Supplementary Information Overview

This Supplementary Information is organized as follows:

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- SI1.1: Data sources (health outcomes from NielsenIQ Ailments Survey; wind turbines from USWTDB)
- SI1.2: Validation of health measures (time zone border discontinuities; correlation with suicide rates)
- SI1.3: Empirical specifications (event study design; two-way fixed effects models)

Section SI2: Distance Calculation Methodology

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- SI2.2: Validation comparing distance measurement approaches (Figure S3)

Section SI3: Spatial Precision and Robustness Checks

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- SI3.2: Distance-based treatment definitions (4 km, 8 km, 10 km thresholds; Figures S12–S15)
- SI3.3: Restricting to close proximities
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Section SI7: Tables and Figures

All supplementary tables and figures with detailed notes. Figures and tables are organized thematically rather than sequentially to facilitate comprehension of related analyses. Figures S1–S3 present validation exercises; Figures S5–S30 present main results and robustness checks; Figures S31–S39 present auxiliary analyses.

SI1 Data and Empirical Specification

SI1.1 Data Sources

SI1.1.1 Health Ailments

Our main analysis combines household-level health outcomes from the NielsenIQ Ailments Survey with turbine locations and construction years from the U.S. Wind Turbine Database (USWTDB). The Ailments Survey is administered annually as a supplement to the NielsenIQ Consumer Panel and records self-reported, doctor-diagnosed health conditions and related behaviors.[1] The module is available beginning in 2011 and covers roughly 28,000-44,000 active households per year, with diagnoses spanning 43 conditions (e.g., diabetes, cancer, heart disease, asthma, digestive disorders). Notably, depression and anxiety information was not collected in 2018–2021; analyses of this outcome are restricted to years when data are available.

The Ailments data contain multiple records per household-year corresponding to household members, but do not include persistent individual identifiers. Accordingly, we cannot track specific individuals within households over time and cannot estimate specifications with individual fixed effects; our main models instead use household fixed effects to absorb time-invariant household characteristics.

Table S1 reports descriptive statistics. Our primary outcomes are indicators for reporting (i) insomnia/sleeplessness (mean: 10%), (ii) depression/anxiety (mean: 12%), (iii) headaches (mean: 13%), and (iv) no reported condition (mean: 18%). Figure S4 reports results for the full set of 43 conditions (see also Table S4).

To gauge external comparability, we benchmark prevalence rates against contemporaneous national surveys. Headache prevalence in NielsenIQ (13%) closely aligns with NHIS estimates of migraine or severe headache (14% 3-month prevalence in 2012; Burch et al. 2015). Insomnia/sleeplessness (10%) is consistent with epidemiologic estimates of chronic

[1] See https://www.chicagobooth.edu/research/kilts/research-data/nielseniq for details.

insomnia disorder (6–10% under strict diagnostic criteria; Morin and Jarrin 2022). Depression/anxiety prevalence (12%) reflects diagnosed conditions and falls between clinical disorder rates (6–10%) and broader symptom-based measures (15–21%; Hasin et al. 2018; Terlizzi and Zablotsky 2024). These comparisons suggest the Ailments module captures diagnosed conditions rather than transient symptoms. Consistent with this interpretation, our validation exercises show that Ailments outcomes respond to well-established environmental variation (Figures S1–S2), making it less likely that our results are driven purely by measurement insensitivity.

Although some households are observed for only a limited number of years, the panel is dominated by long-running households at the observation level. More than half of all observations stem from households observed for at least five years. Our event-study estimates are identified from overlapping cohorts observed at different points relative to turbine installation. As robustness checks, we (i) restrict to households observed for at least five years (Figure S26); (ii) estimate ZIP-year aggregated models (Table S9); and (iii) estimate models without household fixed effects, but controlling for ZIP code (county) fixed effects (see Figure S20), with substantively similar results.

The NielsenIQ Consumer Panel has been widely used to study U.S. consumer and health-related behaviors (Dubois et al., 2022; Oster, 2018; Hut and Oster, 2022). As with other opt-in panels, participants are not a simple random draw and Ailments measures are self-reported, which may affect external representativeness (levels). Our identification relies on within-household changes over time with household fixed effects and flexible time controls. We further examine robustness across exposure definitions and sample restrictions (SI Sections 2–3) and heterogeneity by sociodemographic characteristics (Figures S9–S10), while remaining cautious about precision for the relatively small number of households in very close proximity to turbines.

SI1.1.2 Wind Turbines Data

The U.S. Wind Turbine Database (USWTDB), maintained by the U.S. Geological Survey in collaboration with the U.S. Department of Energy and Lawrence Berkeley National Laboratory, provides a comprehensive public inventory of utility-scale wind turbines in the United States. The USWTDB reports turbine locations, technical specifications (e.g., hub height, rotor diameter, capacity), and commissioning year, and is regularly updated to incorporate new builds, decommissions, and data corrections (see Table S2). We use the USWTDB release downloaded on November 1, 2024 and harmonize turbine commissioning years to our annual panel. Figure S32 summarizes the evolution of U.S. population exposure to wind turbines over time: the left panel reports the number of residents living within alternative distance thresholds of the nearest turbine, and the right panel reports the corresponding population shares.

Our primary treatment definition is ZIP-based: a ZIP code (as reported in NielsenIQ) is treated in year t if it contains at least one turbine classified as active in year t. For robustness checks using distance-based exposure, we compute distances from turbines to population-weighted ZIP centroids. To account for within-ZIP population distribution, we also calculate distances from each turbine to all Census tract centroids within 100 km and aggregate to the ZIP level using tract population weights (see Section SI2). Between 2011 and 2023, the number of treated ZIP codes in our NielsenIQ sample increased from 277 to 433 and the share of NielsenIQ respondents living in treated ZIP codes grew from 1.7% to 3.3% (see Figure S31).

SI1.2 Validation of Health Measures

To validate that our health outcome measures can detect meaningful responses to environmental shocks, we conduct three sets of validation exercises.

We first exploit variation at time zone borders following Gibson and Shrader (2018) and Giuntella and Mazzonna (2019). Residing on the western edge of a time zone creates circadian misalignment: individuals wake at similar clock times but receive less morning sunlight exposure, leading to reduced sleep duration and quality.

Figure S1 presents regression discontinuity estimates for self-reported health around time zone borders. Individuals just west of the border report significantly higher rates of sleep problems and insomnia (Panel A), depression and anxiety (Panel B), headaches (Panel C), and restless leg syndrome (Panel D). These patterns are consistent with documented effects of circadian misalignment on sleep and mental health (Argys et al., 2025; Giuntella et al., 2017). For context, our validation exercises detect effect sizes at time zone borders comparable to those reported by Giuntella and Mazzonna (2019). Figure S2 shows that our NielsenIQ measures of depression/anxiety correlate positively with county-level suicide rates from CDC WONDER, providing further evidence of external validity.

These validation exercises suggest that our health measures are responsive to well-established environmental variation, making it less likely that our wind-turbine results are driven purely by measurement insensitivity.

SI1.3 Empirical Specification

To estimate the effect of living near an active wind turbine on residents' health, we begin by estimating an event study model centered on the year of the first turbine installation within each ZIP code. This approach allows us to assess both potential pre-trends and the dynamic evolution of treatment effects in the years before and after exposure. Our primary treatment variable indicates whether a ZIP code contains at least one active turbine in a given year. Alternative distance-based exposure measures are explored in robustness checks (Section SI3). Our main specification takes the following form:

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

where Y_{iht} denotes the health outcome for household member i at time t, and $\text{EventTime}_{zt}^{k}$ is a set of indicators for years relative to the first turbine activation in ZIP code z, omitting $k = -1$ as the reference period. The vector X_{iht} includes time-varying individual and household characteristics such as age, sex, race, household size and income, residence type, household composition, presence and age of children, marital and employment status, and the age and education of household heads. We include household fixed effects (α_h) to account for time-invariant unobservables, and year fixed effects (λ_t) to absorb aggregate shocks.

In robustness checks, to ensure a more comparable control group and mitigate concerns about differential trends across treated and untreated areas, we restrict the event study sample to ZIP codes that eventually receive at least one turbine. Figure S5 presents event study estimates on ever-treated zip-codes for our three primary health outcomes—insomnia, depression/anxiety, and headaches—as well as reporting no health conditions. Point estimates are small and statistically insignificant across all leads and lags, with no evidence of pre-trends or post-treatment effects.

To better gauge the size of the overall impact, we also estimate a standard two-way fixed effects (TWFE) model:

$$Y_{it} = \beta \text{Turbine}_{zt} + \gamma X_{iht} + \alpha_h + \lambda_t + \varepsilon_{it} \tag{2}$$

where Turbine_{zt} is an indicator for whether a wind turbine is active in ZIP code z in year t.[2]

Table S3 presents TWFE estimates for the full sample (columns 1-3) and the ever-treated sample (columns 4-6). The estimated effects are small and statistically insignificant across all specifications. Given the well-documented limitations of TWFE models with staggered treatment adoption (De Chaisemartin and D'Haultfœuille, 2023), we also employ the estimator of Borusyak et al. (2024) (columns 3 and 6), which is robust to heterogeneous treatment effects and avoids the spurious weighting inherent in standard TWFE specifications. Results

[2] As a robustness check, we incorporated the recently released database of decommissioned turbines. The results remain virtually unchanged, which is unsurprising given that only 377 out of 904,999 observations (0.04%) in our health questionnaire switch from untreated to treated under this definition.

remain unchanged.

In additional robustness analyses, we explore alternative definitions of exposure. Specifically, we: (i) define exposure based on distance-based thresholds rather than ZIP code boundaries, following Krekel et al. (2023); (ii) construct county-level exposure metrics, similarly to Zou (2020); (iii) use actual power generation. Section SI2 discusses the methodology used to calculate distance. These results are presented in Sections SI3 and SI4.

SI2 Distance Calculation Methodology

Our main analysis uses a ZIP-code boundary-based definition: a ZIP code is treated if it contains at least one active turbine. For robustness checks, we construct distance-based exposure measures that account for continuous proximity and within-ZIP population distribution. We first measure distance from turbines to HUD-crosswalked ZIP code population centroids . We further refine this approach using census tract-level distance measures, which provide finer geographic resolution and more precise population weighting within ZIP codes (Figures S12-S17).

SI2.1 Tract-Weighted Distance Methodology

A key challenge is that ZIP Code Tabulation Areas (ZCTAs) vary substantially in land area and population distribution. Simply computing distances from turbines to ZCTA population-weighted centroids can introduce measurement error if population is unevenly distributed. We address this by computing distances at the Census tract level and aggregating to ZCTAs using population weights.

For each turbine, we calculate great-circle distances to all Census tract centroids within 100 km. Census tracts contain approximately 4,000 residents on average. The 100 km radius provides a conservative upper bound on potential exposure, as prior literature documents no property value effects beyond 8–10 km (Guo et al., 2024). For each ZCTA z and turbine j:

$$d_{zj} = \frac{\sum_{i \in z} \text{pop}_i \times d_{ij}}{\sum_{i \in z} \text{pop}_i} \tag{3}$$

where i indexes Census tracts, pop_i is tract population from the 2020 Census, and d_{ij} is the distance from turbine j to tract i's centroid. This weighting ensures that densely populated areas receive greater weight when determining ZCTA-level exposure.

From tract-weighted distances, we construct several ZCTA-level exposure metrics calculating the average minimum distance to the nearest turbine from each tract population weighted centroid and binary indicators for whether the distance falls below 5km or 10km.

SI2.2 Validation of Distance Methodology

Figure S3 compares tract-weighted distances to ZCTA population-weighted centroid distances using HUD-provided ZIP code centroid coordinates. The correlation is 0.94, indicating that the two methods yield very similar distance measures.

Figure S24 presents the cumulative distribution of distances from ZIP code population centroids to the first turbine installed within each ZIP code. Among ZIP codes that ever receive turbines, the median distance is 5.8 km, with an interquartile range of 3.1–10.1 km. 42% have their population centroid within 5 km of the nearest turbine, 75% within 10 km, and 91% within 15 km.

Results are robust to distance measurement methodology. For insomnia, the two-way fixed effects estimate of having a turbine within 10 km is 0.002 (SE: 0.004) when using ZCTA centroid distances, compared to 0.001 (SE: 0.004) when using tract-weighted distances, confirming that the weighting approach does not materially affect our findings.

SI2.3 Census Tract-Level Proximity Analysis

We construct ZIP-level measures of the share of population living in Census tracts at varying distances from wind turbines. For each ZIP code and year, we calculate the share of population residing in Census tracts whose population-weighted centroids fall within 0–5 km, 5–10 km, and 10–25 km of the nearest turbine. This provides a continuous measure of ZIP-level proximity: a ZIP code receives a higher exposure share if more of its population lives in tracts that are centrally located near turbines. We then estimate TWFE models where the treatment variable is this population share rather than a binary indicator.

Figure S23 presents these results. The left panel includes all distance-share measures jointly; the right panel reports separate regressions for cumulative proximity thresholds (within 5 km, 10 km, and 25 km). Coefficients are small and statistically insignificant across all specifications. For example, a 100 percentage point increase in the share of ZIP population within 5 km of a turbine is associated with a 0.002 percentage point increase in insomnia (SE: 0.009), a 0.003 percentage point increase in depression/anxiety (SE: 0.010), and a -0.009 percentage point change in headaches (SE: 0.010).

Figure S16 presents event study estimates using Census tract-weighted distance measures, restricting treatment to turbines within 10 km of the tract-weighted centroid. Unlike Figure S15, which uses ZIP code population centroids, this specification calculates distances from turbines to all Census tract centroids within each ZIP code, then aggregates to the ZIP level using tract population weights. This approach provides finer geographic resolution by accounting for heterogeneous population distributions within ZIP codes. Point estimates remain small and insignificant for both the full sample and ever-treated sample, confirming robustness to distance calculation methodology.

These tract-level analyses provide strong reassurance that our null findings are not artifacts of coarse spatial aggregation. Even when exploiting fine-grained variation in population exposure within ZIP codes, we find no evidence of health effects.

SI3 Spatial Precision and Robustness Checks

A central concern is whether ZIP-level aggregation attenuates estimated effects. This section documents the distribution of exposure in our sample and tests robustness to alternative distance-based definitions.

SI3.1 Distance-Based Treatment Definitions

Prior research documents property value effects concentrated within 1.5–4 km, vanishing beyond 8 km (Guo et al., 2024). We re-estimate specifications with progressively tighter distance restrictions to test whether effects emerge at closer proximities.

Figure S12 presents event study estimates using two alternative distance-based treatment definitions: (i) turbines within 8 km of the ZIP centroid and within ZIP boundaries, and (ii) turbines within 8 km regardless of ZIP boundaries. Each specification is estimated on both the full sample (Panels 1 and 3) and the restricted sample of ever-treated ZIP codes (Panels 2 and 4). The 8 km threshold is motivated by prior literature documenting property value effects within this range. Point estimates remain small and statistically insignificant across all specifications

Figure S14 presents results for distance-band comparisons: 4 km treatment vs. 4–8 km control, 5 km vs. 5–10 km, 10 km vs. 10–20 km, and 25 km vs. 25–100 km. This specification tests for dose-response effects by comparing ZIP codes with turbines at different distances. Treatment and control groups are defined by distance from the ZIP code population centroid to the nearest turbine, regardless of ZIP code boundaries. Results remain null across all distance bands.

Figure S15 applies an even stricter definition, requiring turbines to be both within ZIP boundaries and within 10 km of the ZIP population centroid. This addresses concerns about spatial measurement error in large ZIP codes where turbines may be far from population centers. The 10 km threshold corresponds to the upper bound of distances at which prior literature documents property value effects. Point estimates remain small and insignificant. Table S13 presents two-way fixed effects estimates using a 4 km distance threshold, defining treatment as the first year in which a ZIP code population centroid lies within 4 km of any wind turbine, regardless of ZIP code boundaries. Overall, these results confirm small and insignificant point-estimates.

Figure S17 presents dose-response estimates using continuous distance categories. We estimate TWFE models where the treatment variable is a set of distance-bin indicators (0–5 km, 5–10 km, 10–15 km, 15–20 km, 20–25 km, 25–50 km, 50–100 km), with distances above 100 km as the omitted reference category. This specification tests whether effects attenuate with distance, as would be expected if turbines cause health problems through noise or infrasound exposure. Coefficients are small and statistically insignificant across all distance bins, with no evidence of a monotonic relationship between proximity and health outcomes. Notably, confidence intervals at 0–5 km are comparable in width to those at longer distances, indicating that null findings at close proximity are not driven by insufficient statistical power.

SI3.2 Excluding Large and Rural ZIP Codes

ZIP code size heterogeneity could introduce measurement error if large ZIP codes contain turbines far from population centers. We test robustness by excluding potentially problematic geographies.

Figure S21 excludes ZIP codes in the top quartile of land area (area $\geq$ 485 km^2; median: 277 km^2, 90th percentile: 931 km^2, maximum: 3,896 km^2). Results are unchanged, indicating that our findings are not driven by measurement error in large ZIP codes.

Table S10 and Figure S22 exclude ZIP codes in rural counties (USDA Urban Influence Codes > 5), retaining only metropolitan and micropolitan areas. The sample retains only observations from ZIP codes located in counties classified as metropolitan or micropolitan by the USDA Economic Research Service, excluding nonmetropolitan counties. This restriction tests whether results are driven by rural areas where ZIP codes tend to be larger and population centers may be farther from turbines. Point estimates remain small and statistically insignificant, confirming that rural measurement error does not explain null findings.

SI3.3 Census Tract-Level Proximity Analysis

To further address spatial precision concerns, we exploit finer geographic variation by measuring the share of each ZIP code's population living in census tracts at varying distances from turbines (0–5 km, 5–10 km, 10–25 km). Figure S23 presents TWFE estimates where treatment intensity is defined as the population share within distance thresholds. Coefficients are small and statistically insignificant across all specifications, providing strong reassurance that null findings are not artifacts of coarse spatial aggregation.

SI4 Reconciling Results with Zou (2020)

We conduct several analyses to test whether methodological differences explain the divergence between our null findings and Zou (2020)'s positive results for suicide rates. Below we systematically match Zou's specifications and test alternative explanations.

SI4.1 Exposure Definitions and Spatial Aggregation

Zou (2020) defines treatment at the county level, classifying counties as exposed if any county land lies within 25 km of a wind farm and using counties 25–100 km away as controls, with outcomes measured as county-by-month suicide rates. To test whether our ZIP-code approach masks effects visible at coarser aggregation, we replicate this design as closely as our data permit.

Specifically, we replicate Zou (2020)'s methodology as closely as possible using our health outcomes. We aggregate both outcomes and turbine exposure to the county level and adopt Zou's key design choices: (1) including all turbine installations during our health data period (2011–2023), (2) defining treatment as turbine installation within 25 km of any county area,

(3) using a control group of counties 25–100 km from turbines, and (4) allowing counties to be treated multiple times as new turbines are installed. Table S11 presents results from Zou's two main specifications. Panel A estimates a simple pre–post specification where treatment is defined as the presence of a wind farm within 25 km of any county land. The 'post' coefficient represents the average change in county-level health prevalence after any turbine installation within 25 km. Panel B estimates a spatial difference-in-differences specification comparing treated counties (centroid within 25 km of a wind farm) to control counties located 25–100 km away. The 'post×near' coefficient represents the differential change in treated versus control counties after installation.

The qualitative conclusion is unchanged: estimated effects on our health outcomes remain small and statistically indistinguishable from zero. Point estimates for insomnia range from -0.000 to -0.001, for depression from -0.000 to -0.002, and for headaches from 0.001 to -0.002, all statistically insignificant.

Figure S37 presents event study estimates aggregated to county-year level, replicating Zou's event study approach as closely as our annual data permit. Treatment is defined as the installation of any new wind turbine within 25 km of any county area; counties may experience multiple treatments over time as additional turbines are installed. Point estimates remain small and statistically insignificant across all event-time periods.

SI4.2 Household Spending Outcomes

While our health data cover only the period 2011-2023, we can extend our period of analysis using NielsenIQ household spending data. Table S12 presents county-level specifications for painkillers, coffee, sleep aids, and any sleep aid purchases for the 2004–2013 period to match as closely as possible Zou's sample (2001-2013). The significant coefficient on 'Coffee' in the Pre-Post-specification is substantively small (0.03 standard deviations) in magnitude and the event-study (Figure S36 suggests no evidence of any significant impact).

SI4.3 Wind Direction Heterogeneity

Zou (2020) demonstrates that suicide effects follow an acoustic dipole pattern: suicide rates increase on days when counties are either upwind or downwind of turbines—with similar magnitudes in both directions—but not on crosswind days. This directional heterogeneity provides the key evidence for a causal mechanism operating through low-frequency noise transmission.

To implement a parallel test based on wind direction, we use daily wind direction data from the ERA5 reanalysis (2011–2023). For each ZIP code that is ever treated, we identify the initial treatment wind farm, defined as the first wind farm installed within the ZIP code. Using the population-weighted centroid of the ZIP code, we compute the bearing angle from this treatment wind farm to the ZIP centroid. We then compare this bearing to the daily meteorological wind direction to classify each ZIP–day as downwind (wind blowing from the turbine toward the ZIP centroid, within ±45°), upwind (the opposite direction, 180° ±45°), or crosswind, following the angular classification in Zou (2020).

Figure S30 presents estimates from regressions that interact wind-direction–specific exposure measures—annual counts of upwind and downwind days—with an indicator for the post-installation period, using crosswind exposure as the omitted reference category. Coefficients are scaled by a factor of 12 and correspond to the effect of a one-day increase in monthly exposure. Across all outcomes (insomnia, depression/anxiety, and headaches), point estimates for both upwind and downwind exposure are small and statistically insignificant.

Importantly, while Zou (2020) exploits within-county monthly variation in wind direction to identify acute effects, our analysis aggregates wind exposure to the annual level and therefore does not replicate their high-frequency design. Nonetheless, we find no evidence of a dipole pattern even at this coarser temporal resolution: neither upwind nor downwind exposure is associated with worse health outcomes relative to crosswind locations following installation. The absence of effects in directions where infrasound exposure should be strongest suggests that the acoustic dipole mechanism does not generate detectable chronic health impacts in our setting

SI4.4 Turbine Technology and Project Size

Modern turbines are taller with larger rotors (averaging 86.7m hub height, 109m rotor diameter, 141.3m tip height in our sample), which may alter acoustic profiles, frequency spectra, or propagation distances. Additionally, setback regulations have evolved: many jurisdictions adopted stricter distance requirements after 2010, potentially reducing exposure intensity. When comparing wind farms, installations in our sample (2011–2023) are substantially larger and more modern than those in Zou's sample (2001–2013), averaging 121 MW and 47 turbines versus 71 MW and 42 turbines (see Table S2).[3]

We test whether these differences drive our null results by restricting treatment to projects meeting thresholds comparable to earlier installations. Figure S11 presents results for: (i) capacity $\geq$ 1 MW (Zou's minimum threshold), (ii) capacity $\geq$ 50 MW, (iii) $\geq$ 2 turbines, (iv) $\geq$ 10 turbines, (v) maximum rotor radius $>$ 50m, and (vi) maximum total height $>$ 125m. Results remain null across all specifications, indicating that turbine size and modernity do not explain our divergent findings.

Figure S18 tests whether results are sensitive to systematic differences in turbine characteristics across installation periods. We redefine treatment as the first turbine installed between 2011 and 2023 within a ZIP code, effectively excluding pre-2011 installations from determining treatment timing. Results remain null, suggesting that temporal differences in turbine technology or regulatory environment do not explain our divergent findings.

SI4.5 Age Heterogeneity

Zou (2020) reports that suicide effects are most pronounced among teenagers (15–19) and the very elderly (80+), with weaker or null effects in other age groups. This pattern sug-

[3]For comparability, project capacity is reported at the level of the full wind farm installation for "treatment projects" (defined as projects with a first installation in a Nielsen ZIP code between 2011 and 2023) and is not split across ZIP codes when projects span multiple ZIP code boundaries.

gests vulnerability may concentrate in specific life stages. Although our primary outcomes differ—we study insomnia, depression, anxiety, headaches, and related behaviors rather than suicide—we test whether effects concentrate in these same age groups.

Figure S9 presents age-stratified results across the full age distribution. We estimate two-way fixed effects specifications that interact the turbine treatment indicator with age group indicators: under 6, 6–12, 13–17, 18–20, 21–24, 25–34, 35–44, 45–54, 55–64, and 65+. Outcome variables are binary indicators equal to one if a household member in the age group reports the condition.

While some point estimates are occasionally large in magnitude (e.g., headaches among young adults; depression among the elderly), none is consistently precise across specifications. The pattern differs markedly from Zou's clear concentration in teenagers and those 80+.

SI4.6 Sample Period and Geographic Coverage

Our data span 2011–2023, providing only partial overlap with Zou's 2001–2013 period. To test whether temporal differences matter, we examine household spending outcomes using data from 2004–2013 to match Zou's sample period as closely as possible. Figure S36 presents event study estimates for painkillers, coffee, and sleep aids using our household-level data aggregated to the county level following Zou's empirical approach. Results remain null across all spending categories during this earlier time period, suggesting that our divergent findings are not driven by differences in sample timing.

SI4.7 Interpretation and Synthesis

The stark difference between our findings and Zou (2020) persists across all specifications: spatial scale, distance definitions, turbine characteristics, sample periods, and estimators. Three explanations remain plausible.

First, the outcomes differ substantially: Zou (2020) studies a rare, extreme outcome (suicide) that may respond to acute stressors without manifesting in chronic health conditions.

Our measures of insomnia, depression, anxiety, and headaches capture ongoing symptoms but may not detect tail-risk effects in highly vulnerable individuals. If wind turbines affect suicide through crisis precipitation rather than gradual health degradation, our outcomes would not capture this pathway.

Second, aggregation and power considerations may play a role. Zou (2020) uses county-level monthly suicide rates, which aggregate across thousands of individuals. If effects operate through small vulnerable subgroups, county-level designs may detect aggregate shifts that our household-level approach misses. However, our heterogeneity analyses by age, income, and other characteristics show no evidence of concentrated effects (Figures S9–S10).

Third, mechanism specificity may matter. The acoustic dipole pattern provides Zou's key evidence for a causal noise-based mechanism. Our failure to detect this pattern—even when explicitly testing upwind/downwind heterogeneity (Figure S30)—suggests either that the mechanism operates differently for suicide than for chronic health, or that local factors (terrain, atmospheric conditions, housing characteristics) mediate exposure in ways not captured by our annual wind direction aggregation.

We emphasize that both findings can be informative for policy. Zou (2020) identifies a potential risk for extreme outcomes in vulnerable populations, which warrants attention in siting decisions and mental health screening. Our results suggest that average chronic health impacts across the broader population are not detectable. This distinction matters for risk communication and regulatory frameworks: while localized support services may be appropriate near wind farms, population-wide health concerns appear unfounded.

SI5 Additional Robustness Checks

SI5.1 Alternative Treatment Timing and Definitions

We test robustness to alternative definitions of treatment timing and intensity. Table S6 defines treatment to begin one year after turbine installation (t+1 rather than t=0), testing whether health effects emerge with a lag. Results are substantively unchanged.

Table S7 restricts the sample to observations within a symmetric window around turbine installation ($t \in [2, +2]$ or $t \in [1, +3]$), focusing identification on households observed closely around the treatment event. The reduced sample size (approximately 6,000–7,000 observations) reflects the window restriction, but point estimates remain small and insignificant.

Table S8 uses continuous wind energy generation (in 100 GWh) as the treatment variable rather than a binary turbine indicator. Data on electricity generation are from U.S. Energy Information Administration Forms 860 and 923, aggregated to the ZIP code level. Mean wind generation in treated ZIP codes post-installation is 246 GWh/year (SD = 418). The 'Generation' coefficient represents the change in the probability of reporting the condition associated with a 100 GWh increase in annual ZIP-level wind energy generation. This specification tests whether treatment intensity—rather than binary exposure—affects health outcomes. Results remain null.

Figure S7 validates that turbine installation corresponds to actual increases in local wind energy production, confirming the treatment is meaningful. Wind energy generation increases sharply after installation, while non-wind energy sources remain stable.

Figure S19 presents event study estimates defining treatment based on the time a county (rather than a zip-code) receives the first wind turbine (or farm). Panels 1–2 use household fixed effects; Panels 3–4 use county fixed effects to match specifications common in county-level studies. Panels 1 and 3 show results for the full sample; Panels 2 and 4 restrict to ever-treated counties. Overall, we confirm our baseline findings.

SI5.2 Turbine Characteristics

Modern turbines may differ from earlier installations in size, noise profiles, or acoustic properties. Figure S11 tests whether effects vary by turbine characteristics, defining treatment based on: (i) project capacity ≥ 1 MW, (ii) capacity ≥ 50 MW, (iii) ≥ 2 turbines, (iv) ≥ 10 turbines, (v) maximum rotor radius > 50m, and (vi) maximum total height > 125m. These specifications test whether larger or more numerous turbines—which produce greater noise and infrasound—generate detectable health effects. Results remain null across all specifications.

SI5.3 Restricting to New Installations

Figure S18 tests whether results are sensitive to systematic differences in turbine characteristics across installation periods. We redefine treatment as the first turbine installed between 2011 and 2023 within a ZIP code, effectively excluding pre-2011 installations from determining treatment timing.

SI5.4 Alternative Fixed Effects Specifications

Figure S20 compares event study estimates using alternative fixed effects structures. Panels 1–2 include ZIP code fixed effects; Panels 3–4 include county fixed effects. Results remain null across both specifications and for both the full sample (Panels 1, 3) and ever-treated sample (Panels 2, 4), confirming that our findings are not sensitive to the level of geographic fixed effects, nor to overfitting with household fixed effects.

SI5.5 Spatiotemporal Controls

To address concerns about confounding from regional trends or state-level policies, we re-estimated our main specifications with alternative spatiotemporal controls (Figure S25). Results remain null when adding state-by-year fixed effects (which absorb state-specific annual shocks such as policy changes), census division-by-year fixed effects (controlling for broader regional trends), or county-level linear time trends (allowing for differential secular trends). Point estimates are small and statistically insignificant across all specifications for both the full sample and ever-treated sample.

SI5.6 Leave-One-State-Out Analysis

To test whether results are driven by any single state with concentrated wind development or idiosyncratic characteristics, we conduct leave-one-state-out (LOSO) sensitivity analysis. We sequentially re-estimate our main TWFE specification after excluding each U.S. state, testing whether the null findings depend on any particular geographic area.

Figure S27 presents LOSO estimates for the full sample across our three primary health outcomes: insomnia/sleeplessness, depression/anxiety, and headaches. Each point represents the coefficient from a separate regression excluding the state listed on the x-axis. Point estimates remain consistently small and statistically insignificant regardless of which state is excluded, with coefficients tightly clustered around zero.

Figure S28 presents parallel estimates restricting to the ever-treated sample. Results are similarly stable: no single state drives the null findings. The consistency across specifications confirms that our results are not artifacts of treatment concentration in particular states (e.g., Texas, California, Iowa) or influenced by states with limited wind development.

These analyses provide strong evidence that null findings reflect a general pattern rather than idiosyncratic features of specific geographic areas or regulatory environments.

SI5.7 Attrition and Residential Mobility

To test whether turbine installation induces selective sample attrition or residential sorting that could bias our estimates, we examined whether households differentially exit the panel or relocate after exposure (Figure S29). We find no evidence that turbine installation affects the probability of panel exit (top row), household size (middle row), or residential mobility to a different ZIP code (bottom row). Point estimates are small and statistically insignificant across all event-time periods for both the full sample and ever-treated sample, indicating that selective attrition or avoidance behavior does not confound our health estimates.

SI5.8 Heterogeneity by Other Characteristics

Figures S9 and S10 examine heterogeneity across additional dimensions: age, sex, household income, education, race/ethnicity, urbanicity, political leaning, number of turbines, project capacity, and turbine size. Point estimates are small and statistically insignificant across nearly all subgroups, with no consistent evidence that effects concentrate in vulnerable populations. For individual-level characteristics (age, sex), we use interaction terms to avoid splitting households; for household-level characteristics, we use split-sample analysis.

SI6 Auxiliary outcomes

SI6.1 Energy Generation

To verify that the turbines in our dataset were operational in the stated year—and to rule out the possibility that our null health results reflect inactive installations—we use U.S. Energy Information Administration (EIA) Forms 860 and 923, which report annual net electricity generation at the plant level. Aggregating these data to the ZIP code level, we observe a marked and sustained increase in wind power generation beginning in the year of installation (SI Figure S6 & S7), confirming turbine activity in treated areas. This also underscores the economic relevance of our treatment: turbines in our sample are actively generating electricity and contributing to the local energy supply. We find no comparable increase in non-wind or fossil fuel-based generation, indicating that the observed changes in local energy output—and hence our treatment variation—are specifically driven by wind power installations.

SI6.2 Effects on Air Quality and Birth Outcomes

Using county-level data from the U.S. Environmental Protection Agency (EPA) covering the years 2011 to 2023,[4] we investigate whether the presence of wind turbines affects annual air quality indicators. We estimate an event-study at the county level on these outcomes and find no evidence that wind turbines affect the share of days classified as unhealthy, very unhealthy, or hazardous (Figure S38). However, there is a modest shift in the distribution of air quality categories: the share of "moderate" days increases by about 2 percentage points, while the share of "good" days declines by a similar amount—both significant at the 5% level. No significant effects emerge for other summary measures, including the maximum AQI, the 90th percentile, or the median AQI. These findings are robust to the imputation-based estimator of Borusyak et al. (2024). Yet, when restricting the sample to ever-treated counties, the shifts in "good" and "moderate" days lose statistical significance, suggesting they should be interpreted with caution.

The absence of clear improvements in local air quality is consistent with our earlier result that wind turbine installations are not accompanied by significant declines in non-wind or fossil fuel-based electricity generation. This aligns with prior research showing that air quality gains from wind power typically accrue near displaced fossil fuel sources, which are often located outside turbine-hosting counties (Qiu et al., 2022). For instance, Millstein et al. (2017) quantify sizeable climate and air quality gains from wind and solar deployment between 2007–2015, and more recent analysis finds that the expansion of renewables from 2019–2022 generated $249 billion in combined benefits from reduced SO_2 and NO_x emissions (Millstein et al., 2024).

Moreover, fossil fuel plants and wind farms face different siting constraints, with turbines often placed in remote or elevated areas where population exposure is limited. Overall, while wind energy may generate environmental benefits at broader regional scales, these gains do not necessarily translate into detectable improvements—or harms—for the local population.

[4] On average, 1,009 out of 3,143 U.S. counties are observed per year.

Figure S39 presents event study estimates for birth outcomes, showing no significant effects of wind turbine installation on either average birth weight or the share of low birth weight births. These null effects are consistent with the limited changes we observe in local air quality following wind development. Prior research has established a robust link between maternal exposure to air pollution—especially fine particulate matter—and adverse birth outcomes such as lower birth weight and preterm birth (e.g., Currie et al., 2009; Currie, 2013; Sun et al., 2015; Perera, 2017). The absence of detectable impacts here reinforces the interpretation that wind installations in our sample did not substantially reduce local pollution exposure, likely because they did not displace nearby fossil fuel generation.

SI6.3 Household Spending

We examine whether turbine exposure affects spending on health-related products using NielsenIQ purchase data (2004–2023). Figures S33 to S35 present event study estimates for spending shares on painkillers, coffee, sleep aids, alcohol, tobacco, and medications. We also test for "moral licensing" effects—whether households near turbines compensate by increasing consumption of carbon-intensive foods like dairy and meat. Point estimates are small and statistically insignificant across all categories, with no consistent evidence of behavioral responses. Figure S36 replicates Zou's (2020) county-level approach for 2004–2013; results remain null except for a marginally significant coefficient on sleep aids that does not survive multiple testing correction

SI6.4 Time Use and Well-Being

We test whether wind turbines affect sleep duration and daily activities using the American Time Use Survey (2003–2023). We estimate county-level specifications matching our health analysis. Figure S8 and Table S5 show no evidence that the first turbine installation within a county affects sleep hours, the probability of sleeping fewer than 6 or 7 hours, self-assessed health, time spent on recreation, or time spent outdoors. Point estimates are small and statistically insignificant across all specifications, providing no support for claims that turbines disrupt sleep or reduce quality of life.

SI7 SI: Tables and Figures

SI7.1 Tables

Table S1: Descriptive Statistics: Health Outcomes, Demographics, and Wind Turbine Exposure

Panel A: Outcomes, Treatment (Means %)

Outcome		**Turbine**	
Insomnia/Sleepless	10%	Within ZIP	3%
Depression/Anxiety	12%	Within 2 km	0%
Headache	13%	Within 5 km	2%
None	18%	Within 10 km	7%

Panel B: Categorical covariates (shares, %)

Marital status		**Race**		**Hispanic origin**	
Married/ Cohab.	73%	White/Caucasian	82%	Yes	7%
Widowed	6%	Black	10%	No	93%
Divorced/Separated	12%	Asian	4%		
Single	10%	Other	5%		
Male Head Empl.		**Female Head Empl.**		**Gender**	
No Male/Female Head	21%	No Female Head	7%	Male	45%
Under 30 hours	5%	Under 30 hours	13%	Female	55%
30–34 hours	3%	30–34 hours	5%	Unspecified/Other	0%
35+ hours	46%	35+ hours	32%		
Not Employed for Pay	26%	Not Employed for Pay	43%		
Age Group		**Male Head Age**		**Female Head Age**	
Under 6 years	4%	No Male Head	21%	No Female Head	7%
6 to 12 years	5%	Under 25 Years	0%	Under 25 Years	0%
13 to 17 years	5%	25–29 Years	1%	25–29 Years	2%
18 to 20 years	2%	30–34 Years	4%	30–34 Years	5%
21 to 24 years	2%	35–39 Years	6%	35–39 Years	8%
25 to 34 years	7%	40–44 Years	7%	40–44 Years	9%
35 to 44 years	10%	45–49 Years	8%	45–49 Years	10%
45 to 54 years	16%	50–54 Years	10%	50–54 Years	12%
55 to 64 years	23%	55–64 Years	21%	55–64 Years	25%
65 years or older	26%	65+ Years	22%	65+ Years	22%
Male Head Educ.		**Female Head Educ.**		**Type of residence**	
No Male Head	21%	No Female Head	7%	1-Fam. House	80%
Grade School	1%	Grade School	0%	1-Fam. Condo/Coop	3%
Some High School	3%	Some High School	2%	2-Fam. House	3%
Graduated High School	21%	Graduated High School	22%	2-Fam. Condo/Coop	1%
Some College	21%	Some College	28%	3+ Fam. House	6%
Graduated College	23%	Graduated College	29%	3+ Fam. Condo/Coop	4%
Post College Grad	11%	Post College Grad	12%	Mobile Home or Trailer	4%
Household Income		**Children in HH**		**Household Compos.**	
Under $5,000	1%	Under 6 only	4%	Married or cohabitant	70%
$5,000–$7,999	1%	6–12 only	6%	Head (F) w/ Related	9%
$8,000–$9,999	1%	13–17 only	8%	Head (M) w/ Related	3%
$10,000–$11,999	1%	Under 6 & 6-12	4%	Female Alone	11%
$12,000–$14,999	2%	Under 6 & 13-17	1%	Female w/ Non-Rel.	1%
$15,000–$19,999	3%	6–12 & 13-17	5%	Male Alone	4%
$20,000–$24,999	5%	Under6 & 6-12 & 13-17	1%	Male w/ Non-Rel.	2%
$25,000–$29,999	5%	No Children Under 18	71%		
$30,000–$34,999	6%				
$35,000–$39,999	5%				
$40,000–$44,999	5%				
$45,000–$49,999	6%				
$50,000–$59,999	10%				
$60,000–$69,999	8%				
$70,000–$99,999	22%				
$100,000+	21%				

Notes: Descriptive statistics from the NielsenIQ Ailments Survey (2011–2023). Health outcomes are binary indicators equal to one if a household member reports the condition. Demographic variables include age, sex, household size, income, education, marital status, employment status, and household composition. Shares are computed at the observation level rather than the household level; household characteristics are therefore repeated across household members and may be counted multiple times. Wind turbine exposure is defined as presence of at least one active turbine in the household's ZIP code. Distance measures are calculated using Zip code population-weighted centroids.

Table S2: Descriptive Statistics: Turbines

	Mean	Median	SD	Min	P25	P75	Max	N
Panel A. Turbine characteristics								
Capacity (kW)	2399.8	2300.0	734.4	99.0	2000.0	2820.0	6000.0	47175
Hub height (m)	87.4	85.0	10.1	30.0	80.0	91.5	131.0	47171
Rotor diameter (m)	111.8	110.0	17.2	20.8	100.0	127.0	162.0	47170
Rotor swept area (1000 m^2)	10.1	9.5	3.0	0.3	7.9	12.7	20.6	47170
Total height (m)	143.3	145.1	16.7	43.6	130.1	152.4	200.0	47170
Panel B. Wind farm characteristics								
Number Turbines	47.4	36.5	49.3	1.0	4.0	74.0	377.0	1086
Total Capacity (MW)	123.6	102.0	118.9	0.1	19.8	200.0	1055.6	963
Panel C. Turbine characteristics (Analysis Sample)								
Capacity (kW)	2280.4	2100.0	663.4	99.0	1800.0	2520.0	6000.0	11754
Hub height (m)	86.7	80.0	9.8	30.0	80.0	90.0	131.0	11753
Rotor diameter (m)	109.1	110.0	17.2	20.8	100.0	125.0	162.0	11752
Rotor swept area (1000 m^2)	9.6	9.5	3.0	0.3	7.9	12.3	20.6	11752
Total height (m)	141.3	138.1	16.1	43.6	130.1	150.0	200.0	11752
Panel D. Wind farm characteristics (Analysis Sample)								
Number Turbines	47.2	36.0	50.4	1.0	2.0	76.0	294.0	471
Total Capacity (MW)	121.4	102.2	113.5	0.1	6.0	200.1	643.4	416

Notes: This table reports characteristics of onshore wind turbine installations in the contiguous United States between 2011 and 2023. The sample excludes offshore turbines as well as installations located in Alaska, Hawaii, Guam, and Puerto Rico. Panels A and B include all turbine installations during this period. Panels C and D restrict the sample to turbines installed in the year a ZIP code receives its first wind turbine installation, for ZIP codes that are observed at least once in the Nielsen health data and whose first installation occurs between 2011 and 2023. Turbine characteristics are measured at the turbine level. Wind farm characteristics are measured at the project level (identified by project name, installation year, capacity, and number of turbines), with capacity and size reported for the full installation – rather than split across ZIP codes – for comparability.

Table S3: Wind Turbines and Health - Two-Way Fixed Effects Estimates

	Full sample			**Ever-treated**		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Insomnia						
Turbine	0.003	0.002	0.001	−0.006	−0.007	−0.005
	(0.006)	(0.006)	(0.007)	(0.009)	(0.008)	(0.013)
Estimator	TWFE	TWFE	Borusyak	TWFE	TWFE	Borusyak
Controls	Yes	No	No	Yes	No	No
Observations	828,160	828,328	827,128	28,635	28,640	10,385
R^2	0.402	0.388	—	0.404	0.387	—
Mean Dep. Var.	0.097	0.097	0.099	0.098	0.098	0.099
Std. Dev.	0.296	0.296	0.299	0.297	0.297	0.298
Panel B: Depression & Anxiety						
Turbine	0.006	0.006	0.002	0.006	0.006	−0.023
	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.016)
Estimator	TWFE	TWFE	Borusyak	TWFE	TWFE	Borusyak
Controls	Yes	No	No	Yes	No	No
Observations	578,600	578,865	582,953	20,163	20,174	8,021
R^2	0.502	0.487	—	0.518	0.503	—
Mean Dep. Var.	0.119	0.120	0.123	0.122	0.123	0.120
Std. Dev.	0.324	0.325	0.329	0.328	0.328	0.325
Panel C: Headache						
Turbine	−0.004	−0.005	0.002	−0.010	−0.012	0.001
	(0.006)	(0.006)	(0.007)	(0.010)	(0.010)	(0.014)
Estimator	TWFE	TWFE	Borusyak	TWFE	TWFE	Borusyak
Controls	Yes	No	No	Yes	No	No
Observations	828,402	828,619	827,437	28,636	28,642	10,387
R^2	0.422	0.382	—	0.433	0.392	—
Mean Dep. Var.	0.130	0.130	0.132	0.134	0.134	0.139
Std. Dev.	0.336	0.336	0.339	0.341	0.341	0.346

Notes: Two-way fixed effects estimates of wind turbine exposure on Insomnia & Sleep Problems, Depression & Anxiety, and Headache. Data are drawn from the NielsenIQ Ailments Survey (2011–2023). The 'Turbine' coefficient represents the average change in the probability of reporting the condition after turbine installation in the household's ZIP code. Outcome variables are binary indicators equal to one if a household member reports the condition; outcome means and standard deviations are reported in the final rows. Columns 1 and 4 include the full set of time-varying controls: individual age and sex, household size, income quartile, household composition, residence type, presence and age of children, marital and employment status, and age and education of household heads. Columns 2–3 and 5–6 exclude controls to assess sensitivity. Columns 3 and 6 apply the imputation estimator of Borusyak, Jaravel, and Spiess (2024), which is robust to heterogeneous treatment effects under staggered adoption. All models include household fixed effects (absorbing time-invariant characteristics) and year fixed effects (absorbing common annual shocks). Standard errors in parentheses are clustered at the ZIP code level. Depression and anxiety data are unavailable for 2018–2021. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S4: Wind Turbines and Other Health Conditions - Two-Way Fixed Effects Estimates

Outcome	Coef.	SE	Mean	Std. Dev.	p-value	q-value
Acid Reflux/GERD/Heartburn	-0.006	0.631	0.212	0.409	0.640	1.000
Acne	-0.001	0.848	0.062	0.240	0.850	1.000
Alzheimers/Dementia	-0.002*	0.099	0.004	0.063	0.100	1.000
Allergies food related only	-0.007	0.161	0.042	0.200	0.160	1.000
Allergies other	-0.000	0.973	0.305	0.461	0.980	1.000
Arthritis	0.011	0.386	0.180	0.384	0.380	1.000
Asthma	-0.007	0.179	0.066	0.249	0.190	1.000
ADHD	0.003	0.518	0.036	0.187	0.460	1.000
Autoimmune (Lupus/Graves/etc)	-0.009	0.129	0.018	0.134	0.130	1.000
Blood conditions	0.000	0.979	0.021	0.144	0.980	1.000
Bronchitis/Pulmonary	-0.005	0.471	0.031	0.173	0.470	1.000
Cancer	-0.001	0.911	0.017	0.128	0.910	1.000
Celiac Disease	-0.003	0.128	0.004	0.059	0.130	1.000
Cholesterol Problems	-0.018	0.168	0.190	0.392	0.170	1.000
Constipation chronic	0.001	0.830	0.031	0.174	0.820	1.000
Crohn's Disease / Ulcerative Colitis	0.001	0.481	0.007	0.084	0.490	1.000
Depression / Anxiety	0.010	0.171	0.118	0.322	0.170	1.000
Diabetes Type I	0.001	0.481	0.009	0.096	0.470	1.000
Diabetes Type II	-0.007	0.294	0.089	0.285	0.290	1.000
Dry Eye	-0.004	0.644	0.063	0.243	0.640	1.000
Eye Disease	-0.009	0.184	0.048	0.213	0.180	1.000
Fibrocystic Breast Changes	-0.002	0.775	0.007	0.081	0.770	1.000
Gluten Sensitivity	-0.002	0.722	0.015	0.121	0.720	1.000
Gum Disease	-0.004	0.382	0.030	0.170	0.380	1.000
Hair Loss	0.001	0.923	0.053	0.223	0.930	1.000
Headaches (any kind)	0.001	0.874	0.129	0.335	0.880	1.000
Heart Disease	-0.003	0.612	0.031	0.173	0.620	1.000
Hypertension	-0.006	0.550	0.252	0.434	0.550	1.000
Imperfect Vision	-0.024*	0.051	0.274	0.446	0.050	1.000
Insomnia	-0.003	0.668	0.095	0.293	0.670	1.000
IBS	0.002	0.633	0.037	0.189	0.640	1.000
Neck/Back Pain	-0.029**	0.010	0.147	0.354	0.010	0.410
Lactose Intolerance	-0.003	0.521	0.042	0.200	0.520	1.000
Menopause	-0.004	0.692	0.095	0.293	0.690	1.000
Muscle Pain/Spasms	-0.005	0.516	0.083	0.276	0.520	1.000
None of conditions	0.015	0.168	0.185	0.388	0.170	1.000
Obesity	0.007	0.532	0.191	0.393	0.530	1.000
Osteoporosis	-0.007	0.148	0.036	0.185	0.150	1.000
Pre-Diabetes	-0.011*	0.061	0.030	0.171	0.060	1.000
Psoriasis	-0.001	0.663	0.017	0.128	0.670	1.000
Restless Legs	-0.007	0.129	0.037	0.189	0.130	1.000
Skin Conditions	-0.018**	0.014	0.071	0.256	0.010	0.410
Urinary Incontinence	-0.003	0.546	0.051	0.220	0.550	1.000

Notes: Two-way fixed effects estimates of wind turbine exposure on 43 health conditions from the NielsenIQ Ailments Survey (2011–2023). Each row reports the coefficient, standard error, outcome mean, standard deviation, p-value, and Benjamini, Krieger, and Yekutieli (2006) sharpened q-value for a separate regression. The 'Coef.' column reports the average change in the probability of reporting the condition after turbine installation. Outcome variables are binary indicators equal to one if a household member reports the condition. All models include household and year fixed effects, as well as the full set of time-varying demographic controls described in Materials and Methods. Q-values adjust for multiple hypothesis testing across all 43 outcomes (Benjamini et al., 2006). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S5: Wind Turbines and Time Use

Panel A: Full sample	Sleep hrs	<6 hrs	<7 hrs	SAH	Recreation	Stay outside	Hours worked	Weekly earnings
Turbine exposure	0.004	-0.002	-0.001	0.028	0.016	-0.093	-0.014	-21.223
	(0.043)	(0.006)	(0.007)	(0.027)	(0.022)	(0.061)	(0.260)	(18.408)
Observations	104,352	104,352	104,352	60,072	104,352	104,352	58,762	56,488
R-squared	0.118	0.029	0.052	0.147	0.052	0.141	0.202	0.372
Mean dep. var.	8.853	0.0846	0.194	3.513	0.333	2.884	39.35	966.1
Standard deviation	2.260	0.278	0.395	1.049	0.968	3.197	11.26	704.6
p-value	0.927	0.808	0.935	0.294	0.453	0.129	0.957	0.250
Panel B: Ever-Treated	Sleep hrs	<6 hrs	<7 hrs	SAH	Recreation	Stay outside	Hours worked	Weekly earnings
Turbine exposure	0.069	-0.007	-0.000	-0.022	0.003	-0.100	0.189	-4.913
	(0.068)	(0.010)	(0.011)	(0.035)	(0.032)	(0.110)	(0.308)	(19.422)
Observations	27,016	27,016	27,016	15,639	27,016	27,016	14,705	14,033
R-squared	0.116	0.032	0.056	0.138	0.055	0.163	0.187	0.362
Mean dep. var.	8.927	0.0822	0.188	3.448	0.328	2.938	38.93	912.8
Standard deviation	2.294	0.275	0.391	1.065	0.941	3.228	11.17	681
p-value	0.317	0.510	0.971	0.531	0.924	0.363	0.541	0.801

Notes: Two-way fixed effects estimates of wind turbine exposure on time use and well-being outcomes from the American Time Use Survey (ATUS, 2003–2023). Panel A reports estimates for the full sample; Panel B restricts to ever-treated counties (those receiving at least one turbine within 25 km by 2023). Treatment is defined at the county level: a county is treated beginning in the year when the first turbine becomes operational within 25 km of any county land. Outcome variables are: (i) daily sleep hours from time diary; (ii–iii) binary indicators for sleeping fewer than 6 or 7 hours; (iv) self-assessed health on a 1–5 scale (1 = poor, 5 = excellent); (v) hours spent on sports and recreational activities; (vi) hours spent outside the home; (vii) usual weekly working hours; and (viii) weekly earnings. Columns 7–8 are estimated from the ATUS-CPS supplement and exclude controls for employment status and family income to avoid conditioning on outcomes. All models include county, year, month, and weekday fixed effects, with controls for education, household size, age group, gender, race, marital status, employment status (except columns 7–8), and family income (except columns 7–8). Standard errors are clustered at the county level. Analyses apply ATUS person weights. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S6: Wind Turbines and Health - Alternative Treatment Timing

	Panel A: Full sample			Panel B: Ever-treated		
	(1) Insomnia	(2) Depression	(3) Headache	(4) Insomnia	(5) Depression	(6) Headache
Turbine	0.001	0.005	-0.000	-0.006	0.005	0.002
	(0.006)	(0.006)	(0.007)	(0.009)	(0.008)	(0.010)
Observations	828,160	578,600	828,402	28,635	20,163	28,636
R-squared	0.402	0.502	0.422	0.404	0.518	0.433
Mean of dep. var.	0.097	0.119	0.130	0.098	0.122	0.134
Standard deviation	0.296	0.324	0.336	0.297	0.328	0.341

Notes: Two-way fixed effects estimates with treatment defined to begin one year after turbine installation. Data are drawn from the NielsenIQ Ailments Survey (2011–2023). This specification tests whether health effects emerge with a lag, coding treatment status as beginning in t+1 rather than the installation year t=0. Panel A reports estimates for the full sample; Panel B restricts to ever-treated ZIP codes. Outcome variables are binary indicators equal to one if a household member reports the condition. All models include household and year fixed effects and the full set of time-varying demographic controls described in Materials and Methods. Standard errors in parentheses are clustered at the ZIP code level. Results are substantively unchanged from the baseline specification (Table S3), indicating that delayed treatment onset does not reveal effects masked by contemporaneous noise. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S7: Wind Turbines and Health - Symmetric Event Window Restriction

	Panel A			Panel B		
	(1) Insomnia	(2) Depression	(3) Headache	(4) Insomnia	(5) Depression	(6) Headache
Turbine	0.005	-0.002	-0.024	-0.008	0.008	0.011
	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)	(0.016)
Observations	6,349	5,035	6,347	7,111	5,699	7,106
R-squared	0.478	0.572	0.486	0.466	0.573	0.485
Mean of dep. var.	0.0934	0.117	0.133	0.0937	0.117	0.128
Standard deviation	0.291	0.322	0.340	0.291	0.321	0.334

Notes: Two-way fixed effects estimates restricting the sample to observations within a symmetric window around turbine installation. Data are drawn from the NielsenIQ Ailments Survey (2011–2023). Panel A codes the installation year as the first treated year, restricting to observations from two years before through two years after installation ($t \in [-2, +2]$). Panel B codes the installation year as the last untreated year, so treatment begins at t+1, restricting to observations from one year before through three years after ($t \in [-1, +3]$). This window restriction focuses identification on households observed closely around the treatment event, reducing concerns about differential long-run trends between treated and control areas. Outcome variables are binary indicators equal to one if a household member reports the condition. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors in parentheses are clustered at the ZIP code level. The reduced sample size reflects the window restriction. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S8: Wind Turbines and Health - Using Wind Energy Generation as Treatment

	Panel A: Full sample			**Panel B: Ever-Treated**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Insomnia	Depression	Headache	Insomnia	Depression	Headache
Generation	0.002	-0.000	0.000	0.002	-0.002	-0.001
(100 GWh)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Observations	824,569	575,961	824,808	17,010	11,998	17,001
R-squared	0.402	0.502	0.422	0.405	0.527	0.419
Mean of dep. var.	0.0968	0.119	0.130	0.0995	0.125	0.141
Standard deviation	0.296	0.324	0.336	0.299	0.330	0.348

Notes: Two-way fixed effects estimates using continuous wind energy generation as the treatment variable. Data on health conditions are drawn from NielsenIQ (2011–2023); data on electricity generation are from U.S. Energy Information Administration Forms 860 and 923, aggregated to the ZIP code level. The 'Generation' coefficient represents the change in the probability of reporting the condition associated with a 100 GWh increase in annual ZIP-level wind energy generation. This specification tests whether treatment intensity—rather than binary exposure—affects health outcomes. Panel A reports estimates for the full sample; Panel B restricts to ever-treated ZIP codes. Outcome variables are binary indicators equal to one if a household member reports the condition. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors in parentheses are clustered at the ZIP code level. Mean wind generation in ZIP codes with any wind generation is 246 GWh/year (SD = 418). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S9: Wind Turbines and Health - ZIP-Code × Year Aggregated Analysis

	Full sample			**Ever-treated**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Insomnia	Depression	Headache	Insomnia	Depression	Headache
Turbine	0.003	0.013	-0.004	-0.008	0.009	-0.011
	(0.009)	(0.015)	(0.010)	(0.011)	(0.016)	(0.012)
Observations	157,100	110,806	157,173	6,124	4,334	6,128
R-squared	0.288	0.358	0.289	0.294	0.379	0.337
Mean of Dep. Var.	0.112	0.136	0.140	0.112	0.136	0.144
Std. Dev.	0.215	0.236	0.230	0.223	0.242	0.240

Notes: Two-way fixed effects estimates with outcomes aggregated to the ZIP code × year level. Data are drawn from NielsenIQ (2011–2023). This specification collapses household-level data to ZIP-year means, providing an alternative unit of analysis that may be less susceptible to household-level measurement error. The 'Turbine' coefficient represents the change in ZIP-level prevalence of each condition after turbine installation. Outcome variables are the share of households in each ZIP code reporting the condition. Panel A reports estimates for the full sample; Panel B restricts to ever-treated ZIP codes. All models include ZIP code and year fixed effects and ZIP-level aggregates of time-varying demographic controls. Regressions are weighted by ZIP code population from the 2020 Census. Standard errors in parentheses are clustered at the ZIP code level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S10: Wind Turbines and Health - Leaving Out Rural Areas

	Full Sample			**Ever-Treated Only**		
	(1) Insomnia	(2) Depression	(3) Headache	(4) Insomnia	(5) Depression	(6) Headache
turbine	0.002	-0.003	-0.006	-0.007	0.000	-0.008
	(0.006)	(0.007)	(0.007)	(0.009)	(0.009)	(0.011)
Observations	760,429	530,924	760,640	23,223	16,218	23,220
R-squared	0.403	0.501	0.422	0.402	0.511	0.436
Mean of Dep. Var.	0.096	0.118	0.128	0.096	0.120	0.132
Std. Dev.	0.294	0.322	0.334	0.294	0.325	0.338

Notes: Two-way fixed effects estimates excluding rural ZIP codes. Data are drawn from NielsenIQ (2011–2023). The sample retains only observations from ZIP codes located in counties classified as metropolitan or micropolitan by the USDA Economic Research Service (Urban Influence Codes 1–5 in 2024), excluding nonmetropolitan counties (UIC $>$ 5). This restriction tests whether results are driven by rural areas where ZIP codes tend to be larger and population centers may be farther from turbines. Panel A reports estimates for the restricted full sample; Panel B further restricts to ever-treated ZIP codes. Outcome variables are binary indicators equal to one if a household member reports the condition. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors in parentheses are clustered at the ZIP code level. Results are unchanged from the baseline specification, indicating that rural measurement error does not explain null findings. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S11: Wind Turbines and Health: County-Level Evidence Following Zou (2020)

	Panel A: Pre–Post			**Panel B: Spatial DiD**		
	(1) Insomnia	(2) Depression	(3) Headache	(4) Insomnia	(5) Depression	(6) Headache
post	-0.000	-0.000	0.001			
	(0.001)	(0.001)	(0.001)			
post#near				-0.001	-0.002	-0.002**
				(0.001)	(0.001)	(0.001)
Observations	27,398	19,231	27,409	136,773	96,214	136,802
R-squared	0.306	0.415	0.343	0.309	0.412	0.321
Mean Dep. Var.	0.098	0.113	0.128	0.099	0.120	0.129
Std. Dev.	0.064	0.069	0.071	0.069	0.076	0.076

Notes: Replication of Zou (2020) county-level specifications using household health data from NielsenIQ (2011–2023), aggregated to county $\times$ year. Panel A presents a pre–post specification in which treatment is defined as the presence of a wind farm within 25 km of any county land, corresponding to Zou (2020) Model 1. The 'post' coefficient represents the average change in county-level prevalence after any turbine installation within 25 km. Panel B presents a spatial difference-in-differences specification comparing treated counties (centroid within 25 km of a wind farm) to control counties located 25–100 km away. The 'post#near' coefficient represents the differential change in treated versus control counties after installation. Due to the annual structure of NielsenIQ data, we replace Zou's monthly event window ($\pm$12 months) with a symmetric five-year window ($\pm$5 years). Outcome variables are county-level shares of households reporting each condition. All models include county and year fixed effects. Regressions are population-weighted using 2020 Census data, consistent with Zou (2020). As in Zou (2020), counties may experience multiple treatments from separate wind farm installations. Standard errors are clustered at the wind farm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S12: Wind Turbines and Household Spending: County-Level Evidence Following Zou (2020)

	Panel A: Pre–Post				Panel B: Spatial DiD			
	(1) Painkiller	(2) Coffee	(3) Sleep aids	(4) Any sleep aids	(5) Painkiller	(6) Coffee	(7) Sleep aids	(8) Any sleep aids
post	-0.001	0.011***	-0.000	-0.000				
	(0.003)	(0.004)	(0.001)	(0.001)				
post#near					0.001	-0.007	0.000	0.001
					(0.002)	(0.005)	(0.001)	(0.001)
Observations	20,505	20,505	20,505	20,505	106,955	106,955	132,310	132,310
R-squared	0.551	0.663	0.312	0.374	0.526	0.641	0.309	0.338
Mean of Dep. Var.	0.526	1.121	0.0348	0.0788	0.455	1.131	0.0347	0.0798
Std. dev.	0.453	0.368	0.0473	0.0519	0.181	0.393	0.0486	0.0616

Notes: Replication of Zou (2020) county-level specifications using household spending data from NielsenIQ (2004–2013), aggregated to county × year. Outcomes measure the share of total household spending allocated to each consumption category. 'Painkiller' and 'Coffee' are spending shares; 'Sleep aids' is the spending share on sleep aid products; 'Any sleep aids' is a binary indicator equal to one if a household reports any sleep aid spending in the year. Panel A presents a pre–post specification with treatment defined as turbine presence within 25 km of any county land. Panel B presents a spatial difference-in-differences specification comparing treated counties (within 25 km) to control counties located 25–100 km away. The sample period (2004–2013) matches Zou (2020) as closely as possible. All models include county and year fixed effects and are population-weighted. As in Zou (2020), counties may experience multiple treatments. Standard errors are clustered at the wind farm level. The marginally significant coefficient on 'Sleep aids' in the spatial DiD specification (Panel B, column 3) does not survive correction for multiple testing. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

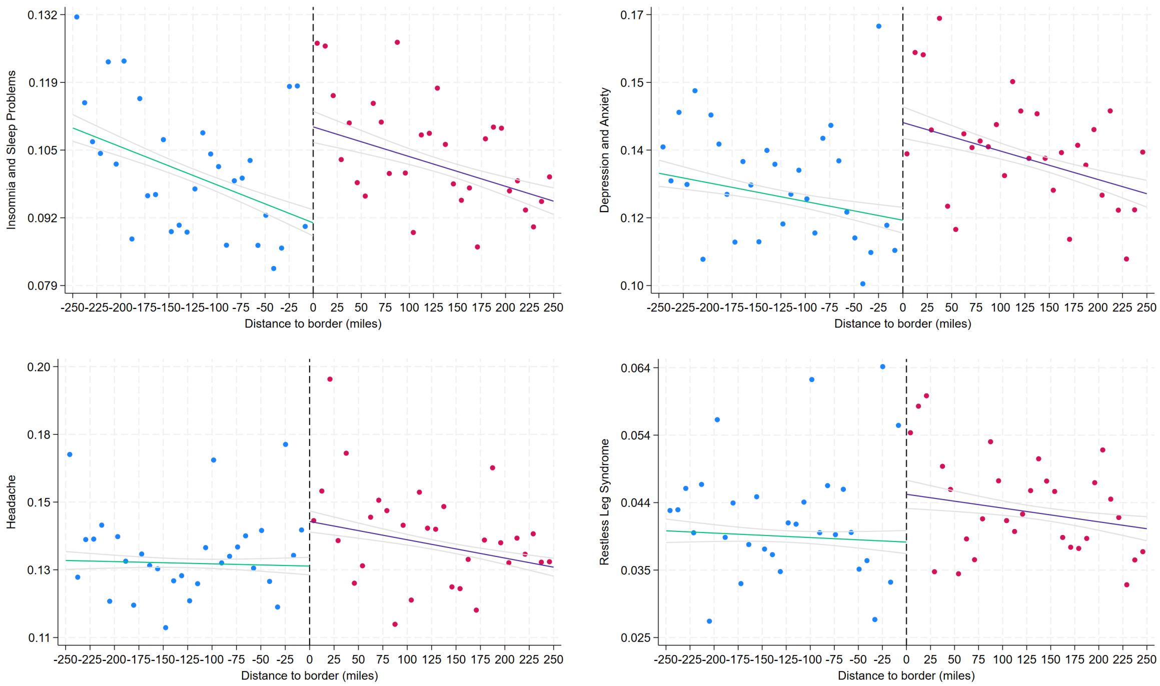
Table S13: Wind Turbines and Health: Exposure Within 4 km of ZIP Population Centroids

	Full Sample			**Ever-Treated Only**		
	(1) Insomnia	(2) Depression	(3) Headache	(4) Insomnia	(5) Depression	(6) Headache
turbine	0.005	-0.003	-0.013	-0.000	-0.010	-0.003
	(0.009)	(0.010)	(0.009)	(0.015)	(0.017)	(0.013)
Observations	828,160	578,600	828,402	13,246	9,249	13,236
R-squared	0.402	0.502	0.422	0.393	0.502	0.426
Mean of Dep. Var.	0.0969	0.119	0.130	0.102	0.119	0.130
Std. Dev.	0.296	0.324	0.336	0.302	0.324	0.336

Notes: Two-way fixed effects estimates following Equation (2), where treatment is defined as the first year in which a ZIP code population centroid lies within 4 km of any wind turbine, irrespective of ZIP code boundaries. Data are drawn from the NielsenIQ Ailments Survey (2011–2023). Panel A reports estimates for the full sample; Panel B restricts the sample to ever-treated ZIP codes. Outcome variables are binary indicators equal to one if a household member reports the condition. All models include household and year fixed effects as well as the full set of time-varying demographic controls described in Materials and Methods. Standard errors in parentheses are clustered at the ZIP code level. Estimates are small and statistically indistinguishable from zero across outcomes, indicating no detectable health effects at distances where turbine-related exposure is expected to be most pronounced. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

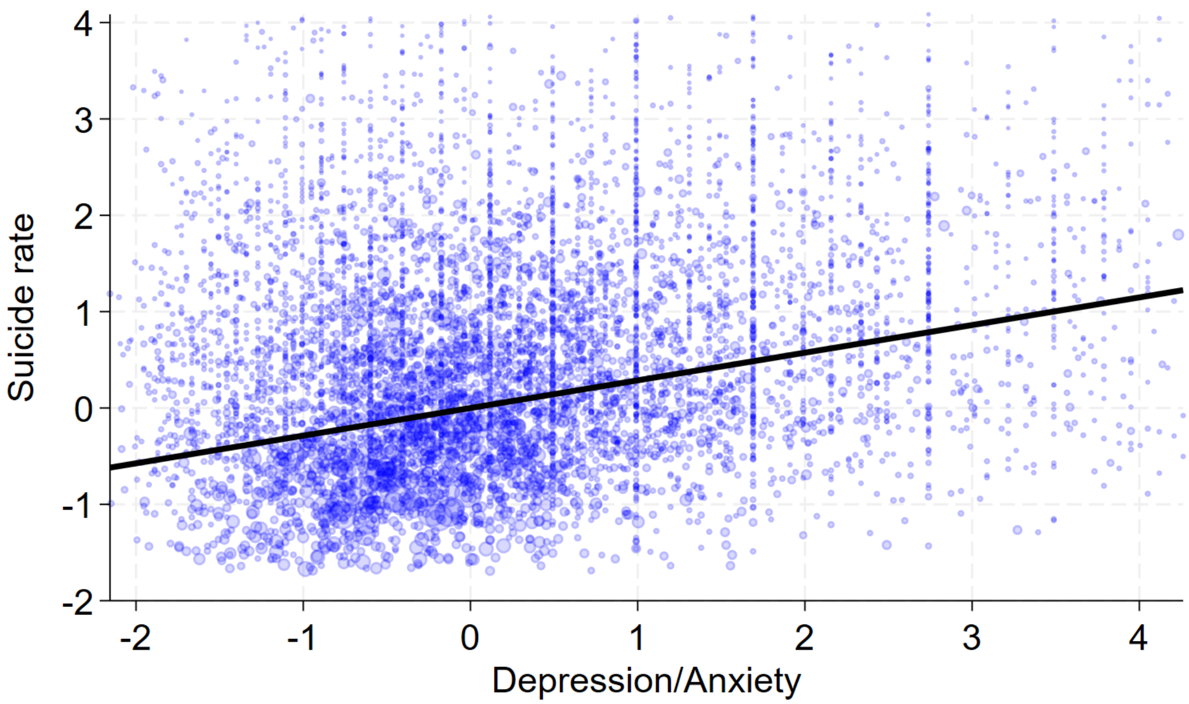
SI7.2 Figures

Figure S1: Validation: Time Zone Border Discontinuity in Health Outcomes



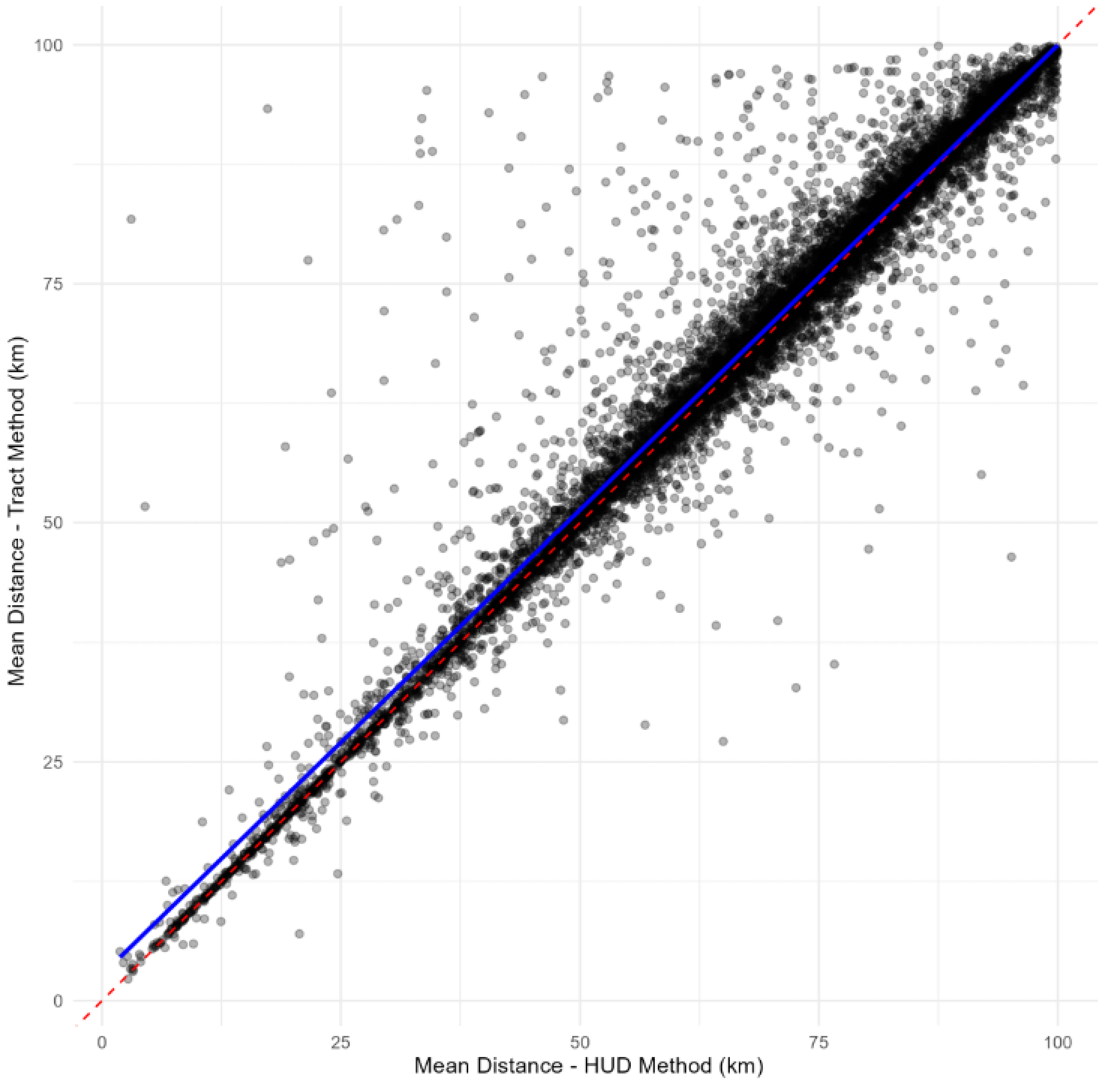
Notes: Validation of NielsenIQ health measures using regression discontinuity estimates at time zone borders, following Giuntella and Mazzonna (2019). Data on health conditions are drawn from the NielsenIQ Ailments Survey (2011–2023). Panels show local polynomial fits of self-reported health conditions against distance from time zone boundaries: insomnia and sleep problems (top-left), depression and anxiety (top-right), headaches (bottom-left), and restless leg syndrome (bottom-right). Negative distance values indicate the western (later sunset) side of the border. Residing west of a time zone border creates circadian misalignment due to reduced morning sunlight at equivalent clock times, which prior literature links to adverse health outcomes. The sample is restricted to households within 250 miles of time zone borders. Shaded areas represent 95% confidence intervals; standard errors are clustered at the county level.

Figure S2: Validation: Association Between Self-Reported Health and County Suicide Rates



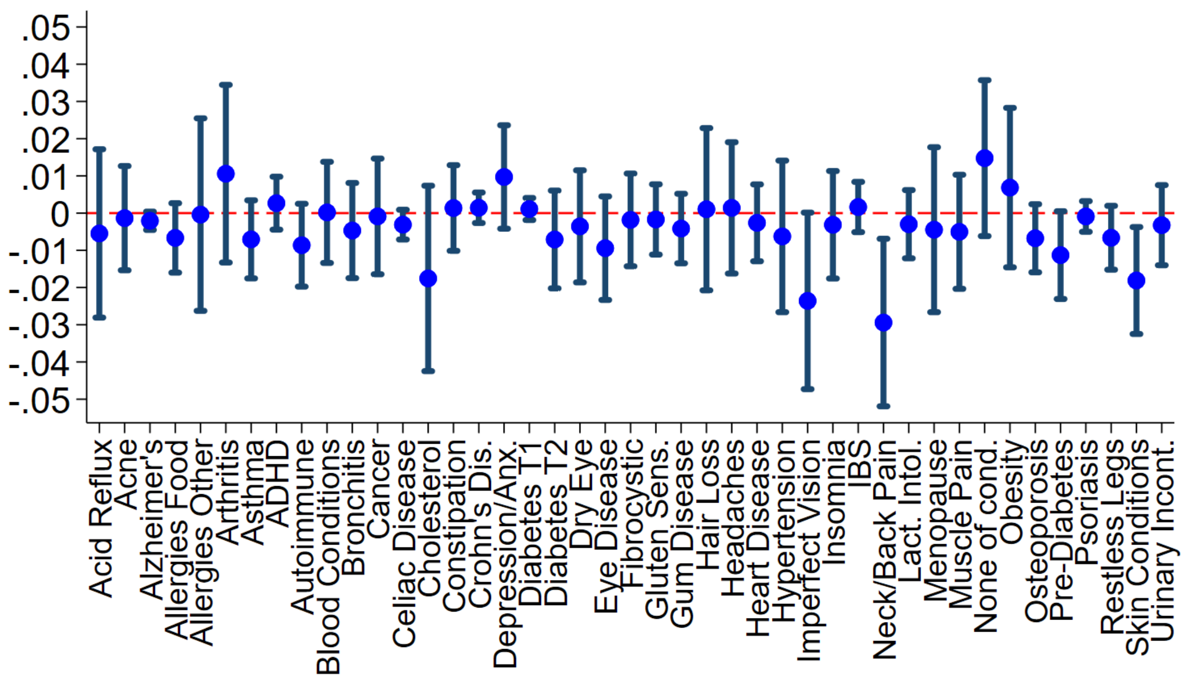
Notes: Validation of NielsenIQ self-reported health measures against objective mortality data. The figure shows the population-weighted association between county-level yearly suicide rates and self-reported depression/anxiety from NielsenIQ. Suicide rates (per million inhabitants) are from CDC WONDER (2011–2023); health measures are county-by-year averages expressed as shares (0–1 scale). Both variables are standardized, and observations in the top and bottom 1% of each distribution are excluded to reduce the influence of outliers. Points represent county-year observations (on average 963 counties per year), weighted by county population; the solid line shows the population-weighted linear fit. Suicide rates are available only for counties with more than ten recorded suicides due to CDC disclosure restrictions. The positive association confirms that our self-reported depression/anxiety measure correlates with objective mental health outcomes, supporting the external validity of NielsenIQ health data.

Figure S3: Validation: Comparison of Distance Calculation Methods



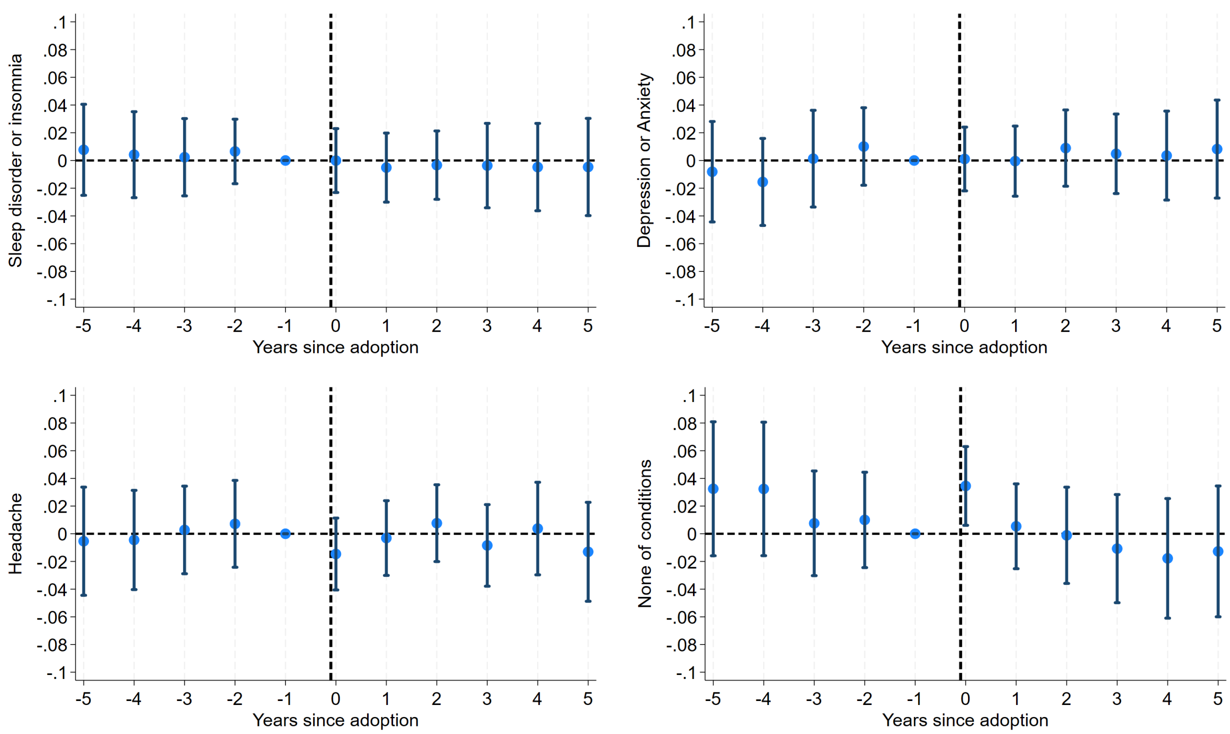
Notes: The figure compares two methods of calculating distance from ZIP codes to wind turbines. The x-axis reports distances computed from HUD-provided ZIP code centroid coordinates to the nearest turbine; the y-axis reports population-weighted distances computed using Census tract centroids aggregated to the ZIP code level (see SI Section 2 for methodology). Each point represents a ZIP code in the NielsenIQ sample with at least one turbine within 100 km. The solid blue line shows the linear regression fit; the dashed red line indicates the 45-degree line. The strong correlation confirms that our tract-weighted distance methodology—which accounts for heterogeneous population distributions within ZIP codes—produces exposure measures consistent with simpler centroid-based approaches. This validation addresses concerns about spatial measurement error: even in large or irregularly shaped ZIP codes, the two methods yield similar distance estimates, and our main results are robust to either approach (see SI Section 3).

Figure S4: Wind Turbines and Other Health Conditions



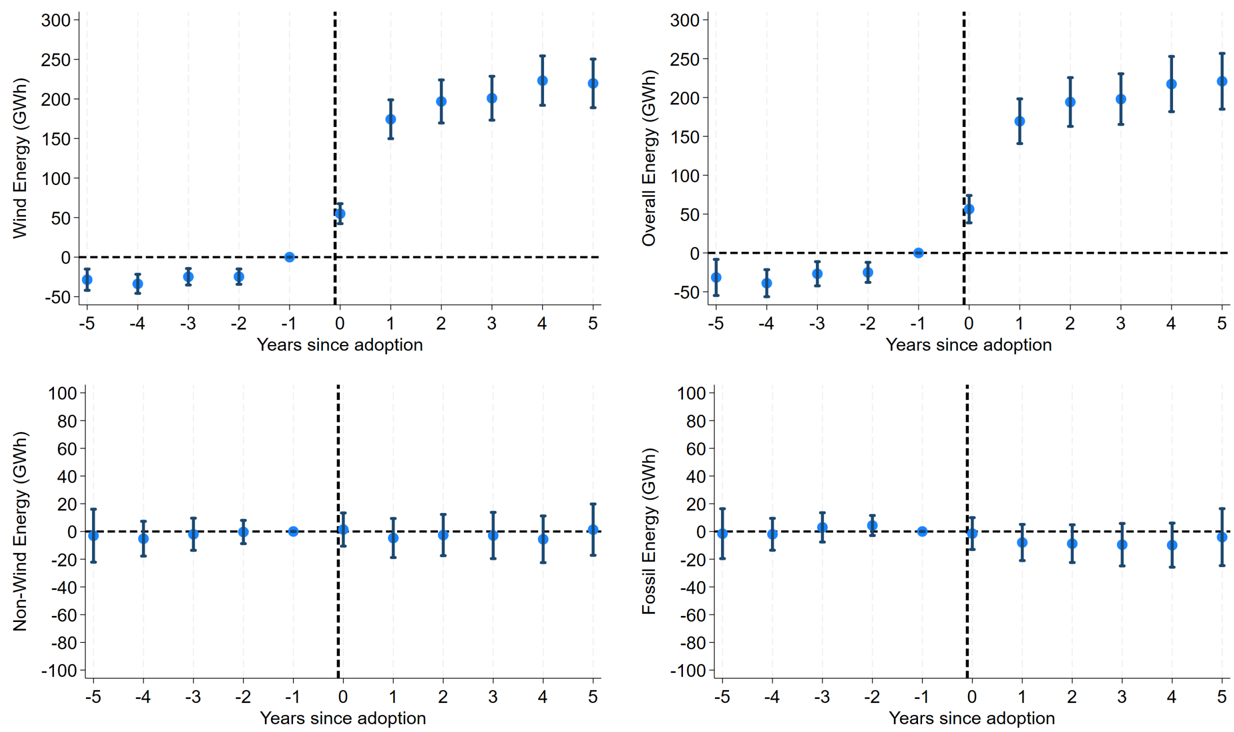
Notes: Two-way fixed effects estimates of wind turbine installation on additional health conditions from the NielsenIQ Ailments Survey (2011–2023). Each coefficient represents the average change in the probability of reporting the condition after turbine installation in the household's ZIP code, relative to the pre-installation period. Outcome variables are binary indicators. All models include household and year fixed effects and the full set of demographic controls described in Materials and Methods. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals. The horizontal red line indicates zero effect.

Figure S5: Wind Turbines and Household Health, Ever-treated ZIP



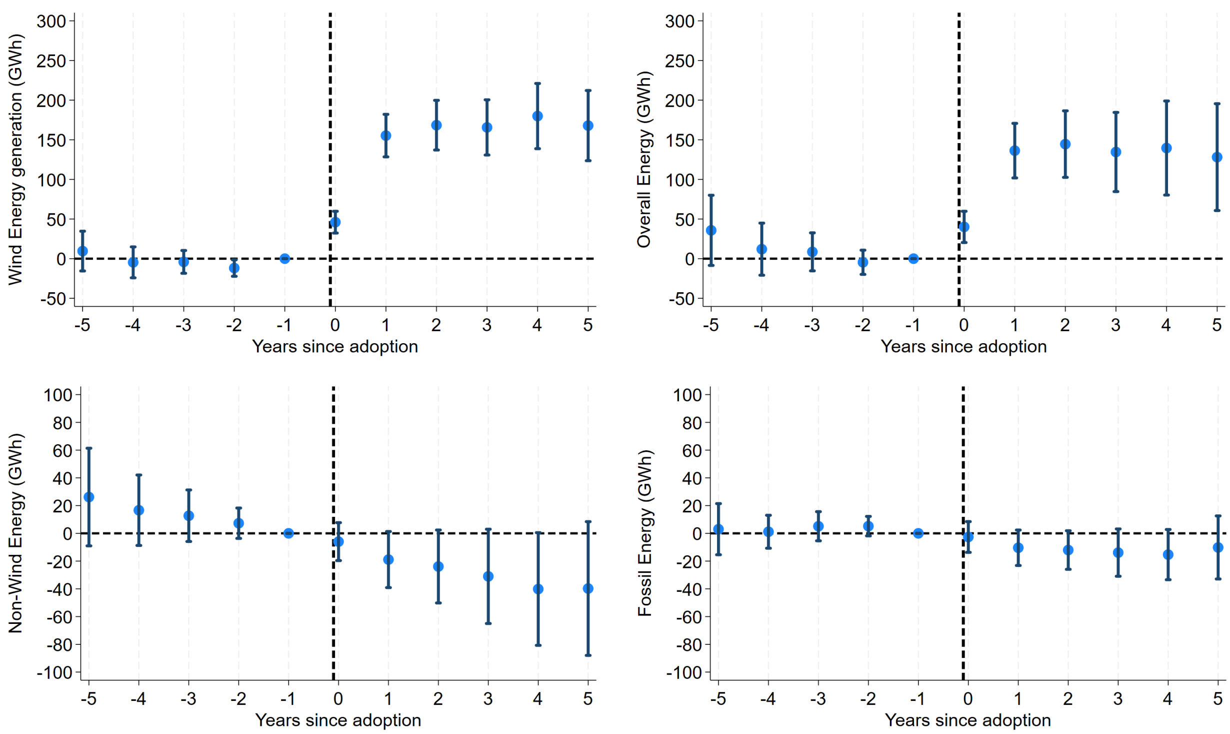
Notes: Event study estimates of wind turbine installation on health conditions from the NielsenIQ Ailments Survey (2011–2023). Each panel plots coefficients from equation (1), representing the change in the probability of reporting the condition in years relative to turbine installation, with $k = -1$ as the reference period. Outcome variables are binary indicators equal to one if a household member reports the condition. The sample is restricted to households in ZIP codes that receive at least one wind turbine by 2023 (ever-treated sample). All models include household and year fixed effects and the full set of time-varying demographic controls described in Materials and Methods. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S6: Wind Turbines and Wind Energy Production.



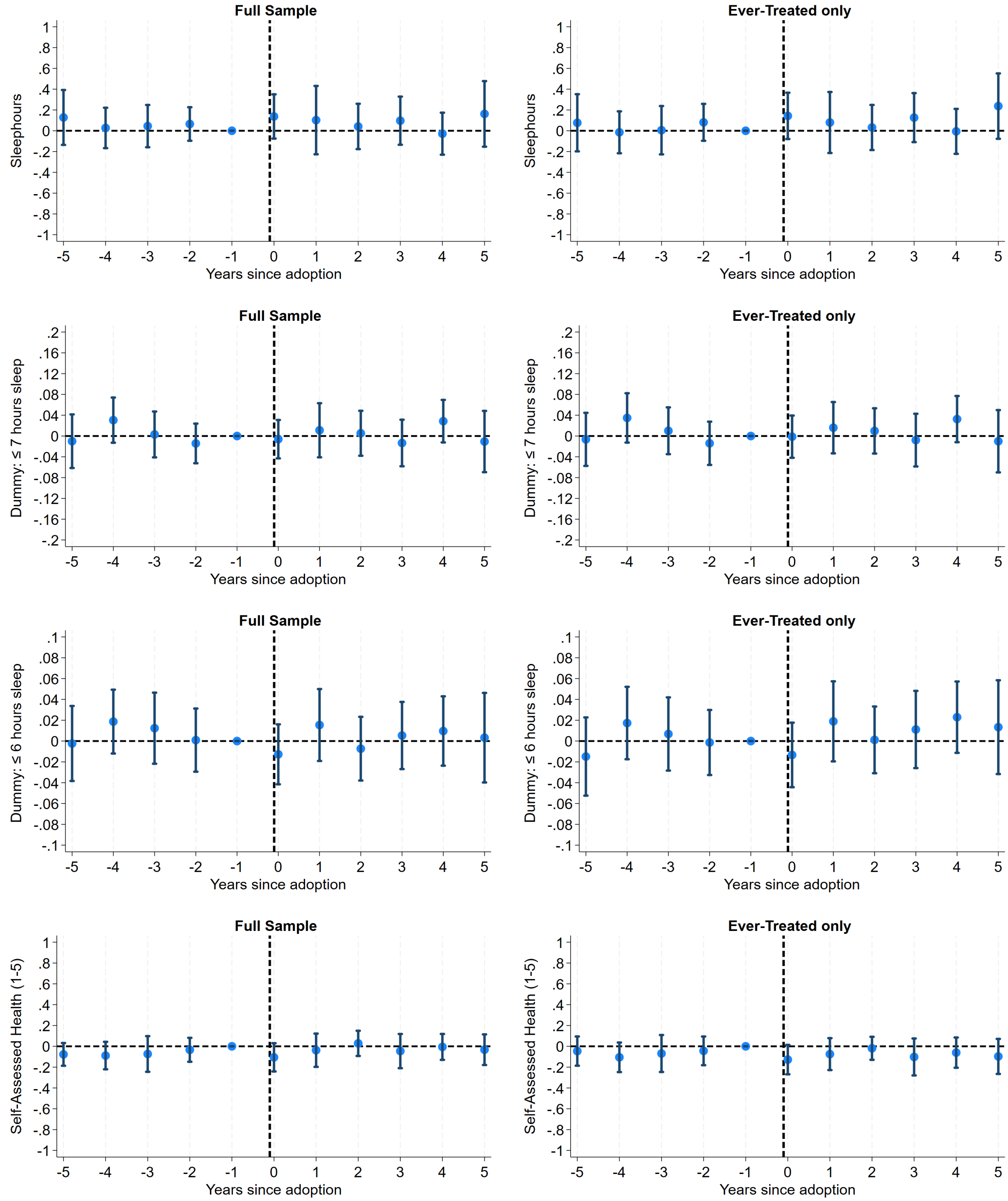
Notes: Event study estimates of wind turbine installation on local electricity generation. Data are drawn from U.S. Energy Information Administration Forms 860 and 923 (2011–2023), aggregated to the ZIP code level. The top-left panel shows wind energy generation (GWh/year); the top-right panel shows total energy generation from all sources; the bottom-left panel shows non-wind generation; the bottom-right panel shows fossil fuel generation. The sharp increase in wind generation at k = 0 confirms that turbines in our sample became operational in the recorded installation year. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S7: Event Study: Energy Production, Ever-treated ZIP



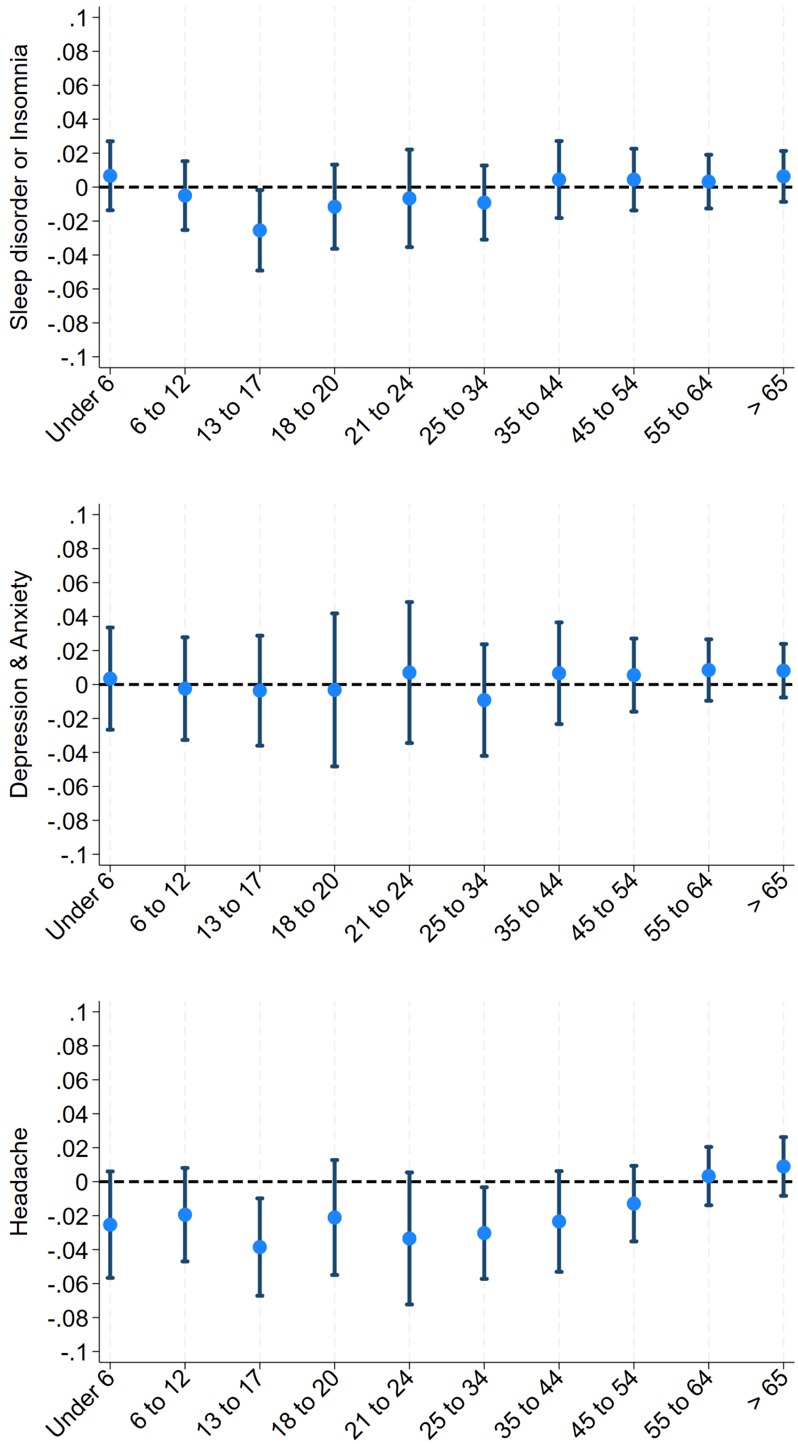
Notes: Event study estimates of ZIP-level energy generation around wind turbine installation, from U.S. Energy Information Administration Forms 860 and 923 (2011–2023), merged to the NielsenIQ sample. Each panel plots coefficients from equation (1), with $k = -1$ as the reference period. Outcome variables are annual ZIP-level electricity generation in GWh: wind energy (top-left), overall energy from all sources (top-right), non-wind energy (bottom-left), and fossil fuel energy (bottom-right). This analysis serves as a first-stage validation, confirming that turbine installation corresponds to actual increases in local wind energy production. The sample is restricted to ever-treated ZIP codes. All models include ZIP code and year fixed effects. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S8: Wind Turbines and Time Use - Event Study



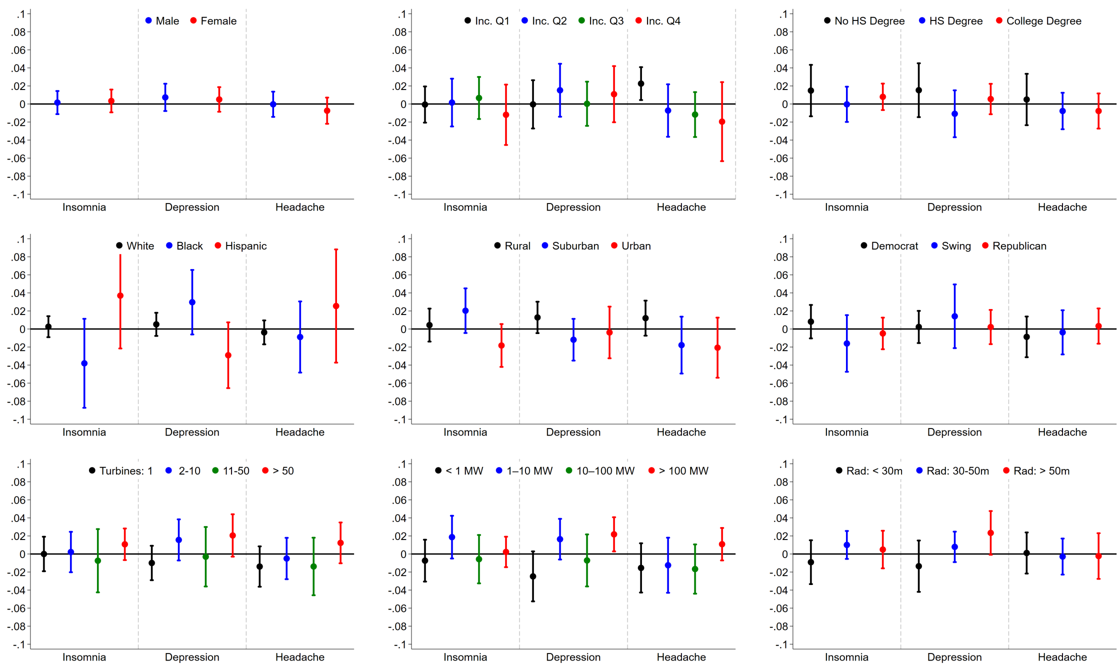
Notes: Event study estimates of wind turbine installation on time use and well-being from the American Time Use Survey (ATUS, 2003–2023). Each panel plots coefficients from equation (1), representing the change in outcomes in years relative to the first turbine installation in a respondent's county of residence, with $k = -1$ as the reference period. Unlike the main analysis, which defines treatment at the ZIP code level, this specification uses county-level treatment to match the geographic resolution of ATUS. Outcome variables are: daily sleep hours (row 1), binary indicators for sleeping fewer than 7 hours (row 2) and fewer than 6 hours (row 3), and self-assessed health on a 1–5 scale (row 4). The left column shows results for the full sample; the right column restricts to ever-treated counties. All models include county, year, month, and weekday fixed effects, as well as controls for education, household size, age group, gender, race, marital status, employment status, and family income. Standard errors are clustered at the county level. Analyses apply ATUS person weights; bars represent 95% confidence intervals.

Figure S9: Wind Turbines and Health - Heterogeneity by Age



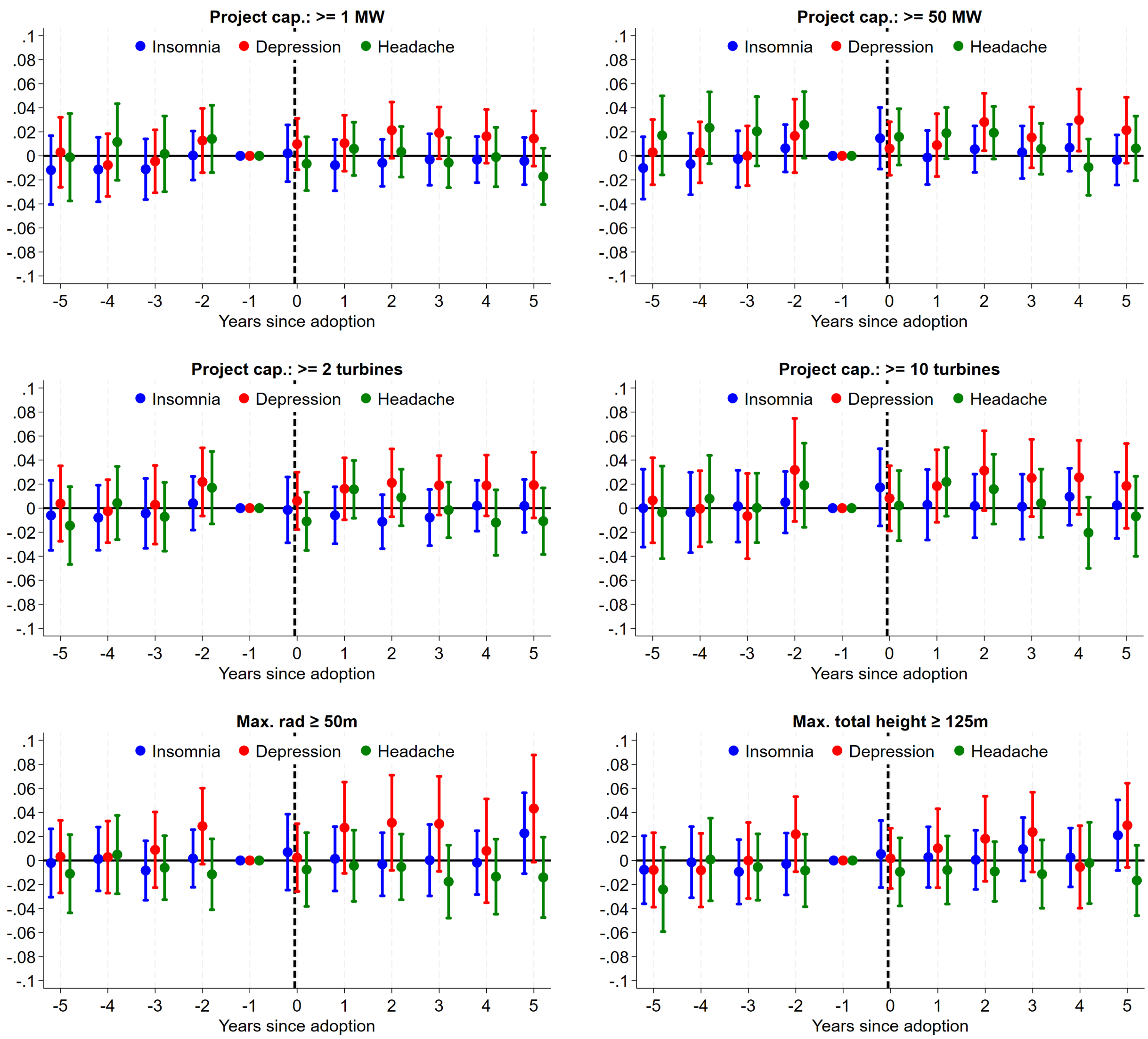
Notes: Heterogeneous effects of wind turbine exposure by age group, using data from the NielsenIQ Ailments Survey (2011–2023). Each panel plots coefficients from a two-way fixed effects specification that interacts the turbine treatment indicator with age group indicators: under 6, 6–12, 13–17, 18–20, 21–24, 25–34, 35–44, 45–54, 55–64, and 65+. Outcome variables are binary indicators for insomnia/sleep problems (top), depression/anxiety (middle), and headaches (bottom), equal to one if a household member reports the condition. This analysis tests whether effects concentrate among vulnerable subpopulations; Zou (2020) finds suicide effects strongest among teenagers and the elderly. All models include household and year fixed effects and the full set of time-varying demographic controls described in Materials and Methods. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S10: Wind Turbines and Health - Heterogeneity



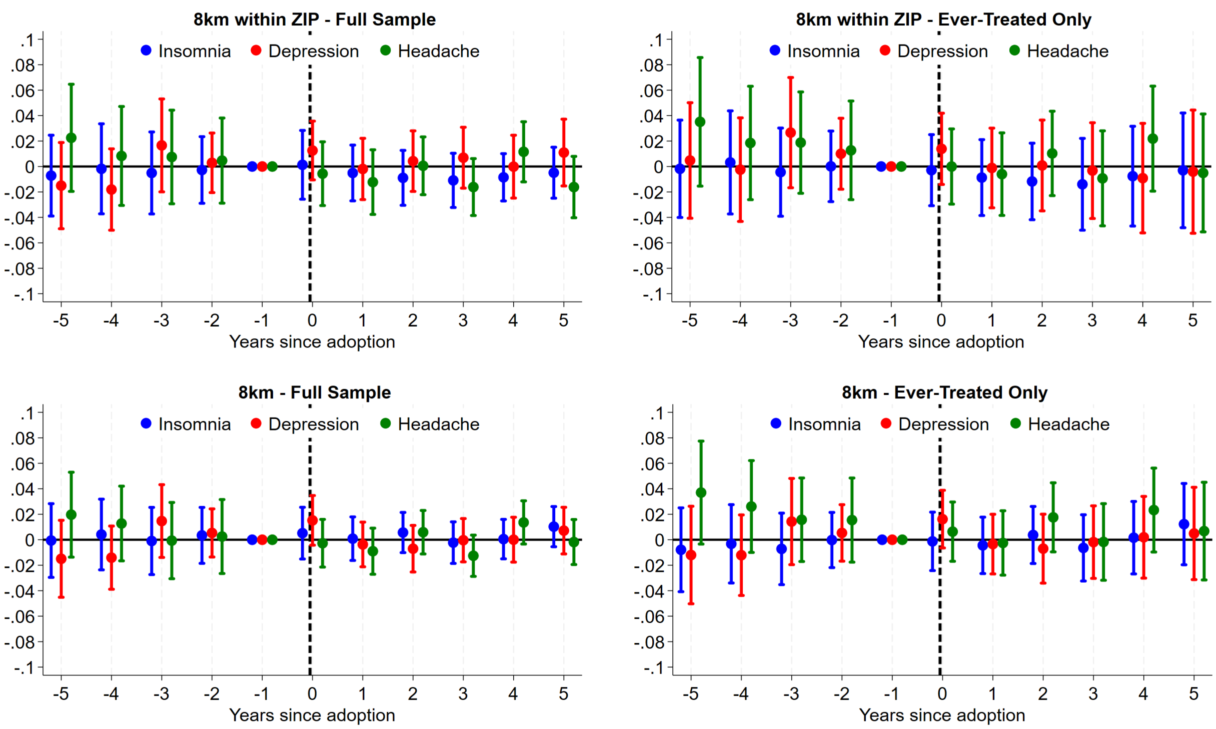
Notes: Heterogeneous effects of wind turbine exposure by individual and household characteristics, using data from the NielsenIQ Ailments Survey (2011–2023). Each panel plots two-way fixed effects coefficients from equation (2), representing the change in the probability of reporting insomnia, depression/anxiety, or headaches after turbine installation. Heterogeneity dimensions include: sex (male, female), household income quartile, highest education of household heads (no high school degree, high school degree, college degree), race/ethnicity (White, Black, Hispanic), urbanicity (rural, suburban, urban), county political leaning (Democrat, swing, Republican), number of turbines in ZIP code (1, 2–10, 11–50, >50), project capacity (<1 MW, 1–10 MW, 10–100 MW, >100 MW), and maximum rotor radius (<30m, 30–50m, >50m). For individual-level characteristics (age, sex), we use interaction terms to avoid splitting households; for household-level characteristics, we use split-sample analysis; for turbine characteristics we constructed separate treatment variables. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S11: Wind Turbines and Health - Alternative Treatments by Turbine Characteristics



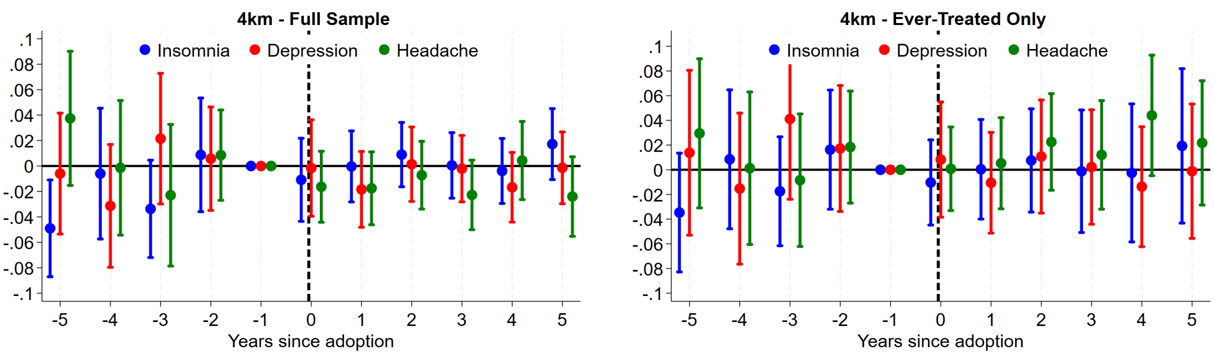
Notes: Event study estimates of wind turbine installation on health conditions using alternative treatment definitions based on turbine characteristics, from the NielsenIQ Ailments Survey (2011–2023). Each panel plots coefficients from equation (1), representing the change in the probability of reporting insomnia (blue), depression/anxiety (red), or headaches (green) in years relative to turbine installation, with $k = -1$ as the reference period. Treatment is defined as exposure to turbine projects meeting different thresholds: (1) at least 1 MW capacity, (2) at least 50 MW capacity, (3) at least 2 turbines, (4) at least 10 turbines, (5) maximum rotor radius exceeding 50 m, or (6) maximum total height exceeding 125 m. These specifications test whether larger or more numerous turbines—which may produce greater noise and infrasound—generate detectable health effects. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S12: Wind Turbines and Health - Distance-Based Treatment (8km)



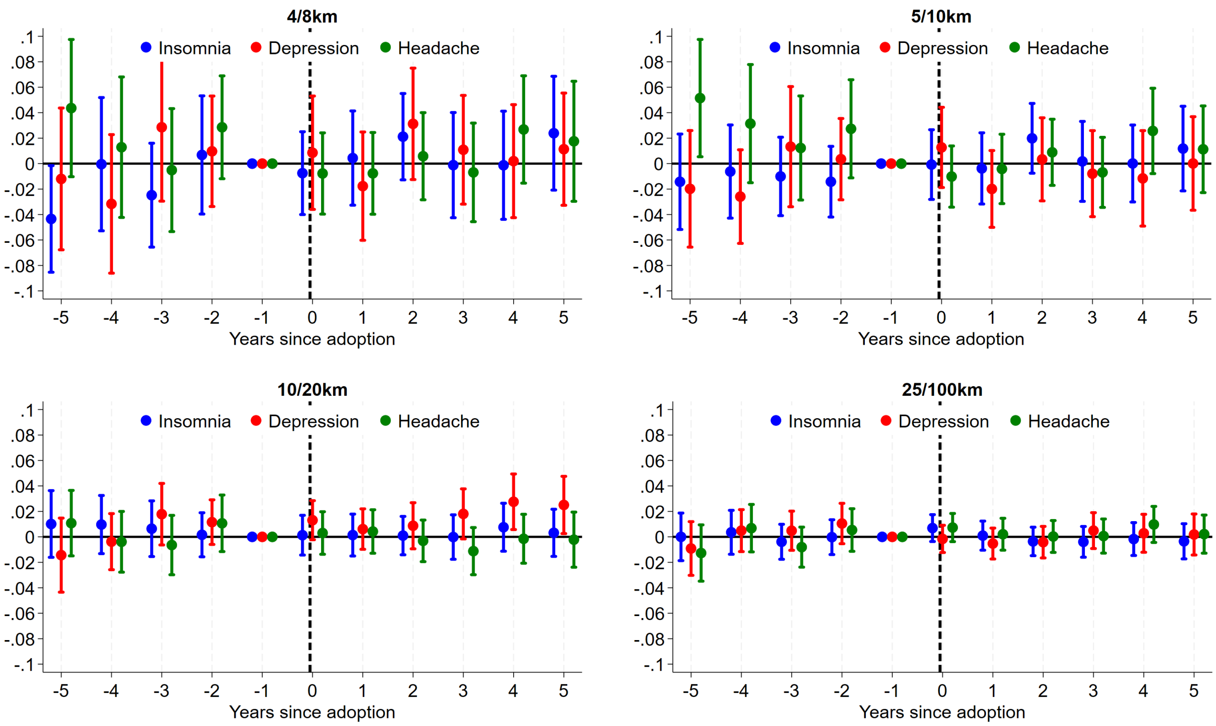
Notes: Event study estimates of wind turbine installation on health conditions using distance-based treatment definitions, from the NielsenIQ Ailments Survey (2011–2023). Each panel plots coefficients from equation (1), representing the change in the probability of reporting insomnia (blue), depression/anxiety (red), or headaches (green) in years relative to turbine installation, with $k = -1$ as the reference period. The 8 km threshold is motivated by prior literature documenting property value effects within this range (Gibbons, 2015; Jensen et al., 2018). Panels 1 and 2 define treatment as a turbine installed within 8 km of the ZIP code population centroid and located within the same ZIP code. Panels 3 and 4 define treatment as a turbine within 8 km of the ZIP code population centroid regardless of ZIP code boundaries, capturing exposure from nearby turbines in adjacent ZIP codes. Panels 1 and 3 show results for the full sample; Panels 2 and 4 restrict to ever-treated ZIP codes. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S13: Wind Turbines and Health - Distance-Based Treatment (4km)



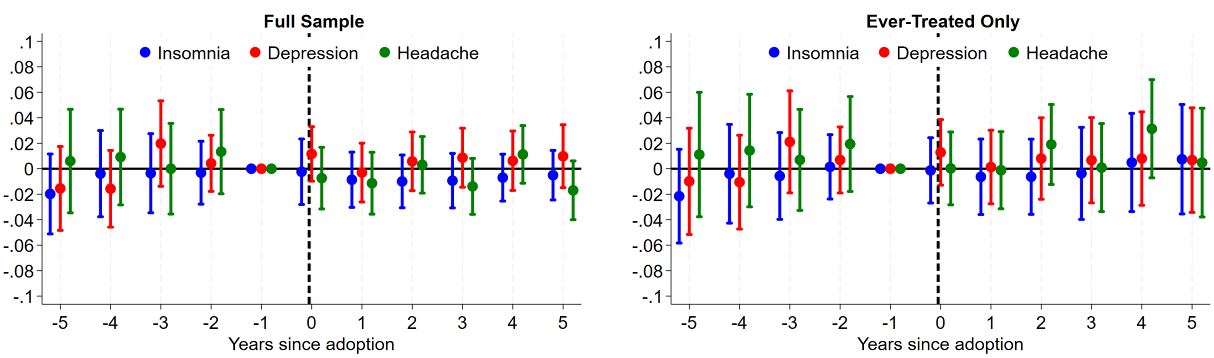
Notes: Event study estimates of wind turbine installation on health conditions using distance-based treatment definitions, from the NielsenIQ Ailments Survey (2011–2023). Each panel plots coefficients from equation (1), representing the change in the probability of reporting insomnia (blue), depression/anxiety (red), or headaches (green) in years relative to turbine installation, with $k = -1$ as the reference period. In this specification installation is defined as the first turbine installation within 4 km around the ZIP population centroid, irrelevant of ZIP borders. Panel 1 shows results for the full sample; Panel 2 restricts to ever-treated ZIP codes. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S14: Wind Turbines and Health - Distance-Based Treatments



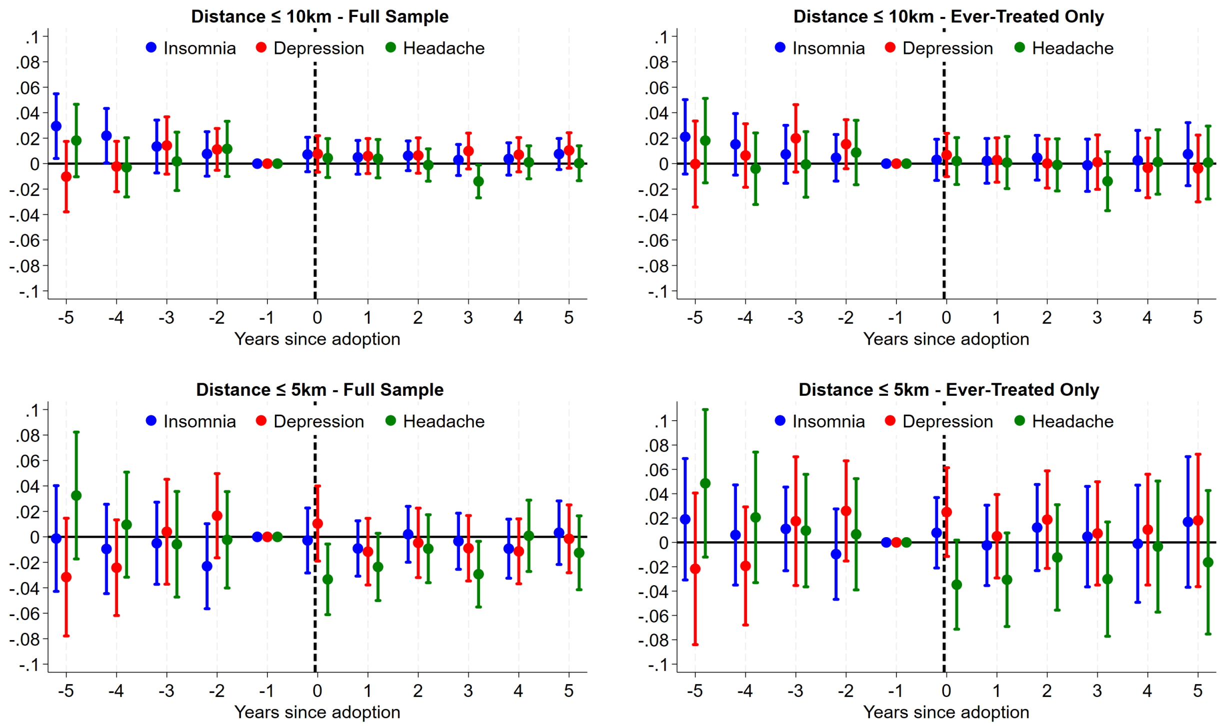
Notes: Event study estimates of wind turbine installation on health conditions using distance-band treatment definitions, from the NielsenIQ Ailments Survey (2011–2023). Each panel plots coefficients from equation (1), representing the change in the probability of reporting insomnia (blue), depression/anxiety (red), or headaches (green) in years relative to turbine installation, with $k = -1$ as the reference period. This specification tests for dose-response effects by comparing ZIP codes with turbines at different distances. Treatment and control groups are defined by distance from the ZIP code population centroid to the nearest turbine, regardless of ZIP code boundaries. Panel titles indicate treatment/control radii: "4/8km" compares ZIP codes with turbines within 4 km (treated) to those with turbines at 4–8 km (control); "5/10km," "10/20km," and "25/100km" follow analogously. ZIP codes receiving turbines in both radii are assigned to treatment only; those with no turbines within either radius are excluded. The sample is restricted to ZIP codes receiving their first turbine within the relevant radius after 2011. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S15: Wind Turbines and Health - Only within-ZIP turbines <10km



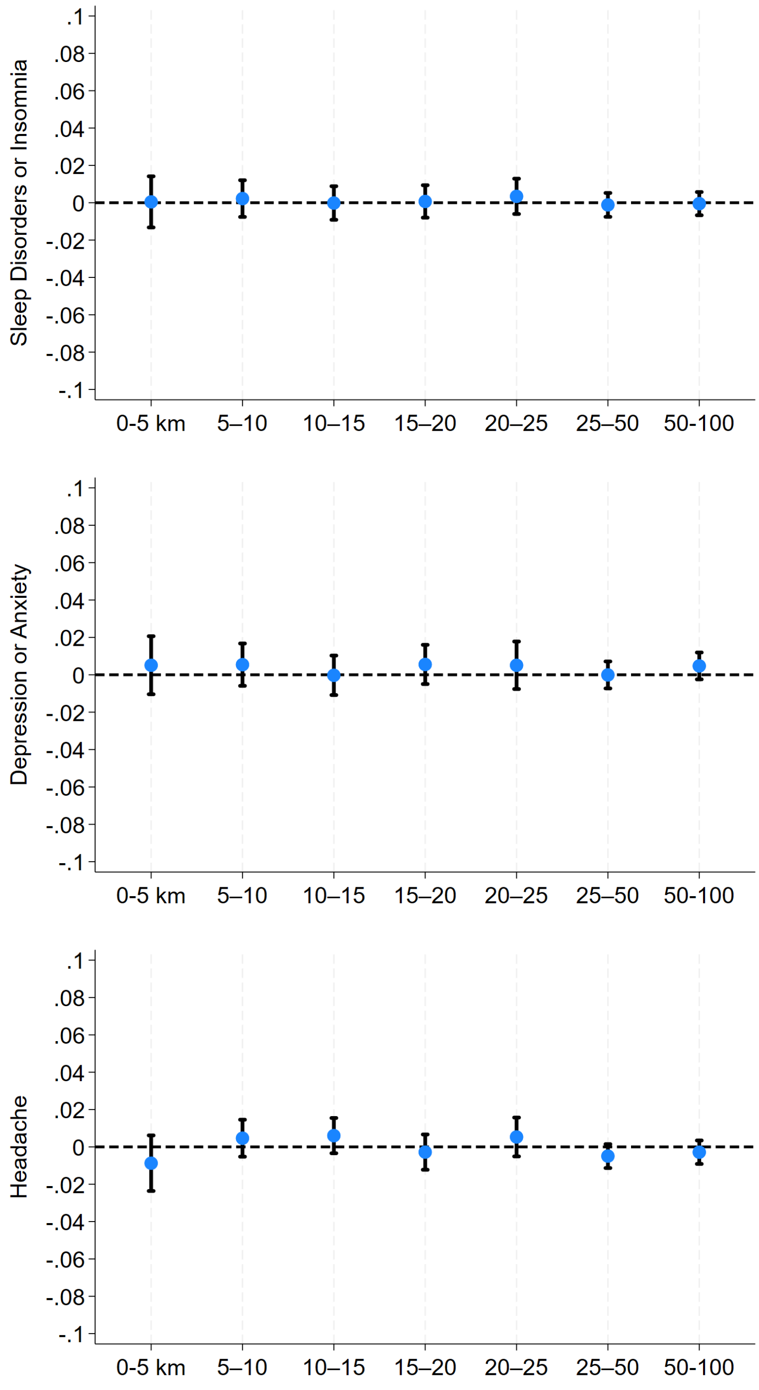
Notes: Event study estimates of wind turbine installation on health conditions using a stricter distance-based treatment definition, from the NielsenIQ Ailments Survey (2011–2023). Each panel plots coefficients from equation (1), representing the change in the probability of reporting insomnia (blue), depression/anxiety (red), or headaches (green) in years relative to turbine installation, with $k = -1$ as the reference period. Treatment requires the first turbine to be located both within the ZIP code boundary **and** within 10 km of the ZIP code population centroid. This stricter definition addresses concerns about spatial measurement error in large ZIP codes where turbines may be far from population centers; the 10 km threshold corresponds to the upper bound of distances at which prior literature documents property value effects. The left panel includes all observations; the right panel restricts to ever-treated ZIP codes. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the county level; bars represent 95% confidence intervals.

Figure S16: Wind Turbines and Health, Census-Tract based avg. distance (<5/ 10km)



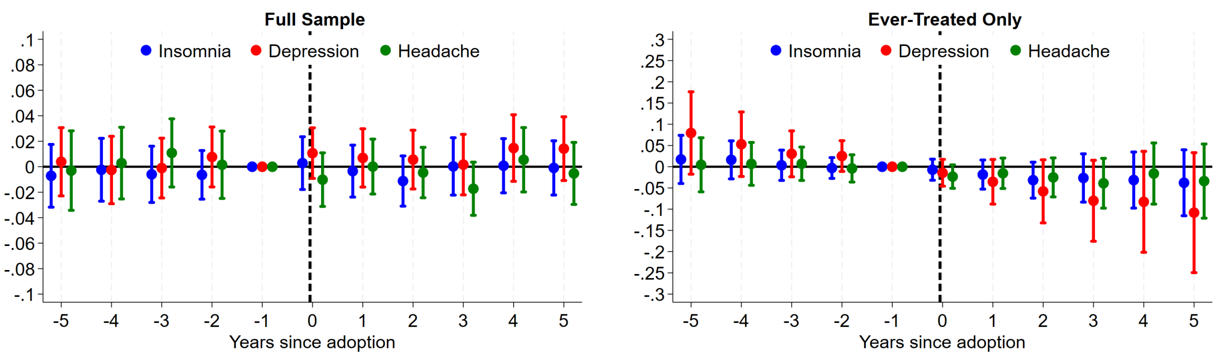
Notes: Event study estimates of wind turbine installation on health conditions using Census tract-weighted distance measures, from the NielsenIQ Ailments Survey (2011–2023). Each panel plots coefficients from equation (1), representing the change in the probability of reporting insomnia (blue), depression/anxiety (red), or headaches (green) in years relative to turbine installation, with $k = -1$ as the reference period. Unlike Figure S15, which uses ZIP code population centroids, distances are computed from all Census tract centroids to the nearest turbine and aggregated to the ZIP level using tract population weights (see SI Section 2). The treatment year reflects the first year where the population-weighted ZIP average of census tract distances to closest turbine is <10km (upper two graphs) or <5km (lower two graphs). This approach provides finer geographic resolution by accounting for heterogeneous population distributions within ZIP codes, particularly in large or irregularly shaped areas. The left panel includes all observations; the right panel restricts to ever-treated ZIP codes. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the county level; bars represent 95% confidence intervals.

Figure S17: Wind Turbines and Health - Dose-Response by Distance to Nearest Turbine



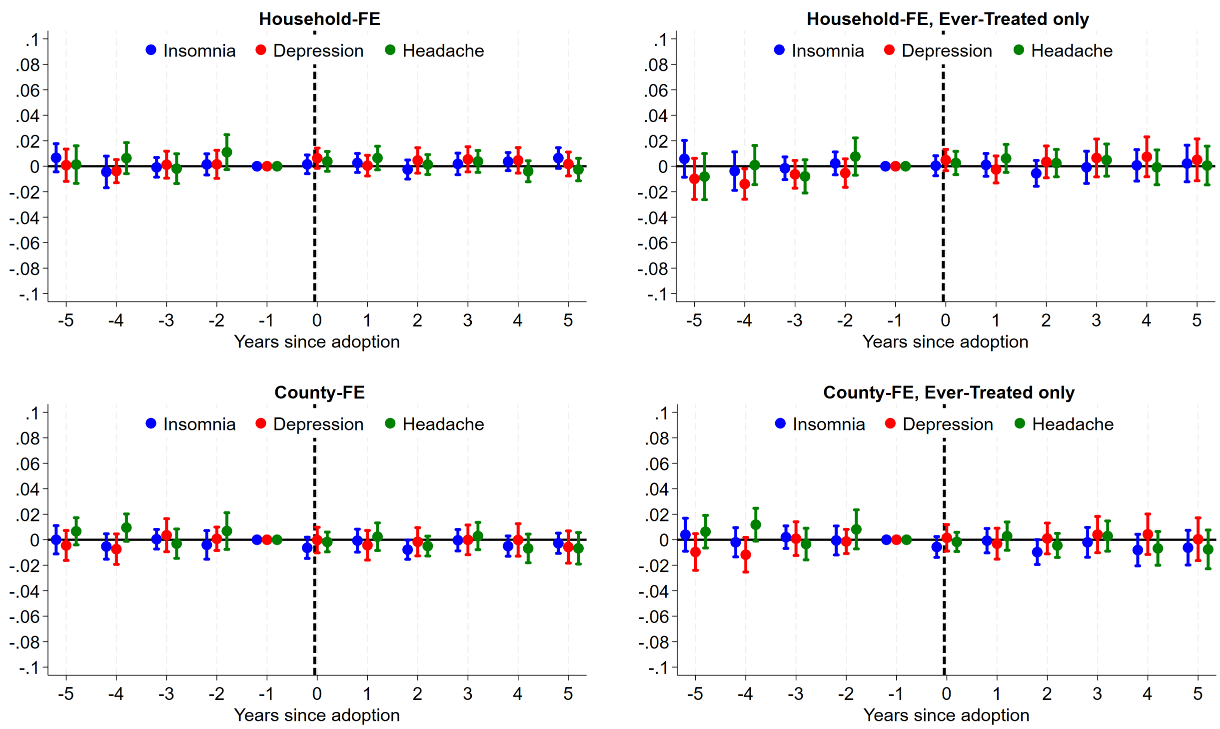
Notes: Two-way fixed effects estimates of the relationship between distance to the nearest wind turbine and health conditions, from the NielsenIQ Ailments Survey (2011–2023). Each panel plots coefficients from equation (2), with distance-to-closest-turbine categories replacing the binary treatment indicator. Distance bins are 0–5 km, 5–10 km, 10–15 km, 15–20 km, 20–25 km, 25–50 km, and 50–100 km, measured from ZIP code population centroids to the nearest turbine irrespective of ZIP code boundaries; distances above 100 km form the omitted reference category. Distance bins may vary over time as closer turbines are installed. Outcome variables are binary indicators for insomnia/sleep disorders (top), depression/anxiety (middle), and headaches (bottom), equal to one if a household member reports the condition. This specification tests for dose-response effects: if wind turbines cause health problems through noise or infrasound exposure, effects should be strongest at close distances and attenuate with distance. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the ZIP code level; points denote coefficients with 95% confidence intervals.

Figure S18: Wind Turbines and Health - First Installation 2011-2023



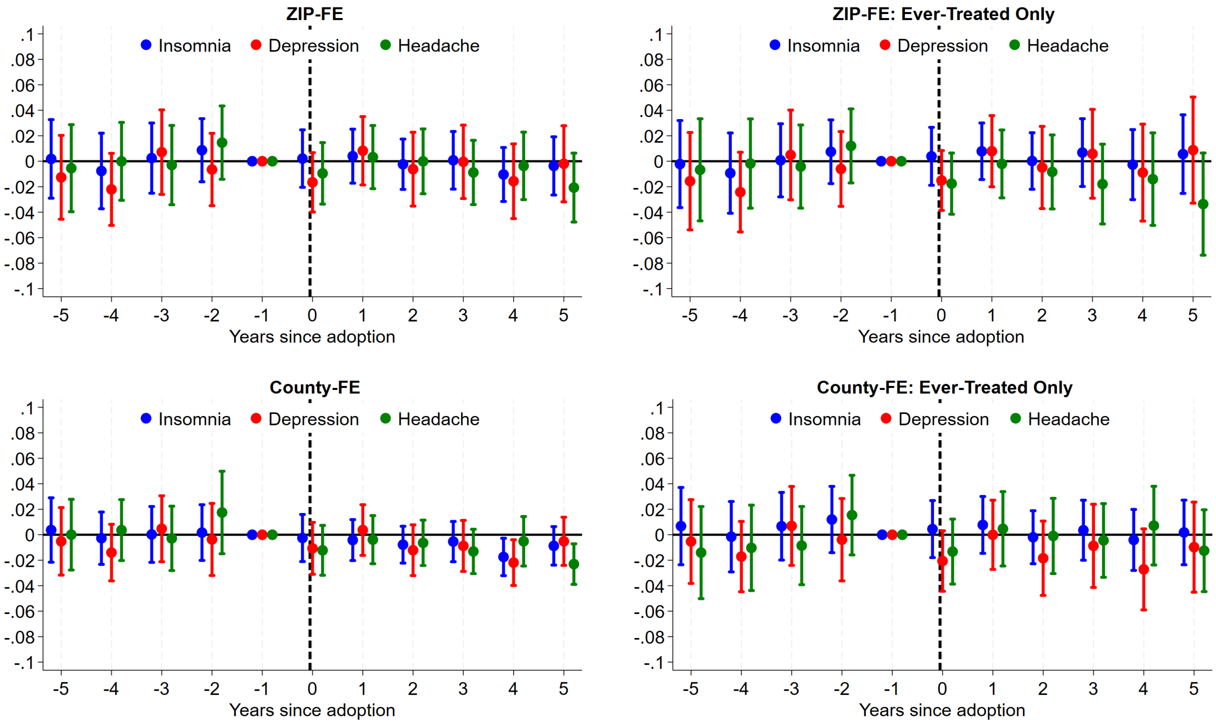
Notes: Event study estimates of wind turbine installation on health conditions, restricting treatment to new turbine installations during the sample period, from the NielsenIQ Ailments Survey (2011–2023). Each panel plots coefficients from equation (1), representing the change in the probability of reporting insomnia (blue), depression/anxiety (red), or headaches (green) in years relative to turbine installation, with $k = -1$ as the reference period. Unlike the baseline specification based on the first turbine ever installed in a ZIP code, this analysis anchors treatment timing to the first installation occurring between 2011 and 2023, focusing on within-period new installations and avoiding legacy timing outside the outcome window. In ZIP codes with multiple projects during this period, the first new installation defines treatment timing. In ZIP codes with multiple projects during this period, only the first new installation defines treatment timing. The left panel includes all observations; the right panel restricts to ever-treated ZIP codes. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the county level; bars represent 95% confidence intervals.

Figure S19: Wind Turbines and Health - County-Level Treatment



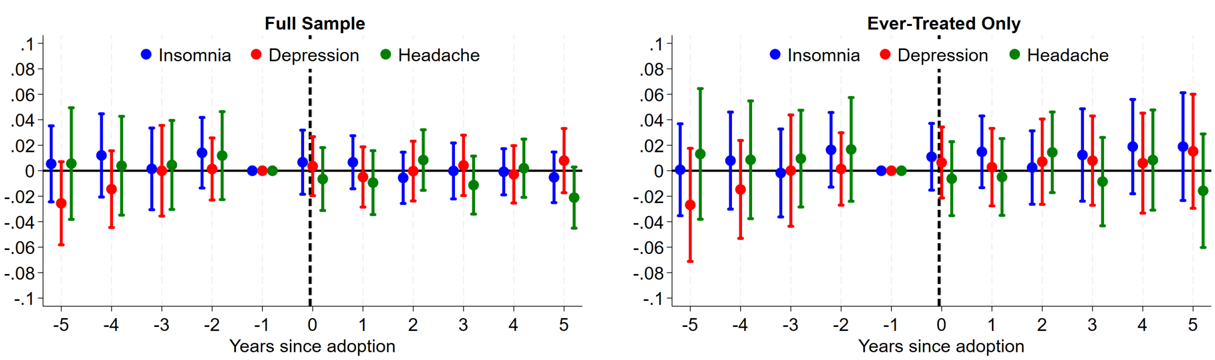
Notes: Event study estimates of wind turbine installation on health conditions using county-level treatment, from the NielsenIQ Ailments Survey (2011–2023). Each panel plots coefficients from equation (1), representing the change in the probability of reporting insomnia (blue), depression/anxiety (red), or headaches (green) in years relative to the first turbine installation in the respondent's county of residence, with $k = -1$ as the reference period. This specification assesses robustness to defining turbine exposure at a broader geographic level. Panels 1 and 2 include household fixed effects; Panels 3 and 4 use county fixed effects to match specifications common in county-level studies. Panels 1 and 3 show results for the full sample; Panels 2 and 4 restrict to ever-treated counties. All models include year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the county level; bars represent 95% confidence intervals.

Figure S20: Wind Turbines and Health - Fixed-Effects Specifications



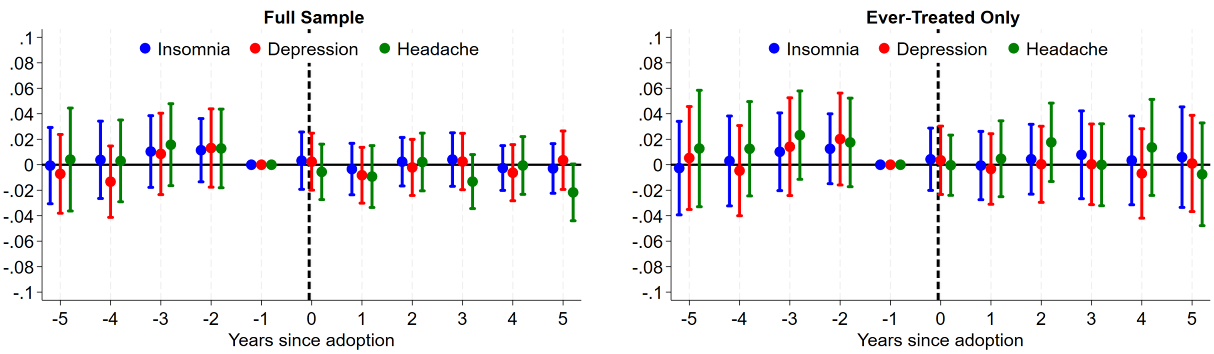
Notes: Event study estimates of wind turbine installation on health conditions comparing alternative fixed effects specifications, from the NielsenIQ Ailments Survey (2011–2023). Each panel plots coefficients from equation (1), representing the change in the probability of reporting insomnia (blue), depression/anxiety (red), or headaches (green) in years relative to turbine installation, with k = 1 as the reference period. Treatment is defined at the ZIP code level. Panels 1 and 2 include ZIP code fixed effects; Panels 3 and 4 include county fixed effects. Panels 1 and 3 show results for the full sample; Panels 2 and 4 restrict to ever-treated ZIP codes. This analysis tests whether results are sensitive to the level of geographic fixed effects. All models include year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the ZIP code level (Panels 1–2) or county level (Panels 3–4); bars represent 95% confidence intervals.

Figure S21: Wind Turbines and Health - Event Study Excluding Top Quartile of ZIP Area



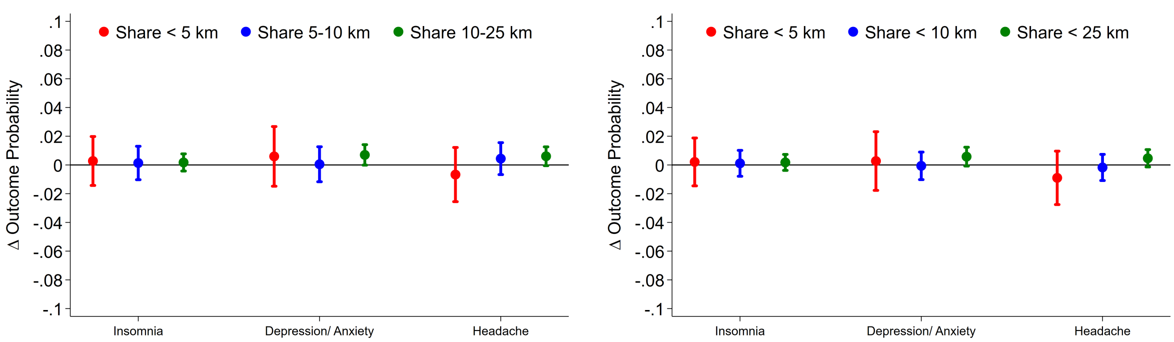
Notes: Event study estimates of wind turbine installation on health conditions, excluding large ZIP codes, from the NielsenIQ Ailments Survey (2011–2023). Each panel plots coefficients from equation (1), with $k-1$ as the reference period. The sample excludes observations from the largest 25% of ZIP codes by land area (ZIP code area $\geq$ approximately 485 km²; median 277 km², 90th percentile 901 km², maximum 3,896 km²). This restriction tests whether results are driven by very large ZIP codes, where population centers may be farther from turbine locations. The left panel shows results for the full sample; the right panel restricts to ever-treated ZIP codes. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S22: Wind Turbines and Health - Event Study, Urban Only



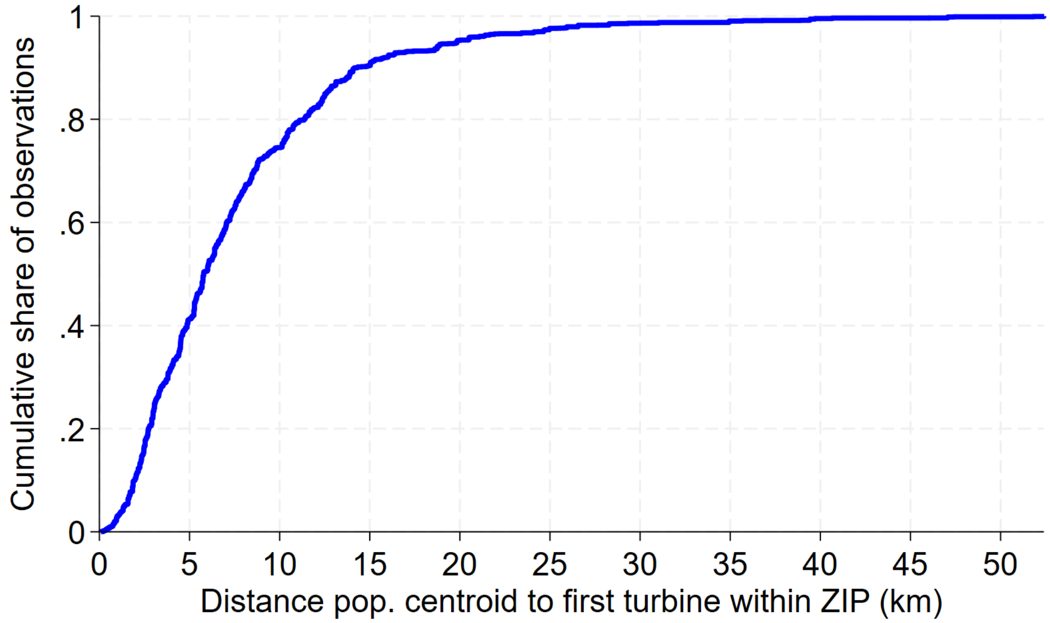
Notes: Event study estimates of wind turbine installation on health conditions, restricting to urban areas, from the NielsenIQ Ailments Survey (2011–2023). Each panel plots coefficients from equation (1), representing the change in the probability of reporting insomnia (blue), depression/anxiety (red), or headaches (green) in years relative to turbine installation, with $k = -1$ as the reference period. The sample retains only observations from ZIP codes located in counties classified as metropolitan or micropolitan by the USDA Economic Research Service (Urban Influence Codes 1–5 in 2024), excluding nonmetropolitan counties (UIC > 5). This restriction tests whether results are driven by rural areas, where ZIP codes tend to be larger and population centers may be farther from turbines. The left panel shows results for the restricted full sample; the right panel further restricts to ever-treated ZIP codes. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S23: Wind Turbines and Health - Census-Tract Distances



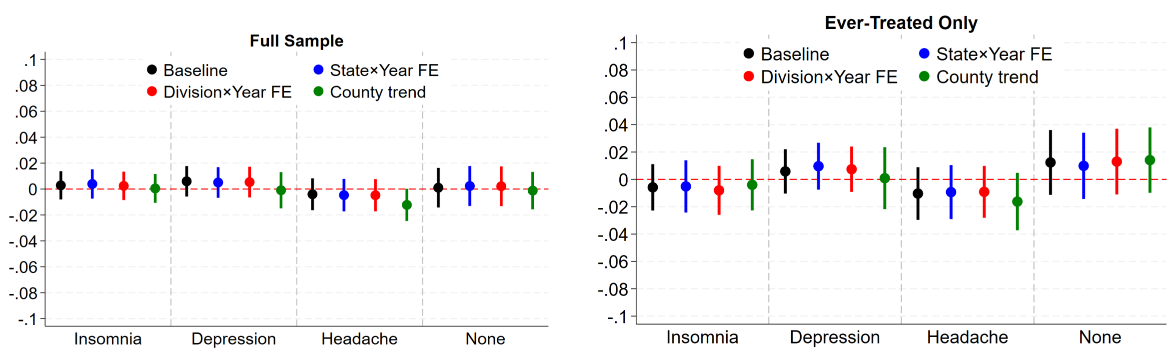
Notes: Two-way fixed effects estimates of wind turbine exposure on health conditions using census tract-level distance measures, from the NielsenIQ Ailments Survey (2011–2023). This specification addresses concerns about spatial precision by exploiting finer geographic variation than ZIP code boundaries permit. While turbine locations are observed at precise coordinates and household outcomes are available only at the ZIP code level, we recover finer spatial variation using census tract centroids. For each census tract and year (2011–2023), we compute the distance between the tract population centroid and the nearest wind turbine, up to 100 km. We then aggregate to the ZIP code–year level using 2020 Census population weights, yielding the share of each ZIP code's population living in census tracts within 0–5 km, 5–10 km, or 10–25 km of the closest turbine. Outcome variables are binary indicators for insomnia (blue), depression/anxiety (red), and headaches (green). The left panel includes all distance-share measures jointly; the right panel reports separate regressions for cumulative proximity thresholds (within 5 km, 10 km, and 25 km). Coefficients reflect how health outcomes change as the share of the ZIP code population living close to a wind turbine increases by 100 percentage points. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S24: Distance from Population Centroid to First Turbine within ZIP



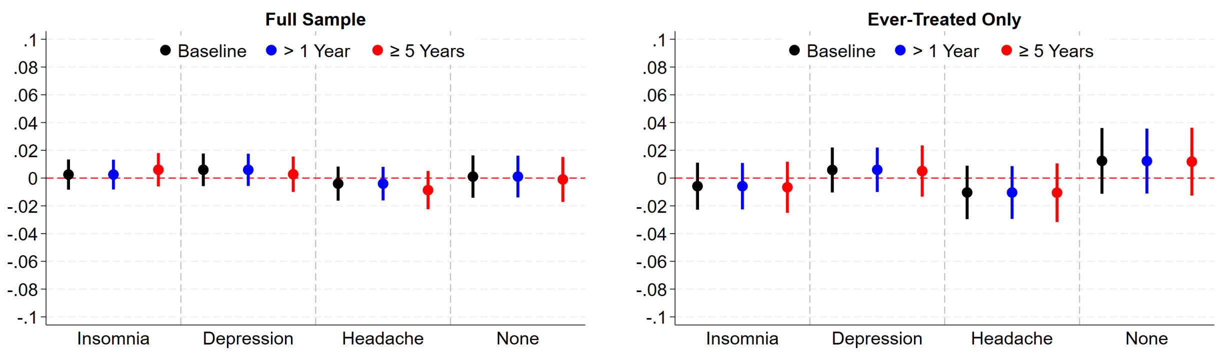
Notes: Cumulative distribution of the distance between ZIP code population centroids and the first wind turbine installed within each ZIP code. The sample is restricted to respondents living in ever-treated ZIP codes observed in the NielsenIQ Ailments Survey (2011-2023). Distances are measured in kilometers using great-circle calculations.

Figure S25: Wind Turbines and Health - TWFE with Spatiotemporal Controls



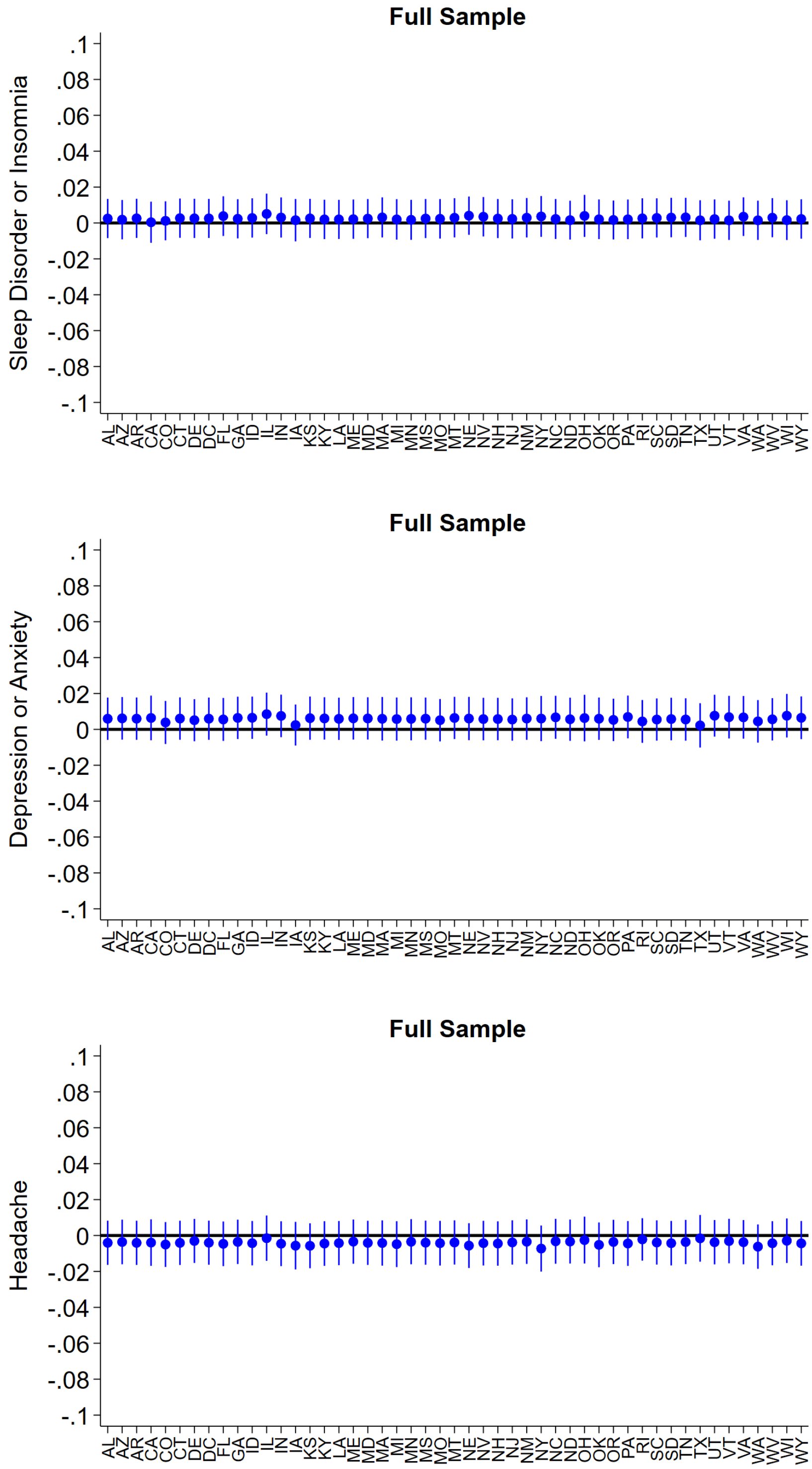
Notes: Two-way fixed effects estimates of wind turbine installation on health conditions with additional spatiotemporal controls, from the NielsenIQ Ailments Survey (2011–2023). Each point represents a coefficient from equation (2), measuring the change in the probability of reporting insomnia, depression/anxiety, headaches, or no condition after turbine installation. Outcome variables are binary indicators equal to one if a household member reports the condition. The baseline specification (blue) includes household and year fixed effects. Alternative specifications add: state-by-year fixed effects (red), which absorb state-specific annual shocks such as policy changes or economic conditions; census division-by-year fixed effects (green), which control for broader regional trends; or county-level linear time trends (orange), which allow for differential secular trends across counties. The left panel uses the full sample; the right panel restricts to ever-treated ZIP codes. All models include the full set of time-varying demographic controls. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S26: Wind Turbines and Health - Robustness by Observation Duration



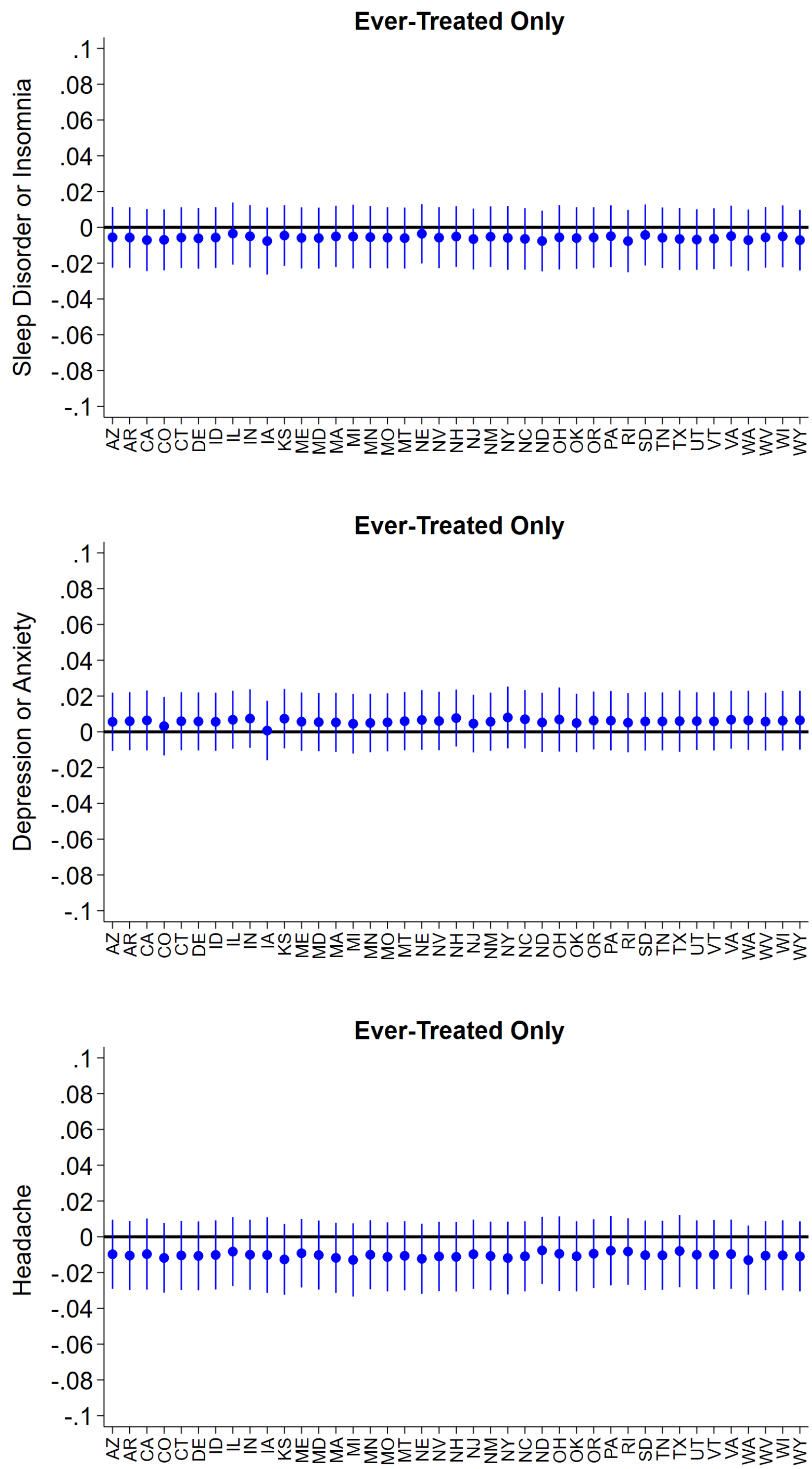
Notes: Two-way fixed effects estimates of wind turbine installation on health conditions, testing robustness to sample restrictions based on household observation duration, from the NielsenIQ Ailments Survey (2011–2023). Each point represents a coefficient from equation (2), measuring the change in the probability of reporting insomnia, depression/anxiety, headaches, or no condition after turbine installation. Outcome variables are binary indicators equal to one if a household member reports the condition. Within each panel, we report: (i) the baseline estimate using all households (blue), (ii) estimates excluding households observed in only one year (red), and (iii) estimates restricting to households observed in at least five distinct years (green). Households observed for longer periods provide more within-household variation for identification and are less susceptible to attrition-related bias. The left panel uses the full sample; the right panel restricts to ever-treated ZIP codes. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S27: Wind Turbines and Health - Leave-One-State-Out (Full Sample)



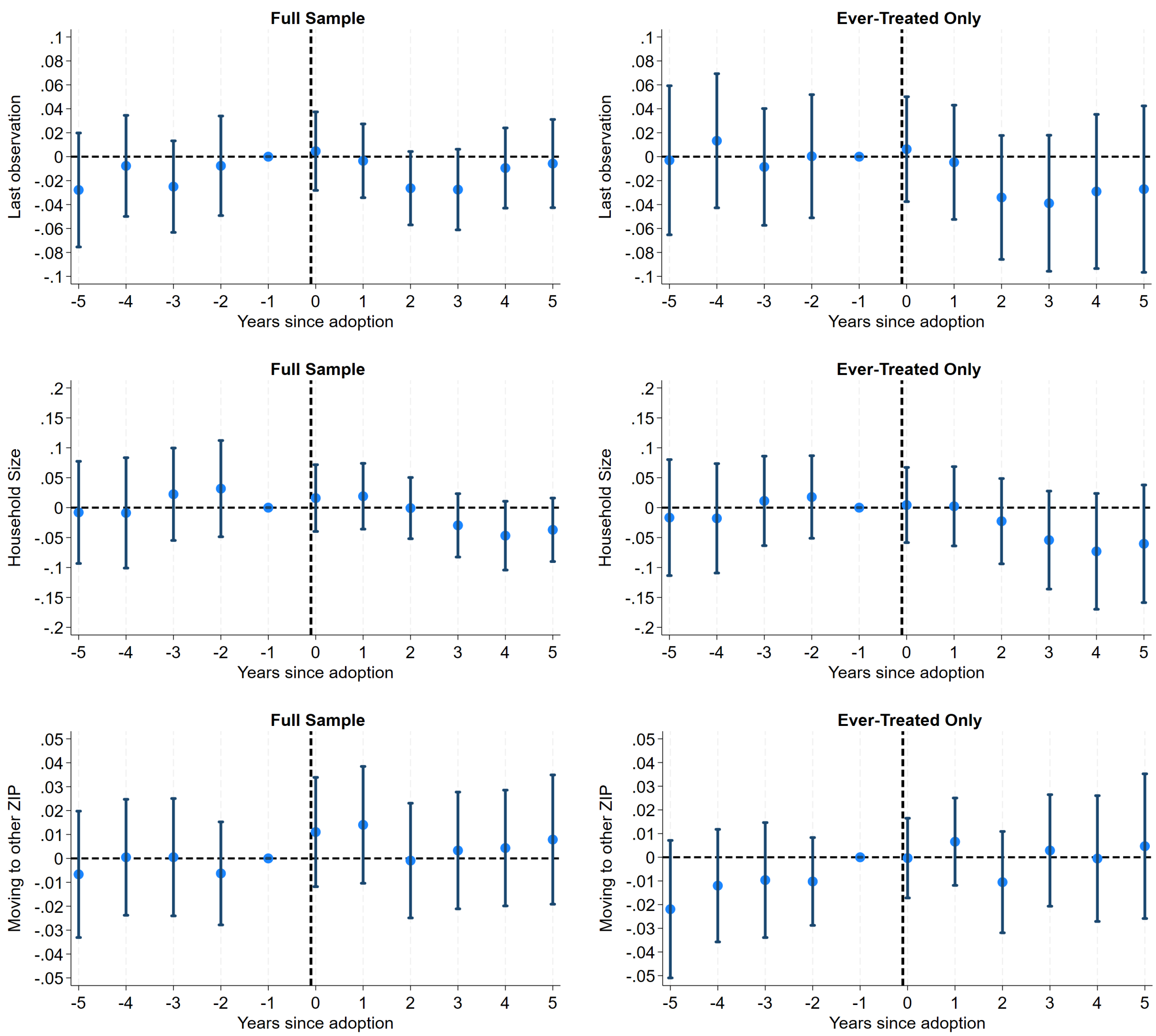
Notes: Leave-one-state-out (LOSO) sensitivity analysis for the effect of wind turbine installation on health conditions, from the NielsenIQ Ailments Survey (2011–2023). Each panel shows coefficients from equation (2) estimated after sequentially excluding one U.S. state, testing whether results are driven by any single state. Outcome variables are binary indicators for insomnia/sleep disorders (top), depression/anxiety (middle), and headaches (bottom), equal to one if a household member reports the condition. The x-axis lists excluded states alphabetically. The full sample is used. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S28: Wind Turbines and Health - Leave-One-State-Out (Ever-Treated Sample)



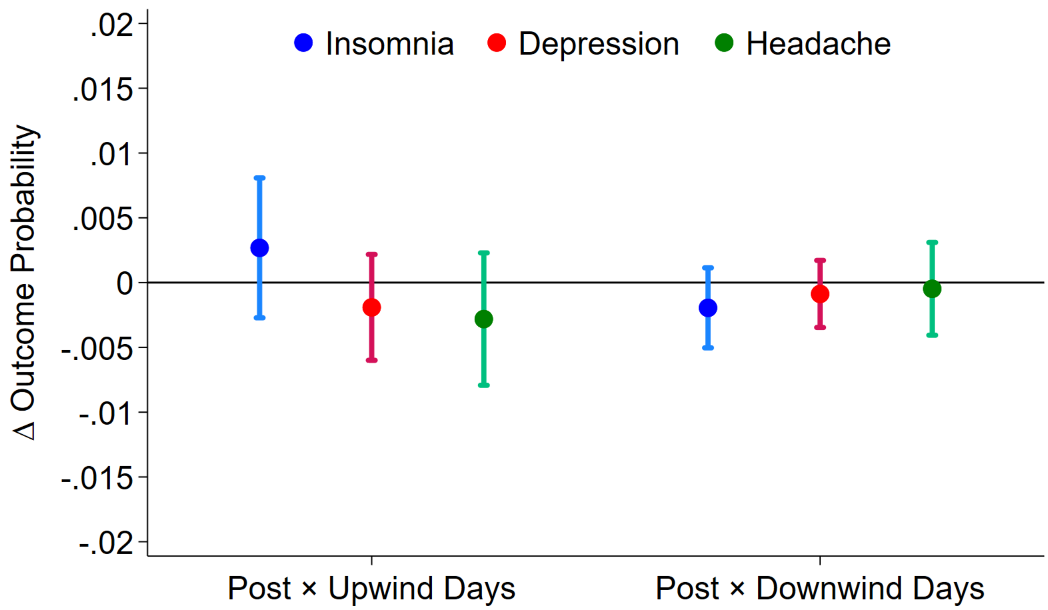
Notes: Leave-one-state-out (LOSO) sensitivity analysis for the effect of wind turbine installation on health conditions, from the NielsenIQ Ailments Survey (2011–2023). Each panel shows coefficients from equation (2) estimated after sequentially excluding one U.S. state, testing whether results are driven by any single state. Outcome variables are binary indicators for insomnia/sleep disorders (top), depression/anxiety (middle), and headaches (bottom), equal to one if a household member reports the condition. The x-axis lists excluded states alphabetically. Unlike Figure S24, which uses the full sample, this analysis restricts to ever-treated ZIP codes to test sensitivity within the most policy-relevant comparison group. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S29: Wind Turbines - Attrition, Household Size and Relocation



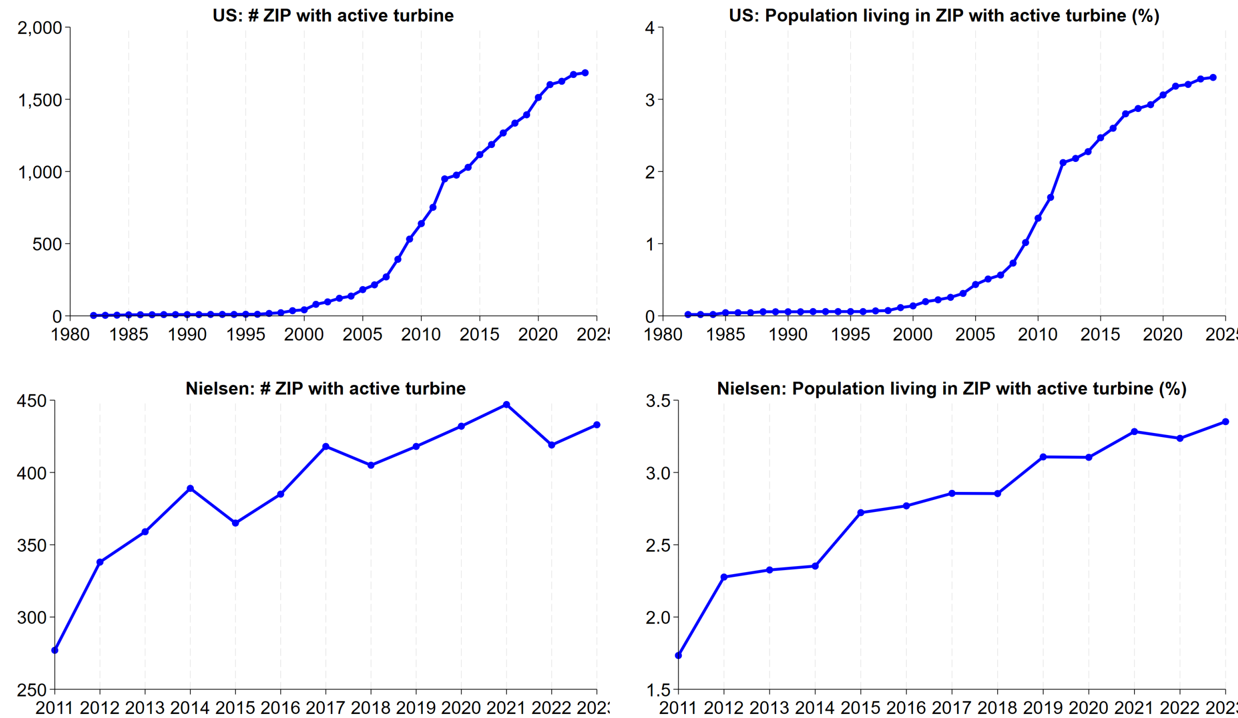
Notes: Event study estimates testing for selective attrition, household composition changes, and residential mobility around wind turbine installation, from NielsenIQ (2011–2023). Each panel plots coefficients from equation (1), with $k = -1$ as the reference period. Outcome variables are: a binary indicator for whether the current year is the household's last observation in the panel (top row), household size (middle row), and a binary indicator for whether the household moved to a different ZIP code (bottom row). These tests assess whether turbine installation induces selective sample attrition or residential sorting that could bias health estimates. If households with latent health vulnerabilities differentially exit the sample or relocate after turbine installation, our main estimates could understate true effects. Specifications include household and year fixed effects but exclude demographic controls to avoid absorbing variation in household composition or mobility that may itself respond to treatment. The left column shows results for the full sample; the right column restricts to ever-treated ZIP codes. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S30: Wind Turbines and Health - Wind Direction Analysis



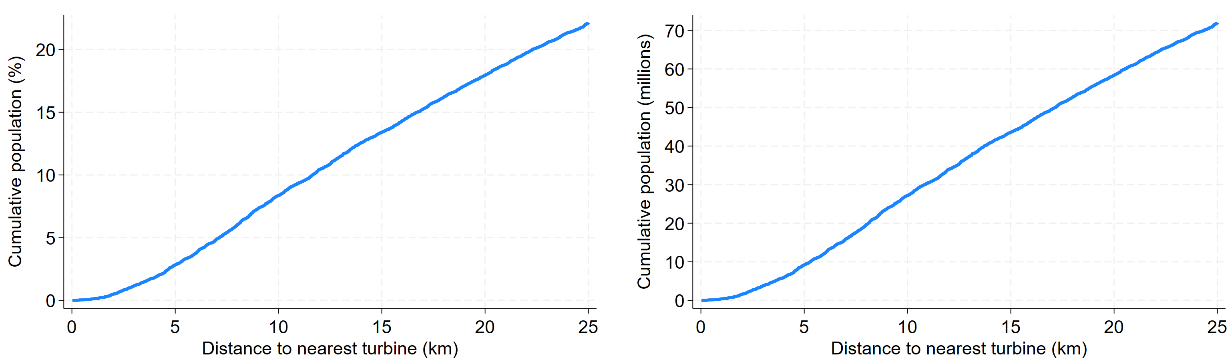
Notes: Two-way fixed effects estimates testing whether wind turbine health effects vary by wind direction, from the NielsenIQ Ailments Survey (2011–2023). Following Zou (2020), we construct annual measures of wind exposure based on the number of days in which the population-weighted centroid of a ZIP code is located upwind or downwind of the first turbine installed in the ZIP code, using daily wind data from ERA5 reanalysis. A ZIP code is classified as downwind when wind blows from the turbine toward the centroid (within ±45°), upwind when wind blows in the opposite direction (180° ±45°), and crosswind otherwise. These exposure measures are interacted with an indicator for the post-installation period. Crosswind exposure is omitted as the reference category, consistent with Zou (2020), who argues that turbine-related effects operate through infrasound transmission along upwind and downwind corridors (the "acoustic dipole" pattern). Coefficients are scaled by a factor of 12 and correspond to the effect of a one-day increase in monthly exposure. Outcome variables are binary indicators for insomnia (blue), depression/anxiety (red), and headaches (green). All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S31: Expansion of Wind Turbine Exposure Across U.S. ZIP Codes



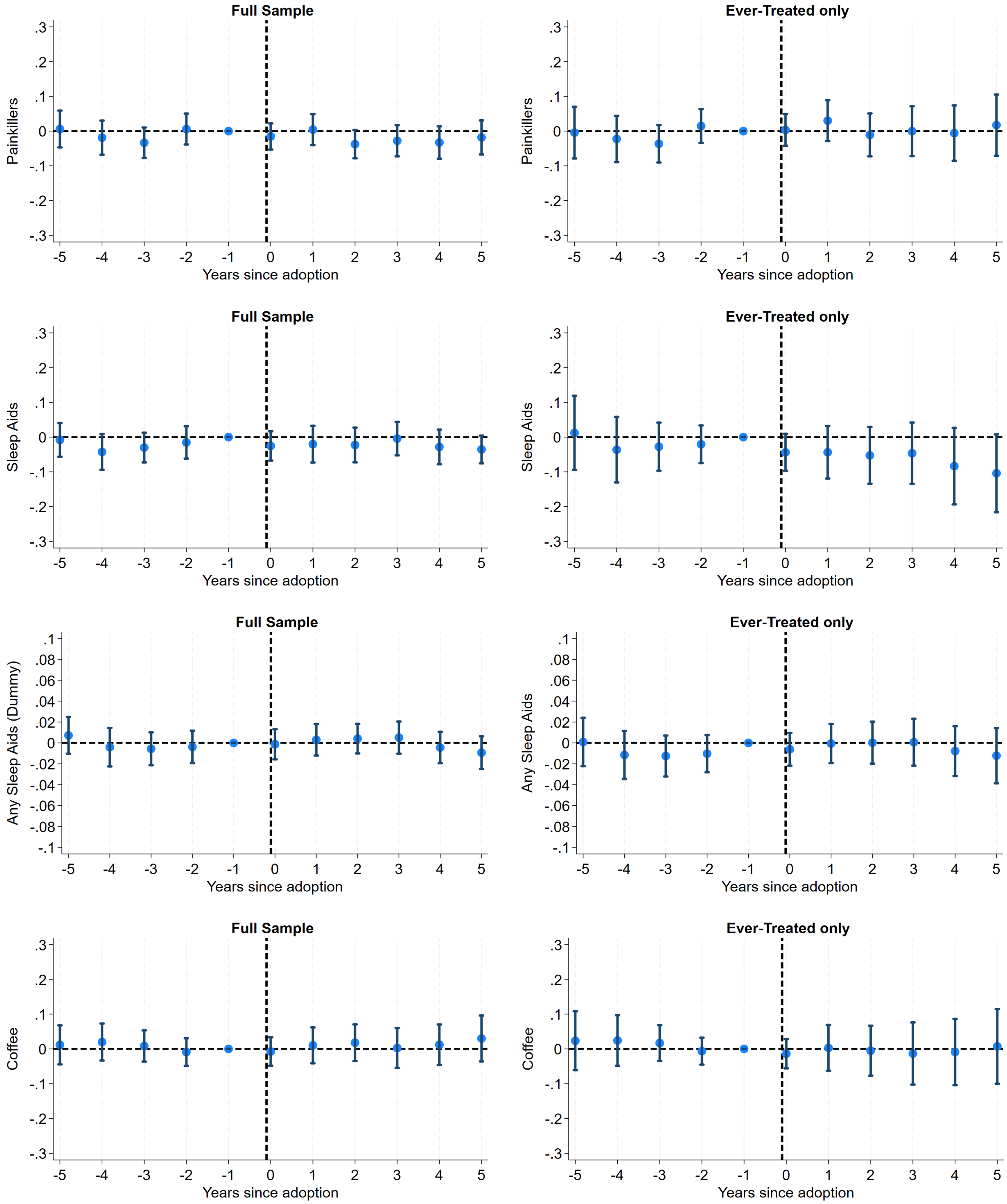
Notes: The figure documents the expansion of wind turbine exposure over time, illustrating the staggered rollout that provides identifying variation for our analysis. Turbine installation data are from the U.S. Wind Turbine Database (USWTDB) through 2023. The top row shows nationwide trends: the number of ZIP codes with at least one active wind turbine (top-left) and the share of the U.S. population living in treated ZIP codes (top-right), using 2020 Census population counts. The bottom row shows parallel trends within the NielsenIQ sample: the number of observed ZIP codes with at least one active turbine (bottom-left) and the share of NielsenIQ respondents living in treated ZIP codes (bottom-right).

Figure S32: US population and distance from turbines (2023)



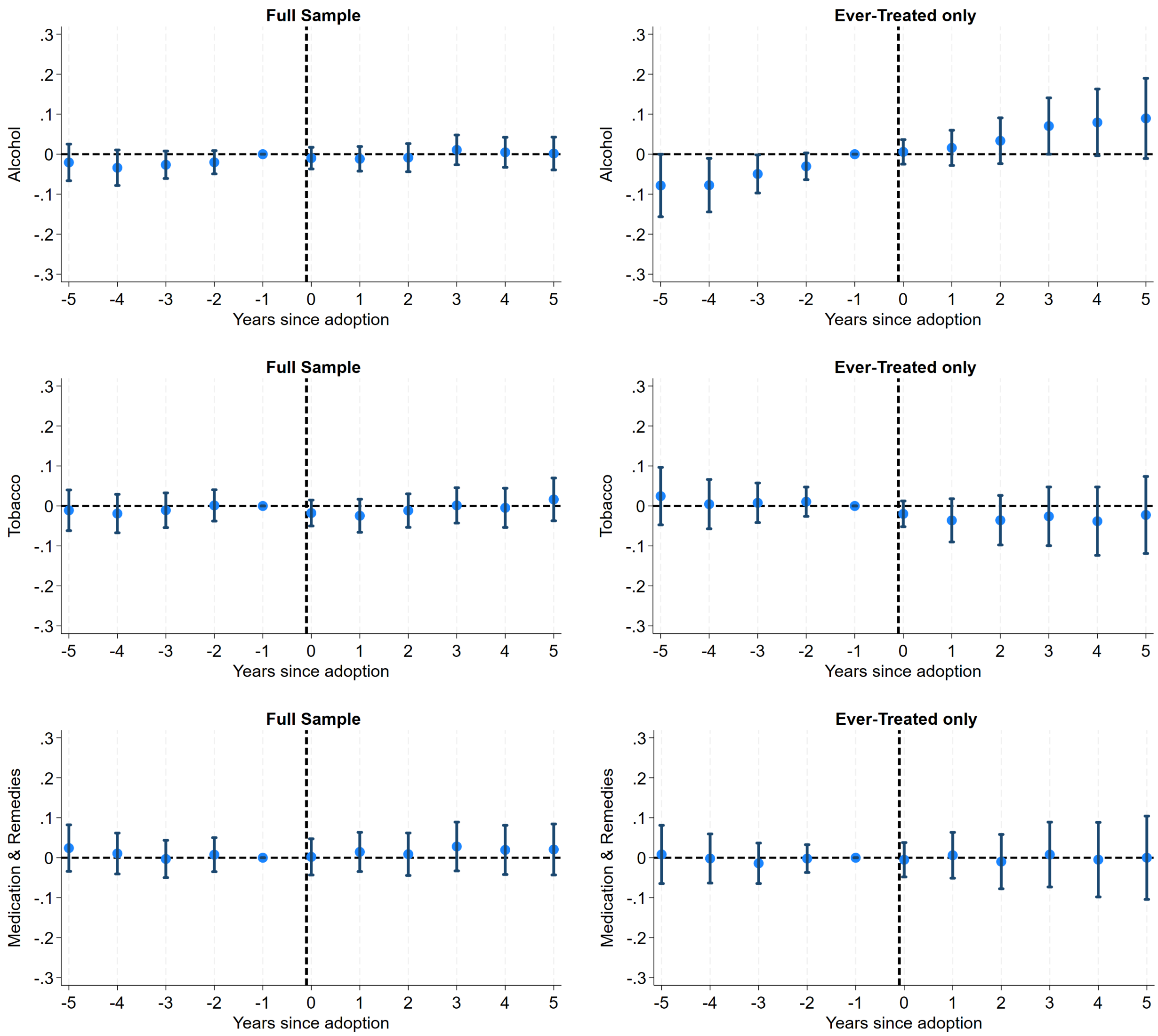
Notes: The figure shows the cumulative distribution of the U.S. population in 2023 by distance from the population centroid of each ZIP code to the nearest wind farm. Distance is defined as the minimum distance between a ZIP code population centroid and the closest operating wind wind turbine. The left panel reports the cumulative share of the mainland U.S. population, while the right panel reports the corresponding cumulative population in millions.

Figure S33: Wind Turbines and Household Spending (2004-2020)



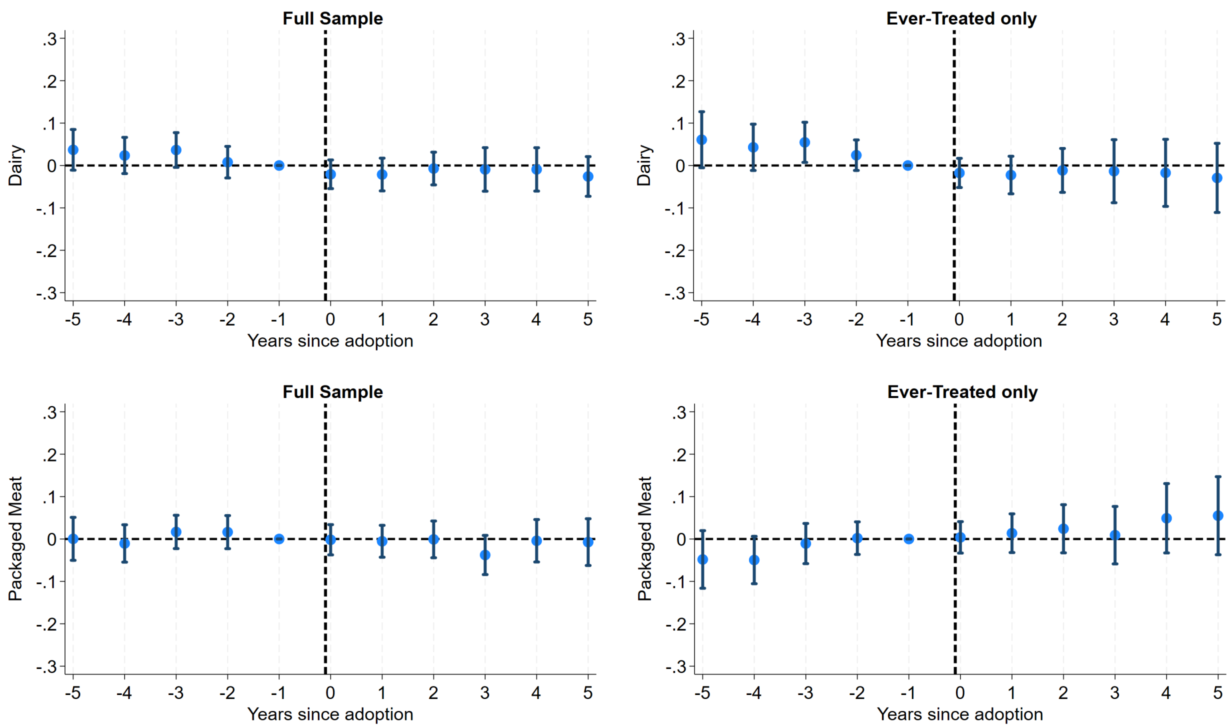
Notes: Event study estimates of wind turbine installation on household spending from NielsenIQ (2004–2020). Each panel plots coefficients from equation (1), representing the change in spending outcomes in years relative to turbine installation, with $k = -1$ as the reference period. Outcomes measure the share of total household spending allocated to each category: (i) painkillers, (ii) coffee, (iii) sleep aids, and (iv) a binary indicator for any sleep aid purchases. Shares in rows (i), (ii) and (iv) are standardized and estimates therefore reflect changes in terms of standard deviations. The left column shows results for the full sample; the right column restricts to ever-treated ZIP codes. All models include household and year fixed effects and the full set of time-varying demographic controls. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S34: Wind Turbines and Household Spending - Other Categories (2004-2023)



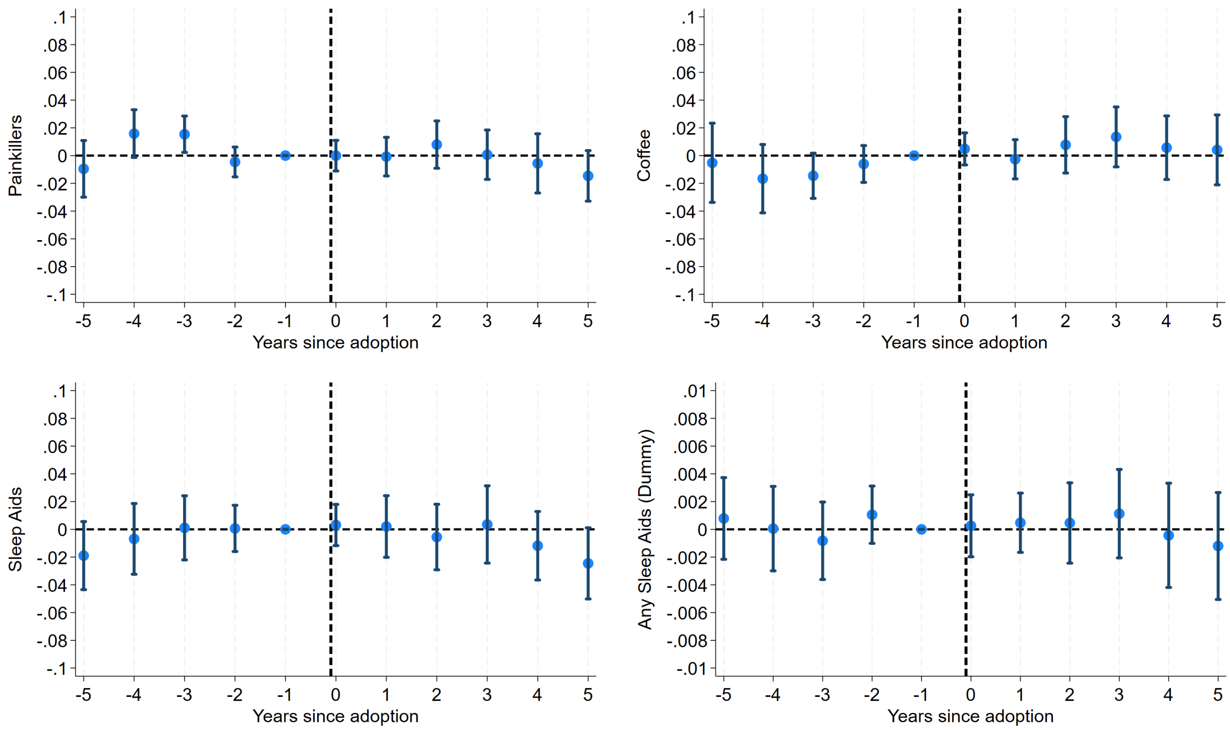
Notes: Event study estimates of wind turbine installation on household spending from NielsenIQ (2004–2023). Each panel plots coefficients from equation (1), representing the change in spending outcomes in years relative to turbine installation, with $k = -1$ as the reference period. Outcome variables are spending shares on: (i) alcoholic beverages, (ii) tobacco and equipment and (iii) medications and remedies, before and after the installation of the first turbine in the household's ZIP code of residence. This analysis examines spending responses related to (mental) health following wind turbine installation. The left column shows results for the full sample; the right column restricts to ever-treated ZIP codes. All models include household and year fixed effects and the full set of time-varying demographic controls. Spending shares are standardized and estimates therefore reflect changes in terms of standard deviations. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S35: Wind Turbines and Household Spending - Moral Licensing (2004-2020)



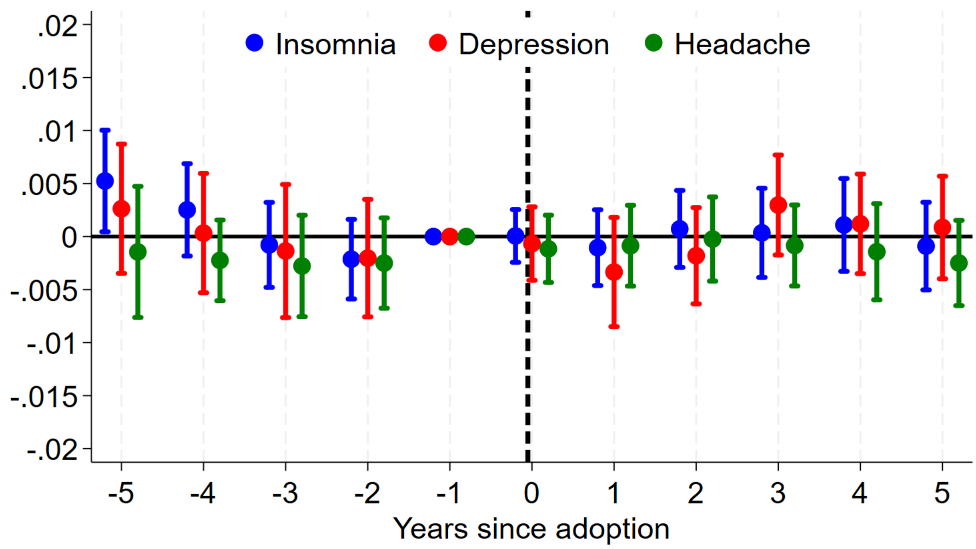
Notes: Event study estimates of wind turbine installation on household spending from NielsenIQ (2004–2020). Each panel plots coefficients from equation (1), representing the change in spending outcomes in years relative to turbine installation, with $k = -1$ as the reference period. Outcome variables are spending shares on: (i) dairy and (ii) packaged meat. This analysis tests for "moral licensing" effects, whereby households living near wind turbines—a visible symbol of environmental responsibility—might compensate by increasing consumption of carbon-intensive foods. The left column shows results for the full sample; the right column restricts to ever-treated ZIP codes. All models include household and year fixed effects and the full set of time-varying demographic controls. Spending shares are standardized and estimates therefore reflect changes in terms of standard deviations. Standard errors are clustered at the ZIP code level; bars represent 95% confidence intervals.

Figure S36: Wind Turbines and Household Spending: County-Level Evidence Following Zou (2020)



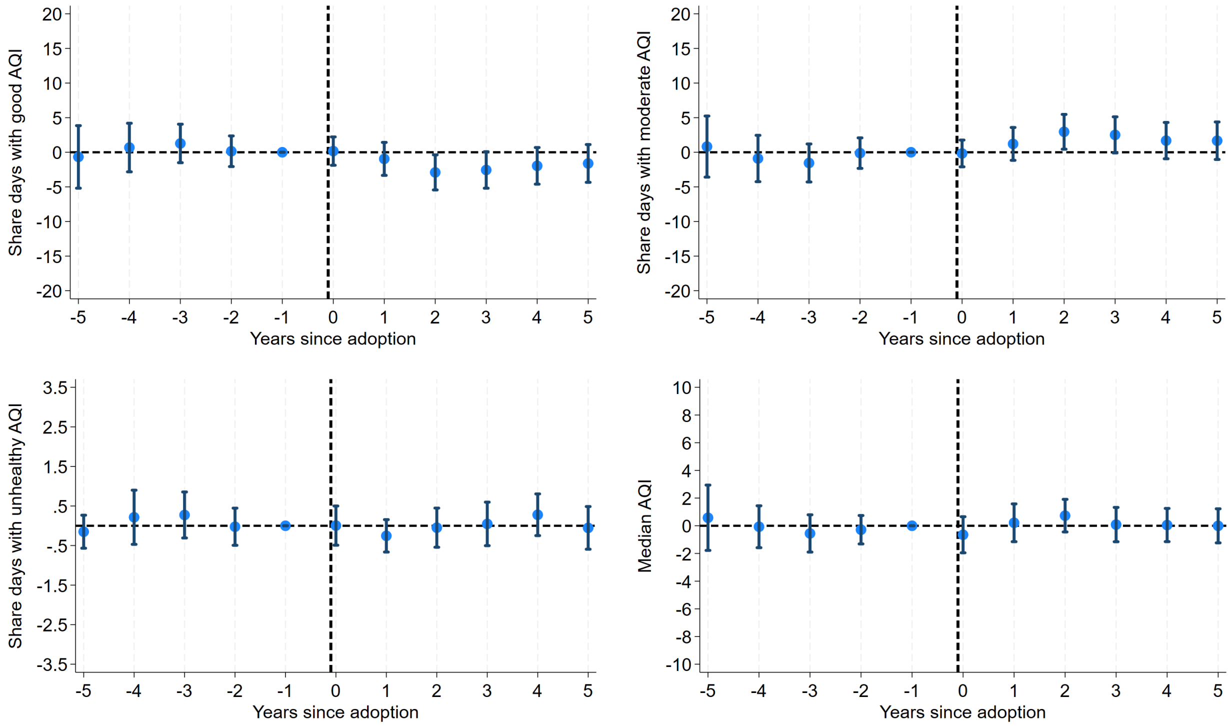
Notes: Event study estimates of wind turbine installation on household spending, replicating the county-level empirical approach of Zou (2020), from NielsenIQ (2004–2013). Each panel plots coefficients representing the change in spending outcomes in years relative to turbine installation, with $k = -1$ as the reference period. Outcomes measure the share of total household spending allocated to each category: (i) painkillers, (ii) coffee, (iii) sleep aids, and (iv) a binary indicator for any sleep aid purchases. Spending shares in categories (i)–(iii) are standardized and estimates therefore reflect changes in terms of standard deviations. Data are aggregated to the county–year level to match Zou's specification. Treatment is defined as the installation of any new wind turbine within 25 km of any county area; counties may experience multiple treatments over time as additional turbines are installed. The sample period (2004–2013) matches Zou (2020) as closely as possible. All models include county and year fixed effects and are population-weighted using 2020 Census data. Standard errors are clustered at the wind farm level; bars represent 95% confidence intervals.

Figure S37: Wind Turbines and Health: County-Level Evidence Following Zou (2020)



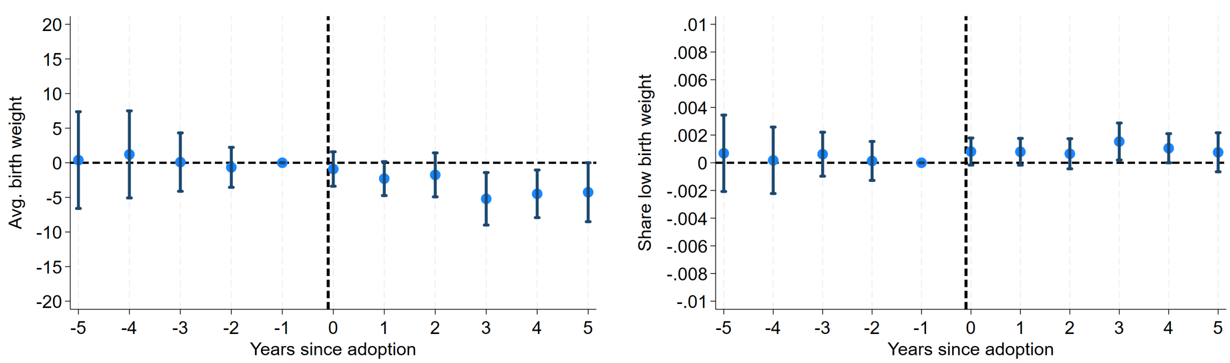
Notes: Event study estimates of wind turbine installation on health conditions, replicating the county-level empirical approach of Zou (2020), from the NielsenIQ Ailments Survey (2011–2023). Each panel plots coefficients representing the change in the probability of reporting insomnia (blue), depression/anxiety (red), or headaches (green) in years relative to turbine installation, with $k = -1$ as the reference period. Data are aggregated to the county–year level to match Zou's specification. Treatment is defined as the installation of any new wind turbine within 25 km of any county area; counties may experience multiple treatments over time as additional turbines are installed. This analysis tests whether our null findings reflect differences in geographic aggregation relative to Zou (2020), who finds effects on suicide at the county level. All models include county and year fixed effects and are population-weighted using 2020 Census data. Standard errors are clustered at the wind farm level; bars represent 95% confidence intervals.

Figure S38: Wind Turbines and Air Quality



Notes: Event study estimates of wind turbine installation on county-level air quality, from EPA data (2011–2023). Each panel plots coefficients from equation (1), representing changes in air quality outcomes in years relative to the installation of the first turbine in the county, with $k = -1$ as the reference period. Outcomes include the share of days classified as having good AQI (top left), moderate AQI (top right), and below-moderate AQI—defined as days classified as unhealthy for sensitive groups, unhealthy, very unhealthy, or hazardous (bottom left)—as well as the median AQI (bottom right). County-level air quality data are drawn from the U.S. Environmental Protection Agency. Figures report 95% confidence intervals for air quality outcomes following turbine installation. Standard errors are clustered at the county level. The y-axis is scaled by the smaller of the outcome's standard deviation or mean.

Figure S39: Wind Turbines and Birth Outcomes



Notes: Event study estimates of wind turbine installation on county-level birth outcomes. Each panel plots coefficients from equation (1), representing changes in birth outcomes in years relative to the installation of the first turbine in the county, with $k = -1$ as the reference period. Outcomes include average singleton birth weight in grams (left panel) and the share of singleton births with low birth weight (below 2,500 grams) (right panel). Figures report 95% confidence intervals for birth outcomes following turbine installation. Standard errors are clustered at the county level. Regressions are weighted by county population.

References

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