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WIND TURBINE PROXIMITY AND HEALTH:
LONGITUDINAL EVIDENCE FROM U.S. HOUSEHOLDS

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ABSTRACT

Rapid growth of wind energy plays a key role in global efforts to reduce carbon emissions, yet public concerns persist about its potential health effects, particularly through noise exposure. While some studies and media reports suggest that wind turbines may contribute to sleep disturbances, anxiety, and even suicide, existing evidence remains limited and inconclusive. This study combines geolocated data on turbines from the U.S. Wind Turbine Database with longitudinal survey data on over 120,000 households (2011–2023) and consumer purchasing records to assess whether proximity to wind turbines affects mental and physical health. We examine a wide range of outcomes, including depression, anxiety, sleep disorders, headaches, and use of sleep aids and painkillers. Comparing households before and after nearby turbine installations, we find no detectable adverse health effects from turbine exposure at typical exposure distances. While we cannot rule out small effects, our confidence intervals exclude moderate-to-large impacts, suggesting that fears about substantial health impacts are not borne out in population-level data. Other disamenities such as noise, shadow flicker, and visual intrusion may still affect quality of life even absent measurable health impacts.

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1 Introduction

Rapid expansions of solar and wind energy are central to global efforts to slow climate change by transitioning away from fossil energy (Jacobson and Delucchi, 2011; International Energy Agency, 2020). With their differing intermittency patterns, these two renewable energy sources can also be complementary (Weschenfelder et al., 2020). Despite helping reduce greenhouse gas emissions, wind turbine installations have raised public concerns about potential health impacts, particularly from infrasound and low-frequency noise emissions (Knopper and Ollson, 2011; PBS, 2018; CBC, 2024; NPR, 2022). Media reports and some studies have linked prolonged exposure to wind turbine noise with adverse outcomes such as sleep disturbances, headaches, anxiety, and even higher suicide rates (Zou, 2020). These concerns have influenced policy debates and, in some cases, fueled legal disputes and local opposition to wind energy projects (Stokes et al., 2023). However, the existing evidence remains inconclusive, often based on small samples, self-reported symptoms, or purely correlational analyses (see Figure 1). Moreover, many studies focus on annoyance rather than establishing a direct pathway from noise exposure to health outcomes. As the expansion of renewable energy continues, it is essential to rigorously assess whether wind turbine exposure impacts health. This study aims to provide design-based empirical evidence to inform whether wind turbines constitute a legitimate public health risk.

We combine data from the U.S. Wind Turbine Database—which records the geographic location and operational timeline of approximately 75,000 turbines installed between 1981 and 2024—with rich, longitudinal survey data on over 120,000 U.S. households collected from 2011 to 2023. These surveys provide detailed information on health conditions such as headaches, sleep disorders, anxiety, and depression. To complement self-reported outcomes, we also incorporate consumer purchasing data on sleep aids and painkillers as objective proxies for sleep disturbance and pain-related issues.

Using this integrated dataset, we employ an event-study approach to estimate the causal impact of wind turbine installations in a given ZIP code on nearby households' health.

We assess changes in both subjective health reports and purchasing behavior around the time of turbine activation. We further explore heterogeneity by age, ethnicity, income, and education to identify potentially vulnerable subpopulations. Robustness checks—including alternative specifications and placebo tests—consistently show negligible evidence of adverse health effects from wind turbine exposure, providing empirical support for the view that wind energy infrastructure's public health risks are minimal.

Our study relates to a growing literature on the health and well-being effects of wind turbines. Zou Zou (2020)[1] found a 2% increase in suicide rates following wind farm installations in the U.S., particularly among teenagers and the very elderly (over 80 years old), using a quasi-experimental design that exploits variation in wind direction and timing. In Germany, Krekel and Zerrahn Krekel and Zerrahn (2017)[2] report that proximity to wind turbines is associated with reduced life satisfaction, while in a later paper Krekel, Rode and Roth Krekel et al. (2023) find no statistically significant effects on a broad set of objective and subjective health outcomes, including mental and physical health scores, self-assessed health, doctor visits, sleep hours, and sleep satisfaction. Notably, some of these cautionary findings are receiving attention from mainstream academic journals.

Our study is the first to link wind turbine exposure to high-resolution, individual-level longitudinal health data in the United States. The dataset spans roughly 20,000 ZIP codes, including 532 that saw their first turbine installed between 2011 and 2023 and for which health outcomes can be tracked. Compared to prior U.S. studies, these projects are substantially larger on average (121 MW vs. 71 MW in Zou's sample) and involve turbines averaging 87 meters in hub height, 109 meters in rotor diameter, and 141 meters in tip height. We move beyond broad well-being indices to examine specific self-reported ailments—such as depression, anxiety, sleep disorders, and physical pain—while also incorporating objective measures from consumer purchasing behavior. This combined approach enables a more granular and

[1]Working paper, R&R at *AEJ Policy*.

[2]Published in *Journal of Environmental Economics and Management*, one of the top field journals in environmental economics.

policy-relevant assessment of the public health implications of wind energy development.

2 Background

2.1 Public and Media Debate on Wind Turbines and Health

Public discourse around wind energy has frequently focused on health and community concerns, even though scientific studies generally show limited evidence of direct harm. In the United States—as in other countries—wind projects often face local opposition centered on noise, visual intrusion, and alleged health effects. While national polls show broad support for wind power, local acceptance can falter when turbines are sited near residential areas (Le Maitre et al., 2024; Susskind et al., 2022).

Media coverage and community organizing have popularized "Wind Turbine Syndrome"—a term describing clusters of symptoms including sleep disturbance, headaches, and dizziness—though this condition lacks formal medical recognition (Knopper and Ollson, 2011; Knopper et al., 2014). News coverage frequently emphasizes uncertainty and personal testimonials, framing that can heighten public concern (Deignan et al., 2013), while social media amplifies anecdotal claims (Lewandowsky et al., 2012). Experimental studies document nocebo effects, whereby expectations of harm can induce symptoms even under sham exposure (Crichton et al., 2014a,b; Crichton and Petrie, 2015; Tonin et al., 2016).

Beyond health-related narratives, opposition is also shaped by distributional equity and environmental justice concerns. Some argue that rural or politically marginalized communities disproportionately bear the burdens of wind energy development while benefits accrue elsewhere (Mueller and Brooks, 2020; Stokes et al., 2023). Property value concerns also influence local sentiment. A substantial body of hedonic research documents negative effects on nearby home prices: Parsons and Heintzelman Parsons et al. (2022) review a decade of studies and find broad consensus that proximity to turbines reduces property values, while Guo, Wenz, and Auffhammer Guo et al. (2024) provide recent U.S. evidence showing visual disamenity effects that are statistically significant but modest in magnitude and diminish with distance and time. These localized economic costs help explain the intensity of opposition from affected homeowners. Design-based work has also shown that turbines can generate localized benefits: Kaffine Kaffine (2019) finds crop yields increase near turbines due to beneficial “vertical mixing" of air currents.

A growing body of research documents the determinants and consequences of local opposition to wind energy. Carley et al. Carley et al. (2020) systematically review three decades of survey research, finding that proximity-based opposition—often termed NIMBYism—is shaped by distributional concerns, procedural justice perceptions, and trust in developers. Hoen et al. Hoen et al. (2019) show that while a majority of U.S. turbine neighbors hold favorable attitudes, opposition increases with proximity and is strongly associated with property value and visual concerns rather than health effects. Germeshausen, Heim, and Wagner Germeshausen et al. (2025) find that public support for wind power declines among those living near existing installations, consistent with experience-based updating of preferences. Stokes Stokes (2016) documents electoral backlash against incumbents who supported wind development, demonstrating that local opposition can impose political costs on policymakers. Winikoff Winikoff (2022) shows that regulatory stringency has increased over time as communities respond to constituent concerns, while Jarvis Jarvis (2025) estimates that NIMBYism-driven permitting barriers substantially reduce wind deployment and raise decarbonization costs. This literature suggests that opposition to wind energy—while often framed around health concerns—is more fundamentally rooted in distributional equity, procedural fairness, and localized costs that do not align with diffuse environmental benefits.

2.2 Previous Evidence

The peer-reviewed literature has not established a consistent causal link between living near turbines and specific diseases (Schmidt and Klokker, 2014; Zou, 2020; Krekel and Zerrahn, 2017; Krekel et al., 2023). Wind turbines generate infrasound—very low-frequency sound

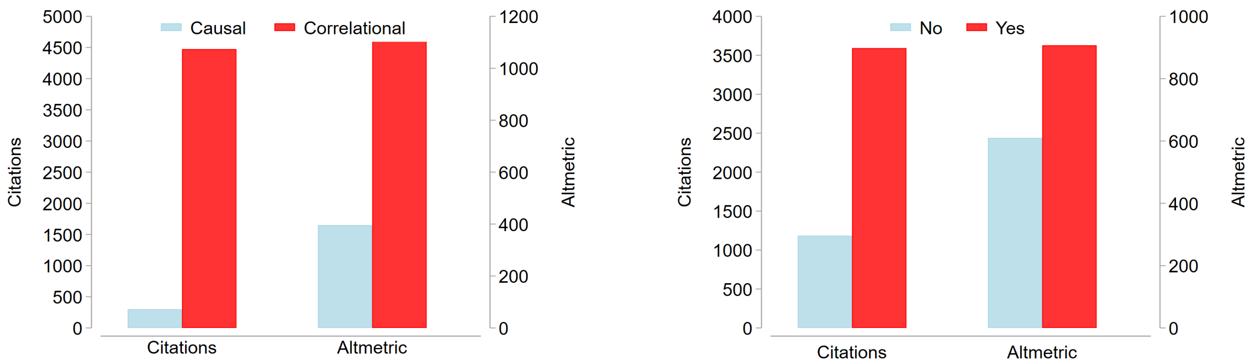

Figure 1: **Research Visibility**: Cumulative Citations and Altmetric Scores. This figure shows aggregated Google Scholar citations and Altmetric scores for 60 scientific and working papers on wind turbine health impacts, identified via Google Scholar, PubMed, and Altmetric searches using keywords including "wind turbine," "wind farm," "health," "noise," and "infrasound." We include observational or survey-based analyses linking turbine proximity or exposure—often through noise or sound pressure levels—to health outcomes, excluding laboratory experiments on information framing or nocebo effects. Results are coded as "No" for studies finding no statistically significant relationship between turbine exposure and health and "Yes" for those reporting any negative or indirect health effects (including annoyance or subjective symptoms). Methodology is classified as "Correlational" for purely cross-sectional proximity–health associations without temporal or spatial controls, and "Causal" for designs employing treatment–control comparisons, before–after analysis, or quasi-experimental variation.

waves (<20 Hz), which has raised concerns about possible effects on sleep and health. Experimental evidence suggests that such exposure can stimulate the outer hair cells of the ear (Salt et al., 2013; Kugler et al., 2014), though evidence for direct impacts on sleep remains limited and inconclusive.

Some studies and systematic reviews document dose–response relationships for noise-related annoyance and self-reported sleep disturbance, particularly at higher sound levels, yet these outcomes are often measured subjectively and in contexts with limited scope for causal inference (Knopper and Ollson, 2011). As shown in Figure 1, studies reporting negative or mixed effects—especially those using purely correlational designs—tend to attract disproportionately high citation counts and media coverage, amplifying their influence on public debate despite methodological limitations.

Large cross-sectional surveys in Europe and North America indicate that a minority of residents experience chronic annoyance or disturbed sleep, especially when turbines are nearby or noise levels exceed 45 dB(A) (Onakpoya et al., 2015; Knopper et al., 2014; Haac et al., 2019). However, these effects are subjective and often shaped by individual expectations. The Health Canada study (2016) found no relationship between noise exposure and objective health measures such as actigraphy-based sleep, blood pressure, or cortisol levels (Michaud et al., 2016a,b,c, 2021). Laboratory studies have found minor, transient changes in sleep structure—such as reduced REM sleep—but no significant alterations in deeper sleep stages or markers of physiological stress (Smith et al., 2020). A recent field study detected small reductions in heart rate variability at higher exposure levels, though the clinical significance of these findings remains uncertain (Chiu et al., 2021).

Closest to our study are two quasi-experimental analyses. Krekel, Rode, and Roth (Krekel et al., 2023) find no statistically significant effects of wind turbine exposure on physical or mental health, self-rated health, doctor visits, sleep quality, or emotional well-being in German household panel data. In contrast, Zou (Zou, 2020) finds that wind farm installations are associated with a 2% increase in U.S. suicide rates, particularly among teenagers and the elderly, with effects following an acoustic dipole pattern consistent with low-frequency noise transmission as the operative mechanism.

3 Data and Empirical Specification

3.1 Data

We combine individual-level health data from the NielsenIQ Ailments Survey (2011–2023) with geospatial data from the U.S. Wind Turbine Database (USWTDB). The survey records self-reported diagnoses including insomnia, depression, anxiety, and headaches for over 120,000 households across approximately 20,000 ZIP codes. We supplement these data with NielsenIQ consumer purchasing records, the American Time Use Survey, EPA air quality data, and county-level natality files. Full details on data sources, sample construction, and validation exercises are provided in Materials and Methods.

3.2 Empirical Specification

We estimate event-study models centered on the year of first turbine installation, with household and year fixed effects and standard errors clustered at the ZIP code level. We also estimate two-way fixed effects (TWFE) models and apply the heterogeneity-robust estimator of Borusyak, Jaravel, and Spiess Borusyak et al. (2024). Full specification details, including robustness checks across alternative distance thresholds and county-level definitions, are provided in Materials and Methods.

4 Results

4.1 Main results

The event study analysis reveals no evidence of adverse health effects following wind turbine installation (Figure 2). Across all event-time coefficients, estimates are small, centered around zero, and statistically indistinguishable from zero at the 95% confidence level. We find no evidence of pre-trends or of delayed or cumulative effects in the years after installation. These results hold both in the full sample and when restricting to residents of ever-treated ZIP codes—those receiving at least one turbine between 1984 and 2024 (SI Figure S5). Estimates for insomnia (and sleep-related problems) and headaches are consistently close to zero and precisely estimated. Results for depression are somewhat noisier but show no systematic pattern or sustained increase. Overall, the absence of any discernible dynamic response indicates that wind turbine exposure has no meaningful impact on self-reported insomnia and sleep-related problems, depression, anxiety, or headaches.

To complement these findings and to provide a benchmark for the average pre–post change, we also estimate a two-way fixed effects (TWFE) model. As shown in SI Table S3, the TWFE point estimates are similarly small and statistically insignificant. To aid in-

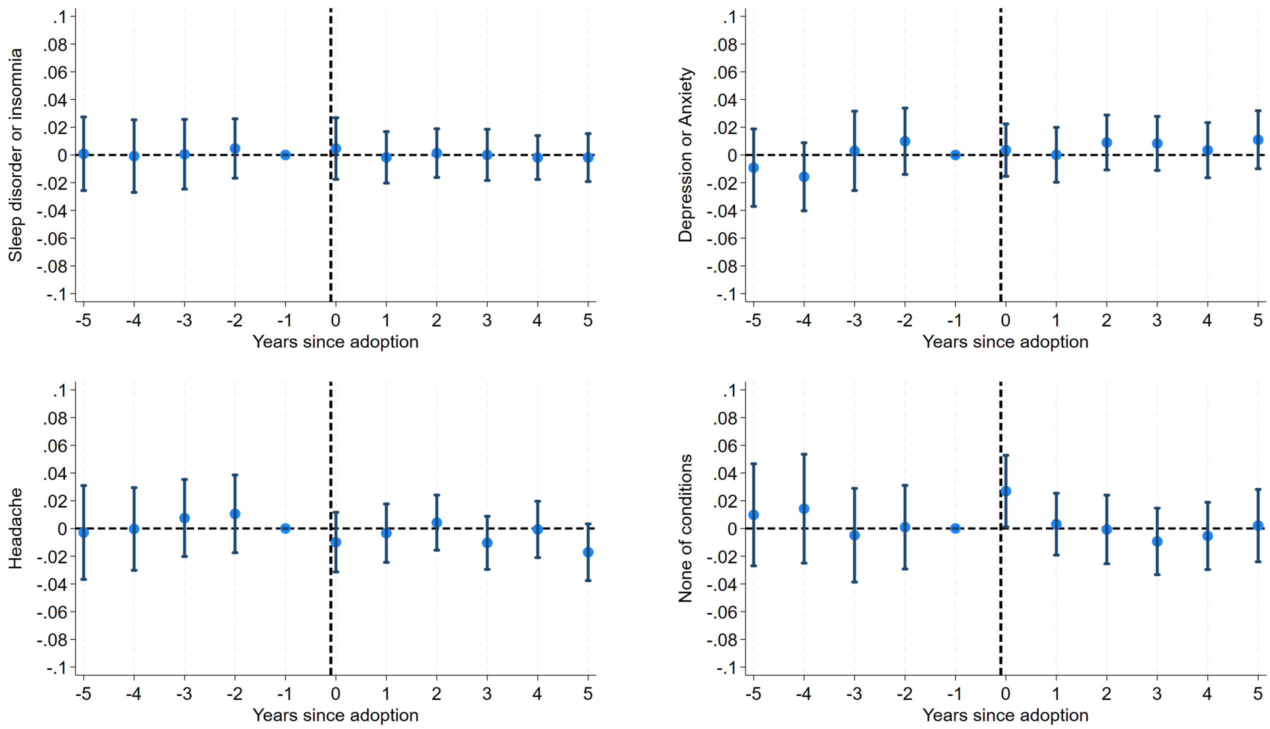

Figure 2: **Wind Turbines and Household Health.** Event study estimates of wind turbine installation on self-reported health conditions. Data are drawn from the NielsenIQ Ailments Survey (2011–2023). Outcome variables are binary indicators equal to one if any household member reports the condition. Coefficients represent changes in the probability of reporting each condition (or count for number of conditions) relative to the year prior to installation (k = -1). For treated ZIP codes, the median distance from turbines to population-weighted ZIP centroids is 6 km (IQR: 3–10 km). All models include household and year fixed effects and control for individual age and sex, household size, income, composition, residence type, marital and employment status, and head of household age and education. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

terpretation, we translate these estimates into predicted case counts. For a hypothetical population of 10,000 individuals exposed to wind turbines, our point estimates imply 25 additional cases of insomnia (95% CI: -84 to +134), 60 additional cases of depression/anxiety (95% CI: -58 to +177), and 40 fewer cases of headaches (95% CI: -163 to +83). These magnitudes are small relative to baseline prevalence: turbine-exposed populations would have approximately 969 insomnia cases (baseline), 1,194 depression/anxiety cases, and 1,298 headache cases per 10,000 individuals, with estimated effects representing changes of 3%, 5%, and -3% respectively—all statistically indistinguishable from zero. The conclusions remain unchanged when we exclude covariates or apply the estimator proposed by Borusyak, Jaravel, and Spiess Borusyak et al. (2024), which is robust to treatment effect heterogeneity. Power calculations confirm that our main specification has 80% power to detect effects of 1.6-1.8 percentage points (approximately 14-16% of baseline prevalence across outcomes) at the 5% significance level. Importantly, null findings persist across specifications that should provide greater statistical power, including ZIP-year aggregation (SI Table S9) and county-level analysis (SI Table S11), suggesting true null or very small effects rather than insufficient power. Precision declines at closer distances where sample sizes are limited: within 5 km, minimum detectable effects increase to 1.9–2.1 pp (16–19% of baseline); within 3 km, to 3.2–3.3 pp (25–33% of baseline) (SI Section 3).

Finally, we examine the effects of turbine exposure on 40 additional health conditions from the same survey instrument (SI Figure S4). We find no evidence of systematic impacts: nearly all estimated coefficients are small in magnitude and statistically insignificant. A few outcomes (imperfect vision, back/neck pain, and skin condition) are individually significant at conventional levels, but none remain so after adjusting for multiple hypothesis testing, with all q-values well above standard thresholds (see SI Table S4).

4.2 Household spending

In addition to health data, the NielsenIQ dataset provides annual household-level information on consumer spending between 2004 and 2023. This enables us to re-estimate our main model to examine whether proximity to wind turbines affects purchasing behavior—specifically, spending on product categories potentially linked to health or stress, such as for instance painkillers, sleep aids, and coffee. Overall, we find no evidence of any effects on these outcomes for our main analysis period (Figure 3) as well as for the entire observation period covered by the spending data (SI Figure S33). The absence of detectable changes in these purchases aligns with the null effects on self-reported health and provides an additional behavioral check, since spending patterns can capture health-related impacts that survey

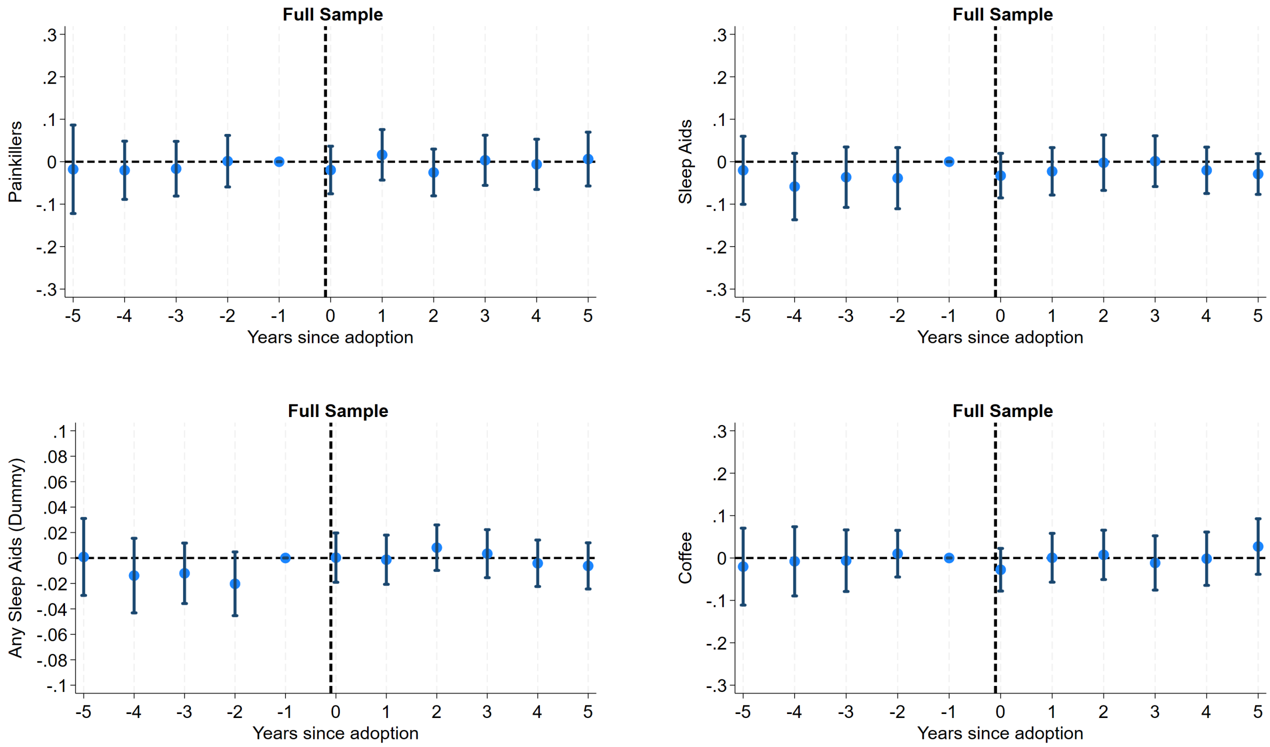

Figure 3: **Wind Turbines and Household Spending.** Event study estimates of wind turbine installation on household purchasing behavior. Data are drawn from NielsenIQ Consumer Panel purchase records (2011–2023), which track itemized expenditures for panelist households. Panel (A) shows the share of total household spending allocated to painkillers . Panel (B) shows the share allocated to sleep aids. Panel (C) shows a binary indicator for any sleep aid purchase in the year. Panel (D) shows the share allocated to coffee. All Shares are standardized and coefficients represent standard deviation changes in the outcome relative to the year prior to installation ($k = 1$). Panel (C) shows increase in probability. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

responses might miss. In line with this, we also detect no significant effects on household spending potentially indirectly associated with (mental) health like alcoholic beverages, tobacco and overall medications and remedies (SI Figures S34).

4.3 Time-use evidence

In addition to health outcomes, we examine behavioral indicators using the county-level treatment definition and data from the American Time Use Survey (ATUS), focusing on activities relevant to mental and physical well-being. We find no significant effects on sleep duration, self-assessed health status, time spent doing sports, time spent outdoor, weekly working hours, or weekly earnings (SI Figure S8 and Table S5).

4.4 Heterogeneity and Robustness Checks

We conduct extensive heterogeneity and robustness analyses to test whether effects vary across subpopulations or research design choices (full results in SI Section 3).

Heterogeneity. We examine variation by age, gender, race/ethnicity, education, income, political leaning, urbanization, and turbine characteristics. Across all specifications, only two estimates reach marginal significance: headaches among the lowest income quartile and depression for large projects (>100 MW). Neither survives restricting to ever-treated ZIP codes, and neither survives adjustment for multiple testing.

Alternative exposure definitions. A key concern is whether our ZIP-code-based treatment assignment accurately captures household proximity. Our main specification defines treatment based on turbine presence within ZIP code boundaries. To test robustness, we estimate alternative specifications using continuous distance measures and distance-based thresholds. For these distance-based specifications, we compute distances from turbines to population-weighted ZIP centroids, refined using Census tract-level population weighting (SI Section 2). Using this approach, the median distance between turbines and ZIP population centers is 6 km (IQR: 3–10 km), with 42% of treated households within 5 km. Results are robust to: (i) progressively tighter distance restrictions (10 km, 5 km, 4 km), where treatment is defined as ZIP centroids within the specified distance and control comprises all ZIPs beyond that threshold; (ii) exclusion of large or low-density ZIP codes; (iii) distance-band definitions (4–8 km, 5–10 km, 10–20 km, 25–100 km) following Krekel, Rode, and Roth Krekel et al. (2023); (iv) turbine size and technology thresholds following Zou Zou (2020); (v) county-level treatment; and (vi) continuous measures of wind power generation. Null effects persist even at close proximities where Guo, Wenz, and Auffhammer Guo et al. (2024) document property value impacts (SI Section 3). Power calculations confirm that our main

TWFE specification can detect effects as small as 1.6-1.8 percentage points at 80% power for all primary outcomes—corresponding to 14-16% of baseline prevalence (SI Table S3). Precision declines when defining treatment based on closer distance thresholds: within 5 km of turbines, minimum detectable effects range from 1.9-2.1 percentage points (16-19% of baseline); within 3 km, they increase to 3.2-3.3 percentage points (25-33% of baseline). We are underpowered to conduct informative event-study analyses for distance-based exposure definitions below 5 km due to limited sample sizes. Our null findings are therefore most informative for the majority of exposed households living at typical distances from turbines, rather than the small number residing in immediate proximity.

Geographic robustness. To address concerns about differential regional trends, we estimate models with state × year fixed effects, county-specific time trends, and Census division × year fixed effects. Results remain unchanged (SI Figure S25). Leave-one-state-out analysis confirms findings are not driven by any individual state, including those with the largest deployments (Texas, Iowa, California, Oklahoma, Kansas) (SI Figures S27–S28).

Selection and attrition. We find no evidence that turbine exposure causes residential relocation, household dissolution, or differential panel attrition (SI Figure S29), suggesting selection bias does not explain our null findings.

Wind direction and comparison to Zou Zou (2020). Zou Zou (2020) documents that suicide effects follow an acoustic dipole pattern—effects occur primarily in months with more upwind and downwind days. Using ERA5 wind data, we test whether our health outcomes exhibit similar patterns. Point estimates remain small and insignificant across all wind directions, with no evidence of a dipole pattern (SI Section 4.3, Figure S30). We also match Zou's specifications through county-level aggregation, pre-2013 installations, and age-stratified analysis. Results remain null across all designs (SI Section 4 for full comparison). We do not claim Zou's Zou (2020) findings are incorrect; rather, we study health conditions at the household level while Zou examines an extreme mortality outcome at county level. Our findings suggest average health impacts are not detectable across the broader population, even if localized effects exist.

5 Conclusion

This study evaluates the health effects of wind turbine exposure in the United States by linking detailed geographic data on turbine installations with rich individual-level panel data on health, time use, and consumer behavior. We examine a broad range of outcomes linked to mental and physical well-being, including subjective measures (such as insomnia and sleep-related problems, depression, anxiety and headaches), objective behavioral proxies (such as purchases of sleep aids and painkillers), and broader health and environmental indicators (such as self-assessed health, time use, and air quality). Across all measures, results are statistically and substantively negligible, providing no evidence that living near wind turbines leads to detectable adverse health effects at typical exposure distances. While we cannot rule out small effects below our minimum detectable threshold, our confidence intervals exclude moderate-to-large impacts on diagnosed health conditions.

Our research makes two main contributions. First, it moves beyond broad well-being indices to focus on specific, policy-relevant health outcomes, using high-resolution longitudinal data covering more than a decade. Second, it systematically tests a wide variety of exposure definitions and turbine characteristics, addressing concerns that earlier null results may have reflected mismeasurement or insufficient statistical power. The consistency of null findings across specifications with varying statistical power—including aggregated analyses that should better detect population-level effects—provides evidence that our results reflect true null or very small effects rather than insufficient power.

Importantly, our findings do not imply that community concerns should be dismissed—localized impacts on property values and visual amenities are well-documented and merit policy attention. Rather, our results suggest that *health-specific* concerns may be more appropriately addressed through transparent communication and procedural fairness than through restrictions premised on direct physiological harm. Transparent engagement, participatory siting processes, and adherence to evidence-based design standards (e.g., noise thresholds and set-back distances) remain essential for maintaining public trust and minimizing conflict.

Future research could build on our findings in several directions. First, while our results show no detectable health effects at typical exposure distances from wind turbine exposure in the U.S., it would be valuable to investigate whether impacts differ in other institutional and geographic contexts—particularly in regions where turbines are sited closer to population centers or where displaced fossil fuel plants are nearby. Second, linking precise residential geocodes to high-frequency environmental data (e.g., noise monitoring, fine-scale air quality) could help narrow confidence intervals and detect more localized effects. Third, given that much of the public opposition to wind energy appears driven by perceptions, fairness concerns, and misinformation rather than direct health impacts, future work could integrate experimental or quasi-experimental designs to test how communication strategies, participatory siting processes, or compensation schemes influence acceptance. Finally, as wind technology evolves—with larger turbines and hybrid renewable systems—it will be important to revisit potential health and environmental effects under these new configurations to ensure that policy remains aligned with both decarbonization goals and community well-being.

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Appendix

Data Sources

The NielsenIQ Ailments Survey is administered annually as a supplement to the NielsenIQ Consumer Panel. It records self-reported diagnoses of conditions including diabetes, cancer, heart disease, ADHD, obesity, high cholesterol, arthritis, asthma, digestive disorders, depression, anxiety, insomnia and sleep-related problems, and headaches. Information on depression and anxiety was not collected in 2018–2021. For 2011–2015, when individual-level data on medical attention are available, medical care was reported for 36% of insomnia (and sleep-related problems) cases, 28% of headaches, and 60% of depression or anxiety cases within the past six months. The panel provides substantial within-household variation for identification, with 58% of observations drawn from households who remain for 5+ years (median tenure: 6 years). While we observe multiple household members per household-year, the absence of individual-level identifiers means we cannot track specific individuals within households over time, preventing the use of individual fixed effects. We therefore estimate specifications with household fixed effects, which absorb time-invariant household-level characteristics. Validation exercises confirm that our health measures detect known environmental health relationships (SI Section 1.2, Figures S1–S2).

The NielsenIQ Consumer Panel provides household-level purchasing data (2004–2023), from which we construct measures of spending on sleep aids, painkillers, coffee, alcohol, tobacco, and medications. We supplement these with: the American Time Use Survey (ATUS, 2003–2023) for sleep duration and time use; EPA county-level air quality data (2011–2023); EIA Forms 860 and 923 for electricity generation; and county-level natality files for birth outcomes.

The U.S. Wind Turbine Database (USWTDB), maintained by the U.S. Geological Survey in collaboration with the Department of Energy and Lawrence Berkeley National Laboratory, provides coordinates, technical specifications (hub height, rotor diameter, capacity), and operational dates for all known utility-scale turbines. Turbines in our sample average 87 meters hub height, 109 meters rotor diameter, and 141 meters tip height, with projects averaging 121 MW capacity and 47 turbines per installation.

Sample Construction

The NielsenIQ panel operates with rolling entry and exit. Our analysis sample includes over 120,000 households across approximately 20,000 ZIP codes, of which 532 received their first turbine during 2011–2023. Event study estimates are identified from overlapping cohorts observed at different points relative to installation.

Treatment Definition

Our primary treatment is ZIP-code-based: a ZIP code is treated beginning in the year when at least one turbine becomes operational within its boundaries. For distance-based robustness checks, we compute distances from turbines to population-weighted ZIP centroids. To account for within-ZIP population distribution, we calculate distances from each turbine to all Census tract centroids within 100 km, then aggregate using tract population weights.

Alternative treatment definitions include: (i) distance thresholds of 5, 10, and 25 km; (ii) county-level exposure following Zou (2020); and (iii) continuous wind power generation from EIA data. We also test restrictions by turbine characteristics: capacity thresholds (1 MW, 50 MW), turbine counts (2+, 10+, 50+), rotor radius (>50 m), and total height (>125 m).

Control Variables

Time-varying controls (X_{iht}) include: individual age and sex; household size, income, and composition; residence type; presence and age of children; marital and employment status; and age and education of household heads. Models include household fixed effects to absorb time-invariant unobservables and year fixed effects to absorb aggregate shocks.

Estimation

We estimate event-study models with leads and lags spanning 5 years before and after the year of first turbine installation, omitting $k = -1$ as the reference period. We also estimate two-way fixed effects (TWFE) models with a binary post-treatment indicator. Formally, we estimated:

$$Y_{it} = \sum_{k \neq -1} \delta_k \text{EventTime}_{zt}^k + \gamma X_{iht} + \alpha_h + \lambda_t + \varepsilon_{it} \tag{1}$$

where Y_{it} is the health outcome for individual i in year t, α_h are household fixed effects, and λ_t are year fixed effects. Standard errors are clustered at the ZIP code level. Given well-documented limitations of TWFE under staggered adoption, we additionally employ the imputation estimator of Borusyak, Jaravel, and Spiess (2024), which is robust to heterogeneous treatment effects. For the "stacked" design, we restrict the sample to ever-treated ZIP codes—those receiving at least one turbine by 2023—ensuring treated and control units share similar characteristics. Standard errors are clustered at the ZIP code level throughout; county-level specifications cluster at the county level. Robustness checks include distance-based thresholds following Krekel, Rode, and Roth Krekel et al. (2023) and county-level definitions following Zou Zou (2020) (SI Sections 3–4).

Validation

To confirm that our health measures detect meaningful environmental effects, we conduct two validation exercises. First, we exploit circadian misalignment at time zone borders: individuals on the western edge report higher rates of insomnia and sleep-related problems, headaches, and depression, consistent with previous work (Gibson and Shrader, 2018; Giuntella and Mazzonna, 2019; Giuntella et al., 2017). Second, we show that NielsenIQ depression and anxiety measures correlate with county-level suicide rates.

Additional Outcomes

Beyond self-reported health, we examine: (i) household spending on sleep aids, painkillers, coffee, alcohol, tobacco, and medications; (ii) time use from ATUS, including sleep duration, self-assessed health, recreation, and time outdoors; (iii) county-level air quality indices from EPA; (iv) ZIP-level electricity generation from EIA; and (v) county-level birth outcomes including average birth weight and low birth weight rates.

Data from the U.S. Wind Turbine Database (USWTDB) are publicly available at https://eerscmap.usgs.gov/uswtdb/. Air quality data are available from the U.S. Environmental Protection Agency at https://www.epa.gov/outdoor-air-quality-data. Electricity generation data are available from the U.S. Energy Information Administration Forms 860 and 923. American Time Use Survey data are publicly available from the Bureau of Labor Statistics. County-level natality data are available from the National Center for Health Statistics.

NielsenIQ Consumer Panel and Ailments Survey data are proprietary and were accessed through the Kilts Center for Marketing Data Center at the University of Chicago Booth School of Business. Researchers may apply for access at https://www.chicagobooth.edu/research/kilts/datasets/nielseniq-nielsen. The conclusions drawn from the NielsenIQ data are those of the researchers and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

Code and instructions for replication are available at https://osf.io/gavjr/overview.