors. Notably, I show that using the most saturated triple-difference method that exploits all three dimensions of variations yields very similar results to ones obtained using simpler designs, such as a pure before-versus-after, event study-style approach. This lends confidence to the identifying assumption that the installation of wind farms can serve as a valid source of exogenous shocks for the purposes of this study.

My empirical analysis yields robust evidence that wind farms increase suicide. I find no significant changes in the suicide rate over the two years (which likely covers a period of time well beyond and including the entire construction period) before the farms' installation, followed by a prompt increase of about 2 percent in the month when the farms began generating power. This effect stays relatively stable for the following years. The suicide impact appears to be geographically widespread; effects can be detected at least within 25 km, but no farther than 100 km, of the wind farm. I find that wind farms have fairly precise zero effects on other major causes of deaths, except for some suggestive evidence of increases in deaths related to mental and nervous system disorders. These later estimates, however, are not precise enough to be conclusive. Importantly, the finding on the suicide effect is robust to overrejection adjustments when simultaneously testing the hypothesized effects of wind farms on other major causes of deaths (Benjamini and Hochberg, 1995; Anderson, 2008).

I explore three tests to shed light on the role of low-frequency noise exposure. I begin by documenting an age profile for suicide, which shows that the most concentrated increase in suicide occurs among the elderly population over than age 80. This is consistent with the view that individuals are sensitive to noise exposure at older ages (e.g., Miedema and Vos, 2003; Kujawa and Liberman, 2006; Muzet, 2007). On a relative basis, I also find a large, 5.82 percent increase in the suicide rate among those in the 15-19 age group. The concentration of suicide effects among the teenagers and the elderly, rather than the working age population, suggests a role of non-economic determinants brought by the new wind farms.

Second, exploiting changes in wind patterns, I find evidence of an agreement between wind farms' low-frequency noise radiation profile and suicide effects heterogeneity with respect to wind directions. Specifically, I find that the suicide effect is explained mainly by days when residents are downwind or upwind of wind farms, while crosswind days are not predictive of the suicide effects. This is consistent with the "acoustic dipole" property that low-frequency noise typically exhibits: measured noise levels are higher at upwind and downwind locations while suppressed at crosswind locations (e.g., Hubbard and Shepherd, 1990; Oerlemands and Schepers, 2009).

Finally, the paper documents evidence of sleep responses to wind farms. I analyze self-reports of sleep in a sample of respondents from a large-scale health survey. I find a significant increase in reported number of nights of insufficient sleep following wind farm installation. This effect appears to be explained by an increase in reports of sustained (more than seven nights per month) sleep insufficiency.

This paper delivers the first national-scale evidence on wind farms' adverse health effects. The suicide effect size seems moderate (2 percent) relative to other well-documented medical correlates of suicidal behavior. For example, the suicide rate is much higher for people with certain diseases and disorders, such as those with multiple sclerosis (who have a twofold greater likelihood of suicide than the general population), AIDS (sevenfold greater likelihood), and bipolar disorder (15-fold greater likelihood).[3] Nonetheless, in the context of the rapid development of the wind industry, the total life value lost is significant. My calculation suggests that wind farms installed between 2001 and 2013 resulted in a total of 33,000 life years lost (997 excessive suicides) due to increased suicides within a year after installation. While the short-term estimate is statistically most precise, evidence suggest that life years lost increases to about 160,000 in the five years following installation. Using a conventional value of statistical life calculation, I compare the suicide cost of wind farms to other widely discussed cost and benefit components. I find that suicide cost is likely an order of magnitude larger than agroecosystem costs (linked to the loss of the bat population and the attendant rise in insect-driven crop losses and/or increased use of pesticides) and comparable to the cost of the "sightline" properties where declining property values have been observed within few kilometers of the farms; at the same time, the suicide cost is roughly a tenth of the social benefits that are likely to accrue from climate and air pollution emission reductions.[4] These cost-benefit parameters have a range of policy and regulatory implications, such as wind farm siting decisions, the potential social returns from the development of quieter wind-generation and noise-insulation technologies, and the determination of subsidy levels to existing wind farms. For example, I calculate that the average Pigouvian tax rate to internalize the short-term suicide costs is $4.26 per MWh, compared to an existing federal renewable electricity tax credit subsidy set at $23 per MWh.

This paper's findings also contribute to the understanding of the external determinants of suicide, a leading cause of death that claims around 0.8 million lives per year globally. While suicide is widely recognized as a consequence of the interplay between multiple medical and social determinants, existing evidence predominantly focuses on internal risk factors such as psychiatric illnesses (e.g., Mann, et al., 2005; Hawton et al., 2013; Zalsman, et al., 2016). However, external determinants of suicide are also important, especially from a suicide prevention viewpoint (e.g., Carleton, 2017; Mullins and White, 2019). My results suggest that exposure to wind farms is a significant stressor, which may be relevant for at-risk individuals' location choice. Moreover, in subsequent analysis I show that wind farms' suicide effects are strongly correlated with higher local access to firearms, which provides suggestive evidence on the scope for firearm restriction policies to mitigate increased propensity for suicide.

The remainder of the paper is organized as follows. Section 2 provides background. Section 3 describes primary data sources. Section 4 presents the identification strategy and main results. Section 5

[3] See, for example, Harris and Barraclough (1997), Cavanagh et al. (2003), and van Orden et al. (2010).
[4] Of course, the cost-benefit analysis is incorporated as a way to illustrate aspects of the potential environmental and economic costs of wind farms, and is in no way equating e.g., loss of bats or property value loss with the human tragedy of suicide.

presents evidence on the role of noise pollution. Section 6 reports the suicide effects heterogeneity by local gun access. Section 7 discusses the interpretation of the results. Section 8 offers conclusions.

2. Background

2.1 Wind Turbine Noise

Noise from modern wind turbines (Figure 1, panel A) is a consequence of blade aerodynamics. Noise is first created upon contact between air flow and the leading edge of the blade. Next, turbulence is produced as air flows over the blade surface. The turbulence is reinforced when it passes the sharp edge of the blade, creating what is known as trailing edge noise. Finally, as air leaves the blade, the tail turbulence (or "wake") interacts with the wind turbine tower as blades pass by, generating impulsive noises (Howe, 1978; Blake, 1986; Wagner, Bareib, and Guidati, 1996; Oerlemans, Sijtsma, and Mendez Lopez, 2007). See Figure 1, panel B for an illustration.

Two unique features of wind turbine noise are relevant to this study. First, acoustic impulses resulting from blade aerodynamics are usually of low frequency, occurring at the blade-passage frequency (i.e., the product of rotational frequency and the number of blades, typically three) along with its higher harmonics. Measurement using modern wind turbines shows peak energy at frequencies typically below 20 Hz (see e.g., Hubbard and Shepherd, 1990; Doolan, Moreau, and Brooks, 2012). While sound in this frequency region is generally inaudible to human ears (i.e., "infrasonic"), exposure may nevertheless create adverse impacts (explained in further detail in Section 2.2). Moreover, low-frequency sound can travel much farther than sound in the audible range due to slower energy loss in propagation. Effective monitoring of the noise profile of wind turbines requires simultaneous measurements from a sound recorder array which is difficult to implement far away from the wind turbine. As a consequence, current understanding of wind turbine's noise distance gradient is restricted to areas in the vicinity of wind farms. However, recent measurements show that receivers up to two kilometers to wind farm can detect low-frequency noise with the pressure level high enough to be perceived by human ear (van den Berg, 2004; Moller and Pedersen, 2011; Ambrose, Rand, and Krogh, 2012).[5] To the best of my knowledge, the literature on longer distances

[5] Sound's ability to penetrate through barriers is much stronger at lower frequencies. Usual barriers such as doors and windows provide little protection against low-frequency noise exposure. At frequencies around 20 Hz, sound may also cause excessive vibration and rattling of doors and windows with similar natural frequencies (e.g., Lovholt et al., 2017). In studios and home theatres, bass traps are used to damp low-frequency sound, but the market for low-frequency noise abatement in usual residential setting is largely missing. Low-cost solutions through insulation may be possible: for example, Noren-Cosgriff et al. (2016) show that stiffening of walls and roofs using 10 cm-thick steel sheet profiles in combination with plywood panels provides more than 70 percent attenuation of low-frequency vibrations around 10 Hz.

measurement is sparse. The best-available evidence is provided in two early studies, led by the U.S. National Aeronautics and Space Administration (NASA), that measured infrasonic noise from wind turbines up to 20 km away (Willshire, 1985; Willshire and Zorumski, 1987). The study data suggest that low-frequency noise decay is consistent with a "spherical" propagation of -6 decibels per doubling of distance. This suggests that atmospheric absorption does not play a substantial role in attenuation the sounds.

Second, wind turbine's low-frequency noise radiation exhibits "acoustic dipole." That is, sound does not radiate in all directions equally, with exposure stronger in the upwind and the downwind directions and weaker in the crosswind directions (see e.g., Hubbard and Shepherd, 1990; Oerlemands and Schepers, 2009). Figure 1, panel C provides a graphical illustration. In Section 5, I exploit this unique acoustic property of wind turbines' low-frequency noise radiation to shed light on the mechanism underlying the impact of wind farms.

Readers are referred to Appendix A for more notes on the acoustics of low-frequency sounds and, more specifically, wind turbine noise.

2.2 Health Effects of Low-Frequency Noise Exposure

Noise pollution has long been understood as a health hazard. Most directly, noise leads to the loss of auditory cells in the ear, causing hearing problems such as hearing loss (e.g., Vos et al., 2012). Noise exposure is also linked to a range of non-auditory responses such as annoyance, sleep disruptions, reduced cognitive functions, and cardiovascular diseases (for a review, see Basner et al., 2013). One puzzle of wind turbine syndrome centers around the debate over whether noise in the low-frequency range can also cause these health effects.

Human hearing is insensitive to sound at low frequencies, especially in the infrasonic domain (below 20 Hz). Biomechanically, this is due to the fact that *inner hair cells* of the cochlea, the primary sensory cells responsible for conscious hearing, exhibit decreasing sensitivity at lower frequencies (Dallos, 1973). However, recent research has discovered a new micromechanism of the ear's low-frequency sound processing. Experiments with guinea pigs (Salt, Lichtenhan, Gill, and Hartsock, 2013) and with humans (Kugler, et al., 2014), have shown that the *outer hair cells* of the ear are strongly activated when exposed to low-frequency sound. Serving as the main acoustical pre-amplifier, the outer hair cells do not directly contact auditory nerves in the brain. Rather, they are responsible for detecting and amplifying incoming sound through fast oscillation of the cell body (von Bekesy, 1960). Exposure to low-frequency sound triggers this amplification process, causing strong stimulation of cochlea. Though it remains unknown why the cochlea appears to process low-frequency sound before discarding it altogether, this mechanism underlies two potential health consequences of exposure to low-frequency sound. First, excessive activation of the cochlea can make the ear more prone to permanent shifts in auditory thresholds, leading to hearing loss. Second, because outer hair cells are connected to neural pathways related to orientation, attention and alerting (Weedman and Ryugo, 1996; Danzer, 2012), exposure to low-frequency sound may explain annoyance responses, such as sleep disturbance, commonly reported by residents near wind farms. To the best of my knowledge, no studies have documented the *direct* link between low-frequency sound exposure and sleep disturbance.

While complaints about wind farms' noise pollution parallel the growth of wind industry worldwide, research evidence is inconclusive regarding whether or to what extent low-frequency noise exposure from wind farms poses significant health risks. On one side, a large peer-reviewed literature exists on the association between wind turbine operation and a broad set of annoyance responses such as headache, dizziness, nausea, tinnitus, and hearing loss. The most robust association is the link between the turbines' presence and sleep disturbance, which was found in numerous cases to respond to wind turbine noise exposure in a dosage manner (Bakker et al., 2012; Schmidt and Klokker, 2014). The other side of the debate points out that some of the observed annoyance responses can be attributed to subjective factors such as attitudes toward wind energy rather than noise exposure (Knopper and Ollson, 2011). Also, many survey-based studies may suffer from biases related to study design, such as self-selection of survey volunteers and errors in measurement based on recall (McCunney et al, 2014).

2.3 Wind Farm Development and Siting

Here I review several aspects of wind farm development and siting that are relevant to the empirical study. The extensive planning that underpins wind project development usually spans multiple years and includes meteorological and environmental studies, community outreach, landowner partnership development, state/county permitting processes, and the establishing of grid connections. One of the most important components is siting, which involves obtaining permits and zoning approval from state and/or local governments. The National Association of Regulatory Utility Commissioners (2012) provides a comprehensive review of such processes. Legislation differs by state in terms of which agencies have primary responsibility for wind farm siting and zoning decisions. In most states, the primary authority lies with the state or local agencies, though there are several exceptions. For example, in the District of Columbia, the public utility commission is responsible for siting utility-owned wind farms. States also differ by evaluation criteria for wind farms. By the end of 2011, 27 states had published mandatory lists of criteria and guidelines. Among these states, however, few have set up mandatory standards for sound impact. For example, Delaware, Rhode Island, and Virginia are the only states with standards for mandatory setback distance and sound.

In the United States, the vast majority of operating wind turbines are located on private land. Landowners often sign decades-long contracts with the wind project developer, and compensation packages vary widely by projects. Because most wind developers prefer not to disclose land agreement compensation, limited information is available in terms of the average level and structure of compensation. However, available data suggest that compensation is in the order of $2,000 per turbine-year. Combination packages most typically provide for a fixed payment plus the royalty payment, rather than a one-off, lump-sum payment (Windustry, 2009).[6] Importantly, there is no reason to expect payment schedule to systematically correlated with the timing when wind farms came on-line. Thus, the monetary compensation should have little interaction with the suicide effects.

3. Data and Summary Statistics

3.1 Primary Data Sources

Wind farm data are obtained from the U.S. Energy Information Administration's form 860 (EIA-860). EIA-860 provides an annual census of existing power generators larger than 1 megawatt (MW) in generation capacity, and it contains information on plant location, nameplate capacity, and month and year in which the new capacity came online.[7] I define wind farm installation events as entries of new capacity in which the primary energy source is specified as wind. My baseline event study estimation includes a total of 828 installation events spanning 39 states in the United States from 2001 to 2013. The average installation contains 42 individual wind turbines (median = 27) or 71 megawatts (median = 50 megawatts) in capacity.

My primary outcome variable is the suicide rate at the county × month level from 2001 to 2013. These data come from the National Center for Health Statistics' Vital Statistics Multiple Cause of Death Data File. Suicide rate is defined as the fraction of individuals in the county who died due to suicide (ICD 10 = X60-X84, Y87.0) relative to the county's total population in the year. I also construct age-specific

[6] My personal search on the internet suggests that loyalty payment for more recent wind project may be in a higher range of $4,000-8,000. See, for example:
http://www.windustry.org/how_much_do_farmers_get_paid_to_host_wind_turbines ;
https://www.wind-watch.org/documents/five-questions-to-ask-before-signing-a-wind-energy-lease/

[7] Comparing the EIA data to a near-census of onshore wind farms in the United States as of March 2014 conducted by the U.S. Geological Survey (Diffendorfer et al., 2014), I find the EIA data capture over 95 percent of all wind capacity installed.

suicide rates using Vital Statistics data on descendants' age of death. Population estimates at both the county × year level and the county × year × age level are from the National Cancer Institute's Surveillance, Epidemiology, and End Results Program (SEER).

I derive wind data from the North American Regional Reanalysis (NARR) produced by the National Centers for Environmental Prediction, which contains information on wind conditions at a spatial resolution of 32km × 32 km grid cell. For each grid cell × day, NARR reports the horizontal (u-wind) and vertical (v-wind) components of the wind vector. I link each wind farm to the corresponding grid cell, and convert u- and v-wind into wind vectors (direction and speed) using trigonometry.

3.2 Summary Statistics

Figure 2 illustrates the rapid expansion of the U.S. wind power industry since late 1990s. While utility-scale wind farms were almost nonexistent until the turn of the 21st century, by the end of 2013, total generation capacity had reached 60,000 MW. That year, electricity generated from wind farms amounted to 167 million MWh, sufficient to meet electricity consumption for more than 15 million U.S. households. Figure 2 also shows that the geographic span of wind farms expanded rapidly. In the 1990s, an average American lived more than 800 kilometers from the nearest wind farm. By 2013, this number had fallen to about 200 kilometers, and to about 100 kilometers for individuals living in states with wind farms.[8]

Figure 3 plots the location of wind farms throughout the study period. My preferred estimation sample contains a group of "close" counties, defined as those counties that incorporate any land area within 25 km of wind farms. This selection criterion is motivated by the 32 km × 32 km spatial resolution of the wind measurement, which allows me to confidently infer wind conditions within an approximately 25-km radius of a given wind farm. This is a liberal sample selection criterion: because the best-available outcome measures are at the county level, relatively little can be explored at finer geographic resolution levels. To address potential concerns, in Appendix Figure B.3 I construct alternative estimation samples, and show that the main findings of the paper are not sensitive to the 25-km selection criterion. I also estimate a "distance gradient," and find evidence that the suicide impacts decrease with a county's distance from wind farms. In a related exercise, I construct an alternative measure of population exposure. I "pixelate" counties using Census Block-level population data, and compute the fraction of county population living within 25 km of wind farms (i.e., the fraction of the county's population living in Census blocks in which the centroid-to-farm distance is less than 25 km). This exercise also provides suggestive evidence of a distance gradient

[8] The distance calculations are based on latitude and longitude of wind farms and the 2010 Census county population centers.

in which counties with a higher fraction of population close to wind farms exhibit stronger suicide effects. The presence of the distance gradient is incorporated in the analysis below, in which I construct a sample of "distant" counties located 25 km to 100 km from the wind farms, and use this “distant” location sample as a control group in specifications that exploit spatial differences.[9]

While all empirical specifications in this paper ultimately control for some form of county fixed effects, in Table 1 I compare observable characteristics across counties that are close to wind farms versus those that are far away; I take this step to shed light on external validity of the research design. Column 1 reports characteristics of close counties (0 to 25 km away from wind farms) in the primary estimation sample. Column 2 represents distant counties (25 km to 100 km away from wind farms) that are used in subsequent analysis for spatial comparison. Column 3 summarizes the same statistics for all other counties (> 100 km from wind farms) that are *not* examined in this study. Finally, column 4 reports national averages. The suicide rate in the close counties is on average 8.56 per million population per month, slightly lower than the rate for the rest of the country, e.g., column 4 shows that national average suicide rate is 9.76. Table 1 also reports suicide statistics for five separate age groups (15-19, 20-39, 40-59, 60-79, and > 80). The difference in the average suicide rate does not appear to be driven by any particular age group. Economic and weather characteristics in counties close to wind farms are generally similar to other counties. One exception is precipitation, which is substantially lower in close counties; this distinction is likely driven by the absence of wind farms in the southeastern region, where wind levels are generally low, and precipitation levels happen to be the nation’s highest. Overall, these statistics suggest no particular concerns over non-representativeness of the study population.

4. Suicide Responses to Wind Farm Installation Events

4.1 Raw Trends

To motivate the empirical strategy, I begin with a simple trend plot of suicide rates around the 828 wind farm installation events from 2001 to 2013. Figure 4 plots the average suicide rate from 24 months before (i.e., about one year before wind farm *construction* began) to 12 months after the new wind farms began generating power. Changes in the suicide rate is measured relative to the level observed one month

[9] The Census Block-level data also allow me to calculate exact population exposure around wind farms. Appendix Figure B.2 shows population counts by distance (in 1-km increments up to a 100-km radius) and by age groups. I calculate that the average wind farm in my study sample has 67,300 individuals living within 25 km.

before the installation event (even month = -1). To remove secular trends in suicide, I condition the regression on 12 month-of-year dummies, and no other controls are included.[10]

Figure 4 shows that the suicide rate stays flat during the two years leading up to the installation event, followed by a prompt increase in the month when the new wind farms began generating power.[11] The graphical pattern provides three key insights for the empirical strategy and interpretation. First, the fact that the suicide rate is flat in years before installation events provides evidence that the pre- "treatment" period serves as a plausible "control" for what would have occurred regarding suicide rates in the absence of new wind farm installation. Second, in addition to a flat pre-treatment suicide trend, the suicide rate trend is also roughly flat *after* installation events happen. This evidence motivates a simple empirical specification that estimates the causal impact of wind farms by comparing changes in suicide rates before and after installation events.[12] Third, the fact that suicide responses are not experienced even in the months shortly before power generation actually begins suggests that the impact is unlikely due to factors related to the *presence* of the wind farm itself (e.g., wind farm construction, which typically lasts for months) but rather due to factors associated with the *operation* of the wind farm (e.g., noise emission).[13] I provide further discussion of potential mechanisms in section 5.

4.2 Empirical Strategy

Figure 4 motivates a straightforward event study style empirical design that estimates the impact of wind farms by comparing suicide rates in county c at time t shortly before and after the installation event. Note that, because wind farms can be close to each other, the same county can be linked to (i.e., within 25km of) different installation events, and therefore can appear multiple times in the regression sample. Hence, in subsequent analysis the subscript c is understood as a county linked to a nearby wind farm.[14] I estimate the following baseline specification

[10] While simple month-of-year fixed effects seem enough to control for seasonal trends in suicide before wind farm installations, in unreported analysis I have confirmed that trends are robust to the full set of month-of-year fixed effects, year fixed effects, and county fixed effects adjustments. Further discussion on control strategies is provided in Section 4.2.

[11] In Appendix Figure B.1, I use power generation data to confirm that wind power production increases sharply starting the event month.

[12] The estimated coefficient for event month 9 (i.e., the 10th month since installation) lies outside of the range of the rest of the coefficients. In Appendix Table B.1, I report that the overall estimates are robust to dropping the 10th month.

[13] Of course, the jump in suicide on the operation month alone does not rule out the possibility that the effect operates through the *expectation* of a permanent change in noise (rather than through the noise itself), or a differential disutility associated with *spinning* wind turbines relative to turbines that are not operating.

[14] In unreported analysis, I obtain similar results using a simple panel fixed effects regression approach. That is, the unit of analysis is a county × months; the treatment variable is an indicator for county × months where any wind farms are in operation within 25 km; the control variables are proper panel fixed effects indicators such as county, month-

$$Suicide_{ct} = \beta \cdot Post_{ct} + \underbrace{F_{ct}\eta}_{\substack{fixed\ effects \\ ctrls}} + \overbrace{X_{ct}\gamma}^{\substack{time-variant \\ ctrls}} + \varepsilon_{ct} \quad (1)$$

The key treatment variable is $Post_{ct}$ that indicates periods after the installation event. Fixed effects controls F_{ct} include county fixed effects, month-of-year fixed effects and year fixed effects. In the analysis I also report specifications with increasingly stringent controls, such as ones that include county × month-of-year fixed effects or wind farm × year fixed effects. More discussions on fixed effects controls are provided as I describe the results. Besides fixed effects controls, time-variant controls X_{ct} include 10-degree F daily temperature bins and quadratic monthly precipitation. Results are robust without any weather controls. I report standard errors clustered at the wind farm level. In Appendix Table B.1, I report specification checks which vary the sample restrictions and other elements of the baseline specification.

Simple before-versus-after comparison, as outlined in equation (1), may confound wind farms' effects with other factors that correlate with installation events in both observable and unobservable ways. Next, I augment the baseline specification in three ways by introducing "control" counties.

First, I compare pre- and post- suicide differences for counties in the baseline sample to distant counties that are farther away from wind farms, forming a spatial difference-in-difference (DD) design. This design controls for potential geographic patterns in suicides, and separates out the component that is specific to counties close to wind farms. The estimation equation is

$$Suicide_{ct} = \beta \cdot Post_{ct} \times Close_c + F_{ct}\eta + X_{ct}\gamma + \varepsilon_{ct} \quad (2)$$

where $Close_c$ indicates counties near wind farms. The rest of the specification is identical to equation (1) except that a) the fixed effects are allowed to vary by close and distant county groups whenever feasible, and b) X_{ct} is understood to include main effects of the interaction terms.[15]

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of-year, and year fixed effects. I do not prefer this approach because it essentially looks only at the first installation event a county experienced, and therefore discards the variation coming from the arrival of additional wind farms in the same county.

[15] For example, while the year and the month-of-year fixed effects can vary by $Close_c$, the county fixed effects cannot. Similar reasoning applies to other double- and triple-difference methods described in subsequent analyses. My conclusions are unchanged if fixed effects controls are not allowed to be conditional on the interaction variables.

Second, I implement a temporal difference-in-difference design. I compare pre- and post- suicide differences within the event window in the year when a wind farm is installed ("event year") to differences within the *same* event window but in other years when a wind farm is not installed ("placebo year"). This specification helps tease out the pre- and post- difference in suicide that is specific to the event window within which an installation event actually occurs. I estimate

$$Suicide_{ct} = \beta \cdot Post_{ct} \times EventYear_t + F_{ct}\eta + X_{ct}\gamma + \varepsilon_{ct} \qquad (3)$$

where $EventYear_t$ indicates whether the event window contains an actual installation event. As before, I allow the fixed effects controls to vary by event year whenever feasible.[16]

Finally, I combine specifications (2) and (3) into a triple-difference (DDD) design, which separates out the part of suicide increase that is specific to counties close to wind farms *and* specific to the year installation occurred. The following equation is fitted

$$Suicide_{ct} = \beta \cdot Post_{ct} \times Close_c \times EventYear_t + F_{ct}\eta + X_{ct}\gamma + \varepsilon_{ct} \qquad (4)$$

Again, whenever feasible I allow fixed effects to vary both by $Close_c$ and by $EventYear_t$. X_{ct} is understood to contain all main effects and two-way interaction terms.

4.3 Main Results

Table 2 reports the primary results. Each panel represents a different comparison strategy as outlined by equations (1) to (4). Within each panel, columns 1 through 3 report specifications with increasingly stringent fixed effects controls. I first focus on panel A, which reports the simple pre- versus post- difference estimates corresponding to equation (1). Column 1 shows that, relative to the year before wind farm installation, the suicide rate increases by a significant 0.183 per million population in the year

[16] To give a concrete example, suppose that Orange County installed a wind farm in March 2005. The temporal DD is the idea that, for the "true" March 2005 installation event, I define the following "placebo" installation events for Orange County: March 2001, March 2002, …, March 2004, March 2006, March 2007, …, March 2013. Thus, the control group is the suicide trend in the same event window (one year before and one year after) using these placebo events. Note that these placebo events help control for the concern that "March" might just generally be a bad time for suicides in Orange County, even in the absence of the wind farm installation. The temporal DD estimate is thus the *differential* increase in suicide following the March 2005 event relative to the placebo events,

after installation. Relative to the monthly mean suicide rate of 8.54 per million, the effect size represents a 2.1 percent increase. Column 2 uses more stringent controls by interacting the county fixed effects and the month-of-year fixed effects. Conceptually, this specification makes the suicide comparison between the two observations for the same county on the same month of the year, but one before installation and one after installation. This specification yields a similar estimate of 0.212 per million. In column 3, I further tighten up the specification by allowing year fixed effects to vary by each wind farm, absorbing common variations among all counties linked to the same wind farm in a given year. This specification yields a slightly larger effect estimate of 0.251 suicides per million, although the estimate becomes less precise and the 95 percent confidence interval of the estimate overlaps with those of the estimates in column 1 and 2.[17]

Panels B through D of Table 2 report estimates from the augmented designs that use richer sources of variation. These include the spatial DD (equation 2), the temporal DD (equation 3), and the triple D (equation 4) approach. Reassuringly, these alternative comparison strategies produce results that are broadly consistent with the primary specification in panel A, which lends strong support to the causal interpretation of the estimates. Notably, magnitudes of these estimates are also consistent with what we have seen in Figure 4. In Appendix Figure B.4, I document that event study trends in suicide for the control groups in the spatial DD and temporal DD specification are flat, with no significant change before and after wind farm installations occurred in treated counties. In subsequent analysis, I use the simple pre- versus post- differences in suicide rates as the preferred estimation method.

4.4 Other Causes of Death

While this study focuses on suicide responses, I can also use the "primary cause of death" information contained in the vital statistics data to explore deaths due to other causes. These additional tests help the analysis in at least two ways. First, they may shed light on the underlying mechanisms by which wind farms affect health. For example, while cardiovascular and nervous system responses are linked to high levels of noise exposure (e.g., Basner et al., 2014), changes in neoplasms and infectious diseases likely reflect shifts in population health due to reasons unrelated to noise. Second, the exercise provides a chance to examine the robustness of the main suicide findings with respect to multiple inference, as other causes of death could have been examined in addition to suicide.

[17] Results do not change with the inclusion of more stringent time controls such as month-of-sample (e.g., January 2001, February 2001, …) fixed effects. I do not prefer these specifications because they are relatively harder to interpret for certain comparisons, e.g., a simple before-vs.-after installation comparison. In Appendix Table B.1, I report the robustness of the results to a range of additional specification changes along the lines of (1) sample selection, (2) control variable selection, and (3) standard error clustering.

To execute these tests, I construct mortality rates for a group of leading causes of death from 2001 to 2013. These include (in rank order) circulatory system, neoplasms, respiratory system, nervous system, accident, metabolic diseases, mental disorders, digestive system, and infectious diseases, all defined using ICD-10's major disease blocks classification.[18] Together with suicide, these 10 causes of death account for more than 90 percent of total deaths. I then estimate the effects of wind farms on these cause-specific mortality rates using estimation equation (1). I present false discovery rate-adjusted significance levels, or "*q*-values", that take into account the fact that 10 hypotheses are being tested simultaneously (Benjamini and Hochberg, 1995; Anderson, 2008).

Table 3 summarizes the results. For reference, I repeat the suicide effect estimate in column 1, which corresponds to the estimate in panel A, column 1 of Table 2. There are two main findings. First, the key result on suicide continues to hold at the conventional significance level post multiple inference adjustment (*q*-value = 0.050). Second, coefficient estimates for causes other than suicide are generally positive, but there is little evidence for statistically significant impacts. Only two individually significant effects emerge: those from deaths due to nervous system and mental disorders which are intuitively related to noise exposure; neither, however, survives multiple hypothesis adjustment. Overall, the point estimates are small in magnitude, and in some cases small effects can be ruled out based on the estimates. For instance, in column 2, the 95 percent confidence interval of the circulatory death estimate implies that a 1 percent effect can be ruled out. Mortality rates from other plausibly "placebo" causes such as neoplasms and infections also show rather precise zero responses.

4.5 Longer-run Effects

The analysis so far focuses on the impact of wind farms on suicide in the first year after installation. A potentially interesting and important aspect to consider in terms of wind farm policies regards the degree to which the suicide effect persists over time. Ideally, one would follow the same county for many years after installation to estimate its longer-term effect. But because the wind industry is relatively new (Figure 2), simply adapting the short-run analysis by expanding the post-event window will likely suffer from substantial sample selection problems because wind farms differ substantially by the amount of available post-event observations.

[18] The exact ICD-10 codes used are: suicide (X60-X84, Y870), circulatory (I00-I99), neoplasm (C00-D48), respiratory (J00-J99), nervous (G00-G99), accident (V01-X59), metabolic (E00-E90), mental (F00-F99), digest (K00-K93), and infection (A00-B99).

In this subsection, I provide a partial solution that gives rise to multi-year estimates. I stratify installation events by year, and therefore by how many years I can follow affected counties in the data. For example, wind farms installed before December of 2012 will have at least one year of follow-up; those installed in 2011 will have at least two years of follow-up, and so on. This approach therefore trades off "N" versus "T" i.e., the number of installation events investigated versus the temporal scope of the multi-year analysis. The longer-run effects are examined by comparing the stability of multi-year estimates as I vary the two trade-off dimensions.

Table 4 presents multi-year estimates. Beginning with panel A, column 1 repeats the one-year estimate as presented in Table 2, panel A, column 1. The estimation sample used here includes all wind farm installation events that occurred between January 2002 and December 2012. In column 2, I drop installation events in 2012, and, therefore, all events have at least two years of follow-up. In this restricted sample, I find that wind farm installations increase the suicide rate by 0.210 per million population over the next two years (Panel A, column 2, row "… year 1 to 2"). Moving to the diagonal cells in the next columns, the three-, four-, and five-year effect estimates are 0.250/0.263/0.294, respectively, per million population (Panel A, columns 3/4/5, row "… year 1 to 3/4/5"). The point estimates therefore grow monotonically as I expand the post-event window. But notice that I lose one year of installation events by extending the post-event window by another year, and so the standard errors are larger for columns on the right. In fact, the multi-year estimates are generally not statistically distinguishable from one another.

One concern with comparing multi-year estimates across samples is that, if wind farms installed in different years differ substantially by type, location, etc., the difference in the multi-year estimates will pick up such selection, rather than the long-run dynamics of the suicide impact. To provide a way to investigate this concern, I examine the coherence of the multi-year estimates with respect to varying post-event time windows. Take panel A, column 5 as an example. While I estimate the five-year effect for this study sample, I can also estimate shorter-run effects by restricting the estimation to a shorter post-event window, and then comparing these estimates with those in other columns. The non-diagonal cells in panel A show that these estimates are fairly stable.

In panel B, I replicate the multi-year estimation using an alternative comparison strategy as described in Section 4.2. Here I only use the spatial difference-in-difference strategy (equation 2), because the temporal difference-in-difference strategies (equations 3 and 4) use non-installation years as control periods, and therefore suffer from contamination when the analysis looks at multi-year time windows. Panel B shows that the results are quantitatively less precise but qualitatively similar. Again, the point estimates show an increasing pattern when I expand post-event windows, although they are not statistically distinguishable across columns.

The multi-year effect estimation reveals that the suicide effect of wind farm installations persists over time. This has two main implications. First, the suicide effect is unlikely explained by "harvesting" – expedition of suicides that would have taken place over a short period of time even in the absence of new wind farms.[19] Second, evaluations of the cost of excessive suicide due to wind farms should take into account multi-year effects. I provide further discussion in Section 7.

4.6 Other Robustness and Placebo Checks

Appendix B documents more robustness and placebo checks. I highlight several exercises here. Appendix Table B.1 reports a series of specification changes based on the regressions in Table 2 panel A. "First installation only" shows that the results are similar if I restrict to the roughly 89 percent of installation events in my study sample that are first-time installations (i.e., no pre-existing wind farms in the county where the new capacity is installed). "No weather controls" shows regressions dropping all weather controls. "All FEs interact with wind resource classes" compares counties with similar wind resources, defined using data provided by the National Renewable Energy Laboratory (NREL) for annual average wind speed at a height of 50 meters; this is executed by interacting all fixed effects by NREL's county wind power classification.[20] "Age-adjusted suicide rate" uses the age-adjusted suicide rate as the dependent variable, where suicides in each 10-year age bins are re-weighted using each age bin's long-run (2001-2013) average population levels.

The main suicide evidence presented in Table 2 uses four different research designs (simple difference, spatial difference-in-differences, temporal difference-in-differences, and triple difference). For all other analyses, I focus on the simple difference approach in the main text in the interest of space. Appendix Tables B.2 through B.5 report versions of Tables 3, 5 ,6, and 7 with the alternative research designs; the findings are similar to those that result using the simple difference design.

Finally, I conduct placebo tests using fertility and birth outcomes.[21] Leveraging the fact that conceptions are sensitive indicators of the environment, I test the possibility that mothers during pregnancy are already experiencing economic or environmental changes even before wind farms are installed. That is, if fertility and birth outcomes change within the nine months after installation, this would falsify the identification assumption that nothing else changes except for the installation of wind farms. I use the

[19] In stylized harvesting dynamics, one would observe a prompt increase in suicides shortly after installation, followed by a compensational decrease in suicides in the following periods. Over a long period of time, the average suicide effect would have been close to zero in this case.
[20] NREL's original data is at the 2-by-2-km resolution. I compute county-level wind power class (WPC) as the modal WPC of all 2-by-2-km grids that fall within the county boundary.
[21] I thank an anonymous reviewer for suggesting these tests.

National Center for Health Statistics' fertility data files to build two measures of birth outcomes at the (mother's residence) county-month level. The first measure is the fertility rate, defined as the number of births per 10,000 women ages 15 to 44. The second is low birth weight per 100 births (that is, 100 times the percent of babies with birthweights less than 2,500 grams). I then repeat the estimation of equations 1 through 4 using fertility rate and low birth weight. To allow for fertility and birth outcomes to change after nine months, I break out the $Post_{ct}$ dummy into two sub-periods: one to eight months after the installation (the placebo period), and nine to 16 months after the installation.

Appendix Table B.6 shows no effect of wind farm installations on fertility rates or low birth weight in the following eight months. I also do not detect effects in the next 8 months. The sign on the fertility coefficients is generally positive, although the 95 percent confidence interval can exclude a 1 percent effect for the placebo period. In unreported exercises, I have confirmed that similar findings result with the use of more stringent fixed effects controls; I have also examined a potential change in the birth sex ratio and in fetal deaths (Almond and Mazumder, 2011; Sanders and Stoecker, 2015), and found no evidence of significant responses.

5. Evidence on the Noise Mechanism

In this section, I explore wind farms' noise pollution as a potential mechanism underlying the suicide effects. Section 5.1 explores age profile of the suicide effects. Section 5.2 exploits an acoustic property of wind farm noise radiation, and leverages changes in wind direction to decompose the suicide effect into days with potentially high versus low noise exposure. Section 5.3 documents responses of insufficient sleep using self-reports data from a large-scale survey.

5.1 Age Profile of the Suicide Effect

The elderly are understood to be a particularly at-risk group for noise-induced annoyance and illnesses (e.g., Miedema and Vos, 2003; Kujawa and Liberman, 2006; Muzet, 2007).[22] Here, I estimate an

[22] For example, Miedema and Vos (2003) analyze data from 28 studies (covering 23,038 respondents), and find a strong correlation between reported noise sensitivity and age. While it is possible that the elderly may report higher incidents of noise sensitivity due to confounding factors (for example, elderly might have a higher rate of "spontaneous" awakening at night, making them more likely to report noise-related sleep disruption), these data do suggest elderly might be more annoyed by the same level of noise than other age groups. One limitation, however, is that the existing literature focuses on specific noise sources (e.g., road traffic), rather than "pure tone" noise at specific frequencies (e.g., infrasound).

age profile of wind farms' suicide effect by allowing the effect estimates to vary by age groups. Specifically, I estimate the following equation

$$Suicide_{act} = (Post_{ct} \times AgeGroup_a) \cdot \beta_a + F_{cta}\eta + X_{ct}\gamma + \varepsilon_{cta} \qquad (5)$$

where the unit of observation now is suicide rate in county c at time t for age group a (15-19 years old, 20-39, 40-59, 60-79, and above 80 years old). $AgeGroup_a$ is a set of dummies indicating each age group. Fixed effects F_{cta} are primary fixed effects interacted with age-group dummies. Hence, equation (5) allows the impact of wind farm installations on suicide to vary flexibly by age groups, yielding an age profile β_a.

Figure 5 graphically summarizes the results. I find that, while suicide effect estimates are positive for every age group examined, the largest effect is observed for the population over 80 years old. Suicide among this group increases about 0.72 per million post wind farm installation, a relative change of 5.33 percent out of the age group's mean rate of suicide.[23] On percentage terms, I find the largest effect occurs among the teenagers (age 15-19) who show a 5.82 percent relative increase in the suicide rate.[24] By contrast, effects on the population between ages 20 and 80 are more modest and less statistically precise.

5.2 The Role of Wind Direction

In the second test for the noise mechanism, I exploit the unique acoustic property of low-frequency noise radiation in which the level of exposure is higher at upwind/downwind locations while impeded in locations in the crosswind direction, as is discussed in Section 2. Moreover, due to wind refraction, downwind noise is expected to be stronger than upwind noise.

I exploit plausibly exogenous variations in wind directions to decompose the suicide effect by days when counties are upwind, downwind, or crosswind of the wind farm. Specifically, I augment equation (1) by allowing the $Post_{ct}$ dummy to vary by the number of days that county c is located upwind, downwind, and crosswind of the wind farm in month t. The estimation equation is

[23] There is some evidence from the public health literature that suicide classification is less accurate at older ages. This might be due to a combination of factors such as higher rates of death from natural causes and lower rates of medical autopsy (e.g., Kapusta et al., 2011; Rockett et al., 2011). Such classification errors are expected to attenuate the results to the extent that they should not correlate with regions/time periods with higher wind farm exposure.

[24] Suicide rates for preteens are close to zero: 0.01 per million people per month for ages 5-9, and 0.82 per million per month for ages 10-14, compared to 5.26 per million per month for ages 15-19. I find no evidence that preteens suicide rates respond to wind farm installation events.

$$Suicide_{ct} = \left(Post_{ct} \times Direction_{ct}^{d}\right) \cdot \beta_d + F_{ct}\eta + X_{ct}\gamma + \varepsilon_{ct} \qquad (6)$$

Consider the angle between the wind direction at the wind farm and the county c's centroid. Let 0 degree (equivalently, -0 degree) denote the county being exactly downwind, and let 180 degree (or -180 degree) denote the county being exactly upwind. On any given day, a county's downwind-ness can therefore be expressed as a number between -180 and 180. In equation (6), $Direction_{ct}^{d}$ counts the number of days the angle is within four different degree bins d where d = {0 to 45 and 0 to -45, 45 to 89 and -45 to -89, 90 to 134 and -90 to -134, 135 to 180 and -135 to -180}. Hence, β_d identifies the impact of spending one more day in relative direction bin d on suicide. As a concise example, β_d where d = {0 to 45 and 0 to -45} identifies the marginal suicide effect if a county has one more day of the month when it locates within a 90-degree cone downwind a wind farm. X_{ct} is understood to contain lower-order interaction terms in addition to weather controls. The remainder of equation (6) is the same with equation (1).

Consistent with the acoustic dipole property of noise radiation, Figure 6 presents evidence that the suicide effects are mostly explained by days when counties are downwind (d = 0 to 45 and 0 to -45) and upwind (d = 135 to180 and -135 to -180) of wind farms. In contrast, days when counties are crosswind of wind farms have low explanatory power on suicide. My estimates do not provide evidence consistent with wind refraction: in fact, I find upwind days are slightly more explanatory than downwind days, although the two are not statistically distinguishable.

Table 5, panel A presents a more parsimonious version of equation (6) in which the suicide effects are allowed to vary only by upwind/downwind and crosswind days. Across different econometric specifications, results confirm that the effects are largely explained by upwind/downwind days. In further analysis, I estimate event study versions of these regressions by replacing the $Post_{ct}$ dummy with a full set of event month indicators. I show that there are no pre-existing trends in the correlation between upwind/downwind or crosswind days and suicide, following by an increase in the upwind/downwind correlation (but not crosswind correlation) after the wind farms began operating (Appendix Figure B.5).

Table 5, panels B and C provide further supportive evidence of the noise channel, showing that the upwind/downwind versus crosswind heterogeneity is stronger when wind speed is higher at the wind farm (panel B) and for larger wind farms as measured by generation capacity (panel C).

5.3 Sleep Responses

In the final test, I turn to survey data to directly examine the effect of wind farms on sleep loss. I use data from the annual Behavioral Risk Factor Surveillance System (BRFSS), a monthly cross-sectional, telephone-based health survey of individuals aged 18 years and older, that is maintained by the U.S. Centers for Disease Control and Prevention. My sleep measure is based on a question that asks the respondents the number of days, if any, in the past month that they "did not get enough sleep or rest" (for an application of the same dataset in sleep medicine literature, see Strine and Chapman, 2005). The question is posed among a total of 706,099 respondents for whom their county of residence can be identified in year 2002 and then from 2004 to 2010. In my analysis, I restrict to a subset of 104,519 respondents who lived in counties within 25 kilometers of wind farm installations, and who were interviewed within the one year before/after installation window. On average, the respondent in my sample reports 8.35 nights of insufficient sleep per month, with 69.9 percent / 39.1 percent / 26.9 percent reporting at least 1 / 7 / 14 days, respectively, of insufficient sleep. Using additional information provided by the BRFSS on the survey interview dates and each respondent's individual-level survey weight, I construct the average number of nights of insufficient sleep at the county × month level. I also construct three additional measures for the fraction of respondents who report at least *k* days of insufficient sleep in the past month, where *k* can take the values of 1, 7, or 14.[25]

As before, I begin by undertaking a simple event study that documents the trends for insufficient sleep before and after wind farm installations. Analogous to Figure 4, Figure 7 plots changes in the number of nights with insufficient sleep before and after wind farm installation events. The plot is again conditional on 12 month-of-year dummies and no other controls. While the individual month-by-month event study estimates appear noisy, a break in trend is evident around the time new wind farm came online.[26] Table 6, column 1 reports that the before-and-after difference in sleep insufficiency is statistically significant at the 5 percent level. Relative to the year before wind farm installations, respondents report on average 0.2 more nights of insufficient sleep in the year after. Based on a mean report of 8.35 nights, this effect represents a roughly 2.4 percent increase. Columns 2 to 4 suggest that the finding on the increased number of nights of

[25] BRFSS also provides information on a range of individual characteristics. I have confirmed that the conclusions are unchanged if the average sleep measure is adjusted for observable heterogeneity using an auxiliary regression approach that 1) extracts the county × month fixed effects component of the sleep insufficiency variable when the correlations of individual characteristics (including age, sex, marital status, reported health condition, health insurance coverage, survey interview day, and survey interviewer fixed effects) are parsed out; and 2) uses the fixed effects coefficients as the independent variable in estimation equation (1).

[26] In Figure 7 I choose to normalize sleep insufficiency data in the *second* month prior to installation to zero. This is because the event study coefficients appear to show an increase in reported sleep insufficiency one month before installation. This pattern may be explained by measurement errors in the reference period for which sleep insufficiency is reported, although it may also arise due to noise in the month-by-month coefficient estimates.

insufficient sleep is likely explained by disproportionate increases in reports of sustained sleep insufficiency rather than increased reports of having *any* sleep insufficiency.

Of course, as in most survey settings, the sleep measures used in this analysis are based on respondents' recall and subjective judgement of sleep quality. Nevertheless, using BRFSS sleep measures provides at least two improvements over previous survey studies of wind farm-related sleep loss. First, BRFSS simply contains a much larger sample, both in terms of the number of respondents and the geographic span, than data used by previous studies that are typically based on hundreds of respondents living in the immediate vicinity of a particular wind farm. Notably, the BRFSS sample selection is based on random-digit telephone dialing, and the sample is constructed to be representative of the U.S. population along many respects, such as age, sex, race, and education levels (CDC, 2012). Second, information on insufficient sleep is elicited as one of the many questions contained in the entire BRFSS survey. This alleviates the concern that many small-scale surveys administered to residents in wind farms' neighborhood tend to frame sleep loss as a consequence of noise or, sometimes explicitly, wind farm noise. To the extent that the BRFSS does not at all instruct respondents to incorporate perceptions of wind farms in sleep reports, it provides a more independent outcome measure for the purpose of this study.

6. Suicide Effects of Wind Farms and Local Gun Access

More than a half of suicides in the United States involve firearms, and a cross-sectional association between gun ownership and suicide has been well documented; nevertheless, the extent to which access to guns influences suicide decisions remains an open question (e.g., Miller and Hemenway, 2008). The context of this paper's study provides an opportunity to expand the current understanding of the issue. This section considers the heterogeneity of wind farms' suicide effects by local areas' levels of gun access.

I examine whether places with easier access to guns experienced stronger suicide effects when exposed to wind farms. I employ two complementary measures of county-level gun access. The first measure is based on the number of Federal Firearm Licensees (FFLs) in the county. These data are obtained from the Bureau of Alcohol, Tobacco, Firearms and Explosives which provides street address of the universe of FFLs by the end of year 2012. To capture gun shops, I restrict to FFLs listed as "dealers in firearms other than destructive devices," and I compute the number of gun stores per capita for each county.[27] My second measure follows Duggan (2001) who proxies for gun ownership by circulation of the magazine *Guns & Ammo*, the most popular magazine dedicated to firearms, competitive shooting, and

[27] This category comprises more than 70 percent of all the FFLs. Other major categories reported in the data are manufacturers of firearms and ammunition (13 percent) and pawnbrokers (11 percent).

hunting. From the Alliance for Audited Media, I obtain county-level counts of print and digital circulation for the August 2005 issue of the magazine. I then convert these counts to per capita scale. The two measures turn out to be highly correlated (raw correlation = 0.84). The geographic patterns are also generally consistent with survey-based measures of residential gun ownership, e.g., Kalesan, Villarreal, Keyes, and Galea (2016).

Table 7 reports estimations of heterogeneous suicide effects by gun access. For both gun measures, I report two types of specifications. First, in columns 1 and 3, I allow suicide effects to vary flexibly by bottom, middle and top terciles of gun access. Second, in columns 2 and 4, I interact the $Post_{ct}$ dummy with continuous measures of gun access. Both types of specifications suggest significantly larger suicide impacts in areas with higher gun access. For example, I find that among counties in the top tercile for gun access, suicide following wind farm installation increases by 1.1 to 1.5 per million population.

7. Social Costs of Wind Farm

Suicide effects imply a new component of the social cost of wind farm. The goal of this section is to compare the magnitude of suicide's cost with other components of the social costs of wind farms that are frequently discussed.

Suicide Costs. I first compute life years lost (LYL) due to excessive suicide as:

$$LYL = \sum_c \beta \times LifeExp \times Population_c$$

where β is the effect of a wind farm on the suicide rate in the next year obtained from equation (1). This is multiplied by expected remaining years of life ($LifeExp$) and population in county c ($Population_c$) to obtain excessive LYL in the county. In this calculation, I set the average remaining life years for a suicide to be 34.3 years (average life expectancy of 77.8 minus the average age of suicide 43.5). Total LYL is computed as the summation of LYL across counties.[28]

[28] It bears mentioning that the LYL approach likely underestimates other social aspects of suicide costs that are difficult to quantify. For example, suicide may impose a substantial burden of grief on surviving family members (Young et al., 2012); suicide bereavement can be especially painful, more so than mourning for deaths from other causes (Jordan, 2001).

This calculation concludes that, from 2001-2013, new wind farms are responsible for 997 excessive suicides in the first year following their installation. This amounts to 33,270 life years lost.[29] Applying a value of statistical life (VSL) of $100,000 per life year implies a total cost of **$3.3 billion** in 2010 dollars. This calculation is in a sense conservative as it assumes that suicide effects occur only in the first year after installation, when the effects are the most precisely estimated. Instead, if I apply the relatively less precise five-year estimate of 0.269 per million in Table 4, panel B, column 5, the LYL estimate rises to about 160,206 life years, or a cost of about **$16 billion** between 2001 and 2013.[30]

Bat Fatality Costs. A salient concern about wind farms is its impact on bat fatalities. Bats may collide with all kinds of anthropogenic structures, but the collision fatality associated with wind farms appears to be uniquely high. Rapid changes in air pressure around wind turbines can also cause lung bleeding in bats. The issue gained attention in 2003, when thousands of bats carcasses were found near a West Virginia wind farm (Kerns and Kerlinger, 2004). Wind farms are now considered a leading cause of bat fatalities (O'Shea et al., 2016). Systematic reviews of the literature suggest a wind turbine-related bat fatality rate of 9.9 deaths per MW × year of installed wind generation capacity (e.g., Arnett et al., 2008; Hayes, 2013).[31] This implies a total of 3.3 million excessive bats deaths due to wind farms installed in the United States from 2001 to 2013.

While it is largely unclear why bats are so susceptible to wind turbines, bat fatalities are likely to be economically important due to the various roles bats play in the ecosystem, including pollinating flowers, spreading seeds, and preying on insects. The economic value of these "services" provided by bats is very complicated to quantify. Here I focus on bats' impact on agriculture through insect consumption. Consider hoary bats, which account for more than half of wind turbine-related bat fatalities in the United States (Arnett et al., 2008; Cryan, 2011). Hoary bats prey mostly on moths whose larvae are among the most destructive agricultural pests (Valdez and Cryan, 2013). To quantify crop damage due to the reduced hoary bat population, I adapt the results from Cleveland et al. (2006), who calculate the economic value of the Brazilian free-tailed bat (henceforth T brasiliensis) on a cotton-dominated agroecosystem in Texas. An adult T brasiliensis weighs about 13 grams, roughly half the weight of an adult hoary bat. Like the hoary bat, T brasiliensis consumes primarily moth abdomens and bollworms (i.e., moth larvae). An adult T brasiliensis can consume about 8 grams of insects per night. Cleveland et al. (2006) estimate that a T

[29] Using the age-adjusted suicide effect estimates β_a from equation (5) and age-specific expected remaining life years yields a similar LYL estimate of 33,939.
[30] That is, I assume five years of increased suicides caused by wind farms installed on or before 2009, and four years of suicide increases for installations that took place in 2010, three years for installations that occurred in 2011, two years for installations that occurred in 2012, and one year for installations that occurred in 2013.
[31] These studies typically conduct bat fatality searches after wind farm construction. Overall the bat fatality rate is then estimated assuming a uniform distribution of actual fatalities between wind turbines and between search days.

brasiliensis consumes about 1.5 female moths that would have laid eggs, which, taking into account population dynamics of bollworms, translates into roughly five larvae that collectively would have damaged about 10 bolls of cotton (roughly $0.02 worth) in their lifetimes. Further, taking into account the decreasing vulnerability of cotton to bollworm damage across the growing season, a single T brasiliensis provides about $0.55 value per year in terms of avoided cotton crop damage. I therefore assume $1 worth of avoided crop damage per bat × year.[32] With an average life span of six years, the implied total crop damage from excessive bat fatality is on the order of **$12 million** from 2001 to 2013.

Another potentially important external cost of bat loss regards the related health effects of compensational pesticide application. In a quasi-experimental study, Frank (2017) studies bat-fatality shocks caused by the spread of white-nose syndrome among the bat population,[33] the compensational increases in pesticide use, and the resulting increases in human infant mortality. His estimate suggests roughly 100 infant deaths linked to the increased pesticide exposure that stems from the white-nose syndrome-related decline in the bat population from 2003-2013. During a similar study period to mine, about 5.5 million bats are known to have died from the disease. I calculate that this equates to about 18.2 infant deaths per million bat deaths. Extrapolating to the context of wind farms, this suggests about 60 infant deaths in the United States from 2001 to 2013 due to wind farm-related bat fatalities. Using EPA's VSL recommendation of $8 million per death, this suggests a **$480 million** human life value lost in 2010$.[34]

Visual Impact Costs. Stated preference studies suggest that wind farms' visual impact, including "shadow flicker" of spinning blades and the general impact on land aesthetics, is a key externality determining public acceptance of wind energy (Devine-Wright, 2005; Pasqualetti, 2011; Mattmann, Logar, and Brouwer, 2016). Hedonic evaluation of wind farm installations give rise to mixed findings regarding how wind farms affect housing prices (e.g., Sims et al., 2008; Hoen et al., 2010; Lang et al., 2014; Vyn and McCullough, 2014). Here I borrow estimates from Gibbons (2015). Though the study was conducted in England and Wales, rather than in the United States, it is favored here because it is based on individual property-transaction records, covers a large geographic area, employs quasi-experimental designs that

[32] This assumes the following: (1) that the damage estimate from the cotton-dominated agriculture in Texas can be extrapolated to all other crops in the United States; and (2) that the hoary bat consumes twice as many insects as a typical T brasiliensis consumes, and that the hoary bat is representative of bat species killed by wind farms. I am not able to evaluate assumption (1) as I am not aware of readily available estimations of bats' value to other crops. Regarding assumption (2), the eastern red bat and silver-haired bat, the other two bat species most commonly killed around wind facilities, are both of similar body size to T brasiliensis. On this front, my calculation likely provides an upper bound of crop damage per wind farm-related bat fatality.
[33] White nose syndrome is a fungal disease that invades bats' skin, causing frequent arousal during hibernation, followed by depletion of fat stores, starvation, and death (e.g., Reeder et al., 2012).
[34] Extreme in-utero exposure to pesticides may also lead to poor birth outcomes, such as low birth weight. See, for example, Larsen, Gaines, and Deschenes (2017).

explore residents' distance to wind farms, and, most importantly, conducts viewshed analyses to analyze how the *visibility* of wind farms affects housing prices. Gibbons (2015) finds precise evidence on housing price reductions linked to the visibility of the wind farms; houses within a 4-km radius of wind farms experience an average 2.5 percent decline when the wind farms are visible, while houses within the same radius show no significant price reductions when wind farms are invisible.[35]

Applying Gibbons (2015) to the U.S. setting, I calculate a measure of property values "at risk" using county-level housing values from the American Community Survey (ACS). To simplify the calculation, I use the average of two non-overlapping five-year estimates (the ACS 2005-2009 and the ACS 2010-2014). I compute the property value "at risk" as the aggregate housing value in the county multiplied by the fraction of population living within 4 km of wind farms. While I cannot precisely determine how many properties would be affected by the sightlines, this calculation gives a rough approximation of the properties that potentially would be affected. I find that about $219 billion are within 4 km of wind farms. This implies about **$5.5 billion** loss in property values over the period of 2001 to 2013.

Emission-displacement Benefits. Wind energy replaces electricity generation from fossil fuel sources, providing local environmental and global climate benefits through reducing local air pollutants (such as particulate matter) and greenhouse gases (such as carbon dioxide). Because energy sources vary substantially by emission concentrations, the environmental benefits of wind energy depend on which alternative fuels are being replaced at each point in time.

I use estimates from three comprehensive evaluations of wind electricity for the Texas electric grid (Cullen, 2013; Kaffine, McBee, and Lieskovsky, 2013; Novan, 2015). Displacement effects are reported for CO2, NOx, and SO2. Across the three studies, point estimates for tons of emissions reduced for each MWh of wind electricity generation range from 0.47 to 0.67 for CO2, from 0.00040 to 0.00053 for NOx, and from 0.00064 to 0.00091 for SO2. I follow Banzhaf and Chupp (2012) and Novan (2015) to apply a social cost (in 2010 dollars) of $32 per ton for CO2, $548 per ton for NOx and $3,194 per ton for SO2. This extrapolates to social benefits of about $11.6 billion to $16.6 billion for CO2, $0.17 billion to $0.22 for NOx, and $1.58 to $2.25 billion for SO2. These add up to a total of **$13.4 billion** to **$19.1 billion** for the entire U.S. wind sector from 2001 to 2013.[36]

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[35] In a similar study using data from the Netherlands, Droes and Koster's (2016) found a 1.4 percent reduction in property values for locations within a 2-km radius of wind farms. Although Droes and Koster (2016) do not perform viewshed analysis, they do find that housing price reductions are stronger for taller wind turbines.

[36] Banzhaf and Chupp (2012) and Novan (2015) adopt the Tracking and Analysis Framework (TAF) integrated assessment model which implicitly takes into account transport of NOx and SO2, as well as other pollutants formed by down-stream reactions, such as particulate matter. An important caveat is that the TAF assumes a VSL of about $3 million (2010$), compared to the $8 million figure used in my infant mortality calculation.

The benefit calculation is likely conservative. For example, generating electricity from coal is associate with tremendous environmental and health costs from the extraction, transport, and processing of coal, in addition to combustion. Epstein et al. (2011) estimate that the life-cycle cost of coal-generated electricity is about \$178 per MWh. Combined with the estimate by Novan (2015) that each MWh generated by wind reduces coal generation by an average of 0.33 MWh, the social benefit of coal displacement is likely in the order of **\$45.5 billion** from 2001 to 2013.

Summary. Table 8 provides a summary of my calculations. It tabulates the cost component, the raw estimates drawn from the studies, and the calculated total cost of wind farms during my study period. The calculations of this section suggest that suicide costs may be a significant component of wind farms' social cost. Suicide costs are likely larger than the costs of bat fatalities (670 to 3,250 percent of the bat-related costs, depending on whether the short- or long-run estimate of suicide effects are used). Suicide costs are likely comparable to the property value losses near wind farms (60 to 290 percent of the property value losses). On the other hand, suicide costs are unlikely to exceed the social benefits from pollution displacement. (Suicide costs represent 5 to 27 percent of the pollution-reducing benefits.).

To the extent that suicide costs are not trivial compared to other components of wind farms' social costs and benefits, findings of this study suggest several lines of inefficiency of current wind energy policies. First, I calculate that the average Pigouvian tax rate to internalize the short-term suicide costs is about \$4.26 per MWh (\$20.67 per MWh if longer-term suicide costs are taken into account). This tax rate, when varying by wind farms' locations, may incentivize better wind turbine design and siting. Second, the existing federal renewable electricity tax credit subsidy, set at \$23 per MWh, is applied identically across renewable sources such as onshore wind, offshore wind, solar, etc. Similarly, states' commitments to achieve higher renewable energy production, such as the State Renewable Portfolio Standards, often do not discriminate among these sources. The suicide cost of onshore wind, therefore, implies a potential misallocation of subsidies across sources. Third, as discussed in Section 2, there is a missing market for low-frequency noise insulation in residential setting. The suicide cost implies a potentially high social return to the development and deployment of such technologies.

8. Conclusion

This paper highlights a new component of the social costs of wind farms by showing a robust relationship between wind farm installations and suicide increases in nearby counties. Quasi-experimental research designs suggest such a relationship is likely causal, and additional tests provide suggestive evidence that the suicide effect may operate through wind farms' low-frequency noise emission. This study has important limitations that bear mention. First, estimates of this paper reflect the effect of exposure to *wind farms*. While I have shown a number of tests that support the view that noise exposure plays a role in wind farms' effect on suicides, more direct evidence is needed to establish the causal effect of *noise*. Ambient noise monitoring data would be particularly useful. Such data could be used to better measure the noise profile of wind farms, and, in combination with medical data, could enhance understanding of any potential effects on those living in proximity to turbines. In addition, such data could be used to test for a potential dosage relationship, to determine a possible threshold at which noise exposure is likely to affect health. Second, this paper's analysis relies upon county-level suicide data. The growing availability of administrative data on health outcomes may provide more granular information regarding the location of any related health outcomes. This may benefit the study of "wind turbine syndrome" in multiple ways. For example, finer geographical data would help identify effects on individuals who live in the immediate vicinity of wind farms – the situation that provided the initial motivation for this literature's area of inquiry. Greater geographic detail would also be particularly useful for studies that use changes in wind directions as quasi-experiments to pinpoint the effects of noise. Third, while the analysis focuses on suicide as the key outcome of interest, it likely captures only the most severe consequence of wind farm exposure. Other health outcomes may also be important to provide a richer characterization of the health effects that may stem from living or working in proximity to wind turbines, and to shed light on the full related costs.

This study also points to several missing pieces in the academic understanding of wind turbine syndrome. First, systematic measurement of low-frequency sound, especially at long distances, needs to be updated from the early evidence provided by Willshire (1985) and Willshire and Zorumski (1987). New information on sound exposure as a function of distance and wind directivity would be particularly useful in guiding health analyses. Second, there is a pressing need for laboratory or field-based experimental evidence on the direct link between low-frequency sound exposure and health symptoms (sleep disruption in particular), in the spirit of the animal-model assessment provided in Salt et al. (2013). Both exercises are certainly outside of the boundary of traditional economics analysis, but they can greatly help guide future research designs that aim to discover population-scale effects and to enhance understanding of underlying mechanisms.

Finally, it is perhaps most important to emphasize that this study estimates wind turbine syndrome clearly as a result of the way wind energy is captured with *today's technology*. It is clear that wind energy, like other renewable sources, will play a significant role in combating climate change. As noted earlier, this research may bring a new perspective to the value of noise abatement in wind technology innovations, and may thus incentivize further progress in that regard.

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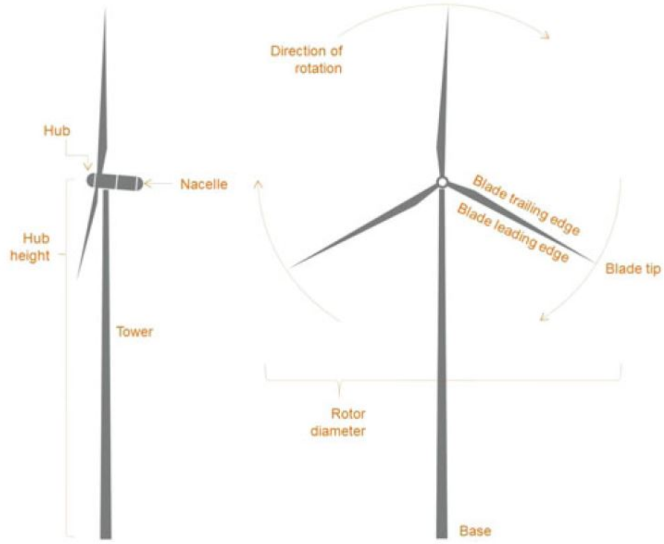
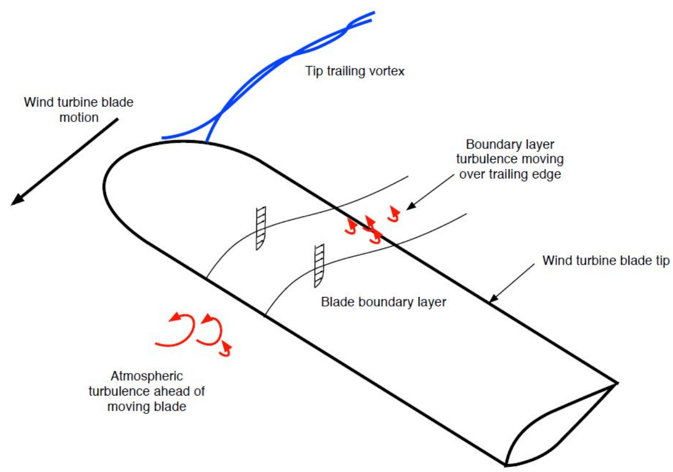
Figure 1: Distribution of Wind Resources and Wind Farms

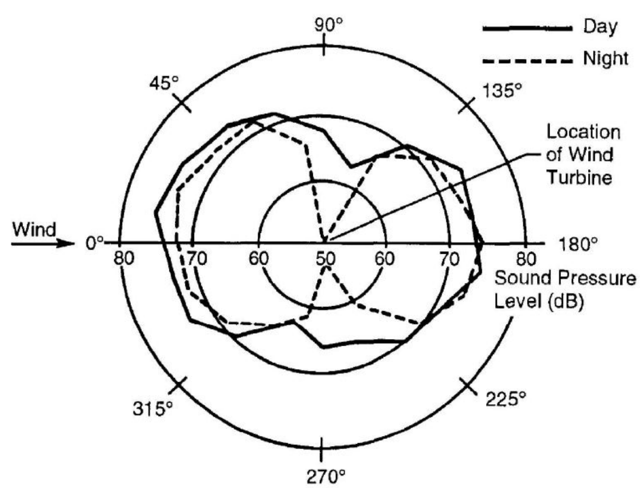
Panel A. Wind turbine (horizontal axis design)



Panel B. Air flow over a wind turbine blade

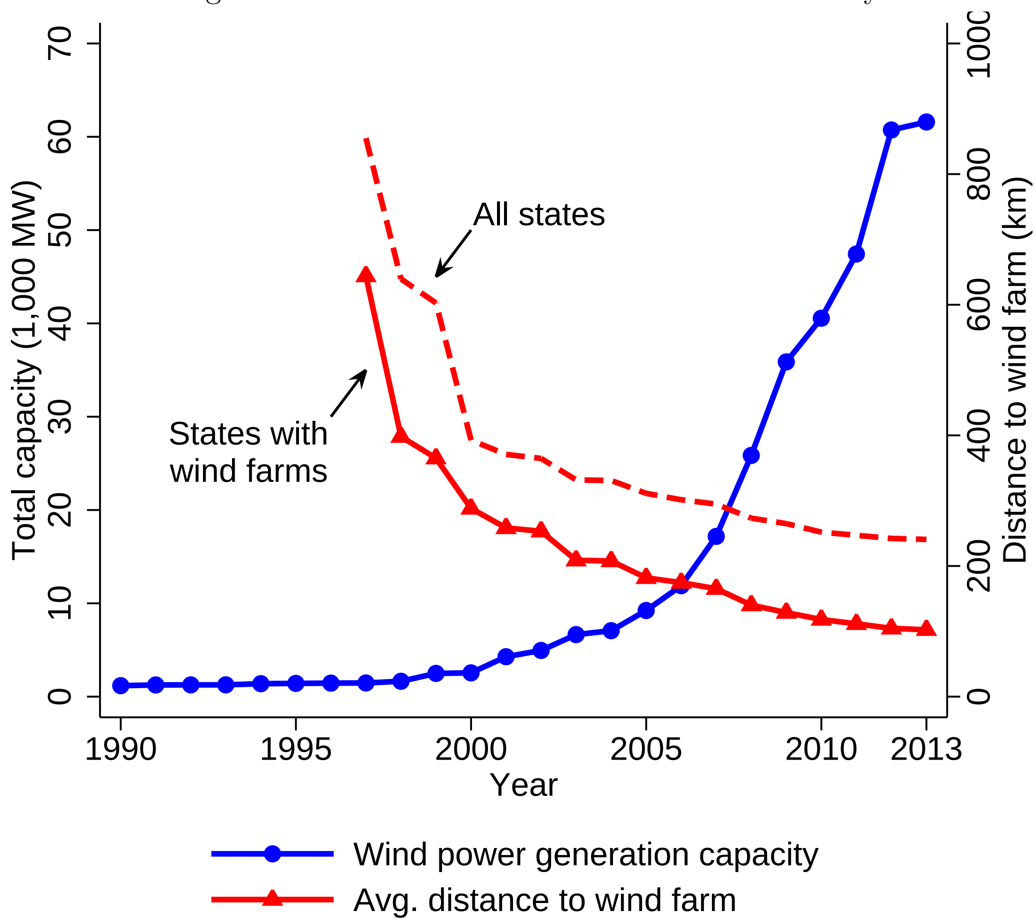


Panel C. "Acoustic Dipole": Wind turbine's low-frequency noise radiation patterns



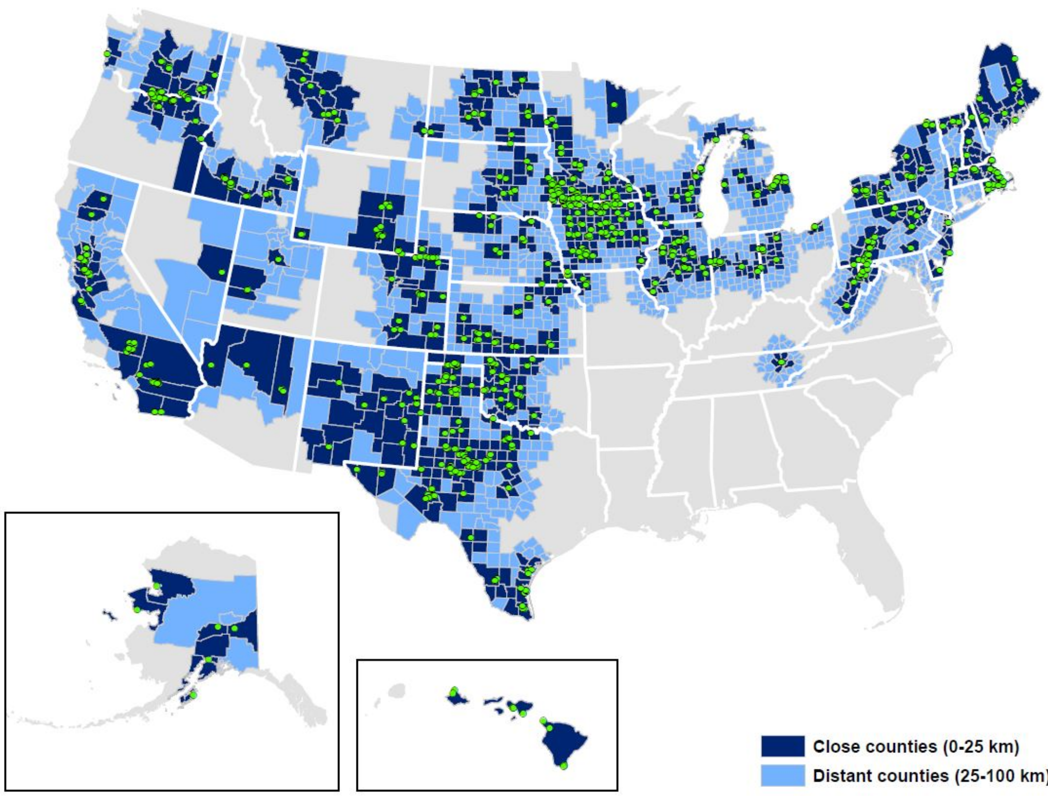
Notes: Panel A is sourced from McCunney et al (2014). Panel B is sourced from Doolan (2011). Panel C is sourced from Hubbard and Shepherd (1990), which shows measured noise level 200 meters from a utility-scale wind turbine when wind speed is 7.2 m/s. Measured frequency of the sound is 8 Hz.

Figure 2: Growth of the U.S. Wind Power Industry



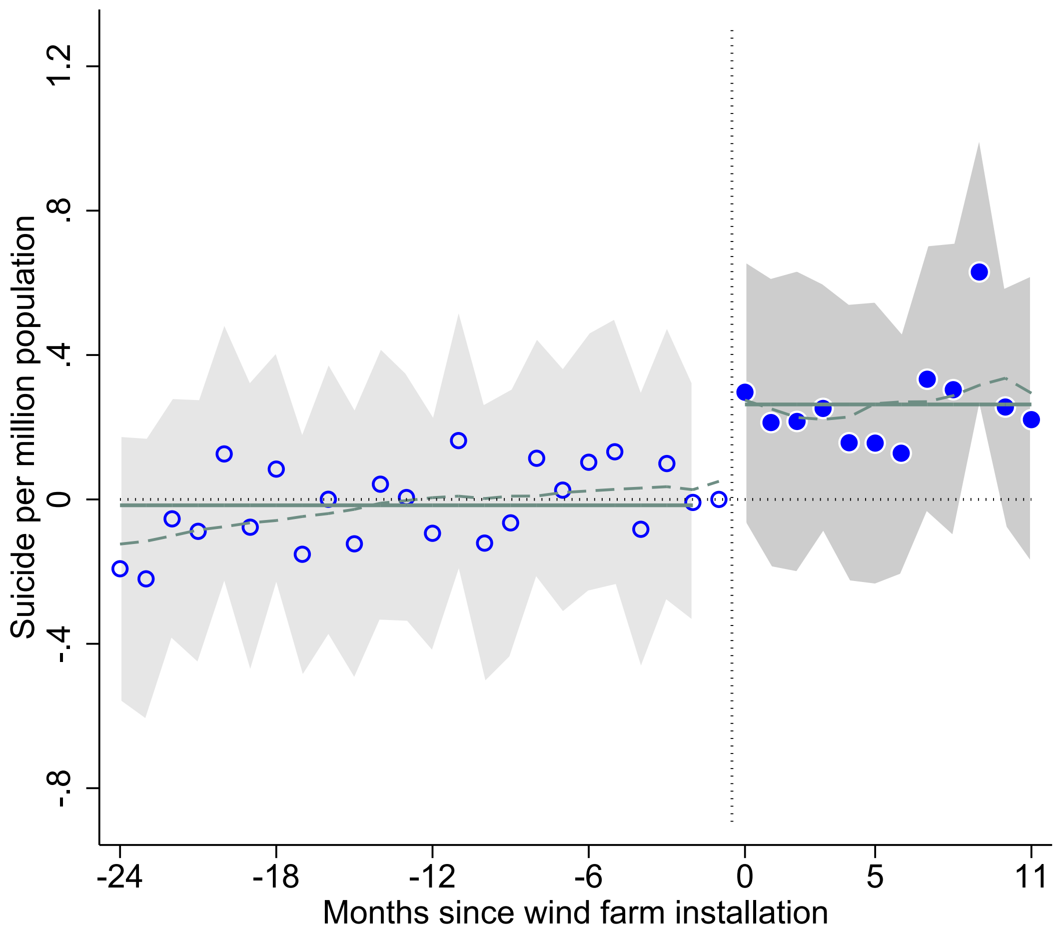
Notes: Circle-connected line plots total wind power generation capacity observed in the EIA-860 form. Triangle-connected lines compute the average distance from county's Census 2010 population center to the nearest wind farm, including states that have wind power capacity by the end of 2013. Dashed line plots distance including all states. Distance statistics before 1997 ranges from 680 km to 1400 km which are not plotted for the sake of readability of the graph.

Figure 3: Distribution of Wind Farms and Sample Counties



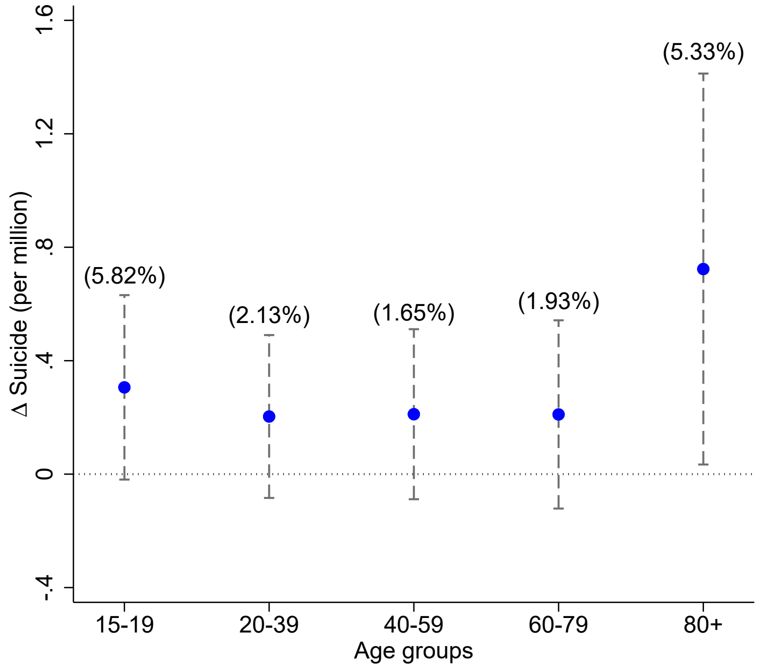
Notes: Map plots location of wind farms and the associated sample counties. Dark color counties are 0-25 km to wind farms. Lighter color counties are 25-100 km of wind farms.

Figure 4: Event Study: Suicide



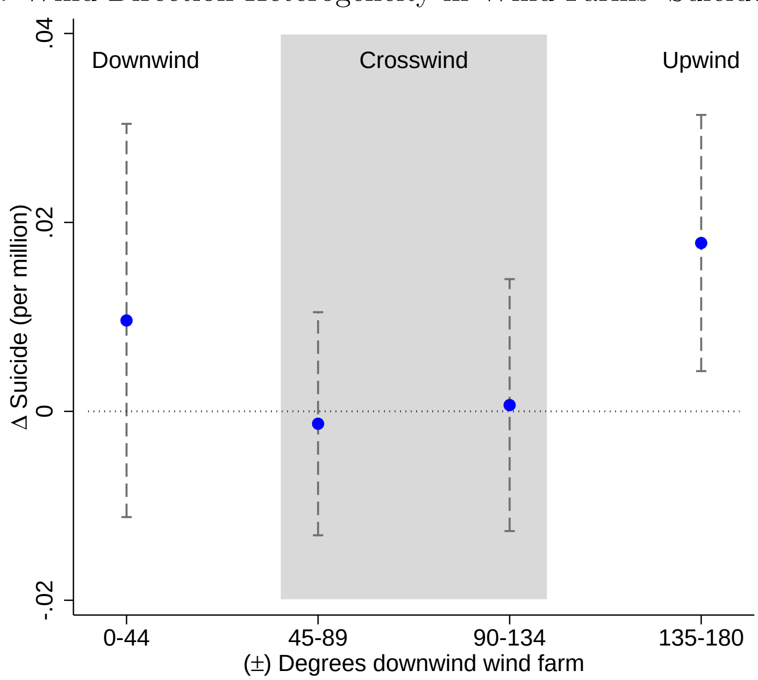
Notes: Graph plots suicide rate (per million population) by months relative to wind farm installation month, using all installation events from 2001-2013. The estimation uses a balanced panel of counties from 24 months before to 12 months after wind farm installations. The month immediately before the installation is the omitted category. The regression is weighted by county×year population and is conditional on 12 month-of-year dummies. Dots show monthly point estimates. Solid lines show before vs. after averages of the point estimates. Dashed lines show lowess smooth of monthly point estimates. Shades show 95% confidence interval constructed using standard errors clustered at the wind farm level.

Figure 5: Age Group Heterogeneity in Wind Farms' Suicide Impacts



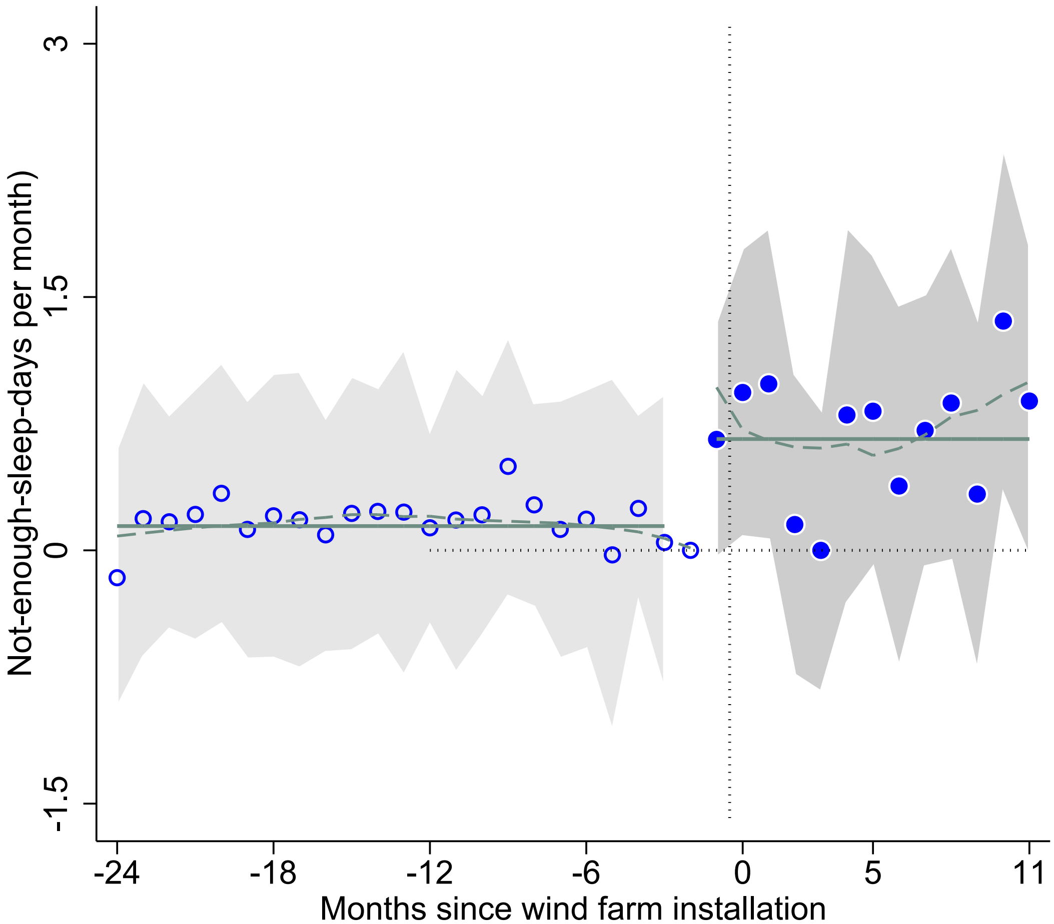
Notes: Graph plots the interaction term between post-event window dummy (Post) and age group category. Percentage numbers in parentheses show coefficient as a fraction of mean suicide rate within each age group. The estimation uses a balanced panel of counties from 12 months before to 12 months after wind farm installations. Regressions include county, month-of-year and year fixed effects fully interacted with age categories. All regressions control for daily temperature bins and quadratic monthly precipitation. Dashed bars show 95% confidence interval constructed using standard errors clustered at the wind farm level.

Figure 6: Wind Direction Heterogeneity in Wind Farms' Suicide Impacts



Notes: Graph plots the interaction term between post-event window dummy (Post) and monthly number of days in four relative wind direction bins, as indicated by x-axis. The "0-44" category is days when a county is within (plus/minus) 0-44 degree of the downwind direction, etc. The estimation uses a balanced panel of counties from 12 months before to 12 months after wind farm installations. Regressions include county, month-of-year and year fixed effects. All regressions control for a full set of lower-order interaction terms, daily temperature bins and quadratic monthly precipitation. Dashed bars show 95% confidence interval constructed using standard errors clustered at the wind farm level.

Figure 7: Event Study: Days “Not Get Enough Sleep” (BRFSS Sample)



Notes: Graph plots monthly average number of days that BRFSS respondents report “did not get enough sleep”, by months relative to wind farm installation month, using all installation events in 2002 and 2004-2010. The estimation uses a balanced panel of counties from 24 months before to 12 months after wind farm installations, subject to BRFSS sleep measure availability. The sample includes all respondents living in counties where the sleep measure is available. The omitted category is two months before the wind farm installation. The regression is weighted by county×year population and is conditional on 12 month-of-year dummies. Dots show monthly point estimates. Solid lines show before vs. after averages of the point estimates. Dashed lines show lowess smooth of monthly point estimates. Shades show 95% confidence interval constructed using standard errors clustered at the wind farm level.

Table 1: Summary Statistics

	(1) Sample: < 25 km counties	(2) Sample: 25-100 km counties	(3) Sample: Other counties	(4) Sample: All counties
Suicide (per million)	8.56	9.51	10.92	9.76
	[3.14]	[3.10]	[3.11]	[3.26]
... age 15-19	5.67	6.56	6.56	6.30
	[4.23]	[4.55]	[4.37]	[4.41]
... age 20-39	9.79	11.23	12.58	11.31
	[4.54]	[4.47]	[4.32]	[4.58]
... age 40-59	12.67	14.02	15.99	14.37
	[4.59]	[4.51]	[5.01]	[4.92]
... age 60-79	10.31	10.99	13.34	11.73
	[3.40]	[4.19]	[3.99]	[4.27]
... age 80+	13.02	13.22	17.46	14.72
	[7.58]	[7.63]	[8.69]	[8.29]
Population (thousands)	114.4	107.5	68.7	90.4
	[436.8]	[302.7]	[180.8]	[294.6]
... fraction age < 20	0.289	0.287	0.283	0.286
... fraction age 80+	0.033	0.032	0.033	0.033
Poverty rate	0.130	0.106	0.135	0.124
High school completion rate	0.788	0.820	0.784	0.797
Fraction white	0.752	0.797	0.762	0.771
Fraction of workers in agriculture	0.019	0.016	0.024	0.020
Fraction of workers in manufacturing	0.140	0.147	0.140	0.142
Per cap. income (2000$)	21,756	23,017	20,117	21,578
	[5,629]	[5,377]	[4,585]	[5,320]
Median home value	171,256	141,884	105,279	137,174
	[136,273]	[73,237]	[39,937]	[92,854]
Racial segregation (Theil index)	0.190	0.197	0.153	0.179
	[0.115]	[0.135]	[0.099]	[0.119]
Gun store (per 100,000)	14.4	16.3	19.1	16.8
	[19.1]	[17.5]	[17.5]	[18.1]
Guns & Ammo circulation (per 100,000)	129	153	154	146
	[90]	[82]	[84]	[86]
Crime rate (per 1,000)	7.49	7.39	7.92	7.60
	[2.98]	[3.32]	[3.93]	[3.44]
Wind speed (m/s)	3.78	3.64	3.37	3.54
	[0.48]	[0.49]	[0.44]	[0.49]
Temperature (degree F)	51.5	51.6	58.8	55.1
	[7.1]	[6.6]	[7.1]	[7.8]
Precipitation (millimeter)	66.7	71.5	98.9	83.6
	[26.8]	[27.3]	[26.3]	[30.6]
N (county)	723	870	1,488	3,081

Notes: All statistics are computed at the county level. Standard deviations in brackets. Suicide, wind speed, temperature, and precipitation statistics are computed as monthly average from 2001-2013. Population, poverty, education attainment, racial composition, employment, income, and home values are from Census 2000, extracted from Minnesota Population Center National Historical Geographic Information System (NHGIS) Version 11.0. Gun store is measured by per capita number of Federal Firearms Licensees in December 2012. *Guns & Ammo* magazine circulation is measured at August 2005. Racial segregation Theil index and violent crime rate are obtained from Chetty et al. (2016). Statistics are weighted by 2001-2013 average annual population (suicide, gun access) and average age-group specific population (age-specific suicide), and census 2000 population (poverty, education attainment, racial composition, employment, income, home values, crime rate). See the text for more details.

Table 2: Wind Farms' Impact on Suicide

Dep. var. = Suicide per million population	(1)	(2)	(3)
Panel A: Simple diff.			
(Post)	0.183***	0.212***	0.251*
	(0.064)	(0.072)	(0.139)
Mean dep. var	8.54	8.54	8.54
Observations	63,075	63,075	63,075
Panel B: Spatial diff. in diff.			
(Post) × (Close)	0.177**	0.184**	0.244*
	(0.073)	(0.078)	(0.134)
Mean dep. var	8.91	8.91	8.91
Observations	320,918	320,918	320,918
Panel C: Temporal diff. in diff.			
(Post) × (Event year)	0.198***	0.217***	0.248*
	(0.069)	(0.071)	(0.132)
Mean dep. var	8.16	8.16	8.16
Observations	820,166	820,166	820,166
Panel D: Triple diff.			
(Post) × (Close) × (Event year)	0.189**	0.197**	0.246*
	(0.078)	(0.080)	(0.132)
Mean dep. var	8.54	8.54	8.54
Observations	4,173,664	4,173,664	4,173,664
County fixed effects	✓		
Month-of-year fixed effects	✓		
Year fixed effects	✓	✓	
County × month-of-year fixed effects		✓	✓
Wind farm × year fixed effects			✓

Notes: Each column × panel cell reports a separate regression. The estimation uses a balanced panel of counties from 12 months before to 12 months after wind farm installations. (Post) indicates months after installation. (Close) indicates counties close to wind farms. (Event year) indicates event windows that contain the actual installation event. All regressions control for a full set of lower-order interaction terms, including those with the fixed effects, daily temperature bins and quadratic monthly precipitation. Standard errors are clustered at the wind farm level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 3: Wind Farms' Impact on Other Causes of Death

Dep. var. = Deaths per million population										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Cause of death:	Suicide	Circ	Neop	Resp	Nervous	Accident	Metabolic	Mental	Digest	Infect
(Post)	0.183	0.314	0.070	0.528	0.408	0.098	-0.004	0.307	0.103	0.087
	(0.064)	(0.449)	(0.256)	(0.322)	(0.163)	(0.151)	(0.130)	(0.164)	(0.107)	(0.089)
p-value	0.005***	0.476	0.786	0.102	0.012**	0.514	0.975	0.063*	0.338	0.332
q-value	0.050**	0.643	0.874	0.255	0.060*	0.643	0.975	0.210	0.564	0.564
Mean dep. var	8.54	200.4	140.9	58.64	34.65	25.21	25.34	25.59	23.17	13.12
Observations	63,075	63,075	63,075	63,075	63,075	63,075	63,075	63,075	63,075	63,075

Notes: Each column reports a separate regression in which the dependent variable is mortality rate by cause of death, indicated by column name. Causes are defined using the 10th revision of the International Statistical Classification of Diseases and Related Health Problems (ICD-10) codes: suicide (X60-X84, Y870), circulatory (I00-I99), neoplasm (C00-D48), respiratory (J00-J99), nervous (G00-G99), accident (V01-X59), metabolic (E00-E90), mental (F00-F99), digest (K00-K93), and infection (A00-B99). The estimation uses a balanced panel of counties from 12 months before to 12 months after wind farm installations. (Post) indicates months after installation. Regressions control for county fixed effects, month-of-year fixed effects, and year fixed effects. All regressions control for daily temperature bins and quadratic monthly precipitation. Standard errors are clustered at the wind farm level. $p-$value is the unadjusted significance level. $q-$value is false discovery rate adjusted significance level based on Anderson (2008). See the text for more details. *: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level.

Table 4: Wind Farms' Impact on Suicide: Multi-year Estimates

Dep. var. = Suicide per million population					
	(1) Sample: 2002-2012	(2) Sample: 2002-2011	(3) Sample: 2002-2010	(4) Sample: 2002-2009	(5) Sample: 2002-2008
Panel A: Simple diff.					
(Post)					
... year 1	0.183***	0.291***	0.284**	0.340**	0.279*
	(0.064)	(0.089)	(0.125)	(0.138)	(0.169)
... year 1 to 2	-	0.210***	0.246**	0.293**	0.234
	-	(0.079)	(0.111)	(0.121)	(0.143)
... year 1 to 3	-	-	0.250**	0.296***	0.265**
	-	-	(0.101)	(0.111)	(0.126)
... year 1 to 4	-	-	-	0.263**	0.255**
	-	-	-	(0.109)	(0.128)
... year 1 to 5	-	-	-	-	0.294**
	-	-	-	-	(0.125)
Panel B: Spatial diff. in diff.					
(Post) × (Close)					
... year 1 to T	0.177**	0.204**	0.217*	0.229*	0.269*
	(0.073)	(0.090)	(0.113)	(0.123)	(0.146)

Notes: Each column × panel cell reports a separate regression. Column names indicate subset of wind farm installation events used. In panel A, (Post) indicates "1 to t" years after installation, as indicated by row names. In panel B, (Post) indicates "1 to T" years after installation, where "T" = 5/4/3/2/1 for column 5/4/3/2/1. (Close) indicates counties close to wind farms. All regressions control for daily temperature bins, quadratic monthly precipitation, county fixed effects, month-of-year fixed effects, and year fixed effects. Regressions in panel B also control for a full set of lower-order interaction terms. Standard errors are clustered at the wind farm level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 5: Wind Farms' Impact on Suicide, by Wind Directions

Dep. var. = Suicide per million population			
	(1)	(2)	(3)
Panel A: By wind directions			
(Post) × Up/downwind	0.0148***	0.0155***	0.0108
	(0.0054)	(0.0059)	(0.0086)
(Post) × Crosswind	-0.0004	0.0011	0.0064
	(0.0036)	(0.0039)	(0.0062)
Panel B: By wind directions and wind speed			
(Post) × (Up/downwind - Crosswind) × (Bot. tercile wind speed)	-0.0087	-0.0060	-0.0208
	(0.0143)	(0.0163)	(0.0179)
(Post) × (Up/downwind - Crosswind) × (Mid. tercile wind speed)	0.0116	0.0103	-0.0009
	(0.0153)	(0.0158)	(0.0166)
(Post) × (Up/downwind - Crosswind) × (Top tercile wind speed)	0.0254**	0.0249**	0.0197
	(0.0106)	(0.0118)	(0.0144)
Panel C: By wind directions and wind farm size			
(Post) × (Up/downwind - Crosswind) × (Bot. tercile wind farm)	0.0018	0.0013	-0.0177
	(0.0189)	(0.0204)	(0.0192)
(Post) × (Up/downwind - Crosswind) × (Mid. tercile wind farm)	-0.0120	-0.0084	-0.0113
	(0.0166)	(0.0183)	(0.0220)
(Post) × (Up/downwind - Crosswind) × (Top tercile wind farm)	0.0250*	0.0233	0.0305*
	(0.0149)	(0.0155)	(0.0181)
County fixed effects	✓		
Month-of-year fixed effects	✓		
Year fixed effects	✓	✓	
County × month-of-year fixed effects		✓	✓
Wind farm × year fixed effects			✓
Observations	63,075	63,075	63,075

Notes: Each column × panel cell reports a separate regression. The estimation uses a balanced panel of counties from 12 months before to 12 months after wind farm installations. (Post) indicates months after installation. "Up/downwind" ("crosswind") counts number of days in a month that the county spend downwind (crosswind) a wind farm. "Bot./Mid/.Top tercile wind speed" ("Bot./Mid/.Top tercile wind speed") is a categorical variable for terciles of monthly wind speed at the wind farm (MW size of the wind farm). In panel B, the top - bottom tercile difference in monthly average wind speed is 1.88 m/s, compared to a within estimation sample average wind speed of 3.87 (SD=0.89). All regressions control for a full set of lower-order interaction terms, daily temperature bins and quadratic monthly precipitation. Standard errors are clustered at the wind farm level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 6: Wind Farms' Impact on Sleep Insufficiency (BRFSS Sample)

Sleep loss measure:	(1) Days of insuff. sleep	(2) Any days of insuff. sleep?	(3) $\geq$ 7 days of insuff. sleep?	(4) $\geq$ 14 days of insuff. sleep?
(Post)	0.201**	0.0039	0.0077**	0.0075**
	(0.091)	(0.0053)	(0.0036)	(0.0036)
Mean dep. var	8.35	0.699	0.391	0.269
Observations	2,172	2,172	2,172	2,172

Notes: Each column reports a separate regression. Dependent variables are monthly measures of insufficient sleep, as indicated by column names. The estimation uses a balanced panel of counties from 12 months before to 12 months after wind farm installations, subject to BRFSS sleep measure availability. (Post) indicates months after installation. All regressions include county fixed effects, month-of-year fixed effects, and year fixed effects. Regressions also control for daily temperature bins and quadratic monthly precipitation. Standard errors are clustered at the wind farm level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 7: Wind Farms' Impact on Suicide, by Firearm Access

Dep. var. = Suicide per million population				
	(1)	(2)	(3)	(4)
Gun access measure:	Gun shop		*Guns & Ammo* circulation	
(Post) × (Bot. tercile gun access)	0.126*		0.106*	
	(0.066)		(0.062)	
(Post) × (Mid tercile gun access)	0.304		0.434	
	(0.263)		(0.290)	
(Post) × (Top tercile gun access)	1.505***		1.117***	
	(0.438)		(0.382)	
(Post) × log(Gun aceess)		0.205***		0.367**
		(0.074)		(0.144)
Observations	63,075	61,755	63,003	62,931

Notes: Each column reports a separate regression. The estimation uses a balanced panel of counties from 12 months before to 12 months after wind farm installations. (Post) indicates months after installation. "Bot./Mid./Top gun access" is a categorical variable for terciles of gun access. Gun access measure is county level Federal Firearms Licensees per 100,000 residents (column 1 and 2) and county level *Guns & Ammo* circulation per 100,000 residents (column 3 and 4). All regressions include county fixed effects, month-of-year fixed effects, and year fixed effects. Regressions control for a full set of lower-order interaction terms, daily temperature bins and quadratic monthly precipitation. Standard errors are clustered at the wind farm level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 8: Social Costs of Wind Farm: Summary

Category	Source	Raw estimates	Calculated total cost, 2001-2013
suicide costs	This paper	0.183 suicides per million population per month.	\$3.3 billion
bat fatality costs	Arnett et al. (2008); Hayes (2013) Cleveland et al. (2006)	9.9 bat deaths per MW installed wind capacity per year; Consumption of 3 female moths = 10 larvae = 20 bolls of cotton saved per bat per night.	\$12 million
	Frank (2017)	18.2 infant deaths per million bat deaths from White Nose Syndrome.	\$480 million
visual impact costs	Gibbons (2015)	2.5% reduction in home price within 4 km radius to wind farms.	\$5.5 billion
emission-displacement benefits	Cullen (2013); Kaffine, McBee, and Lieskovsky (2013); Novan (2015)	Displacement of 0.57 tons of CO_2 per MWh wind energy; Displacement of 0.000465 tons of NO_x per MWh wind energy; Displacement of 0.000775 tons of SO_2 per MWh wind energy.	\$19.1 billion
	Epstein et al. (2011) Novan (2015)	Lifecycle cost of \$178 per MWh coal energy; 0.33 MWh coal energy displacement per MWh wind energy.	\$45.5 billion

Notes: Each "Category" block indicates a category of cost. Each "Source" block indicates a cost component within the category and the associated studies. "Raw estimates" show estimates drawn from the original studies. "Calculated total cost" shows author's calculation for the cost component. See Section 7 for more details.

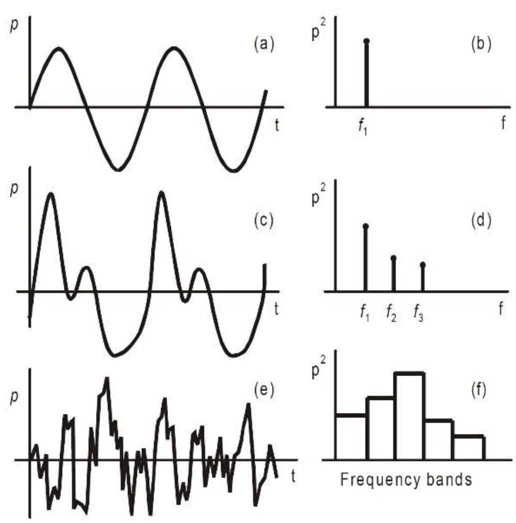
Appendix A. Notes on Wind Turbine Acoustics

In this note I review basic concepts in acoustics, with a focus on explaining how sound energy decays through propagation. I also review scientific and engineering research on wind turbine noise. Virtually all graphics and table exhibits are taken directly from sources which are cited in the figure and table notes. All errors are mine.

A.1. Basic Concepts of Acoustics

Sound comes from pressure oscillations in an elastic medium, such as air. The simplest "unit" of sound is a pure tone, which can be characterized by a single frequency and an amplitude (i.e., intensity). A pure tone sound can be conceptualized by thinking about a sine wave. In reality, sounds are usually complex mixture of different sine waves. A sound can therefore be represented by its frequency *spectrum*. Figure A.1 illustrates a pure tone sine wave and its frequency (top row), a mixture of three sine waves of different frequencies and amplitudes, and the sound's frequency spectrum (middle row), and a more realistic example of sound signal and its associated frequency band spectrum (bottom row).

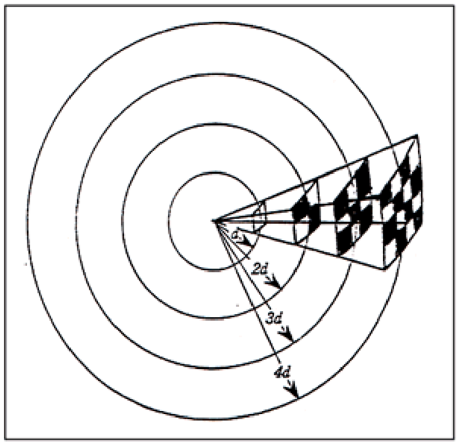
Figure A.1. Illustration of Sound Spectrum



Source: Hansen (2001).

Propagation of Sound. The most basic model of sound propagation is known as spherical propagation. In an ideal, "free field" setting, a sound signal is generated by a single point source, and the energy is then distributed over the spherical surfaces of an ever-increasing ball. Figure A.2 provides an illustration.

Figure A.2. Illustration of Spherical Propagation of Sound in Free Field



Source: www.acousticalsurfaces.com/acoustic_IOI/101home.htm

As sound propagates, the initial energy is scattered on larger and larger surfaces, and thus the sound intensity on any point of the receiving surface becomes weaker. The relationship between the source intensity (sound power level L_p measured in decibels) and the receiver intensity (sound pressure level L_p measured in decibels) r meters apart is governed by the following equation:[1]

$$L_p = L_w - 10 \cdot \log_{10}(4\pi r^2)$$

This equation, commonly referred to as the Inverse Square Law, says that the intensity of the sound is inversely related to the square of the distance of the wavefront from the signal source. This equation also implies the rule that sound intensity diminishes by 6 decibels (dB) with every doubling of distance. In practice, L_p is often approximated by measurement at a location very close (r_0 meters) to the source. In this case, the Inverse Square Law can be rewritten as

$$L_p = L_w - 20 \cdot \log_{10}\left(\frac{r}{r_0}\right)$$

Atmospheric Attenuation. Note that in the spherical model, the attenuation of sound by distance is due to the pure scattering of energy over the sphere. That is, the atmosphere within which the sound propagates does not itself absorb sound energy. In reality, there are sources of "excess attenuations" in additional to that from spherical spread. Weather, barriers, and ground interactions are examples of these sources. One primary source of decay is atmospheric attenuation, which comes from energy losses due to

[1] Decibel (dB) is a relative measure of sound pressure vis-à-vis 20 μPa, which is the minimum acoustic pressure audible to the human ear ($\mathrm{dB} = 20 \cdot \log_{10} \frac{\text{pressure}}{20\mu\text{Pa}}$).

friction between air molecules, resulting in heat generation, and from the air molecules' absorption ability that results in vibration and rotation of molecules.

Atmospheric absorption is summarized by the so-called atmospheric absorption coefficient α, which expresses the loss of intensity per distance (e.g., dB/meter). Approximately, α is proportional to the square of the sound's frequency. That is, sounds with higher frequency are more efficiently attenuated in propagation, and are less able to travel long distances. The exact formula for is given in ISO 9613-1:1996, which is reproduced below:

$$\alpha = 869 \cdot f^2 \cdot \left\{1.84 \cdot 10^{-11} \cdot \left(\frac{T}{T_0}\right)^{\frac{1}{2}} + \left(\frac{T}{T_0}\right)^{-\frac{5}{2}} \cdot \left[0.01275 \cdot \frac{e^{-\frac{2239.1}{T}}}{F_{Oxygen}} + 0.1068 \cdot \frac{e^{-\frac{3352}{T}}}{F_{Nitrogen} + \frac{f^2}{F_{Nitrogen}}}\right]\right\}$$

where f denotes sound's frequency in Hz, T is temperature in degrees Kelvin (T_0 is 293.15 Kelvin, or 20 degrees Celsius), F_{Oxygen} is Oxygen relaxation frequency in Hz, and $F_{Nitrogen}$ is Nitrogen relaxation frequency in Hz. Table A.1 shows example values of α at 1 atm (101.325 kPa), 20°C, and 70% relative humidity. Note that atmospheric absorption is very low for low-frequency sounds.

Table A.1. Examples of Atmospheric Absorption Coefficient

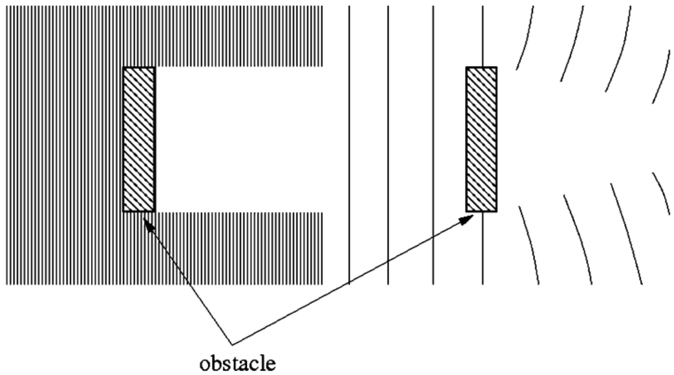
Frequency (Hz)	Temperature (°C)	Relative humidity (%)	Atmospheric absorption (dB/km)
5	20	70	0.004
20	20	70	0.057
40	20	70	0.191
60	20	70	0.346
80	20	70	0.491
100	20	70	0.622
200	20	70	1.22
500	20	70	4.23
1,000	20	70	14.09

Notes: Author's calculation using web application: resource.npl.co.uk/acoustics/techguides/absorption/

Other Forms of Attenuation. There are many other sources of propagation attenuation in addition to atmospheric attenuation. Readers are referred to Sutherland and Daigle (1998) and Lamancusa (2009) for comprehensive reviews. Here, I provide one discussion on the ability of low-frequency noise to go through barriers – both in terms of lower diffraction and lower absorption – which is a particularly relevant feature to my study.

Figure A.3 (Szasz and Fuchs, 2010) shows an example of high-frequency sound that has a wavelength much smaller than the barrier size. This produces a shadow zone with no sound behind the barrier. For low-frequency noise, such effect attenuates. In the extreme case in which the wavelength is larger than the size of the barrier object, the shadow zone would disappear completely. Such a diffraction pattern partially explains why windows and walls have a harder time stopping low-frequency noise.

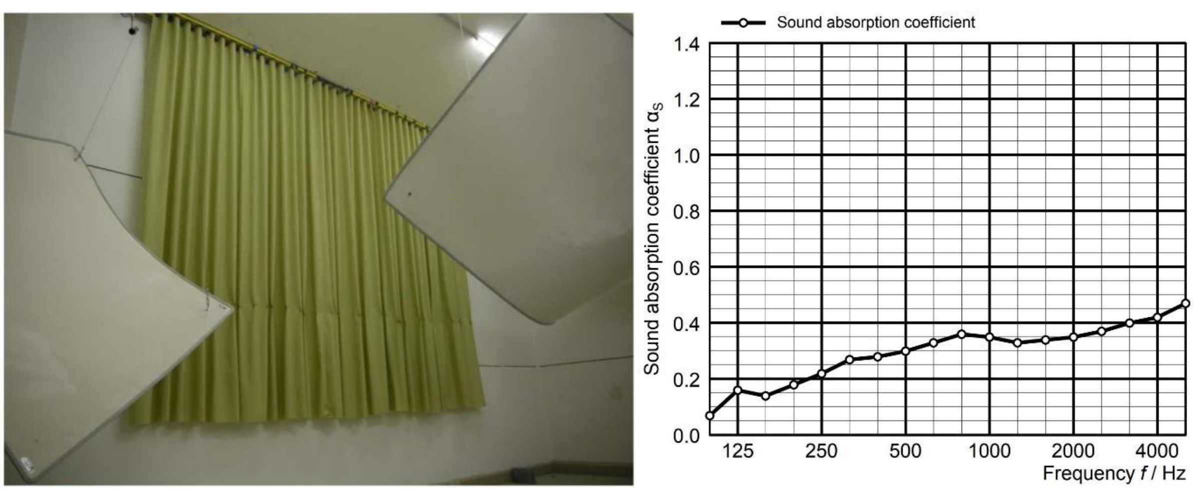
Fig A.3. Diffraction behind obstacles high-frequency (left) and low-frequency (right) waves.

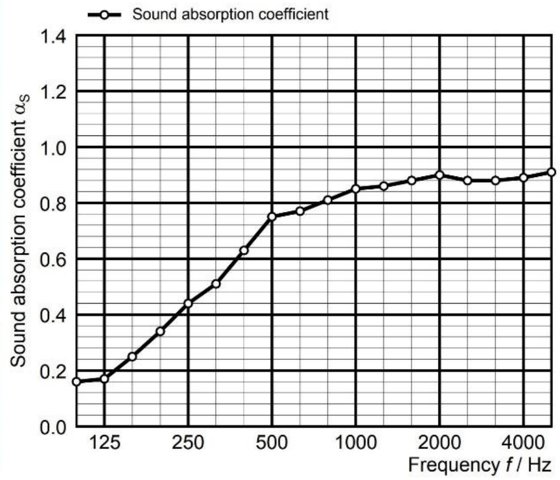


Source: Szasz and Fuchs (2010)

It is also harder for materials to absorb sound energy for low-frequency sounds (e.g., Delany and Bazley, 1970; Arenas and Crocker, 2010). Figure A.4 shows absorption coefficients (the ratio of absorbed energy to source sound energy) of a fabric curtain (top row) and thermal hemp, which is a commonly used wall insulation material (Muller-BBN Test Report M52-297, M60-836). Neither material provides protection against sounds below 100 Hz.

Figure A.4. Examples of Noise Absorption Coefficients





Source: Muller-BBN Test Report M52-297, M60-836

A.2. Wind Turbine Noise

Wind turbine noise consists of both mechanical noise and aerodynamic noise. Mechanical noise is easy to mitigate, e.g., by using a quieter gearbox. Thus, the primary discussion of noise reduction from wind turbines concerns aerodynamic noise. As briefly discussed in Section 2.1 of the paper, the dominant sources of aerodynamic noise are believed to come from the trailing edge noise and inflow turbulence (Wagner, Bareiss, and Guidati, 1996).

To proceed, I review two strands of the engineering literature on wind turbine noise. The first is about wind turbine noise emission, which tells us about the sound power of wind turbines at the source. The second, which is a less developed literature in my view, is on wind turbine noise propagation at receivers. This tells us about sound pressure felt at long distances (measured in kilometers). Most of the investigations I have found are guided by models of sound propagations, parameterized by (often sparse) sound measurements in the field.

Wind Turbine Noise at Source. The aerodynamic noise emission from a wind turbine is a complex function of various aspects of turbine design (such as rotor size and angle), and atmospheric conditions (such as temperature and wind speed) at a turbine's location. Lowson (1993) and Zidan, Elnady, and Elsabbagh (2014) provide a review of various models. The simplest model is provided by Hagg (1990), which expresses a wind turbine's (A-weighted) sound power level L_{WA} as:

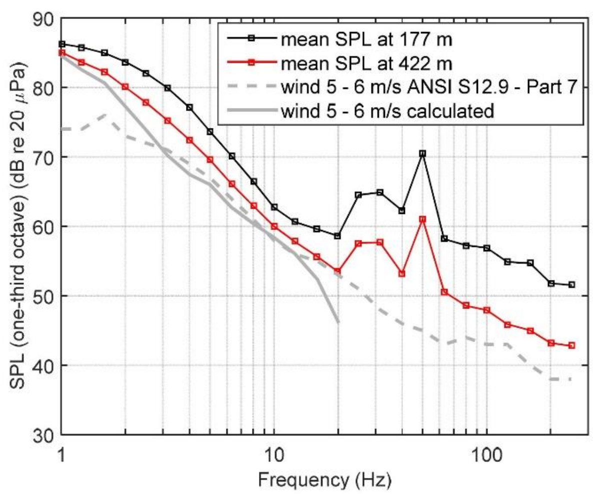
$$L_{WA} = 50 \cdot \log_{10} \frac{\Omega D}{2} \sqrt{1 + \frac{1}{\lambda^2}} + 10 \cdot \log_{10} D - 4$$

$$\lambda = \frac{\Omega D}{2V_{wind}}$$

where Ω is rotor frequency (which is itself a function of wind speed and turbine design), D is blade diameter, and V_{wind} is wind speed at the hub height. Note that the noise level from a wind turbine is roughly inversely related to λ, which is known as the tip-speed ratio (the speed of the blade tip divided by the wind speed). Intuitively, this means that noise is minimized if the rotor of the wind turbine turns slowly relative to wind speed. However, it is understood that a wind turbine's power-generating efficiency is a concave function of λ, i.e., it rises at low levels of tip-speed ratio and declines at high levels of tip-speed ratio (Ragheb and Ragheb, 2011). Therefore, noise minimization is to a large extent at odds with maximization of power-generating efficiency.

Just how loud is wind turbine noise in the field? This question has been repeatedly examined using microphone-based field tests since the late 1980s. To date, most studies have provided consistent answers (e.g., Hubbard and Shepherd, 1990; Hubbard and Shepherd, 2009). Here I cite one recent paper by Hansen et al. (2015) that provides new estimates of the sound spectrum of modern industrial turbines, but also compares the measured sound spectrum to counterfactual levels of "background sound" that would have been produced by winds even in the absence of the wind turbines.

Figure A.5. Spectral Analysis of Sounds Recorded at the Waterloo Wind Farm



Source: Hansen et al. (2015)

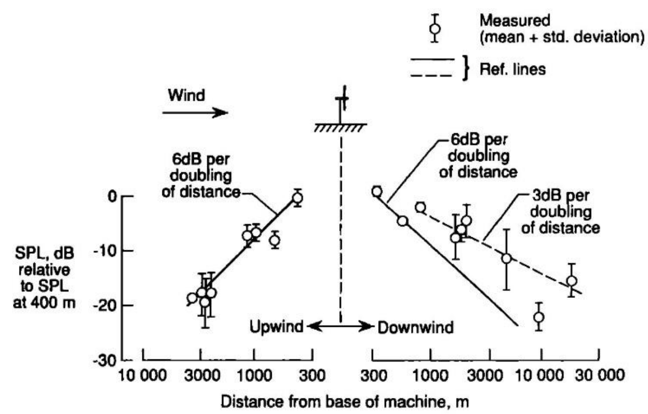
The Hansen et al. (2015) study took place at the Waterloo Wind Farm in Australia near an array of Vestas V90 (3MW) wind turbines, each 80 meters high. Two low-frequency-sensitive microphones measured sounds 177m and 422m downwind of the last wind turbine in the array. Figure A.5 shows the spectral decomposition of the sound recorded, as well as a "control situation," which is the background noise that would have been generated by the winds at the time of recording. Relative to the control situation, recorded sounds exhibit a jump in energy around the 30 – 60 Hz frequency domain, which is about 15 dB higher than the control of 48 dB (about a 30% increase).[2] When factoring in the microphones' locations

[2] Note this does not imply that wind turbines do not emit noise at other frequencies. Sounds follow logarithmic addition, and the louder source is often deterministic of the total sound level.

and local atmospheric conditions, the data suggest that the sound power of wind turbines around the 20 – 50 Hz range could reach 120 dB.

Wind Turbine Noise at Distances. Measuring wind turbine noise at far distances proves to be very challenging due to the complexity of sound propagation. As briefly mentioned in Section 2.1, *audible* levels (i.e., very high intensity) of low-frequency noise from turbines have been recorded up to 2 km away from the wind farm. To the best of my knowledge, the literature on longer distances measurement is sparse. The best evidence is provided in two early studies led by the U.S. National Aeronautics and Space Administration (NASA), which measured infrasonic noise from wind turbines up to 20 km (Willshire, 1985; Willshire and Zorumski, 1987).

Figure A.6. Measured Low-frequency Sound Pressure as a Function of Distance to a Wind Turbine



Source: Willshire and Zorumski (1987); Hubbard and Shepherd (1991).

Figure A.6 shows measured sound pressure at frequencies of 8 – 16 Hz relative to the measurement taken 400m from the WTS-4 wind turbine (4MW, 90m hub height). For example, at a distance of about 20 kilometers, low-frequency noise is attenuated by 20 dB relative to the source. It is interesting to note that the patterns shown in Figure A.6 suggest that low-frequency noise decay seems consistent with a spherical propagation of -6 dB per doubling of distance (see Appendix A.1), which suggests atmospheric absorption does not play a substantial role in attenuation of the sounds. The data also suggest that sound decay is even slower in downwind directions.

Appendix A References

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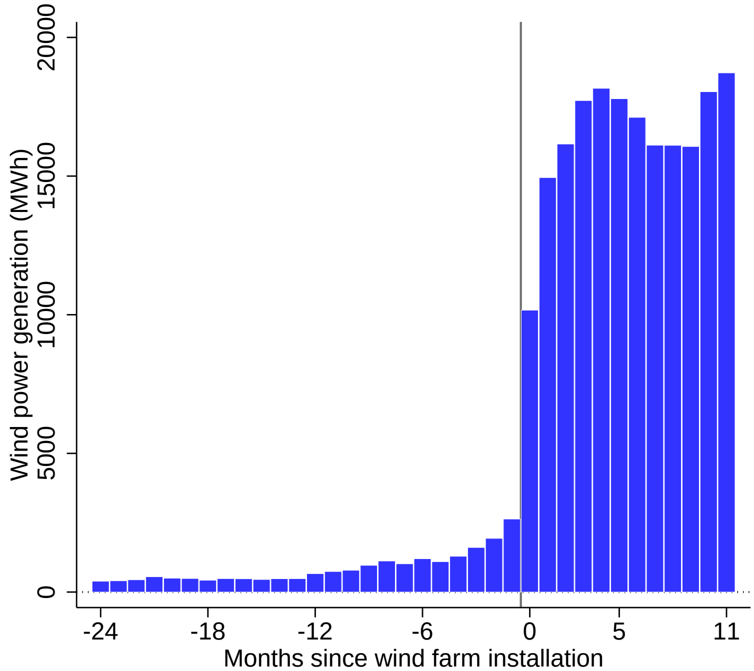
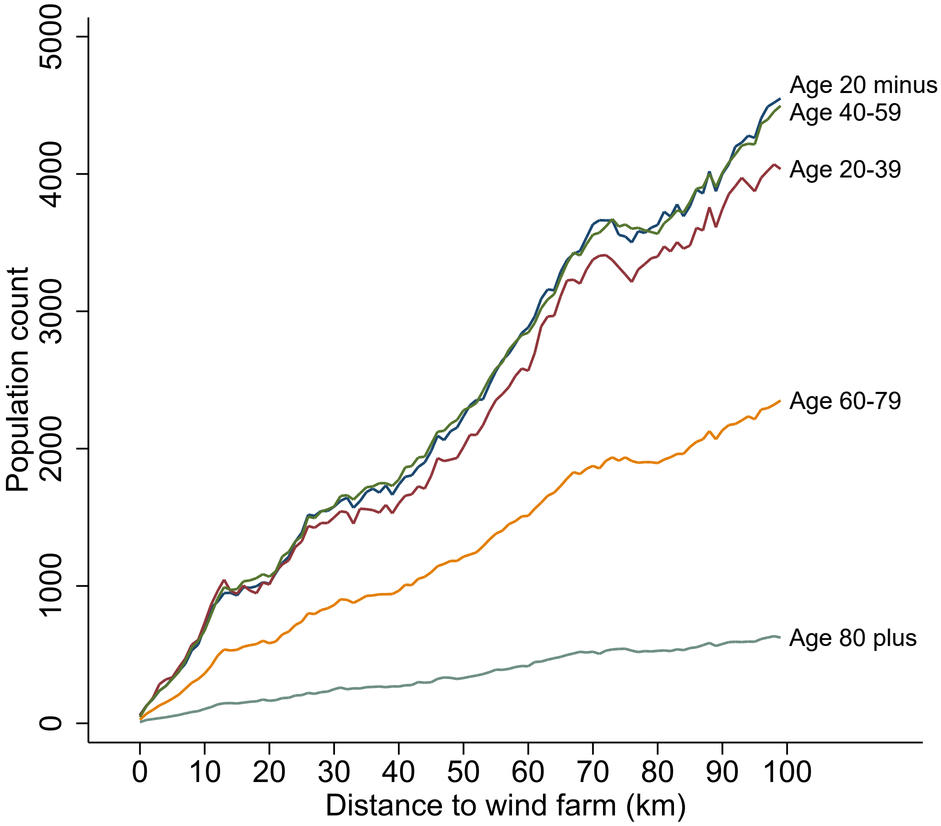
Appendix B. Additional Figures and Tables

Figure B.1. Event Study: Wind Power Generation



Notes: Graph plots wind power generation (MWh) by months relative to wind farm installation month, using all installation events from 2001-2013. In cases where installations are capacity additions to existing wind farms, positive generation are observed before the installation event.

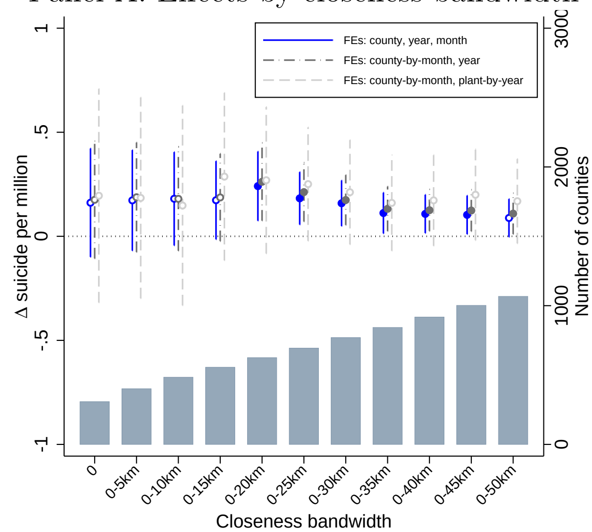
Figure B.2. Population by Distance to Wind Farms



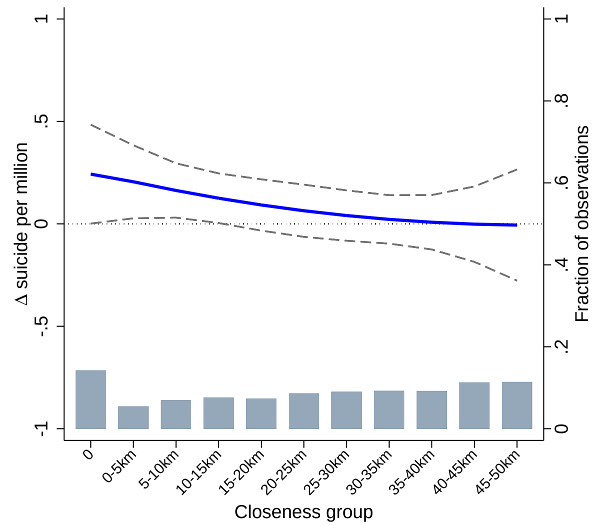
Notes: This graph plots distributions of age group-specific population counts by distance to wind farm. The underlying data are wind farm-block pairs, i.e., these estimates represent population gradient of a "typical" wind farm in my study sample. Data are drawn from the 2010 Census Block estimates.

Figure B.3. Robustness Checks: Alternative Closeness Definitions

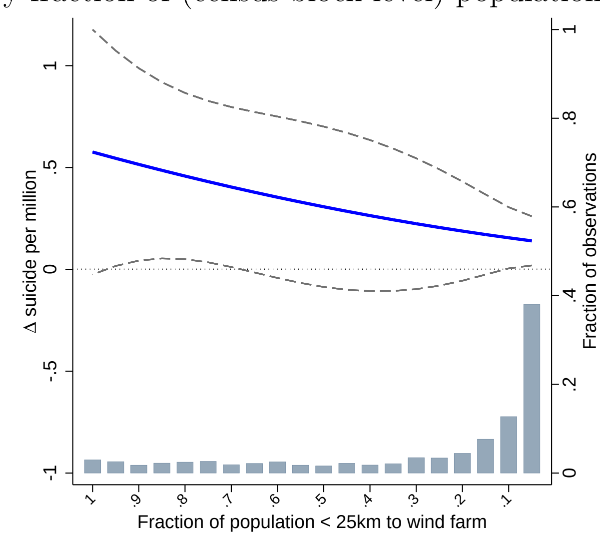
Panel A. Effects by closeness bandwidth



Panel B. Effects by closeness group sequence

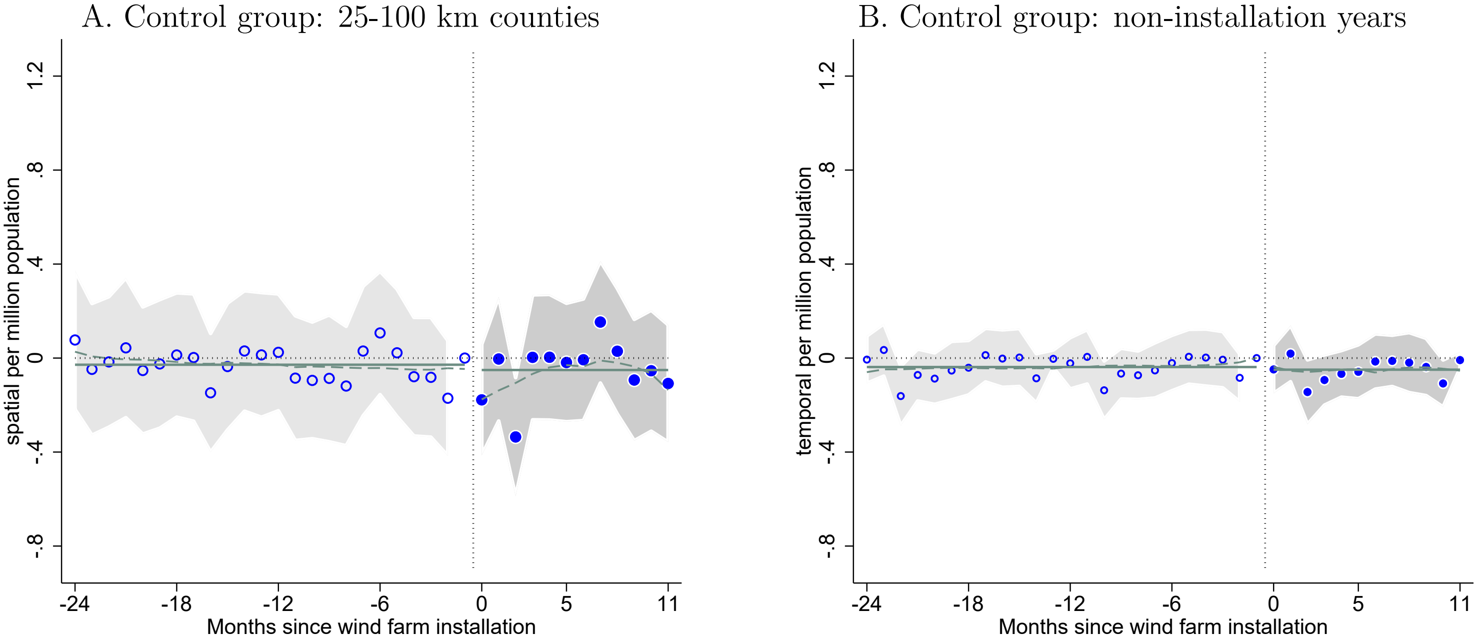


Panel C. Effects by fraction of (census block level) population close to wind farms



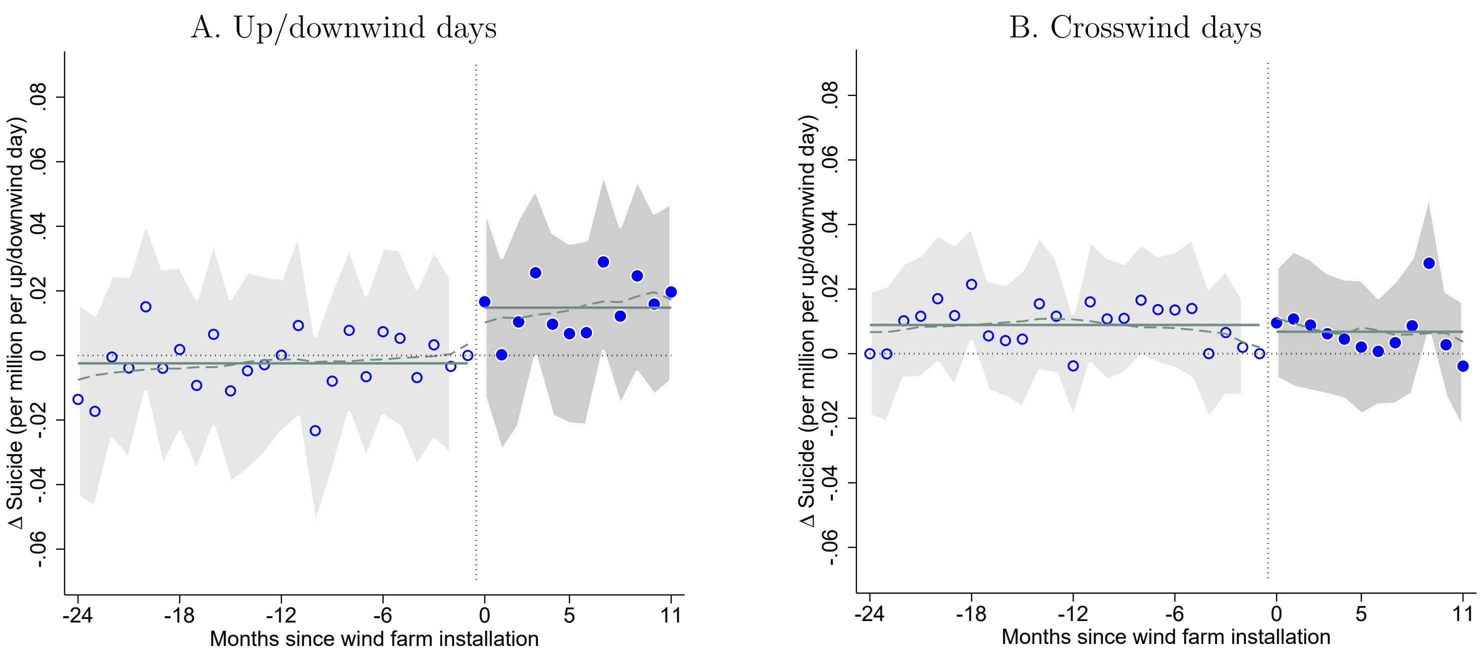
Notes: In panel A, each group of range plot items use the same estimation sample, including counties within certain closeness-bins to the wind farm as indicated by the x-axis. Bar plots number of counties included in each estimation sample. Within each group, each range plot item shows a separate regression with different fixed effects controls as indicated by the legend. Range bar represents 95% confidence interval constructed using standard errors clustered at the wind farm level. Solid dots highlight coefficients that are individually significant at the 5% level. Panel B plots a quadratic effects gradient by sequence of closeness bins. Panel C restricts to counties in the 25km-closeness group (i.e., any part of the county falls within 25km within the wind farm), and shows heterogeneous suicide effects by counties' fraction of population living within 25km to wind farm using Census Block level population data.

Figure B.4. Event Study of Suicide for Control Groups



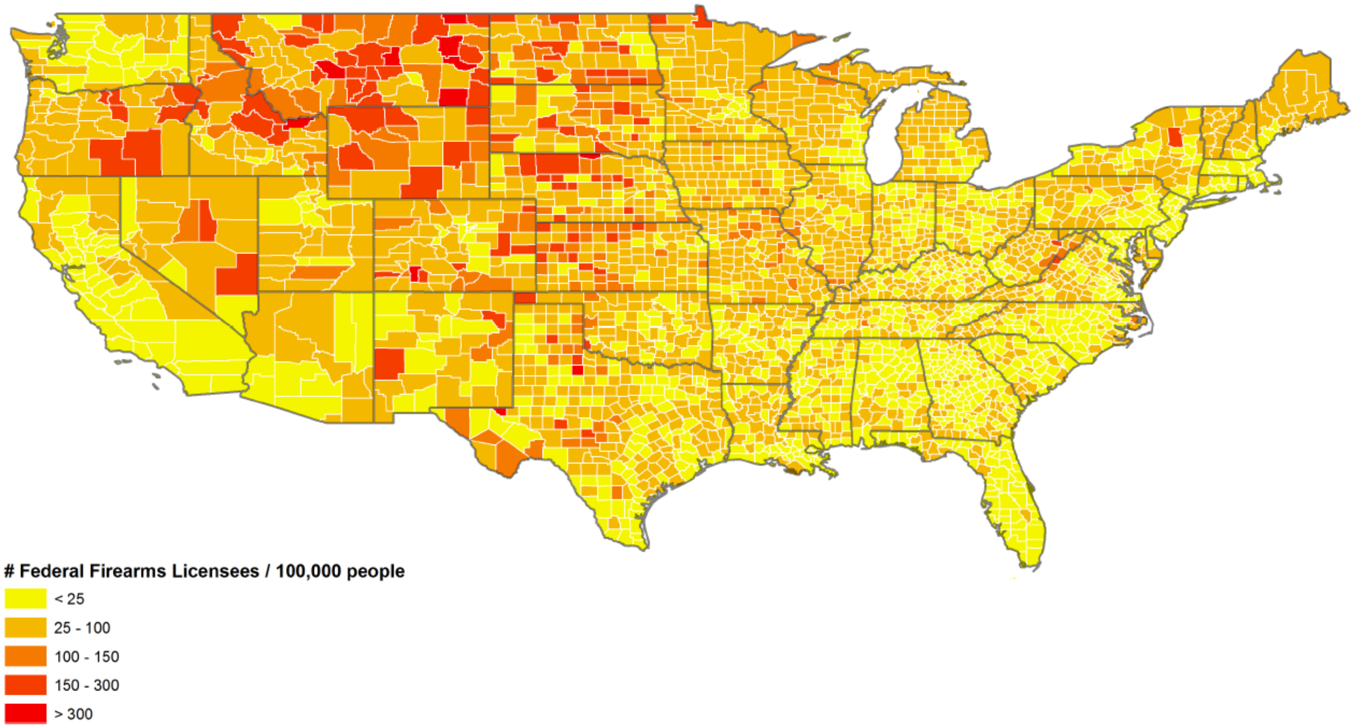
Notes: This figure shows event study of suicide for counties in the control group in the spatial difference-in-differences specification, which is counties 25-100 km to wind farms (panel A), and the temporal difference-in-differences specifications, which is counties 0-25 km in years when no wind farm installations occur (panel B). The estimation uses a balanced panel of counties from 24 months before to 12 months after wind farm installations. The month immediately before the installation is the omitted category. The regression is weighted by county×year population and is conditional on 12 month-of-year dummies. Dots show monthly point estimates. Solid lines show before vs. after averages of the point estimates. Dashed lines show lowess smooth of monthly point estimates. Shades show 95% confidence interval constructed using standard errors clustered at the wind farm level.

Figure B.5. Event Study Estimates of the Correlation between Wind Direction and Suicide



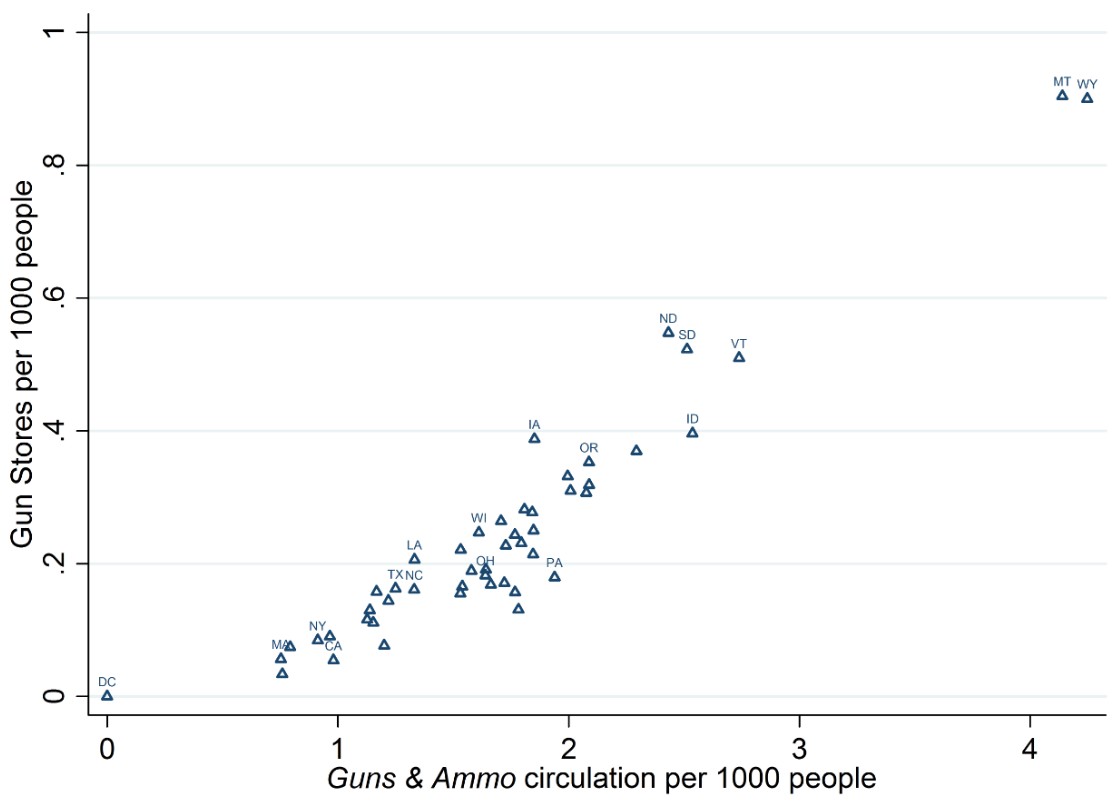
Notes: This figure shows event study version of the "(Post)×Up/downwind" coefficient (panel A) and the "(Post)×crosswind" coefficient (panel B). The "(Post)" dummy is replaced with a full set of indicators for event month. The estimation uses a balanced panel of counties from 12 months before to 12 months after wind farm installations. Regressions control for county fixed effects, month-of-year fixed effects, a full set of lower-order interaction terms, daily temperature bins and quadratic monthly precipitation. Shades show 95% confidence interval constructed using standard errors clustered at the wind farm level.

Figure B.6. Gun Access by County, December 2012



Notes: Map plots county level number of gun shops per 100,000 population in December 2012. Gun shops are defined as Federal Firearms Licensees listed as "dealers in firearms other than destructive devices".

Figure B.7. Correlation of Gun Access Measures



Notes: Graph plots state level gun access measured by per capita number of gun shops (December 2012) vs. per capita circulation of the magazine *Guns & Ammo* (August 2005).

Table B.1. Robustness Checks: Wind Farms' Impact on Suicide

Dep. var. = Suicide per million population			
	(1)	(2)	(3)
Alternative SE clusters	0.183	0.212	0.251
... county level	(0.096)*	(0.097)**	(0.142)*
... state level	(0.101)*	(0.109)*	(0.110)**
... wind farm & month (2-way)	(0.076)**	(0.107)*	(0.251)**
Unbalanced sample	0.198***	0.221***	0.315**
	(0.063)	(0.069)	(0.138)
Drop "event month 9"	0.163**	0.248*	0.204***
	(0.065)	(0.143)	(0.073)
First installation only	0.135**	0.167**	0.329***
	(0.062)	(0.071)	(0.127)
Drop December installations	0.150**	0.177**	0.137
	(0.069)	(0.077)	(0.148)
PTC driven installations only	0.365**	-	-
	(0.158)	-	-
No weather controls	0.198***	0.213***	0.240*
	(0.066)	(0.071)	(0.137)
Weather controls vary by Census Regions	0.157**	0.156**	0.140
	(0.064)	(0.066)	(0.128)
Temperature bins interact precipitation	0.156**	0.153**	0.223*
	(0.065)	(0.071)	(0.123)
County characteristics trends controls	0.176***	0.207***	0.241*
	(0.065)	(0.073)	(0.142)
All FEs interact wind resource classes	0.190***	0.197***	0.242*
	(0.062)	(0.068)	(0.139)
Age-adjusted suicide rate	0.191***	0.219***	0.224
	(0.064)	(0.071)	(0.136)
County fixed effects	✓		
Month-of-year fixed effects	✓		
Year fixed effects	✓	✓	
County × month-of-year fixed effects		✓	✓
Wind farm × year fixed effects			✓

Notes: Each cell reports a separate regression. Unless noted, estimation uses a balanced sample of counties from to 12 months before to 12 months after wind farm installations. "PTC driven installations" refer to installations which occurred on months when the Federal Production Tax Credit expired. As all expirations are all on December, the specifications in column 2 and 3 cannot be estimated as they exploit within month-of-year variations. Unless noted, regressions control for daily temperature bins and quadratic monthly precipitation. Unless noted, standard errors are clustered at the wind farm level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table B.2. Wind Farms' Impact on Other Causes of Death: Robustness to Alternative Research Designs

Dep. var. = Deaths per million population										
Cause of death:	(1) Suicide	(2) Circ	(3) Neop	(4) Resp	(5) Nervous	(6) Accident	(7) Metabolic	(8) Mental	(9) Digest	(10) Infect
Panel A: Simple diff. (Observations = 63,075)										
(Post)	0.183***	0.314	0.070	0.528	0.408**	0.098	-0.004	0.307*	0.103	0.087
	(0.064)	(0.449)	(0.256)	(0.322)	(0.163)	(0.151)	(0.130)	(0.164)	(0.107)	(0.089)
Panel B: Spatial diff. in diff. (Observations = 320,918)										
(Post) × (Close)	0.177**	0.167	0.444	0.099	0.525***	0.034	-0.111	-0.181	0.052	0.070
	(0.073)	(0.501)	(0.292)	(0.378)	(0.197)	(0.177)	(0.144)	(0.211)	(0.122)	(0.108)
Panel C: Temporal diff. in diff. (Observations = 820,166)										
(Post) × (Event year)	0.198***	0.384	0.063	0.586*	0.425**	0.103	0.011	0.344**	0.127	0.086
	(0.069)	(0.489)	(0.267)	(0.354)	(0.178)	(0.165)	(0.142)	(0.174)	(0.120)	(0.094)
Panel D: Triple diff. (Observations = 4,173,664)										
(Post) × (Close) × (Event year)	0.189**	0.133	0.462	0.081	0.539***	0.044	-0.112	-0.161	0.059	0.077
	(0.078)	(0.535)	(0.307)	(0.331)	(0.210)	(0.191)	(0.156)	(0.220)	(0.133)	(0.113)
Mean dep. var (panel A)	8.54	200.4	140.9	58.64	34.65	25.21	25.34	25.59	23.17	13.12

Notes: Each panel-column reports a separate regression in which the dependent variable is mortality rate by cause of death, indicated by column name. Causes are defined using the 10th revision of the International Statistical Classification of Diseases and Related Health Problems (ICD-10) codes: suicide (X60-X84, Y870), circulatory (I00-I99), neoplasm (C00-D48), respiratory (J00-J99), nervous (G00-G99), accident (V01-X59), metabolic (E00-E90), mental (F00-F99), digest (K00-K93), and infection (A00-B99). The estimation uses a balanced sample of counties from to 12 months before to 12 months after wind farm installations. (Post) indicates months after installation. (Close) indicates counties close to wind farms. (Event year) indicates event windows that contain the actual installation event. Regressions control for county fixed effects, month-of-year fixed effects, and year fixed effects. All regressions include full set of lower-order interactions, including those with the fixed effects, and control for daily temperature bins and quadratic monthly precipitation. Standard errors are clustered at the wind farm level. *: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level.

Table B.3. Wind Farms' Impact on Suicide, by Wind Directions: Robustness to Alternative Research Designs

Dep. var. = Suicide per million population			
	(1)	(2)	(3)
Panel A: Simple diff. (Observations = 63,075)			
(Post) × Up/downwind	0.015*	0.015*	0.004
	(0.008)	(0.009)	(0.011)
Panel B: Spatial diff. in diff. (Observations = 320,918)			
(Post) × (Close) × Up/downwind	0.021**	0.022**	0.012
	(0.009)	(0.009)	(0.012)
Panel C: Temporal diff. in diff. (Observations = 820,166)			
(Post) × (Event year) × Up/downwind	0.015*	0.016*	0.005
	(0.009)	(0.009)	(0.011)
Panel D: Triple diff. (Observations = 4,173,664)			
(Post) × (Close) × (Event year) × Up/downwind	0.022**	0.024**	0.013
	(0.010)	(0.010)	(0.013)
County fixed effects	✓		
Month-of-year fixed effects	✓		
Year fixed effects	✓	✓	
County × month-of-year fixed effects		✓	✓
Wind farm × year fixed effects			✓

Notes: Each column × panel cell reports a separate regression. The estimation uses a balanced sample of counties from to 12 months before to 12 months after wind farm installations. (Post) indicates months after installation. (Close) indicates counties close to wind farms. (Event year) indicates event windows that contain the actual installation event. "Up/downwind" counts number of days in a month that the county spend downwind a wind farm. All regressions include full set of lower-order interactions, including those with the fixed effects, and control for daily temperature bins and quadratic monthly precipitation. Standard errors are clustered at the wind farm level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table B.4. Wind Farms' Impact on Sleep Insufficiency (BRFSS Sample): Robustness to Alternative Research Designs

Sleep loss measure:	(1) Days of insuff. sleep	(2) Any days of insuff. sleep?	(3) ≥ 7 days of insuff. sleep?	(4) ≥ 14 days of insuff. sleep?
Panel A: Simple diff. (Observations = 2,172)				
(Post)	0.201**	0.0039	0.0077**	0.0075**
	(0.091)	(0.0053)	(0.0036)	(0.0036)
Panel B: Spatial diff. in diff. (Observations = 5,197)				
(Post) × (Close)	0.212**	0.0030	0.0095**	0.0090
	(0.103)	(0.0057)	(0.0047)	(0.0054)
Panel C: Temporal diff. in diff. (Observations = 22,323)				
(Post) × (Event year)	0.175**	0.0020	0.0067*	0.0068*
	(0.088)	(0.0050)	(0.0037)	(0.0038)
Panel D: Triple diff. (Observations = 60,283)				
(Post) × (Close) × (Event year)	0.157	0.0012	0.0080	0.0064
	(0.105)	(0.0056)	(0.0049)	(0.0057)
Mean dep. var (panel A)	8.35	0.699	0.391	0.269

Notes: Each panel-column reports a separate regression. Dependent variables are monthly measures of insufficient sleep, as indicated by column names. The estimation uses a balanced sample of counties from to 12 months before to 12 months after wind farm installations. (Post) indicates months after installation. (Close) indicates counties close to wind farms. (Event year) indicates event windows that contain the actual installation event. Regressions control for county fixed effects, month-of-year fixed effects, and year fixed effects. All regressions include full set of lower-order interactions, including those with the fixed effects, and control for daily temperature bins and quadratic monthly precipitation. Standard errors are clustered at the wind farm level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table B.5. Wind Farms' Impact on Suicide, by Firearm Access: Robustness to Alternative Research Designs

Dep. var. = Suicide per million population		
	(1)	(2)
Gun access measure:	Gun shop	*Guns & Ammo* circulation
Panel A: Simple diff. (Observations = 63,075)		
(Post) × (Top tercile gun)	1.394***	0.987**
	(0.435)	(0.388)
Panel B: Spatial diff. in diff. (Observations = 320,918)		
(Post) × (Close) × (Top tercile gun)	1.062**	0.371
	(0.499)	(0.434)
Panel C: Temporal diff. in diff. (Observations = 820,166)		
(Post) × (Event year) × (Top tercile gun)	1.504***	1.066**
	(0.469)	(0.418)
Panel D: Triple diff. (Observations = 4,173,664)		
(Post) × (Close) × (Event year) × (Top tercile gun)	1.150**	0.405
	(0.539)	(0.469)

Notes: Each panel-column cell reports a separate regression. The estimation uses a balanced sample of counties from to 12 months before to 12 months after wind farm installations. (Post) indicates months after installation. (Close) indicates counties close to wind farms. (Event year) indicates event windows that contain the actual installation event. "Top tercile gun access" is an indicator variable for counties with top-decile gun access. Gun access measure is county level Federal Firearms Licensees per 100,000 residents (column 1) and county level *Guns & Ammo* circulation per 100,000 residents (column 2). All regressions include full set of lower-order interactions, including those with the fixed effects, and control for daily temperature bins and quadratic monthly precipitation. Standard errors are clustered at the wind farm level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table B.6. Wind Farms' Impact on Birth Outcomes

Birth outcome:	(1) Fertility rate (per 10,000 women)	(2) Low birth weight (per 100 births)
Panel A: Simple diff.		
(Post, months 1-8)	0.134	-0.011
	(0.130)	(0.018)
(Post, months 9-16)	0.216	-0.030
	(0.188)	(0.021)
Mean dep. var	53.78	7.17
Observations	64,633	64,633
Panel B: Spatial diff. in diff.		
(Post, months 1-8) × (Close)	0.049	-0.022
	(0.121)	(0.023)
(Post, months 9-16) × (Close)	0.043	-0.032
	(0.179)	(0.025)
Mean dep. var	54.03	7.30
Observations	329,651	329,651
Panel C: Temporal diff. in diff.		
(Post, months 1-8) × (Event year)	0.169	-0.014
	(0.132)	(0.019)
(Post, months 9-16) × (Event year)	0.268	-0.034
	(0.177)	(0.022)
Mean dep. var	55.63	7.17
Observations	838,961	838,961
Panel D: Triple diff.		
(Post, months 1-8) × (Close) × (Event year)	0.042	-0.023
	(0.123)	(0.024)
(Post, months 9-16) × (Close) × (Event year)	0.105	-0.035
	(0.168)	(0.027)
Mean dep. var	54.79	7.28
Observations	4,309,488	4,309,488

Notes: Each column-panel cell reports a separate regression. Fertility rate is defined as number of births per 10,000 women aged 15-44. Low birth weight is defined as 100 times the percent born with birth weight less than 2,500 grams. The estimation uses a balanced sample of counties from 12 months before to 16 months after wind farm installations. (Post, months 1-8) indicates the first through the eighth months after installation. (Close) indicates counties close to wind farms. (Event year) indicates event windows that contain the actual installation event. All regressions control for full set of lower-order interactions, including those with the fixed effects, daily temperature bins and quadratic monthly precipitation. Standard errors are clustered at the wind farm level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.