

Wind Turbine Syndrome: The Impact of Wind Farms on Suicide*

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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 results in residents' sleep disruptions, among other annoyance symptoms. However, the existence and the importance of wind farms' health effects on a population scale remain unknown. Exploiting over 800 utility-scale wind turbine installation events in the United States from 2001-2013, I show robust evidence that wind farms lead to significant increases in suicide. I explore three indirect tests of the role of low-frequency noise exposure. First, the suicide effect concentrates among individuals who are vulnerable to noise-induced illnesses, such as the elderly. Second, the suicide effect is driven by days when wind blows in directions that would raise residents' exposure to low-frequency noise radiation. Third, data from a large-scale health survey suggest increased sleep insufficiency as new turbines began operating. These findings point to the value of noise abatement in future wind technology innovations.

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1. Introduction

The rising use of large machinery in industrial operation 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.¹ 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 motions 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 made complaints, and on occasion have filed lawsuits, about health effects reportedly due to wind farms’ low-frequency noise. 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. 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 is typically inaudible to humans (“infrasound”), and so it should have no health effects through auditory channels (e.g. Basner et al., 2014). However, recent medical research suggests, although not yet conclusively, 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 (Weedman and Ryugo, 1996; Danzer, 2012; Salt, Lichtenhan, Gill, and Hartsock, 2013). 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

¹ 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).

scale (Bakker et al., 2012; McCunney et al, 2014; Schmidt and Klokke, 2014). Against this backdrop of 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 situation, representing individuals who have reached the depths of despair (e.g., Case and Deaton, 2015; Case and Deaton, 2017), it is likely to be an enveloping 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 suicide deaths (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 (see e.g., Simon et al., 2001) -- thereby cutting short lives for 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 is over 800 events of utility-scale wind turbines installation 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, this rules 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 turbines 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 the entire construction period) before the turbines' installation, followed by a prompt increase by about 2 percent in the month when new turbines began generating power. This effect stays relatively stable for the following year. The suicide impact appears to be geographically widespread; effects can be detected at least within 25 km, but no farther than 100 km, to 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 suicide effect is robust to overrejection adjustments when the hypothesized effects of wind farms on other major causes of deaths are simultaneously tested for (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. This is consistent with the view that individuals are increasingly sensitive to noise exposure at older ages (e.g., Miedema and Vos, 2003; Kujawa and Liberman, 2006; Muzet, 2007).

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 spend downwind or upwind 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; Oerlemans 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 turbine installation. This effect appears to be explained by an increase in reports of sustained (more than seven nights per month) sleep insufficiency.

This paper contributes to the literature by delivering the first national-scale causal evidence on wind farms' adverse health effects. Results of this paper imply that the costs of wind farms are significant even if one considers solely the consequences of suicides. My calculation suggests that wind farms installed between 2001 and 2013 resulted in a total of 34,000 life years lost (LYL) due to increased suicides

within a year after installation. To put this number in perspective, during the same one-year time window, the new wind capacity generated roughly 150 million megawatt hours (mwh) of clean energy; by comparison, based on existing estimates of the per mwh health cost of coal-generated electricity (Epstein et al., 2011), generating the same amount of electricity with coal would have resulted in around 53,000 life years lost due to air pollution.

More broadly, this paper is related to the economic literature for developing empirically grounded cost-benefit analysis of wind energy. Existing literature has documented wind farms' negative externality on nearby residents through evidence of lower levels of life satisfaction (Krekel and Zerrahn, 2017) and, more predominantly, reduced property values (e.g., Ladenburg and Dubgaard, 2007; Gibbons, 2015; Dröes and Koster, 2016). Importantly, wind farms' impact on property value is found to be highly local (usually within few kilometers), and there is evidence that housing price effects are largely explained by whether wind farms are visible from the location of the house (Gibbons, 2015). My estimates show that the health effects of wind farms can occur far beyond "sightline" properties where declining property values have been observed. On the benefit side, wind industry operations may benefit local economies (e.g., Kahn, 2013); wind energy production also displaces electricity generation from fossil fuel sources (Cullen, 2013; Novan, 2015), and therefore may have both short-term air quality benefits and also longer-term climate benefits. Together, these cost-benefit parameters have a broad range of policy and regulatory implications such as wind farm siting decisions, the determination of subsidy levels to existing wind farms, and the social return to the development of quieter wind technologies.²

This paper's findings also contribute to the understanding of the external determinants of suicide, a leading causes 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 and Heeringen, 2009; Zalsman, et al., 2016). However, external determinants of suicide are also important, especially from a suicide prevention viewpoint (e.g., Carleton, 2017). 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

² For example, wind turbines can use vorticity, an aerodynamic effect that produces a pattern of vortices, to produce energy rather than using blades <<http://www.wired.com/2015/05/future-wind-turbines-no-blades/>>; coating wind turbine blades may scatter turbulence when air passes the blades, mimicking the wing structure of owls <www.cnbc.com/id/102777259>; floating wind turbines are able to capture high wind speed in higher altitudes, therefore increasing wind energy generation efficiency <<http://www.altaerosenergies.com/bat.html>>.

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 presents evidence on the role of noise pollution. Section 6 reports the suicide effects heterogeneity by local gun access. Section 7 discusses the interpretation and the limitations of the results, and 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, which occurs 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 show peak energy at frequencies typically below 20 Hz (see e.g., Hubbard and Shepherd, 1990; Doolan, Moreau, and Brooks, 2011). 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 below). 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).

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

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. Whereas 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.

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 Klokke, 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).

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 annual census of existing power generators larger than one 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. I define wind turbine installation events as entries of new capacities whose 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.

My primary outcome variable is the suicide rate at the county \times month level from 2001 to 2013. This 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 suicide rates using Vital Statistics data's information on descendants' age of death. Population estimates at both the county \times year level and the county \times year \times age level are obtained 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 non-existent 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.³

Figure 3 plots the location of wind farms throughout the study period. My preferred estimation sample contains a group of “close” counties that are 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 a 25-kilometer radius of a given wind farm. In the appendix, I show that the main findings of the paper are not sensitive to this selection rule. I also construct a sample of “distant” counties located 25 to 100 kilometers from the wind farms. I use this “distant” location sample in specifications that exploit spatial differences.

While all empirical specifications in this paper ultimately control for some form of county fixed effects, in Table 1 I examine levels of 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 (0-25 km) counties in the primary estimation sample. Column 2 represents distant (25-100 km) counties that are used in subsequent analysis for spatial comparison. Column 3 summarizes the same statistics for all other counties (> 100 km from wind farms)

³ The distance calculations are based on latitude and longitude of wind farms and the Census 2010 county population centers.

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 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 (< 20, 20-39, 40-59, 60-79, and > 80). The different in the average suicide rate does not appear to be driven by any particular age groups. 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 precipitation happens to be mostly concentrated. Overall, these statistics suggest no particular concerns over non-representativeness of the study population.

4. Suicide Responses to Wind Turbine 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 turbine 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 turbines began generating power. Changes in the suicide rate is measured relative to the level observed one month 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.

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 turbines began generating power.⁴ 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 turbine installation. Second, in addition to a flat pre-treatment suicide trend, the evolution of suicide rate 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. Third, the fact that suicide responses are not experienced even in the months shortly before power generation actually begins suggests that the impact

⁴ In the Appendix, I use power generation data to confirm that wind power production increases sharply starting the event month.

is unlikely due to factors related to the *presence* of the wind farm itself (e.g., facility construction, which typically lasts for months) but rather due to factors associated with the *operation* of the wind farm (e.g., noise emission). 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 to) 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. I estimate the following baseline specification

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

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 \times month-of-year fixed effects or wind farm \times 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. I report standard errors clustered at the wind farm level. In the Appendix, 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 suicide 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.⁵

Second, I implement a temporal difference-in-difference design. I compare pre- and post- suicide differences within the event window in the year when wind farm is installed (“event year”) to differences within the *same* event window but in other years when 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 occur. I estimate

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

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.

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

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

⁵ 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 analysis. My conclusions are unchanged if fixed effects controls are not allowed to be conditional on the interaction variables.

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 turbine installation, the suicide rate increases by a significant 0.183 per million population in the year 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-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 tight 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 overlap with that of the estimates in column 1 and 2.⁶

Panels B through D of Table 2 report estimates from the augmented designs that use richer sources of variation. These include spatial DD (equation 2), temporal DD (equation 3), and 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. Thus, 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

⁶ In the Appendix, I examine 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.

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.

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.⁷ 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 (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. Interestingly, the only two individually significant effects emerge in deaths due to nervous system and mental disorders which are intuitively related to noise exposure, although neither 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.

⁷ 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).

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 illnesses (e.g., Miedema and Vos, 2003; Kujawa and Liberman, 2006; Muzet, 2007). Here, I estimate an age profile of wind farms' suicide effect by allowing the effect estimates to vary by age groups. Specifically, I estimate the following equation

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

where the unit of observation now is suicide rate in county c at time t for age group a (< 20 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 and the most precise effect is observed for the population over 80 years old. Suicide among this group increases about 0.72 per million post wind turbine installation. This effect also represents the largest relative change of 5.33 percent out of the age group's mean rate of suicide. The second largest relative increase in suicide occurs among the population below age 20 years (4.53 percent). 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, and crosswind 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

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

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 $d = \{0 \text{ to } 45 \text{ and } 0 \text{ to } -45, 45 \text{ to } 89 \text{ and } -45 \text{ to } -89, 90 \text{ to } 134 \text{ and } -90 \text{ to } -134, 135 \text{ to } 180 \text{ and } -135 \text{ to } -180\}$. 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 $d = \{0 \text{ to } 45 \text{ and } 0 \text{ to } -45\}$ 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.

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 ($d = 0 \text{ to } 45 \text{ and } 0 \text{ to } -45$) and upwind ($d = 135 \text{ to } 180 \text{ and } -135 \text{ to } -180$) to wind farms. In contrast, days when counties are crosswind of wind farms have low explanatory power on suicide. My estimates do not provide suggestive 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 4, panel A presents a more parsimonious version of equation (6) where 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. Panel B and panel 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 turbine 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 report at least 1 / 7 / 14 days 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 \times 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 from 1, 7, or 14.⁸

As before, I begin by a simple event study that documents the trends for insufficient sleep before and after wind turbine installation. Analogous to Figure 4, Figure 7 plots changes in the number of nights with insufficient sleep before and after wind turbine 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 turbines came online.⁹ Table

⁸ 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 first extracts the county \times 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 then second, uses the fixed effects coefficients as the independent variable in estimation equation (1).

⁹ 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

5, 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 turbine 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 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 influence 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 wind farms' suicide effects heterogeneity by local area's gun access.

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.

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.¹⁰ 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 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 (2015).

Table 6 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. Discussion and Conclusion

I conclude the paper with a back-of-envelop calculation of the external costs of wind farms as the result of suicides. Given the findings on the age profile of suicide effects, life years lost (LYL) are computed as the summation of age-specific effects across age groups:

$$LYL = \sum_a \sum_c \beta_a \times Population_{ca} \times LifeExp_a$$

¹⁰ This category comprises more than 70% of all the FFLs. Other major categories reported in the data are manufacturers of firearms and ammunition (13%) and pawnbrokers (11%).

where β_a is the age group specific effect of a wind farm on the suicide rate obtained from equation (5). This is multiplied by population in county c of age group a ($Population_{ca}$) and expected remaining years of life ($LifeExp_a$) to obtain excessive life years lost in the county. $LifeExp_a$ is computed as the difference between average Social Security Administration life expectancy and average age at suicide for individuals in age group a .¹¹ 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 33,939 life years lost.¹²

I now contrast this number with life years that would have been lost in the one-year window had the energy instead been generated by coal. I use the estimate of the social cost of coal-generated electricity at \$178 per megawatt hour (MWh) from Epstein et al (2011).¹³ Applying their adopted value of statistical life (VSL) of \$7.66 million and an average remaining life years of 15.2 years per death, this number is converted to 0.00035321 LYL per MWh coal electricity. New wind farms generated a total of 148.7 million MWh wind power within the first year of operation, which implies a total of 52,523 avoided life years lost had the power been generated entirely from coal. Of course, these numbers do not immediately inform welfare; however, they do suggest that wind farm-related suicides potentially reduce the overall value, even though the technology offers a renewable source of energy, providing an alternative to fossil fuel-based sources, which contribute to greenhouse gas emissions and detrimentally affect air quality.

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 location of related health outcomes. This may benefit the study of wind turbine

¹¹ Expected remaining years of life among individuals committed suicide are: 63.7 (age < 20), 49.4 (age 20-39), 30.9 (age 40-59), 15 (age 60-79), and 4.6 (age > 80). The average expected remaining years of life is 34.3. This is similar to SEER's estimates https://seer.cancer.gov/archive/csr/1975_2012/results_merged/topic_year_lost.pdf

¹² Assuming homogeneous treatment effects across age groups yields a similar estimate of 33,270 life years lost.

¹³ The estimate reflects health and environmental cost of coal during its entire life cycle from extraction, transport, processing, and combustion.

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, such as emergency room visits and hospitalization, may also be important to provide a richer characterization of the health effects that may stem from living or working in close proximity to wind turbines, and to shed light on the full related costs.

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, together with 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.

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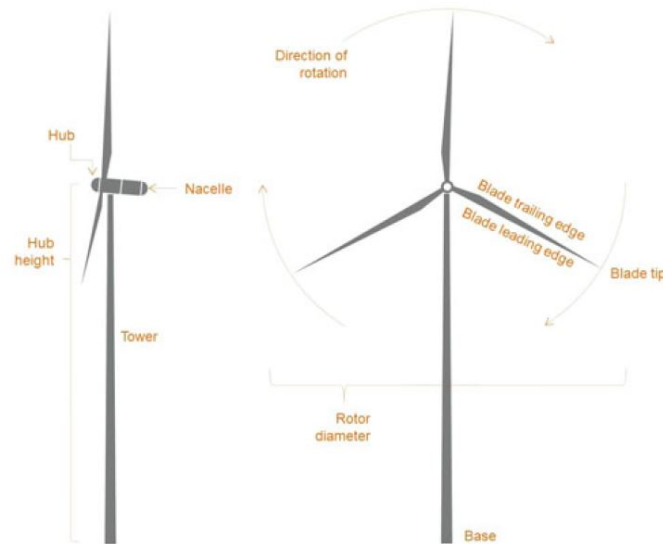
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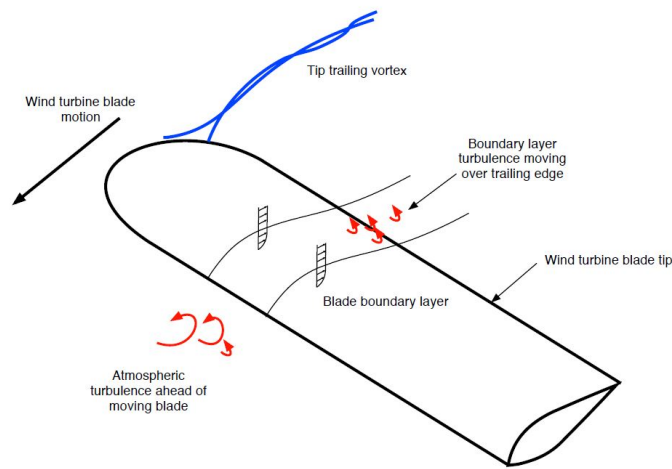
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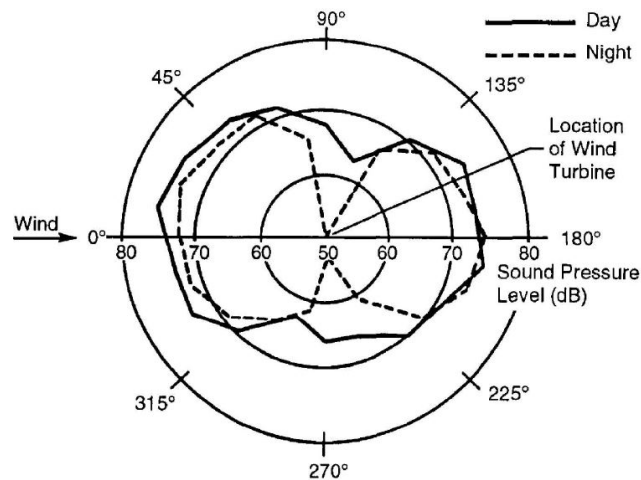
Figure 1: Distribution of Wind Resources and Wind Farms
 Panel A. Wind turbine (horizontal axis design)



Panel B. Air flow over a wind turbine blade

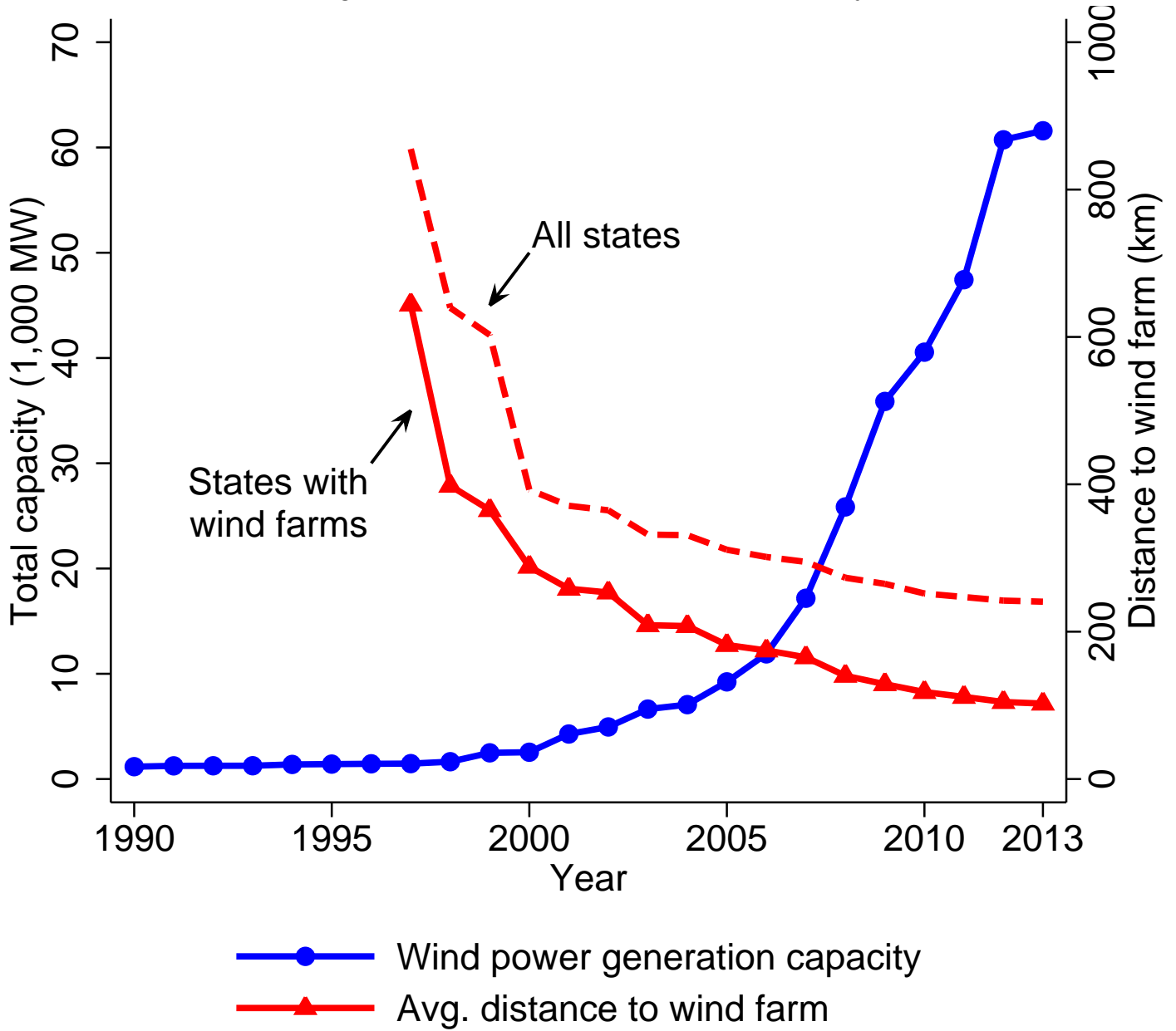


Panel C. "Acoustic Dipole": Wind turbine's low-frequency noise radiation patterns



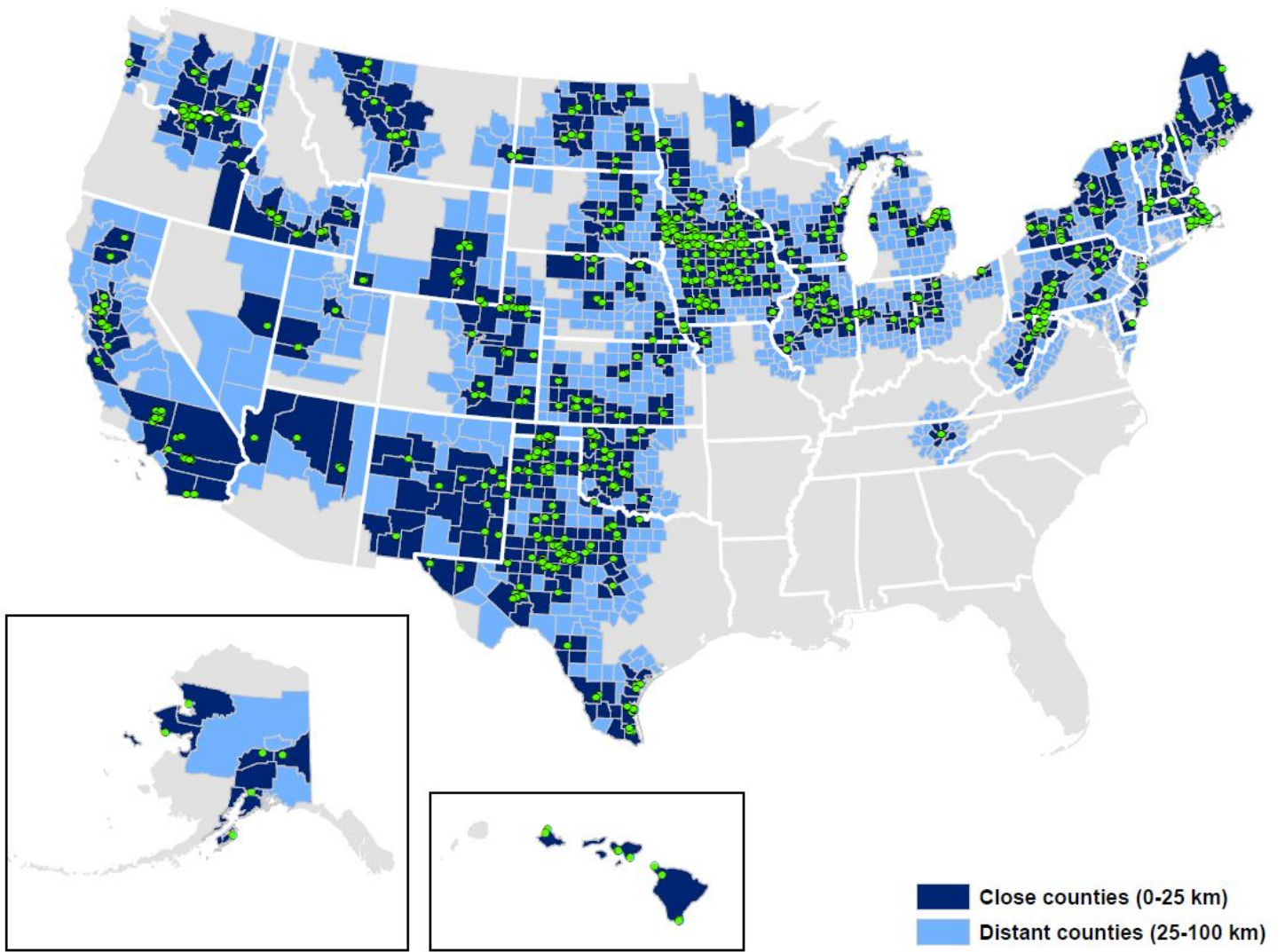
Notes: Panel A is sourced from McCunney et al (2014). Panel B is sourced from Doolan (2011). Panel C is sourced from Hubbard and Shepherd (1990), which shows measured noise level 200 meters from a utility-scale wind turbine when wind speed is 7.2 m/s. Measured frequency of the sound is 8 Hz.

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



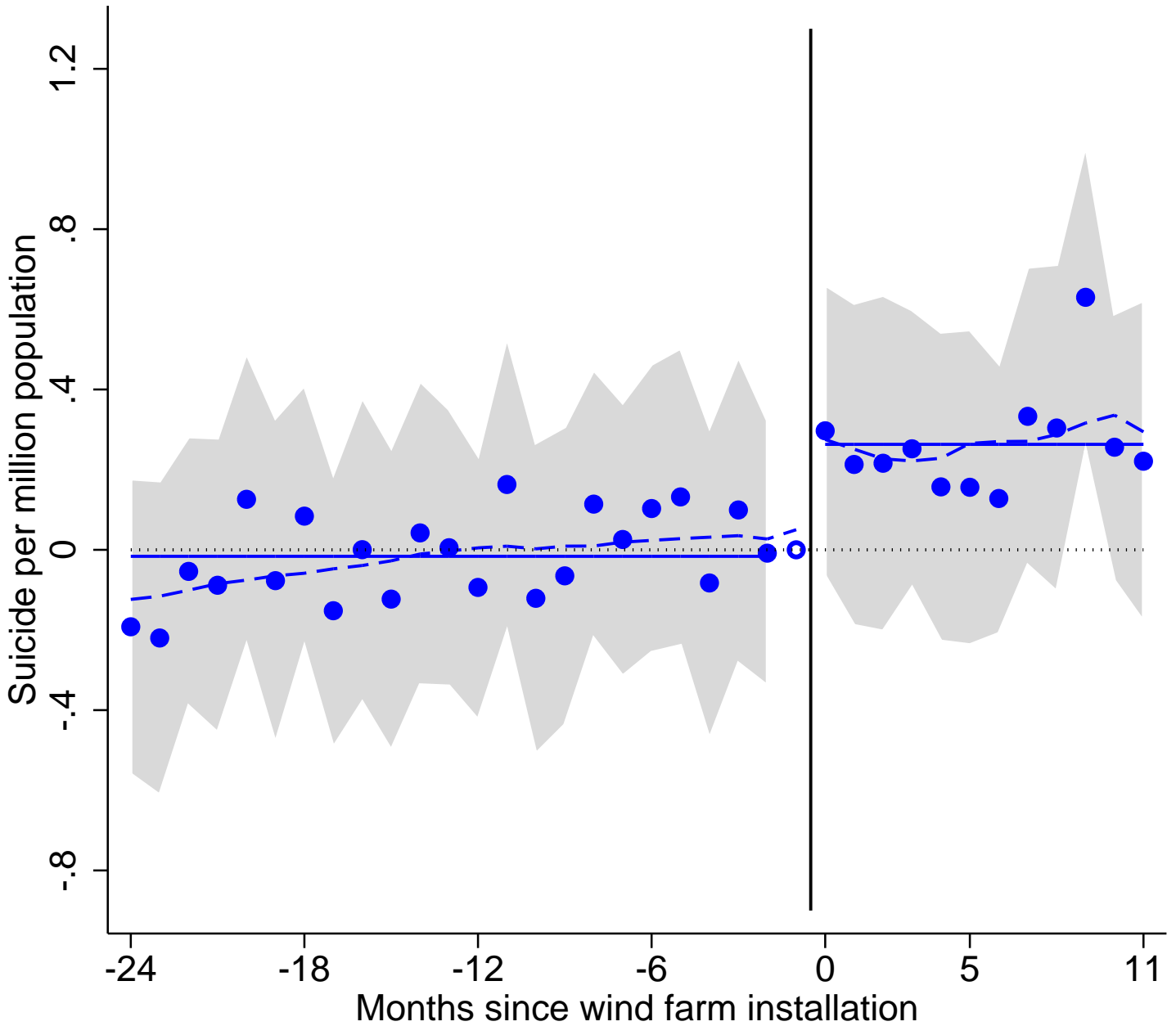
Notes: Circle-connected line plots total wind power generation capacity observed in the EIA-860 form. Triangle-connected lines compute the average distance from county's Census 2010 population center to the nearest wind farm, including states that have wind power capacity by the end of 2013. Dashed line 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



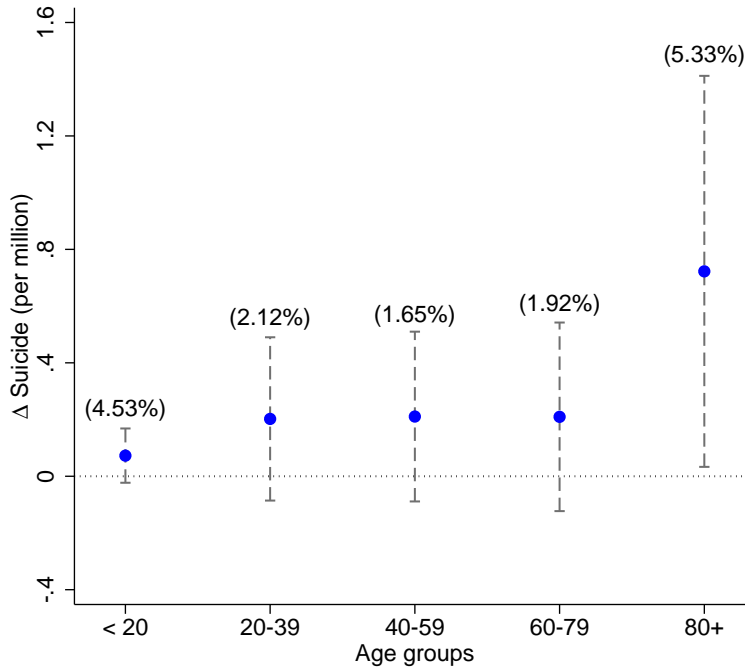
Notes: Map plots location of wind farms and the associated sample counties. Dark color counties are 0-25 km to wind farms. Lighter color counties are 25-100 km of wind farms.

Figure 4: Event Study: Suicide



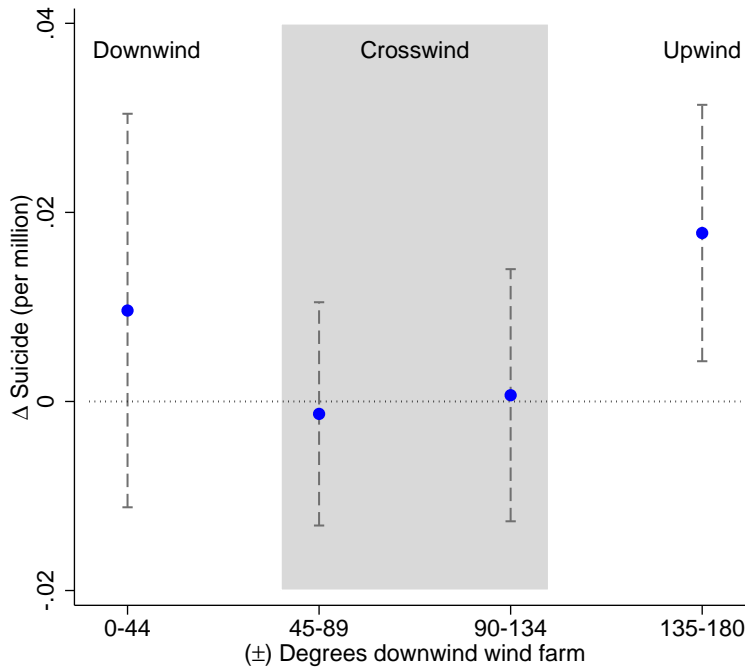
Notes: Graph plots suicide rate (per million population) by months relative to wind farm installation month, using all installation events from 2001-2013. The month immediately before the installation is the omitted category. The regression is weighted by county \times year population and is conditional 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 less 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 Farm's Suicide Impacts



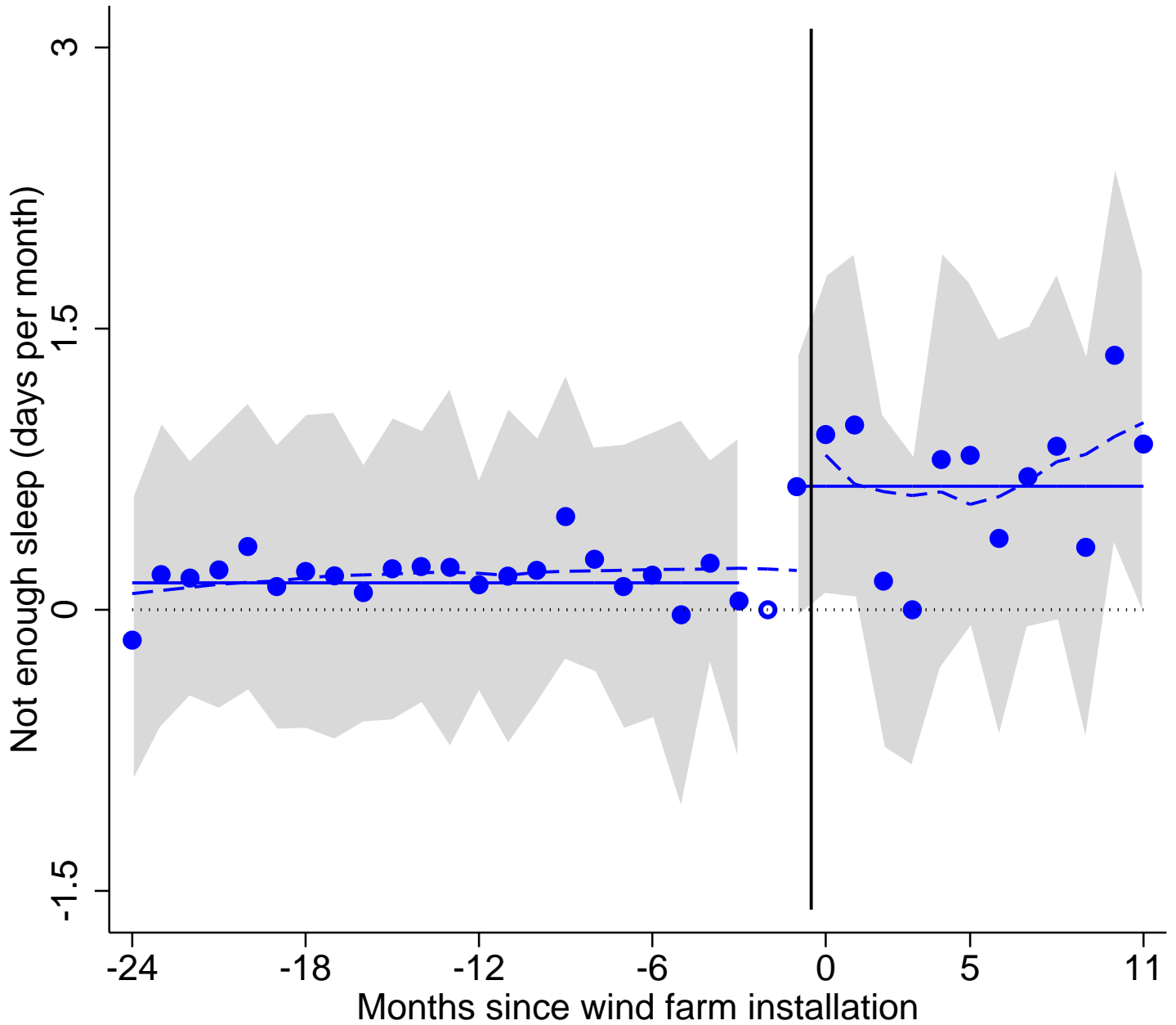
Notes: Graph plots the interaction term between post-event window dummy (Post) and age group category. Percentage numbers in parentheses show coefficient as a fraction of mean suicide rate within each age group. Estimation uses a balanced sample of counties from 12 months before to 12 months after wind turbine 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 Farm's 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. Estimation uses a balanced sample of counties from 12 months before to 12 months after wind turbine installations. Regressions include county, month-of-year and year fixed effects. 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 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 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 less 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
<u>Suicide (per million)</u>	8.56 [3.14]	9.51 [3.10]	10.92 [3.11]	9.76 [3.26]
... age < 20	1.75 [1.29]	1.98 [1.31]	1.98 [1.32]	1.91 [1.31]
... age 20-39	9.79 [4.54]	11.23 [4.47]	12.58 [4.32]	11.31 [4.58]
... age 40-59	12.67 [4.59]	14.02 [4.51]	15.99 [5.01]	14.37 [4.92]
... age 60-79	10.31 [3.40]	10.99 [4.19]	13.34 [3.99]	11.73 [4.27]
... age 80+	13.02 [7.58]	13.22 [7.63]	17.46 [8.69]	14.72 [8.29]
<u>Population (thousands)</u>	114.4 [436.8]	107.5 [302.7]	68.7 [180.8]	90.4 [294.6]
... fraction age < 20	0.289	0.287	0.283	0.286
... fraction age 80+	0.033	0.032	0.033	0.033
<u>Poverty rate</u>	0.130	0.106	0.135	0.124
<u>Per cap. income (2000\$)</u>	21,756 [5,629]	23,017 [5,377]	20,117 [4,585]	21,578 [5,320]
<u>Median home value</u>	171,256 [136,273]	141,884 [73,237]	105,279 [39,937]	137,174 [92,854]
<u>Gun store (per 100,000)</u>	14.4 [19.1]	16.3 [17.5]	19.1 [17.5]	16.8 [18.1]
<u>Guns & Ammo circulation (per 100,000)</u>	129 [90]	153 [82]	154 [84]	146 [86]
<u>Wind speed (m/s)</u>	3.78 [0.48]	3.64 [0.49]	3.37 [0.44]	3.54 [0.49]
<u>Temperature (degree F)</u>	51.5 [7.1]	51.6 [6.6]	58.8 [7.1]	55.1 [7.8]
<u>Precipitation (millimeter)</u>	66.7 [26.8]	71.5 [27.3]	98.9 [26.3]	83.6 [30.6]
<u>N (county)</u>	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, 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. 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, income, home values). 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*** (0.064)	0.212*** (0.072)	0.251* (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** (0.073)	0.184** (0.078)	0.244* (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*** (0.069)	0.217*** (0.071)	0.248* (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** (0.078)	0.197** (0.080)	0.246* (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. Estimation uses a balanced sample of counties from 12 months before to 12 months after wind turbine 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 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										
Cause of death:	(1) Suicide	(2) Circ	(3) Neop	(4) Resp	(5) Nervous	(6) Accident	(7) Metabolic	(8) Mental	(9) Digest	(10) Infect
(Post)	0.183 (0.064)	0.314 (0.449)	0.070 (0.256)	0.528 (0.322)	0.408 (0.163)	0.098 (0.151)	-0.004 (0.130)	0.307 (0.164)	0.103 (0.107)	0.087 (0.089)
<i>p</i> -value	0.005***	0.476	0.786	0.102	0.012**	0.514	0.975	0.063*	0.338	0.332
<i>q</i> -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). Estimation uses a balanced sample of counties from 12 months before to 12 months after wind turbine 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, by Wind Directions

Dep. var. = Suicide per million population			
	(1)	(2)	(3)
Panel A: By wind directions			
(Post) × Up/downwind	0.0148*** (0.0054)	0.0155*** (0.0059)	0.0108 (0.0086)
(Post) × Crosswind	-0.0004 (0.0036)	0.0011 (0.0039)	0.0064 (0.0062)
Panel B: By wind directions and wind speed			
(Post) × (Up/downwind - Crosswind) × (Bot. tercile wind speed)	-0.0087 (0.0143)	-0.0060 (0.0163)	-0.0208 (0.0179)
(Post) × (Up/downwind - Crosswind) × (Mid. tercile wind speed)	0.0116 (0.0153)	0.0103 (0.0158)	-0.0009 (0.0166)
(Post) × (Up/downwind - Crosswind) × (Top tercile wind speed)	0.0254** (0.0106)	0.0249** (0.0118)	0.0197 (0.0144)
Panel C: By wind directions and wind farm size			
(Post) × (Up/downwind - Crosswind) × (Bot. tercile wind farm)	0.0018 (0.0189)	0.0013 (0.0204)	-0.0177 (0.0192)
(Post) × (Up/downwind - Crosswind) × (Mid. tercile wind farm)	-0.0120 (0.0166)	-0.0084 (0.0183)	-0.0113 (0.0220)
(Post) × (Up/downwind - Crosswind) × (Top tercile wind farm)	0.0250* (0.0149)	0.0233 (0.0155)	0.0305* (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. Estimation uses a balanced sample of counties from 12 months before to 12 months after wind turbine 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). All regressions 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 5: Wind Farms' Impact on Sleep Insufficiency (BRFSS Sample)

	(1) Days of insuff. sleep	(2) Any days of insuff. sleep?	(3) ≥ 7 days of insuff. sleep?	(4) ≥ 14 days of insuff. sleep?
Sleep loss measure:				
(Post)	0.201** (0.091)	0.0039 (0.0053)	0.0077** (0.0036)	0.0075** (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. Estimation uses a balanced sample of counties from 12 months before to 12 months after wind turbine installations. (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. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

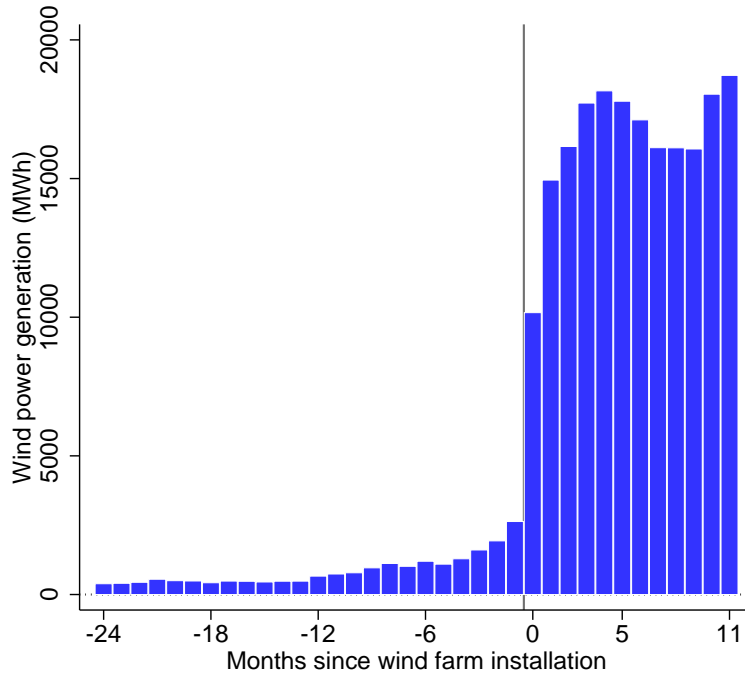
Table 6: Wind Farms' Impact on Suicide, by Firearm Access

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* (0.066)		0.106* (0.062)	
(Post) × (Mid tercile gun access)	0.304 (0.263)		0.434 (0.290)	
(Post) × (Top tercile gun access)	1.505*** (0.438)		1.117*** (0.382)	
(Post) × log(Gun access)		0.205*** (0.074)		0.367** (0.144)
Observations	63,075	61,755	63,003	62,931

Notes: Each column reports a separate regression. Estimation uses a balanced sample of counties from 12 months before to 12 months after wind turbine 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 also control for daily temperature bins and quadratic monthly precipitation. Standard errors are clustered at the wind farm level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

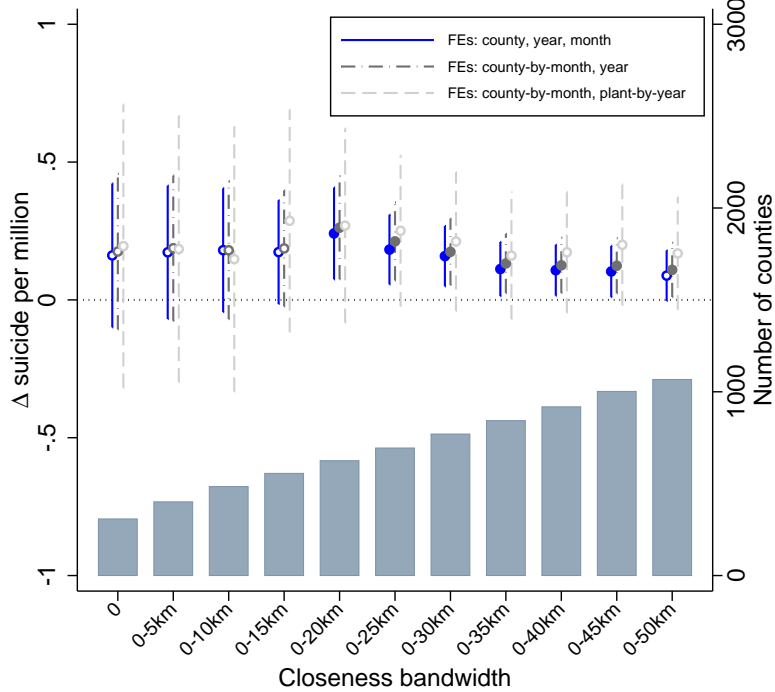
Appendix Figures and Tables

Figure A.1: Event Study: Wind Power Generation



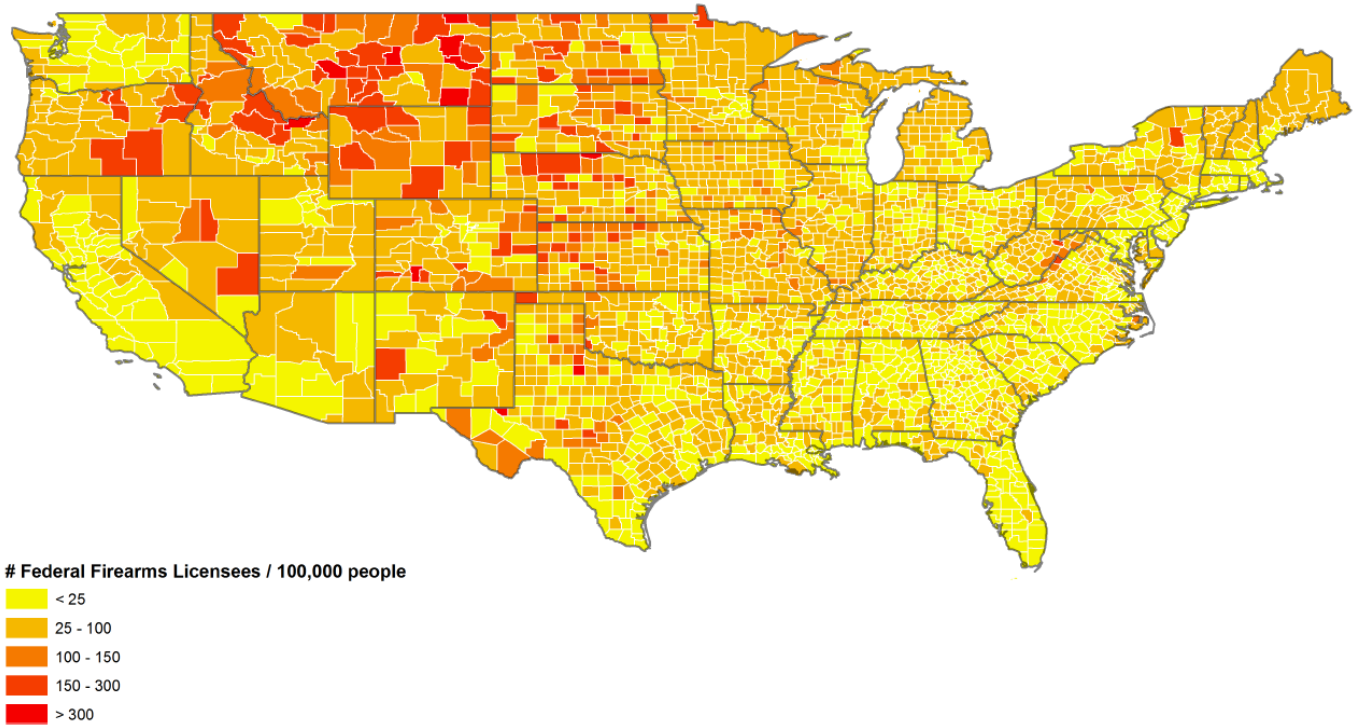
Notes: Graph plots wind power generation (MWh) by months relative to wind farm installation month, using all installation events from 2001-2013. In cases where installations are capacity additions to existing wind farms, positive generation are observed before the installation event.

Figure A.2: Robustness Checks: Closeness Bandwidth



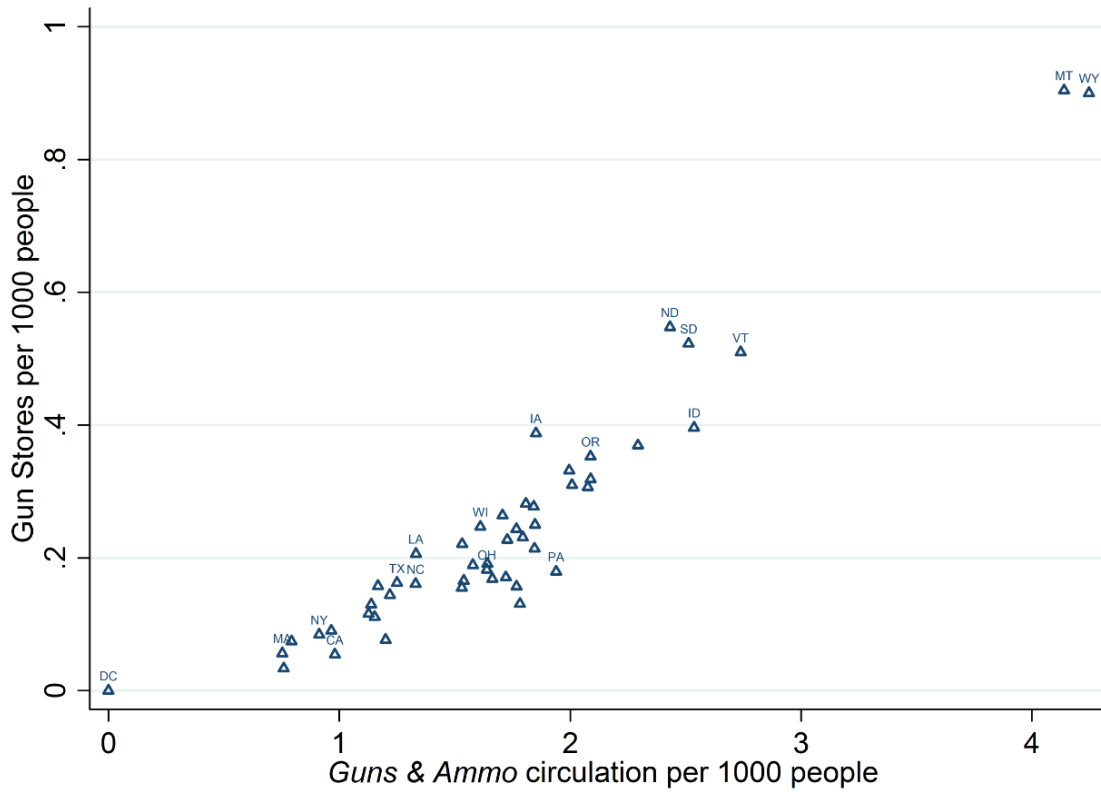
Notes: Each group of range plot items use the same estimation sample, including counties within certain distance to the wind farm as indicated by the x-axis. Bar plots number of counties included in each estimation sample. Within each group, each range plot item shows a separate regression with different 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.

Figure A.3: 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 A.4: 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 A.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*** (0.063)	0.221*** (0.069)	0.315** (0.138)
First installation only	0.135** (0.062)	0.167** (0.071)	0.329*** (0.127)
Drop December installations	0.150** (0.069)	0.177** (0.077)	0.137 (0.148)
PTC driven installations only	0.365** (0.158)	- -	- -
No weather controls	0.198*** (0.066)	0.213*** (0.071)	0.240* (0.137)
Weather controls vary by Census Regions	0.157** (0.064)	0.156** (0.066)	0.140 (0.128)
Temperature bins interact precipitation	0.156** (0.065)	0.153** (0.071)	0.223* (0.123)
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 turbine 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. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.