Sensory Pollution and Mental Health: Evidence from Roadway Noise and Nighttime Light

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Abstract

While federal regulation has delivered major improvements in air and water quality, sensory pollutants - such as traffic noise and artificial nighttime illumination - remain largely unregulated and understudied. These environmental stressors are pervasive in urban infrastructure and increasingly linked to mental health risks, yet little causal evidence exists on their impacts. We provide the first national-scale analysis of the effect of ambient roadway noise and nighttime light pollution on mental health. We link restricted-use survey microdata from approximately 14,000 respondents in the United States to high-resolution sensory exposures, and leverage natural variation in topography, temperature, and atmospheric conditions to isolate the causal effect of roadway noise and nighttime light on self-reported mental health. Both pollutants exert statistically and economically meaningful effects: road noise increases the likelihood of mild psychological distress by 11%, while light pollution increases it by 13%. These effects are are partially mediated through reductions in sleep duration. Welfare losses are up to $25 billion annually.

Keywords— Road noise; Nighttime light; Mental health; Area and road ruggedness; Wind speed; Wind direction; Cloud cover; HINTS; DARTE; $PM_{2.5}$

JEL codes: Q53, I12

1 Introduction

US environmental regulation over the past half-century has been tremendously successful in lowering conventional pollution. The 1970 Clean Air Act (CAA) in particular has driven dramatic declines in ambient air pollution from transportation, power generation, and industry (Aldy et al., 2022). This pollution reduction has been credited with substantial public health and welfare gains. For example, a 1% reduction in ambient particulate matter was found to reduce infant death rates by about 0.35%, implying thousands of infant lives saved (Chay and Greenstone, 2003). Likewise, cohorts who benefited from lower air pollution in early life enjoyed better economic outcomes in adulthood (Isen et al., 2017). Parallel gains occurred in water quality following the 1972 Clean Water Act (CWA). Government and industry have invested over $1 trillion to abate water pollution since 1972, yielding cleaner waterways - the share of U.S. rivers and streams safe for fishing increased by about 12% by 2001 (Keiser and Shapiro, 2019).

Amid these regulatory milestones, “sensory” pollutants - namely environmental noise and artificial light - have received comparatively little federal attention. The early 1970s wave of environmental legislation included the Noise Control Act of 1972, signaling national recognition that “unwanted sound” is a threat to public health (Reilly, 2023). The Environmental Protection Agency (EPA) established a noise abatement office and began setting noise emission standards for aircraft, highways, and equipment. However, this federal noise control program was abruptly defunded in 1981 (Reilly, 2023), and responsibility for noise mitigation has largely devolved to state and local governments. In the case of light pollution, there was never a national regulatory framework; and lighting standards are set only by states or municipalities (DarkSky International, 2018). Eighteen US states have enacted “dark sky” laws to curb light pollution, but these laws are piecemeal and often contain broad exemptions (e.g., for street lighting, construction, or industrial sites) (Kliewer, 2023).

The absence of federal leadership on roadway noise and outdoor night light stands in stark contrast to the aggressive national efforts on air and water quality. It also reflects a gap in research emphasis: economists and policy analysts have only recently begun to quantify the impacts of noise and light pollution. For instance, it is estimated that over 42 million Americans experience medium to high levels of traffic noise, imposing an aggregate annual cost of about $110 billion (Moretti and Wheeler, 2025). Spatial models linking nighttime illumination to economic activity and urban growth, highlight the interconnections between artificial light, energy use, and economic development (Bresson et al., 2023). These emerging studies underscore the significant externalities associated with sensory pollutants.

Our motivation for addressing noise and light pollution is the pervasive human exposure embedded in modern infrastructure, which often mirrors broader social inequities. The US contains the world's largest road network - spanning roughly 6.6 million kilometers of highways and roads (World Population Review, 2025), and approximately 11.3 million US residents (3.7% of the population) live within 150 meters of a major highway, where they are subject to elevated noise and exhaust levels (Boehmer et al., 2013). Many of these highways carry over 100,000 vehicles per day, exposing nearby communities to near-constant traffic noise and vibration.

Similar patterns emerge with respect to artificial light at night (ALAN). With the rapid proliferation of outdoor lighting - from streetlights and billboards to parking lots and architectural illumination - over 99% of the US population lives under light-polluted nighttime skies (DarkSky International, 2018). Urban neighborhoods, especially dense inner-city areas, are blanketed by intense nighttime lighting. Moreover, noise and light co-occur in many built environments. The same communities can be subject to multiple sensory stressors.

A growing interdisciplinary literature links these ambient environmental stressors to adverse health outcomes, including sleep disturbance, illness, and mental health risks (Gong et al., 2022). Noise pollution has long been studied for its auditory and cardiovascular effects (e.g. hearing loss, hypertension), but mounting evidence indicates that chronic noise exposure also erodes mental well-being by disrupting the hypothalamic–pituitary–adrenal (HPA) axis disruption, which increases susceptibility to depression, anxiety, and behavioral disorders in children and adolescents (Hahad et al., 2024; Arregi et al., 2024). Artificial light pollution has, likewise, been increasingly implicated in health problems, especially those tied to the circadian system. Exposure to ALAN can suppress nocturnal melatonin production and confuse the normal day–night physiological rhythms (Kliewer, 2023). Additionally, ALAN is associated with greater risks of depression and disrupted sleep in both human and animal populations (Carta et al., 2018; Senzaki et al., 2020).

Despite the evidence that sensory pollutants harm mental health, policy responses remain scant and the causal relationship is not yet fully understood. Establishing causality is challenging because individuals living in noisy, brightly lit environments may differ systematically in terms of their socio-economic and mental health characteristics from those in quieter, darker locales. We address this gap by providing the first national-scale, microdata-based causal analysis of mental health impacts from both roadway noise and nighttime light pollution.

We draw on restricted-use microdata, which provide rich information on health and demographics of roughly 14,000 US adults and include the full 9-digit ZIP code for each respondent's residential address. This granular geolocation enables us to merge individual records with high-resolution measures of environmental exposures at the street/household level. Mental health outcomes are quantified using a composite index of psychological distress symptoms (e.g. anxiety, sadness, hopelessness, restlessness, fatigue) reported in the two weeks prior to the survey. We measure chronic road noise using the US Department of Transportation's National Transportation Noise Map, which modeles sound levels on a 30-meter grid across the country. We link these data to respondents' residences for survey years 2016, 2018, and 2020, focusing on noise from road traffic - a ubiquitous source of sensory pollution. To measure ALAN, we use NASA/NOAA's high resolution remote sensing data on nocturnal radiance, geocoded to each respondent's residential location. These data capture stable night lights (filtering out ephemeral sources like fires or moonlight) and provide an annual measure of ambient brightness in the vicinity of the respondent's home.

To address the potential endogeneity in exposure to ambient noise and light pollution, we construct instruments for noise and light pollution based on local topography, annual wind speed and direction, average annual temperature, and nighttime cloud cover, variables that affect the ambient levels of sensory pollution in a location but are unlikely to directly influence mental health outside of pollution channels, especially conditional on location and time fixed effects. For example, steeper terrain can absorb or amplify traffic noise independent of local demographics; wind direction influences the drift and accumulation of road noise (as well as co-occurring airborne particles, an issue we discuss in greater detail in section 5.2); higher temperatures can affect both sound propagation and dispersion dynamics of airborne pollutants and cloud cover is known to amplify the intensity and dispersion of artificial light (e.g., Freeman et al., 2017; Votsi et al., 2017), particularly in urban areas where ground-based illumination is widespread.

We find robust and statistically significant causal evidence that both roadway noise and nighttime light pollution contribute to worse mental health outcomes. A 1 dB increase in ambient noise results in a 0.0022 standard deviation increase in psychological distress, which translates to a 11% rise in mild mental health symptoms among individuals who were previously asymptomatic. In parallel, a unit increase in satellite-measured radiance causes a 0.0026 standard deviation increase in distress, corresponding to a 13% increase in mild mental health symptoms. We find clear evidence that the effects of road noise operate through sleep disruption: a 1 dB increase in road noise reduces weekend sleep time by approximately 5 minutes. The correlation between nighttime light and sleep is not as robust.

The economic implications of these findings are substantial. Based on national prevalence rates and our estimated effect sizes, we estimate a welfare loss of up to $12 billion annually attributable to roadway noise exposure, and an additional $13 billion annually due to nighttime light pollution. Together, these results underscore the neglected costs of sensory environmental stressors and highlight the importance of accounting for sensory pollution in environmental regulation and urban policy. Our findings suggest that policy interventions, ranging from zoning and noise abatement to dark-sky ordinances, may yield significant economic benefits, particularly in urban, high-density communities.

The remainder of the paper proceeds as follows. Section II outlines the empirical strategy, including the IV framework and identification assumptions. Section III describes the data and variable construction in detail. Section IV presents the main results, and Section V conducts robustness checks. Section VI discusses potential mechanisms, and Section VII concludes.

2 Empirical Strategy: Instrumental Variables

The reduced-form model describing the relationship between human mental health and sensory pollution is as follows:

$$\begin{aligned} S_{izt} = \beta_0 + \alpha_1 Sensorypollution1km_{zt} + \alpha_2 Airpollution1km_{zt} \\ + \boldsymbol{\Gamma}' X_{izt} + \boldsymbol{\Theta}' W_{zt} + \theta_c + \eta_t + \epsilon_{izt} \end{aligned} \tag{1}$$

where S_{izt} represents the mental health outcome for an individual respondent i from zip code area z (5 or 9 digit) in year t. $Sensorypollution1km_{zt}$ and $Airpollution1km_{zt}$ represent two types of sensory pollution and two types of air pollution co-generated with traffic noise, respectively, both measured within a 1-kilometer radius of each respondent. X_{izt} includes individual-level demographic characteristics commonly associated with mental health outcomes in the literature. W_{zt} captures 5-digit zip code–level environmental conditions that have been shown to influence mental health. θ_c and η_t are county and year-of-survey fixed effects, respectively.

The biggest challenge in identifying the causal effect of sensory pollution on mental health is that ambient sensory pollution (and also correlated pollutants like vehicular/roadway air pollution) may not be randomly assigned due to residential sorting based on respondents' socioeconomic and demographic correlates. Although we do not observe obvious patterns in our data, like people with higher incomes and education living in areas with less ambient noise or less/more ALAN, there is clear evidence in the literature that less privileged people are disproportionately exposed to higher pollution (Banzhaf et al., 2019). To address these concerns, we implement an instrumental variable (IV) strategy.

2.1 Roadway Noise

Road noise is generated primarily through the friction between vehicle tires and the road surface, with slower-moving vehicles generating lower noise. Combined with the fact that people drive relatively slowly in areas with greater topographic variation, we anticipate that road noise is generally lower in such areas. The USDA's Area and Road Ruggedness Scales, which include the Area Terrain Ruggedness Index and the

Road Ruggedness Index, provide information on topographic variation at the census tract level.[1] While the Area Ruggedness Index is computed using the change in elevation in all 8 neighboring cells, the Road Ruggedness Index is based only on the neighboring cells through which a road passes (see Figure ??), with lower values indicating smaller changes in elevation in both cases. We expect a negative correlation between the Area Ruggedness Index and road noise. However, conditional on the Area Ruggedness Index, we anticipate that road noise is higher in areas with a higher Road Ruggedness Index because of the more frequent deceleration and acceleration of vehicles. We also anticipate that topography affects local air pollution since driving behavior also impacts the fuel efficiency of vehicles, which contributes to variation in traffic-generated air pollution.

Noise travels through the air as a sound wave. Wind can accelerate or slow down the propagation of sound waves. When the wind blows in the same direction as the noise source, like the wind coming from the direction of a highway, the sound waves will bend and be refracted to the ground, which increases ambient noise. However, when the wind blows in the opposite direction to the noise source, the sound waves will be refracted upwards and the propagation of noise will be diluted (Nijs and Wapenaar, 1990). Wind speed also impacts noise propagation; noise travels a further distance with a higher wind speed. However, high wind, captured in our data through maximum wind speed, can counteract ambient noise by creating noise from air friction, canceling road noise. Wind also blows local air pollutants to other areas, depending on wind speed and direction. Thus, we exploit the daily variation in wind conditions to address the endogeneity of ambient noise and traffic related air pollution (see also Zou, 2017; Deryugina et al., 2019; Burton and Roach, 2022; Persico and Marcotte, 2022; Barnor, 2025). To account for local variation in the effect of wind direction on noise and air pollution propagation, we interact the wind direction variables with county fixed effects. That is, we allow the effect of an east wind to differ for a county in NY relative to a county in CA, for example.[2]

Furthermore, roadway noise and, likewise, traffic-related air pollution, is not a point source pollutant (unlike, for example, toxic emissions from a manufacturing plant). Rather we think of them as being generated along "line segments". Thus, we do not emphasize the idea of respondents being upwind or downwind of

[1] https://www.ers.usda.gov/data-products/area-and-road-ruggedness-scales/

[2] We also interact wind directions with States or census divisions as a robustness check.

these pollution sources since a respondent who lives downwind from one roadway (or one section of a roadway) could also be living upwind from another roadway (or section, thereof) given the same prevailing wind. Instead, we focus on the number of days with the four prevailing wind directions. Since some areas usually have heavier traffic (and therefore higher roadway noise and air pollution) than other areas, we utilize the fact that the variation in wind speed and wind direction propagates pollution from high-traffic areas to different respondents based on changes in daily wind conditions.

The propagation of noise is not only affected by wind but also by ambient temperature. At higher temperatures, lower density air refracts noise away from the ground and reduces ambient noise. Although there is a link between temperature and very serious mental health outcomes like emergency department visits and suicide, there does not appear to be a link between ambient temperature and self-reported mental health during the "last 30 days" (similar to our outcome variable) (Mullins and White, 2019). Thus, we control for the number of days during each survey period with extreme temperatures to capture the direct effect on mental health, and use the average daily temperature during each survey year to address the impact of associated variation in the propagation of noise.[3]

2.2 ALAN

Nighttime cloud cover is an exogenous meteorological phenomenon (footnote 5 here) that can influence ALAN detected by satellites, but is plausibly unrelated to individual mental health outcomes.[4] Clouds reflect and scatter ALAN emitted from the ground, acting as an amplifier for ALAN, especially in an urban setting (Kyba et al., 2011). Figure **??** shows the correlation between the ALAN and the nighttime cloud cover.[5]

Although nighttime cloud cover does not directly affect daytime solar energy, it may correlate with solar energy and approximate intra-day cloud conditions and daytime cloud cover, which may directly affect

[3]The survey period is from August to November for 2014; from January to May for 2017, 2018, and 2019; and from February to June for 2020.

[4]Nighttime cloud cover is influenced by factors external to the atmosphere, such as changes in temperature, humidity, and air pressure, and is independent of local economic activity, demographic characteristics, pollution patters and other unobserved variables in the error term.

[5]The absorption of light by clouds can also reduce observed light pollution. However, Hakuba et al. (2017) find that the absorption effect appears most distinctly at desert-like locations, where have little occurrence of clouds in general.

self-reported mental health. To mitigate potential bias from this correlation, we control for daily average solar energy during each survey period. We deliberately avoid including daytime cloud cover directly in the regression, despite its possible effect on mental health, because it is highly correlated with nighttime cloud cover. Including both variables would invalidate the exclusion restriction by introducing an alternative pathway through which the instrument could influence the outcome.

2.3 Combined IVs

To sum up, the first-stage equation for our baseline two-stage least squares regression model is:

$$\begin{gathered}
\mathsf{Pollution}_{izt} = \alpha_0 + \alpha_1 \cdot \mathsf{RoadRI}_z + \alpha_2 \cdot \mathsf{AreaRI}_z + \\
\beta_1 \cdot windspeed_{zt} + \beta_2 \cdot maxwindspeed_{zt} + \sum_{c \in C} \sum_{k=0}^{2} \gamma_c \cdot Winddir_{zt}^{90k} + \\
\delta \cdot averagetemp_{zt} + \rho \cdot \mathsf{Nighttimecloudcover}_{zt} + \boldsymbol{\Gamma}' X_{izt} + \boldsymbol{\Theta}' W_{zt} + \theta_c + \eta_t + \epsilon_{izt}
\end{gathered} \tag{2}$$

The dependent variable $\mathsf{Pollution}_{izt}$ represents either annual ambient road noise, ALAN or annual average traffic related air pollution (specifically, fine particulate matter or $PM_{2.5}$, and traffic related CO_2 concentrations) within a 1 km buffer of each individual i located in 9-digit zip code area z in year t. The excluded instruments in Eq.(2) are the census tract level Area Ruggedness Index (AreaRI_z) and Road Ruggedness Index (RoadRI_z), annual average wind speed and maximum wind speed, and the annual average temperature for each HINTS survey wave.[6] $Winddir_{zt}^{90k}$, which represents the number of days in each survey year that the prevailing wind falls in the 90-degree interval $[90k, 90k+90)$ (split into four bins, with interval $[270, 360)$ as the base group), is interacted with county fixed effects (γ_c).[7] $\mathsf{Nighttimecloudcover}_{zt}$ represents the zip-5 level annual average nighttime cloud cover in year t.[8]The included instruments (control

[6]For 77% of the respondents in our sample, there is a one-to-one mapping from zip codes to census tracts. Hence, for notational ease, we suppress the census tract subscripts of the ruggedness indices.

[7]We interact wind directions with county fixed effects rather than 5- or 9-digit zip code fixed effects for several reasons. First, county fixed effects capture a broader regional variation that aligns with the scale of wind directionality and its potential environmental and health impacts, ensuring sufficient variation within the data for robust estimation. Interacting with more granular fixed effects, such as 5- or 9-digit zip codes, could lead to overfitting and a significant loss of statistical power, as these finer spatial units may absorb much of the variation in the wind direction variable. Additionally, data limitations in certain zip code regions (e.g., sparsely populated) further constrain the feasibility of such interactions, whereas county-level interactions maintain a balance between granularity and generalizability.

[8]We obtained hourly cloud cover data and daily sunrise/sunset times from Visual Crossing to calculate the annual nighttime cloud cover data. For more details, visit https://www.visualcrossing.com/weather/weather-data-services.

variables) at the individual or zip code area level are represented by the vectors X'_{izt} and W'_{zt}, respectively, and are the same as in Eq.(1).

We then utilize the predicted pollution from Eq.(2) to estimate the causal effect of sensory and air pollution on mental health using the following second-stage regression:

$$\begin{aligned} Stdphq4_{izt} &= \alpha + \beta_1 \cdot Road\widehat{noise}1km_{izt} + \beta_2 \cdot AL\widehat{AN1}km_{izt} \\ &+ \beta_3 \cdot CO_2E\widehat{missi}on1km_{izt} + \beta_4 \cdot PM\widehat{_{2.5}1}km_{izt} \\ &+ \boldsymbol{\Gamma}' X_{izt} + \boldsymbol{\Theta}' W_{zt} + \theta_c + \eta_t + \epsilon_{izt} \end{aligned} \tag{3}$$

3 Data

3.1 Mental Health and Demographic Data

We utilize restricted-access microdata from the National Cancer Institute's Health Information National Trends Survey (HINTS), which provide rich information on US adults' physical and mental health, demographic characteristics, and residential location at the full 9-digit ZIP code level. These detailed geocodes enable us to merge each respondent with high-resolution environmental exposures, including ambient noise and annual average ALAN, at a fine spatial scale. Our analysis sample comprises approximately 14,000 individuals residing in the contiguous US, surveyed across five waves: 2014, 2017, 2018, 2019, and 2020.[9] The survey's design is nationally representative, with sampling weights constructed through post-stratification and calibrated to population benchmarks from the American Community Survey to adjust for coverage and nonresponse bias.[10] HINTS is well suited to our research objectives because it gathers mental and physical health data independently of respondents' environmental exposures, reducing the risk of reporting bias driven by perceived pollution or neighborhood conditions.

Our primary outcome is a continuous index measuring psychological distress. This index is constructed from four self-reported items, each asking how frequently the respondent experienced a given symptom

[9]We use the same individual health dataset as Wei (2024).

[10]For more details about the sampling and weighting process, see https://hints.cancer.gov/about-hints/frequently-asked-questions.aspx.

over the prior two weeks: (1) little interest or pleasure in doing things; (2) feeling down, depressed, or hopeless; (3) feeling nervous, anxious, or on edge; and (4) not being able to stop or control worrying. Each item is scored on a four-point Likert scale ranging from 0 ("not at all") to 3 ("nearly every day"), yielding an index with a possible range from 0 to 12.[11] Higher scores indicate greater distress and more severe symptoms. The distribution of the index is right-skewed, with nearly half of respondents reporting no symptoms (a score of zero), and approximately one-quarter reporting mild symptoms (scores between 1 and 4). To harmonize across survey years and account for secular trends, we standardize the mental health index following the recommendation from the NCI (Richard Moser, personal communication, September 21st, 2022) within each wave prior to estimation. This normalization enables comparability across time and mitigates potential confounding from cross-year variation in population mental health or survey response patterns.

We include rich demographic controls in X_{izt}. $Female$ and $Married$ are dummy variables which equal to 1 if an individual respondent i from zip-code area z in year t is a female or married, respectively. We also capture the association between mental health and the respondent's age and highest completed education.[12] $Race_{izt}$ is a vector of indicator variables for non-Hispanic black, Hispanic, and non-Hispanic other race, with non-Hispanic White as the base group. $Hhnum_{izt}$ counts the total number of people living in the respondent's household. Some studies show that both early life circumstances and childhood physical and mental health, which could be related to the number of children living in the household, have durable effects on adulthood outcomes including adulthood mental health and labor market outcomes (Goodman et al., 2011; Adhvaryu et al., 2019).

There is extensive literature documenting the direct and indirect association between income and mental health outcomes for adolescents, adults, and the elderly (Baird et al., 2013, Lin et al., 2013, Watson and Osberg, 2018). We include the annual personal income for each HINTS respondent in our sample. Annual income is potentially endogenous since it could be determined simultaneously with or be related to other

[11] For example, respondents who report having all four mental health issues nearly every day will get an index of $3 \times 4 = 12$, indicating the worst case of mental health. If a respondent reports "several days" for one of the questions, and "not at all" for all the other questions, the corresponding index value will be 1+0+0+0=1.

[12] The highest level of schooling is a categorical variable that includes "less than high school"; "high school graduate"; "some college"; "college graduate or more". The base group in our specification is "less than high school".

unobservables that also affect mental health. However, the specific question in HINTS regarding income is: "What is your combined annual income, meaning the total pre-tax income from all sources earned in the *past year*?" while the specific question regarding mental health is: "Over the *past 2 weeks*, how often have you been bothered by…". Thus, we believe that this concern is reasonably diluted given the (i) long time interval between the two variables, and (ii) the disparate time span over which they are measured. We also include as control variables the fraction of residents owning a house at the block group level.[13] Joshi (2016) finds individuals tend to report worse mental health when local house prices decline, but this association is most significant for individuals who are least likely to be homeowners.

It is well established that physical health plays an important direct and indirect role in explaining mental health. See, for example, Kristiansen, 2021; Kesavayuth et al., 2022. Thus, we include many variables related to each respondent's physical health condition. "DocVis" counts the number of times a respondent goes to see a doctor, nurse, or other health professional during the *past 12 months*; "Cancer" and "CancerFam" indicate whether a respondent or their family members ever had cancer, respectively. We also include Body Mass Index, and the occurrence of two common diseases, diabetes and hypertension. "Exercise" counts the days a respondent does any physical activity or exercise of at least moderate intensity in a typical week and accounts for the positive link between exercise and mood states like anxiety, stress and depression (Mikkelsen et al., 2017).[14]

One of the most valuable characteristics of the restricted version of HINTS is that it offers detailed geographic information for each respondent besides their demographic and health information. The geographic information provides residential location including rural/urban designation, county FIPS code, and, most importantly for us, 9-digit zip code. The 9-digit zip code is a relatively precise spatial indicator and can identify a respondent's location within a few houses or at the street level.[15] We assume that each respondent

[13] We link respondents' zip-5 information to the block groups by overlapping the zip-5 area centroids with the block-group map from the Census Bureau. Block group level information is obtained from the 2018 American Community Survey.

[14] As in the case of household income, we believe that the concern regarding the potential endogeneity of the physical health controls is diluted because of the disparate time span over which they are measured as compared to the questions regarding mental health.

[15] A typical zip+4 (zip-9) code covers an area much smaller than a standard zip code. According to the US Postal Service, a zip+4 code identifies a specific delivery route or location, often corresponding to a group of 10-20 addresses on a single street, a small building, or a block-face in urban areas. In rural areas, the coverage might be slightly

resides at the centroid of the zip-9 area and use data from GeoLytics, Inc, Inc. to identify the latitude and longitude of each centroid. The zip-9 centroid geocodes are then used to locate the HINTS respondents on the DoT's National Transportation Noise Map and NASA's VIIRS Nighttime Lights Yearly. Zip code information is unavailable in the first three waves of the HINTS survey (2011-2013) and our analysis is restricted to the respondents from the next five waves. But, in Section 6, we use the respondents from the first three waves as a separate sample to disentangle the mechanism through which sensory pollution affects mental health.

3.2 Sensory Pollution Data

The DoT's National Transportation Noise Maps provide spatially gridded nationwide annual noise data for 2016, 2018 and 2020 due to aviation, highway, and rail transportation. Although rail noise information is available in the 2018 and 2020 waves, it is not included in the 2016 wave. Also, the areas exposed to rail noise in the US are relatively limited compared with the widespread road noise exposure. A vast majority of the respondents in our sample are exposed to relatively low and undetectable levels of aviation noise as well. Thus, we only focus on road noise in this study. As an example of the information provided by the noise maps, Figure 2 shows the ambient noise surrounding one of our institutions.

The road noise data used for the National Transportation Noise Map are modeled using Average Annual Daily Traffic (AADT) values, along with vehicle types and speeds, calculated through the Federal Highway Administration's Traffic Noise Model (TNM) algorithms. AADT values are sourced from the Highway Performance Monitoring System (HPMS), which also details road types. Speed data is either taken from HPMS, if available, or assigned based on road and area types (e.g., urban or rural). Vehicle categories included in the noise modeling are automobiles, medium trucks, and heavy trucks, with average speed limits assigned to different road types. Road noise levels are determined using TNM's acoustic algorithms and calculated at receptor points located in a uniform grid every 98.4 feet, positioned at 4.92 feet above ground level to simulate human exposure. The data also considers ground effects and distance from noise sources.[16]

larger but still remains much more precise than a 5-digit zip code, allowing for highly localized environmental measurements.

[16]Key assumptions in road noise modeling include default weather conditions (68°F and 50% humidity), acoustically soft ground (which may under-predict noise levels for hard surfaces like water or pavement), and average pavement

Shielding effects such as natural barriers, terrain, or buildings are not included, which may lead to overestimated noise levels in densely populated areas. Additionally, noise levels below 45 dB(A) are excluded from the results. Importantly for us, the noise data are available on a fine spatial grid of 30-meter square, which allows us to estimate ambient road noise, a highly localized pollutant, near a respondent's place of residence.

The average noise level of a busy highway is around 70 to 80 dB. However, noise does not move through long distances (unlike, for example, some air pollutants), and audible noise decreases non-linearly by 6 dB as the distance from the noise source is doubled (Zou, 2017). For example, 78 dB ambient noise at 15 m from the noise source will be equivalent to 42 dB at a distance of 960 m.[17] To estimate respondents' ambient road noise, we create a circular buffer with a radius of 1 km around each respondent's 9-digit zip code centroid.[18] Figure 4a, depicts the zip-9 centroids for a sample of hypothetical HINTS respondents near one of our institutions. The blue circles are the 1-km noise buffers and the white/black segments represent ambient road noise from roadways. Within a buffer, each 30 m^2 pixel area has a unique value for ambient noise. We calculate a respondent's ambient noise as the average across all pixels in the buffer that have detectable noise.[19]

A limitation of the Department of Transportation (DoT) noise data is that it is not available on an annual basis. To address this, we assign the 2016 noise data to respondents from the 2014 HINTS wave, the 2018 noise data to respondents from the 2017 and 2018 waves, and the 2020 noise data to respondents from the 2019 and 2020 waves as reasonable approximations. Local noise pollution is very strongly correlated over time (the correlation coefficient exceeds 0.95),[20] so we anticipate that this approximation has minimal measurement error.

types. The AADT values are assumed to be evenly distributed over 24 hours.

[17]The noise data reported by the DoT account for this non-linearity in the propagation of noise.

[18]Anderson (2020) sets the buffer with a radius of 500 m in his study, but the spatial resolution of his study (census tract) is different from ours and mainly focuses on the effect of highway-related air pollution. The 1 km buffer suits our study well since it captures the decay of general traffic noise (e.g. 78 dB) to a non-detectable level (e.g. 42 dB) at the margin of the buffer size (e.g. 960m).

[19]We consider an alternative way of measuring the ambient noise at the centroid of each zip-9 in section 5 under the robustness checks.

[20]We locate each zip-9 centroid from the three waves of HINTS on the noise maps for the corresponding three years. We then calculate the annual within-buffer average noise for every zip-9 centroid in our sample and calculate the correlation across years. Note that our sample is a pooled cross-section with very limited overlap in respondents' 9-digit zip codes across survey years. Hence the temporal correlation in roadway noise is represented as cross-sectional variation in our sample.

To isolate the effect of roadway noise from that of traffic-related air pollution, we exploit the Database of Road Transportation Emissions (DARTE) from NASA. DARTE provides annual on-road emissions based on roadway-level traffic data and state-specific emission factors for multiple vehicle types, and covers the conterminous US for 1980-2017 at a spatial resolution of 1km. One limitation of DARTE is that it only provides estimates of on-road CO_2 emissions, and lacks estimates of other traffic-related air pollutants. However, traffic-related CO_2 is correlated with other pollutants like SO_2 and NO_X (Liang et al., 2024), and we use on-road CO_2 emissions to approximate traffic-related air pollution. Appendix Figure B.1 shows the 2017 CO_2 emission map for New York City and its surrounding areas; areas with more traffic-generated CO_2 emissions (cells with a deeper red color in the figure) tend to be fairly close to the highways. Similar to the noise measurement, we approximate a respondent's surrounding on-road air pollutants as the average across all pixels in the 1km buffer that have detectable CO_2 emissions. To address the concern that traffic-generated CO_2 emissions might not fully capture respondents' surrounding traffic-related air pollution, we estimate $PM_{2.5}$ concentrations in the 1 km buffer using data from Shen et al. (2024). These data combine satellite aerosol optical depth data, a chemical transport model, and ground monitor data, and offer a very precise and high-resolution (i.e. approximately 1 km $\times$ 1 km) estimate of local air pollution (Kayastha et al., 2024).

To measure ALAN, we rely on satellite-derived measurements from the Visible Infrared Imaging Radiometer Suite (VIIRS) instrument onboard the NASA/NOAA Suomi National Polar-orbiting Partnership (NPP) satellite. Specifically, we use the VIIRS Day/Night Band (DNB) Annual Composite data, which provide consistent, calibrated estimates of upward radiance at approximately 500-meter spatial resolution across the contiguous US. These data are available annually beginning in 2012 and allow us to match respondents from different survey waves to contemporaneous light conditions in their residential area. Radiance is recorded in nanowatts per square centimeter per steradian ($nW/cm^2/sr$) and reflects the intensity of light reaching the satellite sensor from the Earth's surface and lower atmosphere. This measure captures cumulative light emissions from a variety of sources including street lighting, commercial signage, residential lighting, vehicle headlights, and industrial facilities. Higher radiance values indicate greater artificial skyglow and light spillover, both of which are known to interfere with circadian rhythms and sleep physiology.

The ALAN data are available on a spatial grid of 500-meter squares. To measure localized ambient ALAN, we apply the same spatial buffer as used for ambient roadway noise: a 1 km radius centered at each respondent's zip-9 centroid, which captures the immediate neighborhood environment where individuals spend most of their time at home and during nearby activities, and aligns with conventions in environmental health and urban planning studies that examine local environmental exposures(Frank et al., 2017; Martin et al., 2024). Figure 4b, depicts a sample of hypothetical HINTS respondents near one of our institutions and the corresponding 1-km light buffers. The orange to purple cells represent weak to substantial ambient ALAN. As with road noise, we estimate ambient ALAN as the average across all pixels in the buffer.

3.3 Other Environmental Data

Higher temperatures (relative to the mean values) are known to be associated with poorer mental health outcomes (Mullins and White, 2019). Thus, we account for temperature anomalies by including the number of days within a survey year with extreme temperatures (i.e. above $85°F$ and below $32°F$) at the 5-digit zip code level provided by the National Oceanic and Atmospheric Administration (NOAA) through the National Centers for Environmental Information. We also get the 5-digit zip code level average daily temperature during the survey year for each HINTS wave to be used as one of our instrument variables.

To account for seasonal variation in light and winter depression, we include the average solar energy during each survey period, which indicates the total energy from the sun that builds up in a day at the 5-digit zip code level. We obtain daily information on other environmental factors from Visual Crossing, which offers rich historical data on weather conditions like temperature, precipitation, wind speed, and wind direction. The weather data originates from individual NOAA weather stations; Visual Crossing organizes the data in a way that allows us to utilize it directly at the 5-digit zip code level.

4 Results

4.1 Summary Statistics

There are more than 19,000 respondents with 9-digit zip code information across 5 HINTS survey years. However, some demographic questions are not asked in all the waves (e.g. employment status is not asked in the 2019 wave), and we lose some individuals due to missing information. Our final sample size is a pooled cross-section of around 14,000 individuals across all the survey years. 99.8% (14,621 out of 14,640) of the respondents are the single observation in their 9-digit zip code areas, covering 2070 counties (610 respondents are the single observation in their counties) and all 48 contiguous US states plus the District of Columbia. On average, there are 7 respondents in each county.

With the development of modern transportation and urbanization, most people live in areas with convenient commuter infrastructure. Not surprisingly, 95% of the respondents in our sample live within 1 km of a primary or secondary road and are exposed to road noise. Figures 5a and 5b show the distribution of ambient road noise and ALAN within a 1 km buffer for our sample respondents.[21] There is a small positive correlation of 0.256 between roadway noise and nighttime light, suggesting that these environmental stressors may co-occur in certain neighborhoods. Most respondents experience ambient road noise between 50 and 60 dB and only a very small fraction of respondents reside with undetectable ambient road noise; the average annual ambient road noise within a 1 km buffer of the sample respondents' 9-digit zip code centroids is 50.96 dB (53.81 dB for those with detectable road noise). The lowest detectable noise value reported in DoT data is 45 dB, and the minimum average ambient road noise recorded is 45.1 dB within the 1 km buffer. The maximum average ambient road noise is 60.83 dB, which is well above the 55 dB cutoff set by the EPA for human health and welfare protection (EPA, 1974).

ALAN is measured as upward radiance using data from the VIIRS satellite, reported in nanoWatts per square centimeter per steradian (nW/cm^2/sr). For reference, radiance levels below 5 are typical of rural or natural areas, 5–20 for suburban neighborhoods, 20–50 for small and mid-sized cities, and values above 100 are

[21] DoT data do not detect/record ambient noise below 45 dB, which explains the large gap between 0 dB and 45 dB in the figure.

commonly observed in dense urban centers such as downtown New York or Los Angeles. In our sample, the average light exposure is 29.3 nW/cm^2/sr (SD = 28.0), suggesting that the typical respondent resides in a suburban or small urban area. Unlike noise or air pollution, there is no internationally recognized threshold for harmful ALAN exposure. Therefore, we rely on the observed continuous distribution of radiance in our sample, which spans from near-natural dark-sky conditions ($<$5 nW/cm^2/sr) to high-intensity urban lighting ($>$100 nW/cm^2/sr), to characterize variation in ALAN.

As for the outcome variable of interest, nearly half of the respondents in our sample have a value of 0 for the PHQ-4 index, which means they do not report any mental health problems. About a quarter of respondents report their index values between 1 and 4, indicating that they experience symptoms of anxiety or depression on some days in the two weeks immediately preceding the survey time. In general, older respondents in our sample report better mental health: the average age for respondents who report a value of 0 is 58.46 while the average age for the respondents with the worst mental health (a value of 12) is 52.73. This is consistent with the national averages reported in the 2021 National Survey on Drug Use and Health.[22] People with diabetes or hypertension as well as those with a higher BMI are more likely to have poorer mental health.[23] Table 1 summarizes our data separated into demographic, health, and environmental variables, respectively.

4.2 IV Results

As noted earlier, we acknowledge the possibility that ambient pollution is not random and utilize instrumental variables, viz, local topography, wind speed, wind direction, annual average temperature and nighttime cloud cover, to extract the exogenous variation in ambient noise and light pollution, respectively. To assess whether our instruments are confounded with demographic variables, we estimate separate sets of regressions for each instrument (except for wind direction $\times$ county fixed effects) on only one potentially confounded variable at a time and plot the estimated coefficients and their standard errors for each IV

[22] https://www.nimh.nih.gov/health/statistics/mental-illness

[23] The fraction of people with cancer (15%) or whose family had cancer (56%) might appear to be quite high. Note that the question HINTS asks respondents regarding cancer is "Have you ever been diagnosed as having cancer?" This means that cancer survivors and those currently under treatment for cancer answer "Yes" to this question. According to the National Cancer Institute, men have a one in two chance of being diagnosed with cancer while women have a one in three chance.

separately. For instance, we estimate a regression of wind speed on all income/education level indicators and plot the coefficients in Figures B.2a and B.2b. In general, we find all the 95% confidence intervals overlap with the 0 value line, indicating that our IVs are mean independent of income and education levels. Figures B.3a to B.8b show the plots for other instruments.

While the unconditional relationships in Figures B.9a and B.9b reveal some correlation between nighttime cloud cover and education or income, these associations largely disappear once we include county and year fixed effects, as shown in Figures B.10a and B.10b. This aligns with our 2SLS specification, which absorbs both geographic and temporal variation, and suggests that our identifying variation in nighttime cloud cover is plausibly exogenous. The only exceptions are the two ruggedness indices where we find respondents in the highest income brackets tend to reside in areas with higher values for these two indices.

The first-stage regressions for both sensory pollutants are shown in Tables A.2 and A.3, respevtively. Wind speed shows a strong positive correlation with roadway noise, while exhibiting a negative correlation with $PM_{2.5}$ concentrations. Annual average temperature is significantly associated with both road noise and air pollution levels. Road and area ruggedness indices are strongly correlated with ambient road noise as well as traffic-related air pollutants, and the signs are consistent with our expectations.[24] Nighttime cloud cover emerges as a strong and statistically significant predictor of ALAN, with a positive coefficient significant at the 1% level.

Table 2, columns (1)-(3), report the IV estimates where we regard both sensory pollution and the two measures of traffic related air pollution as endogenous. We report the separate effect of each sensory pollutant in columns (1)-(2) and include both in column (3). The 2SLS estimates suggest that the mental health of respondents worsens by 0.0022 standard deviations when their ambient road noise increases by 1 dB, or that around 16 out of 2528 respondents (in the survey year 2018) go from having "little" to "mild" depressive symptoms because of a 1 decibel increase in ambient road noise (recall that an increase in the

[24]We expect relatively small first stage F-values in our main specification given the large number of county-interacted-wind-direction instruments. To address the concern about the validity of our instruments, Table 2 also shows the first-stage results without wind-related instruments. Since we believe wind speed-related instruments are only valid when combined with wind direction, we only keep the two ruggedness indices and annual average temperature as our instruments. We find much larger F-statistics in both specifications.

standardized PHQ-4 index indicates worsening mental health). This is equivalent to a 11% increase in the number of respondents experiencing mild mental health symptoms.[25] This is conditional on traffic-related air pollution, which also has a negative effect on mental health albeit it is statistically significant only when we measure emissions in the larger area of 5 km radius (see Table 3). At the same time, we find that respondents' mental health deteriorates by 0.0026 standard deviations with a one-unit increase in ambient nighttime light. This effect translates to approximately 13% of respondents who previously reported minimal mental health issues exhibiting mild mental health symptoms.

The association between most control variables and mental health also align well with our expectations and intuition. Column (3) of Appendix Table A.1 shows that better education, higher income, and marriage are associated with improved mental health, which aligns with the evidence from the literature (Bartel and Taubman, 1986; Jiang et al., 2020). Like Blanchflower and Bryson (2024), we find that women are generally unhappier than men. Mental health also improves nonlinearly with age, and the results are significant at a 5% significance level. In addition, we find that respondents who live in a block group where a larger fraction of people own their current residence have better mental health.

Respondents who visit doctors more frequently, have larger BMI, and ever had diabetes or hypertension have significantly worse mental health (see Goodman et al., 2011; Kristiansen, 2021; Kesavayuth et al., 2022). We also find a positive relationship between exercise and respondents' mental health, which fits with the evidence from the literature (Windle et al., 2010). Black and Hispanic respondents have significantly better mental health compared with the base group of White respondents. Respondents whose family members ever had cancer have worse mental health, and the result is significant at a 1% level. Interestingly, whether a respondent has ever had cancer herself seems immaterial to her mental health.

[25] First, we calculate the weighted average of the standardized mental health index for each year in our sample. The weights are the fraction of respondents in the sample for each year. Then, for any specific year, for example 2018, we manipulate the data lowering of respondents whose raw phq4 index equals 2 to and raise the number of respondents with an index value of 3, indicating the marginal change from none to mild mental health problems based on HINTS' data description (see https://hints.cancer.gov/view-questions/question-detail.aspx?PK_Cycle=13&qid=1182), and calculate the new corresponding weighted average standardized mental health index. The difference between the original weighted average index and the manipulated weighted average index equals 0.0022 (the coefficient on ambient road noise in our main specification). The 11% increase in the number of respondents experiencing mild symptoms is calculated as 16/142.

While we observed significant effects at the 5 km level, we do not find significant associations between strictly local traffic-related air pollution and mental health in our sample. Although there is some evidence in the literature on the negative effects of air pollution on mental health, most of these studies focus on China (Zhang et al., 2017; Chen et al., 2018; Gu et al., 2020; Yang et al., 2021; Xie et al., 2023), which has generally much worse air quality (averaged at $29\mu g/m^3$ in 2022) than the US (averaged at $7.8\mu g/m^3$ in 2022). There is evidence that air pollution is positively associated with the suicide rate in the US, but it is at the aggregated (county) level (Persico and Marcotte, 2022). Barnor (2025) documents the adverse effects of air pollution on mental health using hospital diagnosis data, although the study is limited to Texas. To the best of our knowledge, there is no evidence in the literature indicating traffic-related air pollution directly affects individual-level mental health for the general population in the US.

We find a negative association between extreme temperature and mental health (see also Li et al. (2020) and Mullins and White (2019)). Respondents' mental health is positively associated with the number of days when the maximum daily temperature is below freezing and negatively associated with the number of days with a maximum daily temperature above $85°F$, conditional on other environmental factors. But, we do not find any significant association between solar energy and mental health.

5 Robustness Check

5.1 Measurement Error

5.1.1 Alternative Sensory Pollution Measurement

In our baseline analysis, we estimate ambient noise in a respondents' residential location as the average noise in all $30m$ pixels in the circle of 1 km radius from the centroid of the 9-digit zip code area of their street address, conditional on noise being recorded in the pixel. Here, we utilize an alternative measurement in which we assume each respondent from HINTS lives exactly at their zip-9 centroid, and we assign them the ambient noise from the DoT noise pixel that overlaps with that centroid. One limitation of this measurement is that 81% of all respondents are associated with 0 ambient noise since the centroids will not be assigned noise values unless they fall in a 30 m pixel with noise recorded on the noise map.

Column (1) in Table 4 summarizes the 2SLS estimates using the point noise measurement. The coefficient on road noise becomes negative, has a much smaller magnitude compared with the baseline estimate obtained using the within-buffer noise measurement, and is not statistically significant. Nor does traffic-generated CO_2 emissions have a statistically significant effect on mental health. The lack of statistical significance of these coefficients is likely due to the fact that less than 20% of the respondents are assigned ambient noise using the point noise approach, which contributes to a much smaller variation in the data. In column (2) of Table 4, we still find ALAN has a significantly negative impacts on mental health though we do not find any impacts of road noise when we calculate it via the point measurement.

While NASA's nighttime light maps provide a comprehensive top-to-bottom view of light pollution, humans experience of light viewed from a bottom-to-top perspective. To account for this difference in perception of light, we utilize skyglow data from Loss of the Night (LON), a web application that leverages citizen science and ground-level observations, and offers a more accurate reflection of how humans perceive light. In addition, satellites cannot adequately capture the blue part of the visible spectrum, such as light emitted by LED streelights (Kyba et al., 2017; Argys et al., 2021) whereas LON relies on human eyes as sensors. A potential shortcoming of LON data in our context is that the data are dominated by a large number of urban LON records for large cities and have relatively few rural users.

The LON mobile app utilizes Google's Sky Map and prompts users to identify specific stars in the sky. If a designated star is located, the app then instructs users to search for another dimmer star. If the dimmer star is not visible, the app guides users to locate a brighter star instead. By repeating this exercise, the LON app aims to enhance the accuracy of Naked-Eye Limiting Magnitude (NELM) values based on users' observational records. A higher NELM value indicates that more stars are visible to the naked eye, signifying less skyglow and reduced light pollution. A simple rule of thumb suggests that an increase in the NELM by one unit indicates that approximately three to four times as many stars could be seen with the naked eye.

The LON project provides precise geographic locations for each observation record. We utilize this information by drawing a buffer with a radius of 50 km centered at the zip-9 centroid of each HINTS respondent.

While a 50 km buffer is larger than our baseline 1 km radius, this choice is justified by several factors. First, the LON project offers user-reported observations of stars, and a smaller 1 km buffer would result in very limited matched respondents with star observations surrounding their residences. We assume the level of star observation is relatively uniform within the 50 km buffer, allowing us to obtain a sufficient number of observations to make reliable inferences. Second, this approach aligns with studies such as Falchi et al. (2016) and Kyba et al. (2017) that document how light pollution from urban areas can impact regions up to tens of kilometers away. By using a larger buffer, we aim to capture the extended influence of light pollution, providing a comprehensive assessment of its impact on mental health.

Within each buffer, we calculate the average NELM values from all observation records for each respondent's survey year, and assign it as the respondent's NELM measurement. The second stage results using each respondent's NELM value are reported in column (3) of Table 4. As before, we find that greater nighttime light causes mental health to deteriorate with the PHQ-4 score increasing by 0.3324 standard deviations per unit of NELM.[26]

5.1.2 Different Wind Flexibility

Although our main specification (column (3) of Table 2) uses wind direction×county fixed effects as instruments to allow for the most flexible wind instruments across respondents' geographic areas, in Appendix Table A.5 we also consider alternative specifications in which we interact wind direction with state or census division dummies. The effects of road noise remains negative and significant in the specifications without the consideration of ALAN (see columns (1) and (3)). While this specification is less flexible, the first stage regression results are stronger. The coefficient on traffic-generated air pollution while negative is no longer statistically significant.

5.2 Confounding Air Pollution

In dense urban environments, traffic-related air pollution often co-occurs with sensory pollutants such as noise and light, as all are primarily emitted by vehicles and infrastructure concentrated along major

[26] The first-stage effective F-statistic is greater than the conventional weak instrument threshold of 10, and the Anderson-Rubin weak IV test suggests a significant effect of NELM on the PHQ-4 (standardized) score.

roadways. To address the concern that our approximation of traffic-related air pollution - using $PM_{2.5}$ concentrations and CO_2 emissions from vehicles - may not fully capture localized pollution intensity, we incorporate an additional control for spatial variation in clean energy usage in an alternative specification. Alternative fuel vehicles, such as, those powered by biodiesel and electric vehicles have lower or no tailpipe emissions. Importantly for us, while EVs are far quieter than internal combustion engine vehicles at low speeds, at higher speeds alternative fuel and gasoline-powered vehicles are associated with the same roadway noise which is generated by drag due to wind resistance and tire friction against the road surface. We generate an index indicating the local clean energy demand/supply by exploiting the map of the Alternative Fueling Station Locator from the US Department of Energy.[27] This map contains all the clean energy/alternative fueling stations in the US (e.g. biodiesel, CNG, electric, ethanol, etc.), which we use to approximate the local usage of clean energy for each respondent in our sample.

To generate the local clean energy index, we first create a 5 km buffer for each respondent to approximate the range that people usually travel to fuel their vehicles. Second, within each 5 km buffer, we get the fraction of every census tract that has an intersection with the buffer and calculate the area-weighted population density for each buffer based on US Census Data (2020). Finally, we generate *CSperwpd* by using the count of all clean energy/alternative fueling stations within each buffer divided by its weighted population density to approximate the local clean energy usage for each respondent. The larger value of *CSperwpd*, the more clean energy supply/demand, and the lower the tailpipe emissions, in the respondents' local neighborhood.[28] We add the interaction between *roadnoise1km* and *CSperwpd* as an additional control variable to further disentangle the impact of air pollution, conditional on the ambient noise level.

We report our results in column 1 and 2 of Table 5. We do not find have any statistically significant effect of traffic related air pollution on respondents' mental health, while the negative effect of road noise on mental health remains significant at the 5% level.

[27] The Alternative Fueling Stations dataset is updated daily by the National Renewable Energy Laboratory (NREL) and we accessed it on May 2nd, 2023. Unfortunately, we do not have the historical location of clean energy stations and there were probably far fewer clean energy stations during the early waves of the HINTS data that we use. Thus, by assigning clean energy fueling stations to locations where there were none, we obtain a lower bound, but possibly biased, estimate of the causal effect of noise on mental health. For data details, refer to https://afdc.energy.gov/stations/#/find/nearest.

[28] The mean of *CSperwpd* is 0.0073 with a standard deviation of 0.0154. The 50%, 75%, 90%, and 95% percentiles are 0.0045, 0.0089, 0.0162, and 0.0230, respectively.

5.3 Hearing Impaired Sample

HINTS includes a question on hearing impairment: "Are you deaf or do you have serious difficulty hearing?" Approximately 7%-9% of all respondents answered "Yes" to this question across the five waves. We run a "placebo test" by comparing the results for a group of respondents who are hearing impaired with those who are not. The 2SLS results are shown in Table 6 and Appendix Table A.4. The sample size is much smaller for the group of respondents who are hearing impaired, and since these respondents may have unobservable characteristics that are correlated with mental health, we are cautious to ascribe causality to the estimates from this model. Still, it is notable that there is no significant effect of ambient noise on the mental health of the hearing-impaired respondents whereas there is a negative and statistically significant effect of ambient road noise on mental health for those without any hearing impairment (see column (2) of Appendix Table A.4).[29] We should also note that while hearing-impaired respondents are immune to the effects of ambient noise, they receive the same effects of air pollution as non-hearing-impaired respondents, though the coefficient is not significant for the hearing-impaired sample. The comparison between these two sub-samples reinforces our argument that the effect of ambient noise is independent of air pollution.

To account for systematic differences in the spatial distribution of the hearing-impaired respondents from other respondents, we extract another sub-sample of hearing-impaired and non-impaired respondents from the counties where the hearing-impaired respondents reside by survey year (see column (4) of Table 6). We find a significantly negative (at 5%) effect of road noise on mental health for this sub-sample of respondents allaying fears that the lack of statistical significance for the sub-sample of hearing-impaired respondents is driven by geographically correlated unobservables.

Finally, we also extract a sub-sample of senior citizens (60+ years) from the general sample without any hearing impairment. While this group of respondents does not report hearing impairment, the National Institute on Aging reports that nearly one third of older adults have hearing loss and that many older adults are unaware or don't want to admit that they have a problem with hearing. We do not find road noise has a significantly negative effect on these respondents' mental health (see column (3) of Table 6).

[29]Note that the number of observations in columns 1 and 2 of Table 6 does not add up to our full sample size of 14,030 because the question on hearing impairment is not surveyed in 2014.

Ideally, we would also like to conduct a similar analysis for respondents with vision impairments. However, in the HINTS data, only the 2012 and 2013 waves include questions on vision problems, and we do not have the corresponding ZIP code information for any waves prior to 2014. As a result, we cannot construct meaningful measures of sensory pollution for respondents in those waves, nor can we conduct a comparable analysis using the same framework.

6 Noise, Light, Sleep Deprivation and Mental Health

To better understand the pathways through which sensory pollution influences mental health, we explore the potential mechanisms linking noise and light pollution to individual well-being. The deleterious effect of noise works mainly through the activation of the hypothalamic pituitary adrenal (HPA) axis in the brain (Hoffmann, 2018), which is a significant part of the human central stress response system. The activation of the HPA axis can lead to the release of stress hormones and contribute to sleep disturbance (Argys et al., 2020). There is strong evidence that sleep quality is a key mediator of mental health outcomes. Also, artificial outdoor nighttime light is linked to altered sleep behavior in the US general population (Ohayon and Milesi, 2016). Light pollution directly interferes with natural light-dark cycles and disrupts the circadian rhythm of organisms, leading to adverse effects. Individuals living in regions with elevated nighttime light typically encounter delayed bedtime and wake-up times, shortened sleep durations, and heightened daytime sleepiness (Cao et al., 2023). On the other side, sleep issues are frequently observed in individuals with mental health disorders. Freeman et al. (2017) offer strong evidence suggesting that insomnia plays a causal role in the development of psychotic experiences and other mental health challenges.

In the HINTS surveys, respondents were asked the following questions in three waves (2011, 2012, and 2013): "How much sleep do you usually get on a workday or school day (i.e., weekday)? Hours & Minutes"; "How much sleep do you usually get on a non-work or non-school day (i.e., weekend)? Hours & Minutes". We use the answers to these questions to calculate the daily average sleep within a week for every respondent from these three waves. However, the 5-digit/9-digit residential zip code information is not available for the three waves with sleep data. We are restricted to utilizing the average county-level noise pollution from the available three waves (2016, 2018, and 2020) as an approximation.[30] We also include some individual-level demographic information that could be correlated with sleep duration. Liu et al. (2020) report that air pollutants are negatively associated with sleep health and we control for county-level average traffic generated CO_2 emissions and $PM_{2.5}$ concentrations to approximate air pollutants. The reduced-form specification for individual i residing in county c in survey year t is as follows:

$$
\begin{aligned}
Avgsleep_{ict} = \beta_0 + \gamma_1 Sensorypollution_{ct} + \gamma_2 CO_2Emission_{ct} + \gamma_3 PM_{2.5}Concentration_{ct} \\
+\beta_1 Female_{ict} + \beta_2 Urban_{ict} + \beta_3 Married_{ict} \\
+\beta_4 Age_{ict} + \beta_5 Age^2_{ict} + \beta_6 Educ_{ict} + \beta_7 Hhnum_{ict} + \beta_8 Race_{ict} + \beta_9 Income_{ict} \\
+\lambda_1 DocVis_{ict} + \lambda_2 Cancer_{ict} + \lambda_3 CancerFam_{ict} \\
+\lambda_4 BMI_{ict} + \lambda_5 Exercise_{ict} + \lambda_6 Own_{ict} + \epsilon_{ict}
\end{aligned}
\tag{4}
$$

We keep most of the individual-level variables from Eq.(1) though information on some health conditions is not available in these three waves (e.g. whether the respondent suffers from diabetes and hypertension). However, information about whether a respondent owns their current residence is available in these three waves, so we are able to include it at an individual level instead of the block group level.

The estimated coefficients from Eq.(4) fit our intuition and expectations well. We find that respondents with higher education levels, larger households, higher BMI values, and older respondents, have significantly less sleep whereas female and married respondents have significantly more sleep.

Most notably, we find that average road noise in the county has a significantly negative impact on respondents' sleep duration which is reduced by around 2.3 minutes when the ambient road noise increases by 1 dB. This effect is primarily driven by reductions in weekend sleep, which declines by about 5 minutes per 1 dB increase in noise and is statistically significant at the 1% level (column 3 of 7), whereas the impact on weekday sleep is smaller and statistically insignificant (column 2). This suggests that individuals may be more sensitive to environmental noise during weekends, when they have more flexibility in their sleep schedules. We also find that average traffic-generated CO_2 emissions and $PM_{2.5}$ concentrations are

[30] We reiterate that noise pollution is a very local pollution source, and we anticipate measurement errors when we utilize the average noise exposure in a relatively large area.

negatively associated with sleep duration, but the estimates are not statistically significant. However, we do not find a significant impact of ALAN on sleep duration.

7 Conclusion

It is well established that the human stress response system is triggered by non-chemical stimulants such as light and noise (Jariwala et al., 2017, Kumar et al., 2019). The resulting release of stress hormones can fragment and disrupt sleep, increase oxidative stress in the vasculature and brain, and ultimately affect mental health (Münzel et al., 2021). The United States is singular among developed nations in its high prevalence of mental health disorders (Tikkanen et al., 2020). At the same time, it is characterized by one of the highest rates of private vehicle ownership and the most extensive network of roadways. Not surprisingly, the regulation of noise and light pollution has emerged as a growing policy concern. The Quiet Communities Act of 2021, introduced in the U.S. House of Representatives, requires the EPA to reestablish the Office of Noise Abatement and Control to support local noise control programs, research, and education. Yet, despite the pervasive nature of traffic noise, the lack of high-frequency, nationally representative data on roadway noise and congestion hampers our understanding of its health consequences. Until federal agencies such as the EPA or DoT systematically collect and disseminate such data, many of these questions will remain unaddressed.

Nonetheless, recognizing the urgency of sensory pollution as a public health risk, this study focuses on general vehicular noise from major roadways, ALAN, and their potential role in the elevated incidence of mental health issues in the U.S. Leveraging variation in topography, daily wind conditions, cloud cover, and annual temperature, we identify exogenous variation in ambient roadway noise exposure and ALAN. Our empirical design reveals robust causal evidence of the negative effects of both sensory pollution on mental health among approximately 14,000 adults surveyed by the National Cancer Institute, even after controlling for co-generated vehicular air pollution and average daily solar energy. Sleep disruption plays a central role in the noise–mental health relationship. This result is consistent with a broader literature linking stress hormones and sleep loss to adverse mental outcomes, and supports the plausibility of the stress–sleep–mental health pathway in our context.

Beyond roadway noise, our study also provides the first causal estimates of the effect of ALAN on adult mental health in the U.S., leveraging precise geolocation-linked light exposure and novel instruments to overcome endogeneity. Although 19 states, the District of Columbia, and Puerto Rico have enacted light abatement laws, more proactive federal or regional coordination, such as using fully shielded, warm-spectrum, and adaptive energy-efficient lighting and expanding "dark-sky" zoning, may yield considerable health benefits.

To quantify these benefits, we translate our estimates into economic terms. Based on wage and employment losses associated with mild depressive symptoms documented in Germinario et al. (2022), we estimate that the marginal increase in mild mental illness symptoms caused by each additional decibel of road noise results in an annual welfare loss of $12 billion. For light pollution, the analogous calculation yields a $13 billion annual loss. These estimates are conservative, excluding indirect costs related to health care use, absenteeism, and broader spillovers into productivity and well-being.

Taken together, our findings show that non-chemical sensory pollutants, long neglected in economic analyses of environmental quality, have measurable and meaningful effects on mental health. Our dual focus on noise and light pollution fills an important gap in the literature, and we demonstrate that both stressors independently degrade well-being. By leveraging rich microdata and quasi-experimental variation, we provide a robust empirical foundation for incorporating these exposures into environmental and public health policy.

As policymakers debate how to invest in infrastructure, climate resilience, and mental health services, our findings underscore the urgency of incorporating environmental sensory exposures into regulatory frameworks. Relatively low-cost interventions, such as noise barriers, quiet pavement, improved urban planning, or dark-sky ordinances, could offer significant returns in population mental health, particularly in high-density areas. The economic rationale is compelling, and the potential for improved quality of life is substantial.

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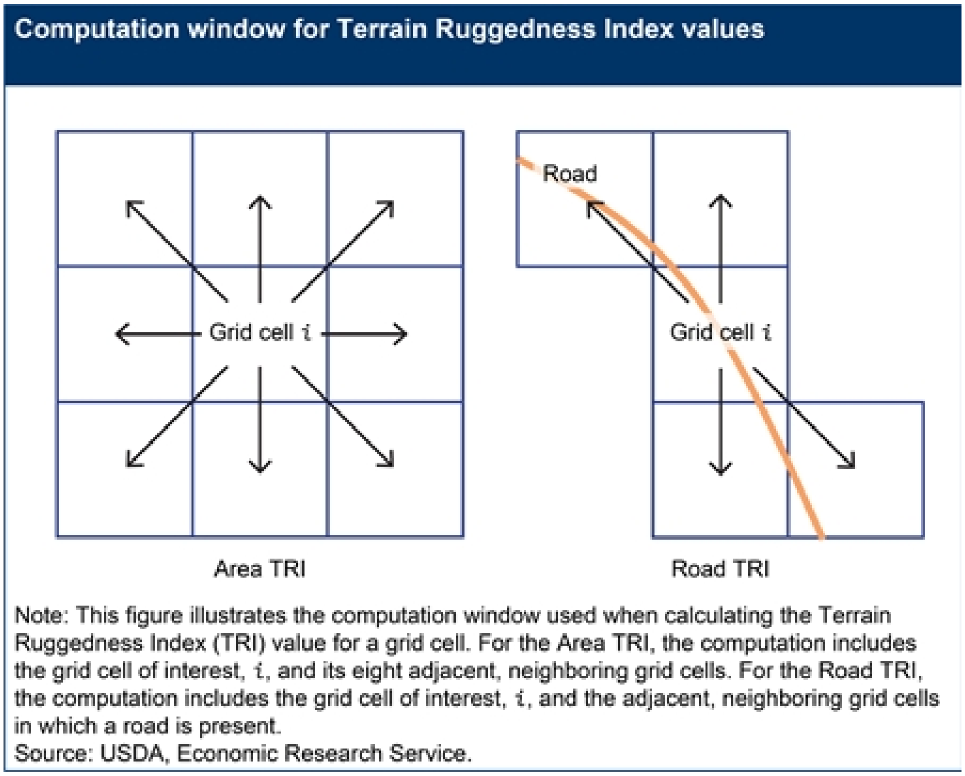
Figures

FIGURE 1 –TERRAIN RUGGEDNESS INDEX COMPUTATION



Note: From Area and Road Ruggedness Scales - Documentation, by U.S. Department of Agriculture, Economic Research Service, 2023. https://www.ers.usda.gov/data-products/area-and-road-ruggedness-scales/documentation

Figure 2 –Institution Noise Map

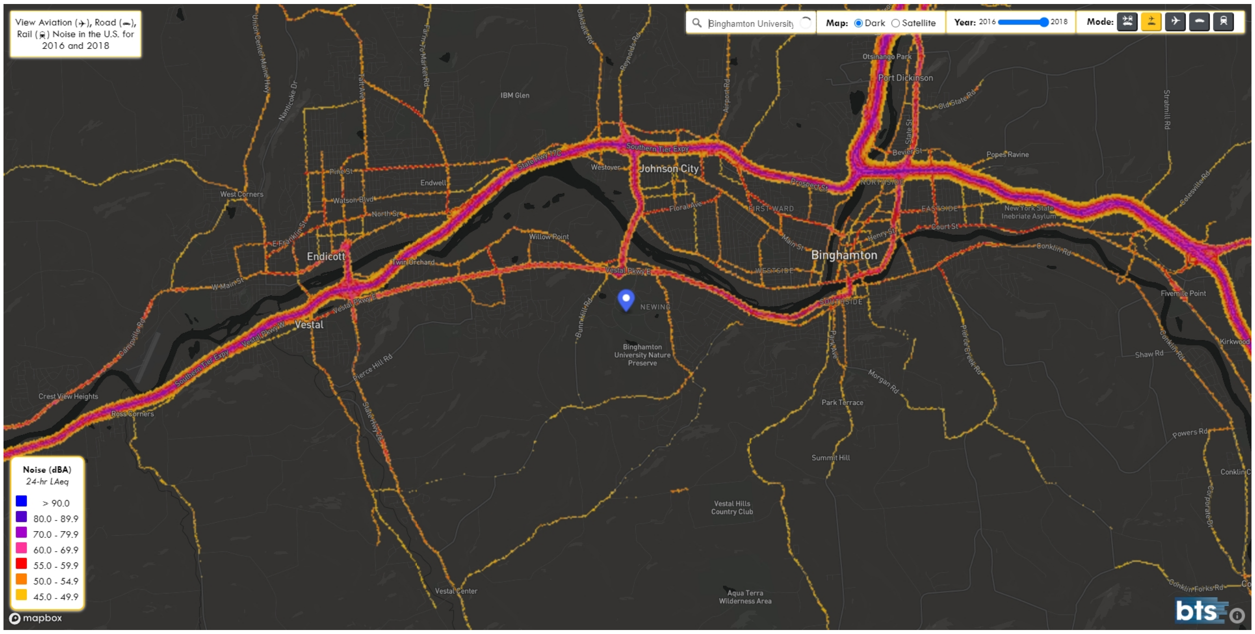
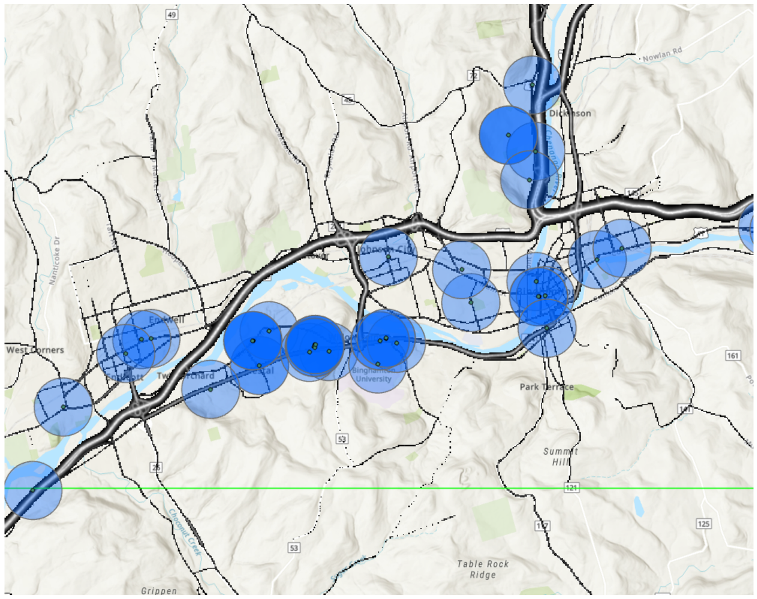
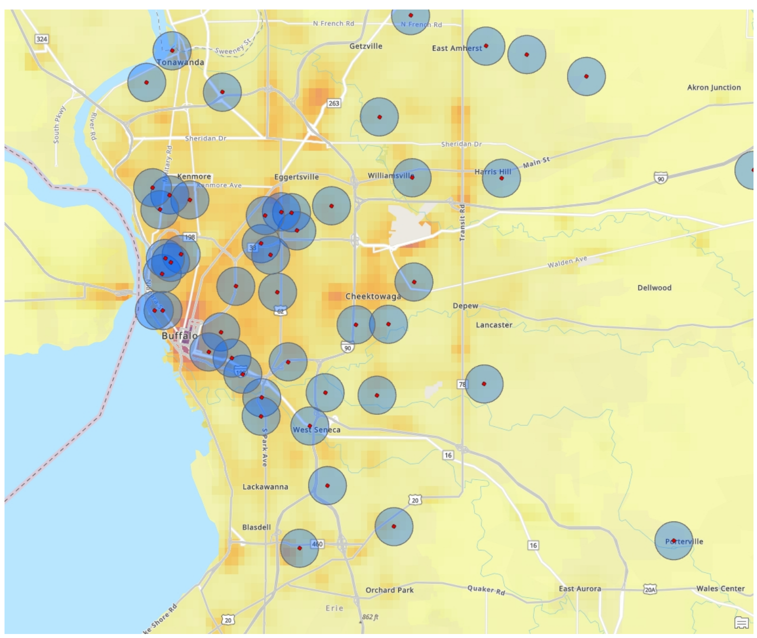


Figure 3 –Noise Buffers and Light Buffers



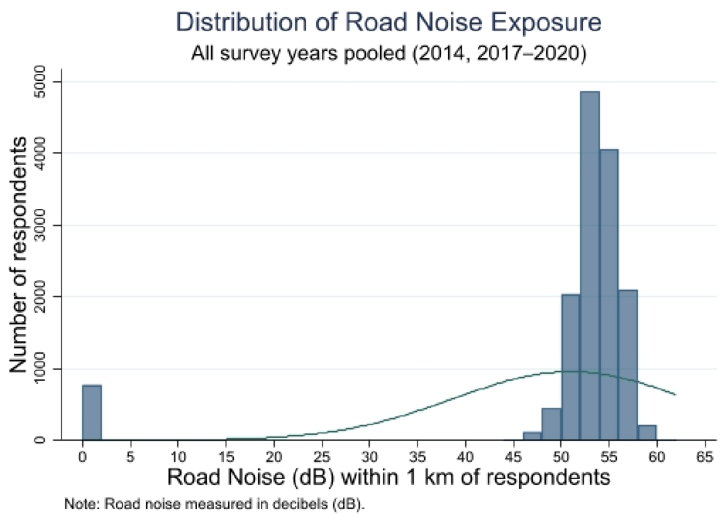
(a) Noise Buffers for Hypothetical HINTS Respondents



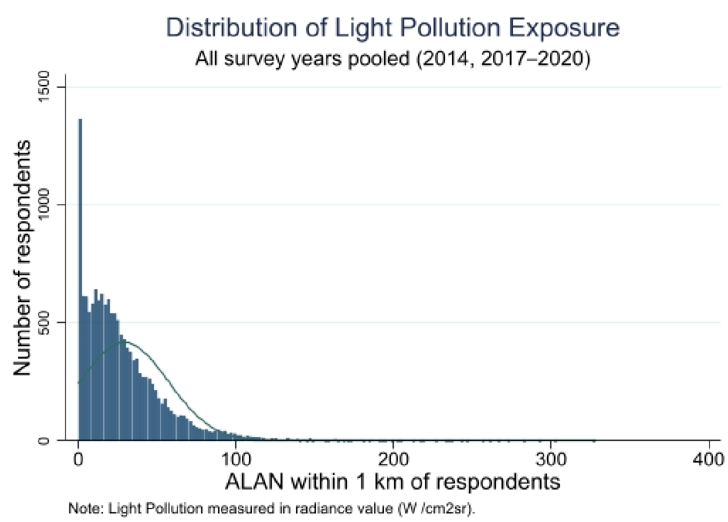
(b) Light Buffers for Hypothetical HINTS Respondents

Note: These figures depict the buffer approach for estimating environmental exposures. Each red circle marks a hypothetical HINTS respondent's location based on their 9-digit ZIP code centroid. Noise and light exposures are computed by averaging pollution intensity within a 1km radius (blue circle) surrounding each respondent. Panel A shows the noise pollution buffer for a hypothetical respondent. Panel B shows the nighttime light pollution buffer using the same spatial method.

Figure 5 –Distribution of Seneroy Pollution (all survey years pooled).

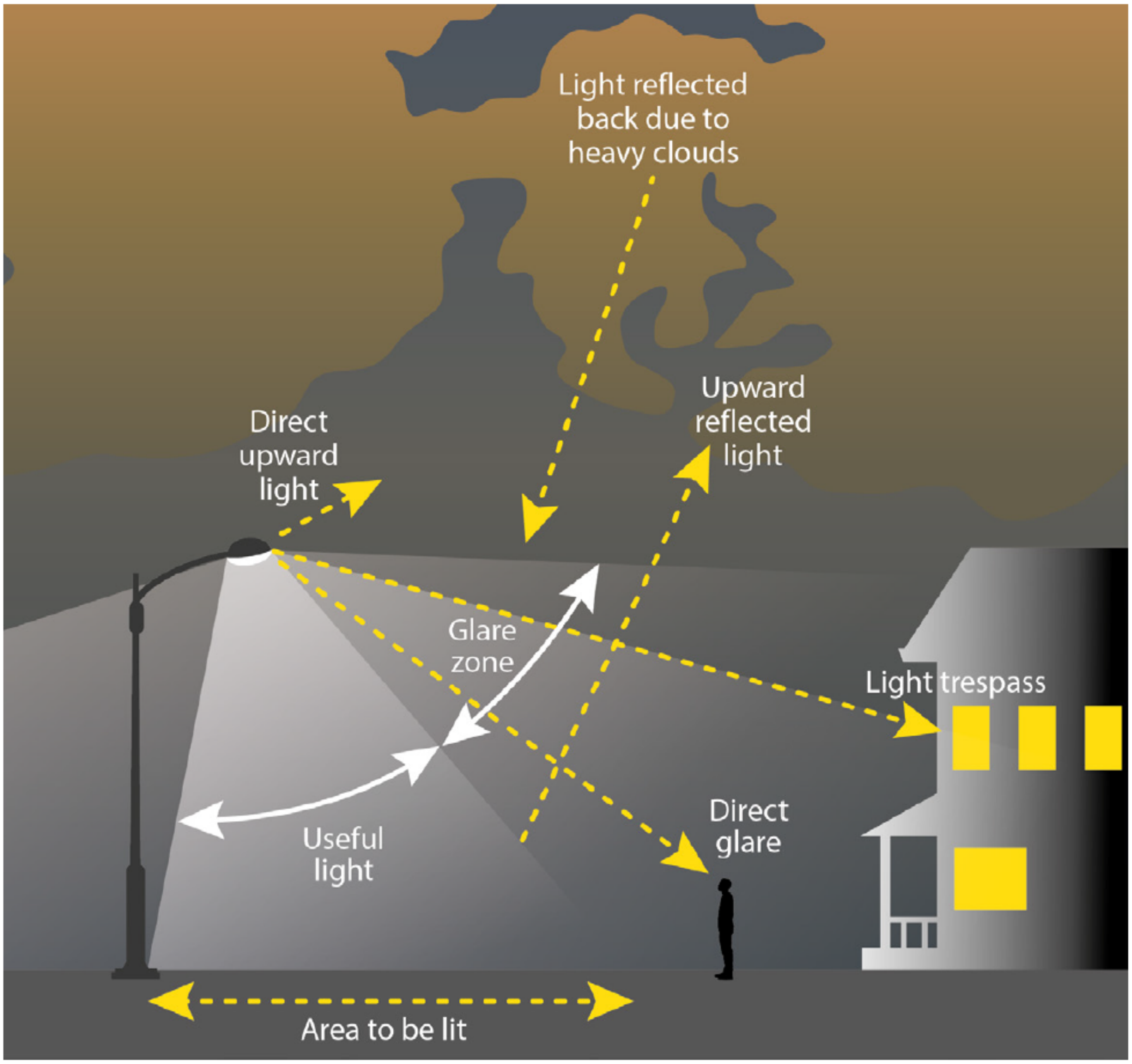


(a) Distribution of road noise exposure (all survey years pooled).



(b) Distribution of Light Pollution exposure (all survey years pooled)

Figure 6 –Light Pollution and Cloud Cover



Note: This figure illustrates the different forms of light pollution and showcases the correlation between cloud cover and light pollution. Source: Bureau of Land Management (BLM). (2021). *Night Sky and Dark Environments: Best Management Practices for Artificial Light at Night on BLM-Managed Lands*. U.S. Department of the Interior, Bureau of Land Management, p.14.

Tables

Table 1 –Data Summary

Descriptive Statistics	Mean	SD
Mental health index		
PHQ-4 Score (raw index)	1.90	2.79
PHQ-4 Score (standardized)	-0.00	0.99
Seneroy Pollution		
Road Noise Pollution (1km)	50.96	12.24
ALAN (W/cm^2sr)	29.03	28.01
Zip-9 CO_2 emission (Kton/year)	4.99	9.61
Zip-9 $PM_{2.5}$ concentration (μg/m^3)	7.65	1.76
Demographics variable		
Age(years)	55.19	16.51
Female (percentage)	0.58	0.49
Married (percentage)	0.51	0.50
White (percentage)	0.63	0.48
Hispanic (percentage)	0.15	0.36
Black (percentage)	0.14	0.35
Other race (percentage)	0.08	0.27
Own house (percentage)	0.55	0.25
Household Size (number of people)	2.43	1.45
College graduate (percentage)	0.28	0.45
Income ($50K-$75K) (percentage)	0.18	0.38
Health indices		
Exercise (days/week)	2.75	2.24
Body Mass Index	28.44	6.59
Diabetes (percentage)	0.20	0.40
Hypertension (percentage)	0.43	0.50
Had cancer (percentage)	0.15	0.36
Family had cancer (percentage)	0.56	0.50
Environmental factors		
Zip-5 Annual average temp (°F)	60.13	8.46
Zip-5 During-survey solar energy (MJ/m^2)	15.16	4.14
Zip-5 During-survey nighttime cloud cover (%)	43.18	12.67
Daily maximum temperature below freezing (days/year)	6.28	10.93
Daily maximum temperature above 85$\circ$F (days/year)	18.50	20.88

Note: N=14,640

Table 2 –Baseline Results - The Impact of Pollution (1km) on Mental Health

	IV			OLS
	(1) Noise Pollution	(2) Light Pollution	(3) All Sensory Pollutants	(4) All Sensory Pollutants
Road Noise Pollution (1km)	0.0027**		0.0022*	0.0014*
	(0.0012)		(0.0012)	(0.0008)
CO_2 emission (1km)	0.0040		0.0022	-0.0003
	(0.0033)		(0.0036)	(0.0009)
$PM_{2.5}$ concentration (1km)	0.0003		0.0003	-0.0040
	(0.0143)		(0.0143)	(0.0093)
ALAN (1km)		0.0109**	0.0026**	0.0013***
		(0.0046)	(0.0012)	(0.0005)
Individual controls	✓	✓	✓	✓
Environmental controls	✓	✓	✓	✓
County-level Fixed Effect	✓	✓	✓	✓
Year Fixed Effect	✓	✓	✓	✓
Instrument Variables:				
County × wind direction	✓	-	✓	-
Nighttime Cloud Cover	-	✓	✓	-
Other Instruments	✓	-	✓	-
Observations	14,030	14,030	14,030	14,030

Notes: Road noise refers to the ambient roadway noise in the 1km buffer surrounding the centroid of each respondent's 9-digit zip code area. Note that a higher value for the standardized mental health index indicates worse mental health. Other Instruments include the area ruggedness index, road ruggedness index, annual average temperature, wind speed, and maximum wind speed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 –The Impact of Pollution on Mental Health (Air Pollution within 5km)

	IV			OLS
	(1) Noise Pollution	(2) Light Pollution	(3) All Sensory Pollutants	(4) All Sensory Pollutants
Road Noise Pollution (1km)	0.0026**		0.0022*	0.0013*
	(0.0012)		(0.0012)	(0.0008)
CO_2 emission (5km)	0.0117**		0.0106*	0.0004
	(0.0052)		(0.0058)	(0.0025)
$PM_{2.5}$ concentration (5km)	-0.0070		-0.0058	-0.0038
	(0.0145)		(0.0146)	(0.0098)
ALAN (1km)		0.0109**	0.0018	0.0013***
		(0.0046)	(0.0013)	(0.0005)
Individual controls	✓	✓	✓	✓
Environmental controls	✓	✓	✓	✓
County-level Fixed Effect	✓	✓	✓	✓
Year Fixed Effect	✓	✓	✓	✓
Instrument Variables:				
County × wind direction	✓	-	✓	-
Nighttime Cloud Cover	-	✓	✓	-
Other Instruments	✓	-	✓	-
Observations	14,030	14,030	14,030	14,030

Notes: Road noise refers to the ambient roadway noise in the 1km buffer surrounding the centroid of each respondent's 9-digit zip code area. We measure CO_2 emission and $PM_{2.5}$ concentration in the 5km buffer to capture more surrounding air pollution. Note that a higher value for the standardized mental health index indicates worse mental health. Other Instruments include the area ruggedness index, road ruggedness index, annual average temperature, wind speed, and maximum wind speed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 – Alternative Measurement for Noise and Light

	Alternative Noise Measurement		Alternative Light Meausrement - NELM		All Alternative Measurement
	(1) Noise Pollution	(2) All Sensory Pollutants	(3) Light Pollution	(4) All Sensory Pollutants	(5) All Sensory Pollutants
Point Road Noise	-0.0001	-0.0004			-0.0003
	(0.0009)	(0.0009)			(0.0012)
Road Noise Pollution (1km)				0.0034**	
				(0.0016)	
CO_2 emission (1km)	0.0051	0.0027		0.0043	0.0056*
	(0.0033)	(0.0036)		(0.0034)	(0.0034)
$PM_{2.5}$ concentration (1km)	0.0028	0.0017		-0.0025	-0.0001
	(0.0142)	(0.0143)		(0.0159)	(0.0159)
ALAN (1km)		0.0030**			
		(0.0012)			
NELM			-0.3324**	0.0053	0.0055
			(0.1401)	(0.0154)	(0.0154)
Individual controls	✓	✓	✓	✓	✓
Environmental controls	✓	✓	✓	✓	✓
County-level Fixed Effect	✓	✓	✓	✓	✓
Year Fixed Effect	✓	✓	✓	✓	✓
Instrument Variables:					
County × wind direction	✓	✓	-	✓	✓
Nighttime Cloud Cover	-	✓	✓	✓	✓
Other Instruments	✓	✓	-	✓	✓
Observations	14,030	14,030	11,294	11,294	11,294

Notes: Point Road Noise provides an alternative approach to measuring noise pollution, whereas NELM provides an alternative approach to measuring light pollution. Other Instruments include the area ruggedness index, road ruggedness index, annual average temperature, wind speed, and maximum wind speed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 –Robustness Check for Confounding Air Pollution: 2SLS Estimates

	Air Pollution within 1 km	Air Pollution within 5 km
	(1)	(2)
Road Noise Pollution (1km)	0.0023*	0.0023*
	(0.0012)	(0.0012)
CSwpd × Road noise	-0.0090	-0.0101
	(0.0171)	(0.0170)
ALAN (1km)	0.0026**	0.0018
	(0.0012)	(0.0013)
CO_2 emission (1km)	0.0023	
	(0.0036)	
$PM_{2.5}$ concentration (1km)	0.0001	
	(0.0143)	
CO_2 emission (5km)		0.0108*
		(0.0058)
$PM_{2.5}$ concentration (5km)		-0.0061
		(0.0146)
Individual controls	✓	✓
Environmental controls	✓	✓
County-level Fixed Effect	✓	✓
Year Fixed Effect	✓	✓
Instrument Variables:		
County × wind direction	✓	✓
Nighttime Cloud Cover	✓	✓
Other Instruments	✓	✓
Observations	14,030	14,030

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 6 –HEARING IMPAIRED/NON-HEARING IMPAIRED SUB-SAMPLE: 2SLS ESTIMATES

	HI	NHI	ENHI	Comparable Sample
	(1)	(2)	(3)	(4)
Road Noise Pollution (1km)	-0.0033	0.0019	0.0019	0.0040**
	(0.0076)	(0.0013)	(0.0018)	(0.0020)
ALAN (1km)	0.0001	0.0023*	0.0018	0.0020
	(0.0036)	(0.0013)	(0.0016)	(0.0014)
CO_2 emission (1km)	0.0027	0.0041	0.0001	0.0028
	(0.0072)	(0.0034)	(0.0040)	(0.0043)
$PM_{2.5}$ concentration (1km)	0.0139	-0.0051	-0.0238	0.0089
	(0.0664)	(0.0163)	(0.0243)	(0.0170)
Individual controls	✓	✓	✓	✓
Environmental controls	✓	✓	✓	✓
County-level Fixed Effect	✓	✓	✓	✓
Year Fixed Effect	✓	✓	✓	✓
Instrument Variables:				
County × wind direction	✓	✓	✓	✓
Nighttime Cloud Cover	✓	✓	✓	✓
Other Instruments	✓	✓	✓	✓
Observations	583	10,466	3,906	10,687

Notes: The headings HI, NHI, and ENHI represent hearing impaired, non-hearing impaired, and elderly non-hearing impaired, respectively. Column 4 consists of another sub-sample of hearing-impaired and non-impaired respondents from the counties where the hearing-impaired respondents reside by survey year. Note that a higher value for the standardized mental health index indicates worse mental health. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 7 –NOISE, LIGHT, AND SLEEP DEPRIVATION

	Avergae Sleep Time(mins)	Workday Sleep Time(mins)	Weekend Sleep Time(mins)
	(1)	(2)	(3)
Average Road Noise	-2.2717*	-1.1418	-5.0962***
	(1.3314)	(1.4490)	(1.5442)
Average ALAN	-0.0018	-0.0168	0.0357
	(0.1329)	(0.1446)	(0.1541)
CO_2 emission	-0.3043	-0.3210	-0.2623
	(0.9406)	(1.0237)	(1.0909)
$PM_{2.5}$ concentration	-0.3449	-0.2665	-0.5409
	(0.6072)	(0.6608)	(0.7042)
Individual controls	✓	✓	✓
Environmental controls	✓	✓	✓
Observations	8,010	8,010	8,010

Notes: Columns (1)–(3) calculate sleep measures using responses to the following survey questions: "How much sleep do you usually get on a workday or school day (i.e., a weekday)? (Hours and minutes)" and "How much sleep do you usually get on a non-work or non-school day (i.e., a weekend)? (Hours and minutes)." All pollution exposure estimates are measured at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix

A Tables

Table A.1 –Full Model Specifications (OLS)

	1km		
	(1)	(2)	(3)
	Noise Pollution	Light Pollution	All Sensory Pollutants
Education: High School	-0.0565*	-0.0559*	-0.0559*
	(0.0304)	(0.0304)	(0.0304)
Education: College (Not Graduate)	-0.0403	-0.0400	-0.0397
	(0.0288)	(0.0288)	(0.0288)
Education: College (Graduate)	-0.0920***	-0.0924***	-0.0919***
	(0.0291)	(0.0291)	(0.0291)
Education: Postgraduate	-0.1152***	-0.1168***	-0.1168***
	(0.0318)	(0.0318)	(0.0318)
Gender	0.0777***	0.0785***	0.0783***
	(0.0170)	(0.0170)	(0.0170)
Marital Status	-0.1503***	-0.1495***	-0.1486***
	(0.0195)	(0.0195)	(0.0195)
Age	-0.0071**	-0.0066**	-0.0066**
	(0.0030)	(0.0030)	(0.0030)
agesqr	-0.0000*	-0.0001*	-0.0001*
	(0.0000)	(0.0000)	(0.0000)
Household Size (number of people)	0.0024	0.0038	0.0037
	(0.0066)	(0.0066)	(0.0066)
Race: Black	-0.2274***	-0.2278***	-0.2284***
	(0.0269)	(0.0269)	(0.0269)
Race: Hispanic	-0.0510*	-0.0530**	-0.0533**
	(0.0265)	(0.0265)	(0.0265)
Other Race	-0.0148	-0.0154	-0.0160
	(0.0316)	(0.0316)	(0.0316)
History of Cancer	0.0220	0.0221	0.0219
	(0.0240)	(0.0240)	(0.0240)
Family History of Cancer	0.0664***	0.0675***	0.0671***
	(0.0203)	(0.0203)	(0.0203)
Family Income Ranges: 20,000 - 34,999 dollars	-0.2564***	-0.2539***	-0.2546***

Continued on next page

	1km		
	(1)	(2)	(3)
	Noise Pollution	Light Pollution	All Sensory Pollutants
	(0.0304)	(0.0304)	(0.0304)
Family Income Ranges: 35,000 - 49,999 dollars	-0.3320***	-0.3300***	-0.3300***
	(0.0306)	(0.0306)	(0.0306)
Family Income Ranges: 50,000 - 74,999 dollars	-0.4056***	-0.4032***	-0.4037***
	(0.0295)	(0.0295)	(0.0295)
Family Income Ranges: 75,000 - 99,999 dollars	-0.4523***	-0.4499***	-0.4502***
	(0.0328)	(0.0328)	(0.0328)
incomehigh	-0.4830***	-0.4813***	-0.4806***
	(0.0312)	(0.0312)	(0.0312)
Doctor, nurse, or other health professional health care (per month)	0.0381***	0.0382***	0.0382***
	(0.0029)	(0.0029)	(0.0029)
Physical Activity or Exercise (per week)	-0.0426***	-0.0428***	-0.0427***
	(0.0038)	(0.0038)	(0.0038)
Body Mass Index	0.0046***	0.0046***	0.0046***
	(0.0014)	(0.0014)	(0.0014)
Diabetes or High Blood Sugar	0.1457***	0.1461***	0.1458***
	(0.0224)	(0.0224)	(0.0224)
High Blood Pressure of Hypertension	0.0891***	0.0888***	0.0889***
	(0.0193)	(0.0193)	(0.0193)
Zip-9 level fraction of people own home	-0.1690***	-0.1290***	-0.1278***
	(0.0356)	(0.0383)	(0.0383)
Number of Days (year) with daily maximum temperature below freezing	0.0001	0.0002	0.0002
	(0.0018)	(0.0018)	(0.0018)
Number of Days (year) with daily maximum temperature above $85°$F	0.0010	0.0010	0.0010
	(0.0009)	(0.0009)	(0.0009)
Zip-5 Solar energy (MJ/m^2)	-0.0001	0.0000	0.0000
	(0.0030)	(0.0030)	(0.0030)
Road Noise Pollution (1km)	0.0016**		0.0014*
	(0.0008)		(0.0008)
Carbon Dioxide (1km)	0.0003	-0.0002	-0.0003
	(0.0009)	(0.0009)	(0.0009)
PM2.5 (1km)	-0.0010	-0.0032	-0.0040
	(0.0093)	(0.0093)	(0.0093)

Continued on next page

	1km		
	(1)	(2)	(3)
	Noise Pollution	Light Pollution	All Sensory Pollutants
Light Pollution (1km)		0.0014***	0.0013***
		(0.0005)	(0.0005)
Constant	0.7602***	0.7711***	0.7093***
	(0.1309)	(0.1270)	(0.1320)
Observations	14,030	14,030	14,030

Notes: Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2 –2SLS First-stage Results - Part 1

	Panel A:		
	Dependent variable: Road noise		
	(1)	(2)	(3)
RoadTRI	0.1907***	0.2374***	0.2334***
	(0.0206)	(0.0232)	(0.0231)
AreaTRI	-0.16815***	-0.2113***	-0.2099***
	(0.0144)	(0.0156)	(0.0155)
Averagetemp	0.2403***	0.1709*	0.1737**
	(0.0812)	(0.0892)	(0.0868)
Windspeed	0.2980**	0.4246***	0.3502***
	(0.1205)	(0.1170)	(0.1135)
Windspeed Maximum	-0.0590	-0.1155*	-0.1004
	(0.0754)	(0.0688)	(0.0666)
Nighttime Cloud Cover	0.0179	0.0031	0.0018
	(0.0174)	(0.0180)	(0.0174)
First-stage F Statistic	4.04	3.55	7.85
County × wind direction	✓	-	-
State × wind direction	-	✓	-
Census Division × wind direction	-	-	✓

	Panel B:		
	Dependent variable: CO_2 *emission*		
	(1)	(2)	(3)
RoadTRI	0.0699***	0.0774***	0.0757***
	(0.0246)	(0.0203)	(0.0209)
AreaTRI	-0.0684***	-0.0685***	-0.0647***
	(0.0171)	(0.0137)	(0.0141)
Averagetemp	0.3465***	0.2901***	0.2963***
	(0.0965)	(0.0716)	(0.0788)
Windspeed	0.1806**	-0.0343	-0.0563
	(0.1432)	(0.1020)	(0.1030)
Windspeed Maximum	-0.1234	-0.0279	0.0021
	(0.0897)	(0.0603)	(0.0604)
Nighttime Cloud Cover	0.0935	0.0594***	0.0592***
	(0.0207)	(0.0150)	(0.0158)
First-stage F Statistic	0.37	1.40	3.32
County × wind direction	✓	-	-
State × wind direction	-	✓	-
Census Division × wind direction	-	-	✓

Notes: All regressions include county and year fixed effects with observations of 14,033. For brevity, we do not report the first stage results for the wind direction×geographic area terms. The first-stage F-values of columns (1)-(2) are small which is expected given the large number of instruments relative to the sample size when we interact wind directions with counties. We also observe that F-values increase when we use larger geographic areas to interact with wind directions* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3 –2SLS First-stage Results - Part 2

	Panel C:		
	Dependent variable: $PM_{2.5}$ *concentration*		
	(1)	(2)	(3)
RoadTRI	0.0051***	0.0051***	0.0059***
	(0.0018)	(0.0018)	(0.0019)
AreaTRI	-0.0117***	-0.0118***	-0.0124***
	(0.0013)	(0.0012)	(0.0013)
Averagetemp	0.0457***	0.0384***	0.0265***
	(0.0072)	(0.0064)	(0.0072)
Windspeed	-0.0297***	-0.0415***	-0.0363***
	(0.0106)	(0.0091)	(0.0094)
Windspeed Maximum	-0.1457***	-0.0915***	-0.0842***
	(0.0067)	(0.0054)	(0.0604)
Nighttime Cloud Cover	0.0191***	0.0082***	0.0066***
	(0.0015)	(0.0013)	(0.0014)
First-stage F Statistic	3.53	13.36	33.86
County × wind direction	✓	-	-
State × wind direction	-	✓	-
Census Division × wind direction	-	-	✓

	Panel D:		
	Dependent variable: ALAN (1km)		
	(1)	(2)	(3)
RoadTRI	0.1351***	0.1714***	0.1508***
	(0.0471)	(0.0402)	(0.0408)
AreaTRI	-0.3093***	-0.3097***	-0.2816***
	(0.0329)	(0.0270)	(0.0274)
Averagetemp	1.378***	1.1891***	1.2858***
	(0.1851)	(0.1416)	(0.1535)
Windspeed	0.7872***	0.5387***	0.3521*
	(0.2747)	(0.2017)	(0.2006)
Windspeed Maximum	-0.4159**	-0.2454***	-0.1483
	(0.1720)	(0.1192)	(0.1178)
Nighttime Cloud Cover	0.4593***	0.3229***	0.3055***
	(0.0397)	(0.0297)	(0.0308)
First-stage F Statistic	0.93	5.57	15.11
County × wind direction	✓	-	-
State × wind direction	-	✓	-
Census Division × wind direction	-	-	✓

Notes: All regressions include county and year fixed effects with observations of 14,033. For brevity, we do not report the first stage results for the wind direction×geographic area terms. The first-stage F-values of columns (1)-(2) are small which is expected given the large number of instruments relative to the sample size when we interact wind directions with counties. We also observe that F-values increase when we use larger geographic areas to interact with wind directions * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.4 –HEARING IMPAIRED/NON-HEARING IMPAIRED SUB-SAMPLE: 2SLS ESTIMATES

	HI	NHI	ENHI	Comparable Sample
	(1)	(2)	(3)	(4)
Road Noise Pollution (1km)	-0.0033	0.0022*	0.0021	0.0045**
	(0.0076)	(0.0013)	(0.0018)	(0.0020)
CO_2 emission (1km)	0.0027	0.0056*	0.0006	0.0043
	(0.0071)	(0.0031)	(0.0038)	(0.0040)
$PM_{2.5}$ concentration (1km)	0.0166	-0.0017	-0.0233	0.0079
	(0.0652)	(0.0160)	(0.0239)	(0.0170)
Individual controls	✓	✓	✓	✓
Environmental controls	✓	✓	✓	✓
County-level Fixed Effect	✓	✓	✓	✓
Year Fixed Effect	✓	✓	✓	✓
Instrument Variables:				
County × wind direction	✓	✓	✓	✓
Nighttime Cloud Cover	✓	✓	✓	✓
Other Instruments	✓	✓	✓	✓
Observations	583	10,466	3,906	10,687

Notes: The headings HI, NHI, and ENHI represent hearing impaired, non-hearing impaired, and elderly non-hearing impaired, respectively. Column 4 consists of another sub-sample of hearing-impaired and non-impaired respondents from the counties where the hearing-impaired respondents reside by survey year. Note that a higher value for the standardized mental health index indicates worse mental health. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5 –Different FEs to be interacted with wind direction - The Impact of Pollution on Mental Health

	Panel A		Panel B	
	(1) w/o Light Pollution	(2) w/ Light Pollution	(3) w/o Light Pollution	(4) w/ Light Pollution
Road Noise Pollution (1km)	0.0081*	0.0060	0.0121*	0.0081
	(0.0045)	(0.0046)	(0.0068)	(0.0075)
CO_2 emission (1km)	0.0125	0.0119	0.0120	0.0168
	(0.0084)	(0.0092)	(0.0127)	(0.0143)
$PM_{2.5}$ concentration (1km)	-0.0406	-0.0400	-0.0351	-0.0381
	(0.0279)	(0.0281)	(0.0366)	(0.0382)
ALAN (1km)		0.0023		0.0018
		(0.0025)		(0.0041)
Individual controls	✓	✓	✓	✓
Environmental controls	✓	✓	✓	✓
County and Year Fixed Effect	✓	✓	✓	✓
Instrument Variables:				
Census Division × wind direction	-	-	✓	✓
State × wind direction	✓	✓	-	-
Nighttime Cloud Cover	✓	✓	✓	✓
Other Instruments	✓	✓	✓	✓
Observations	14,030	14,030	14,030	14,030

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

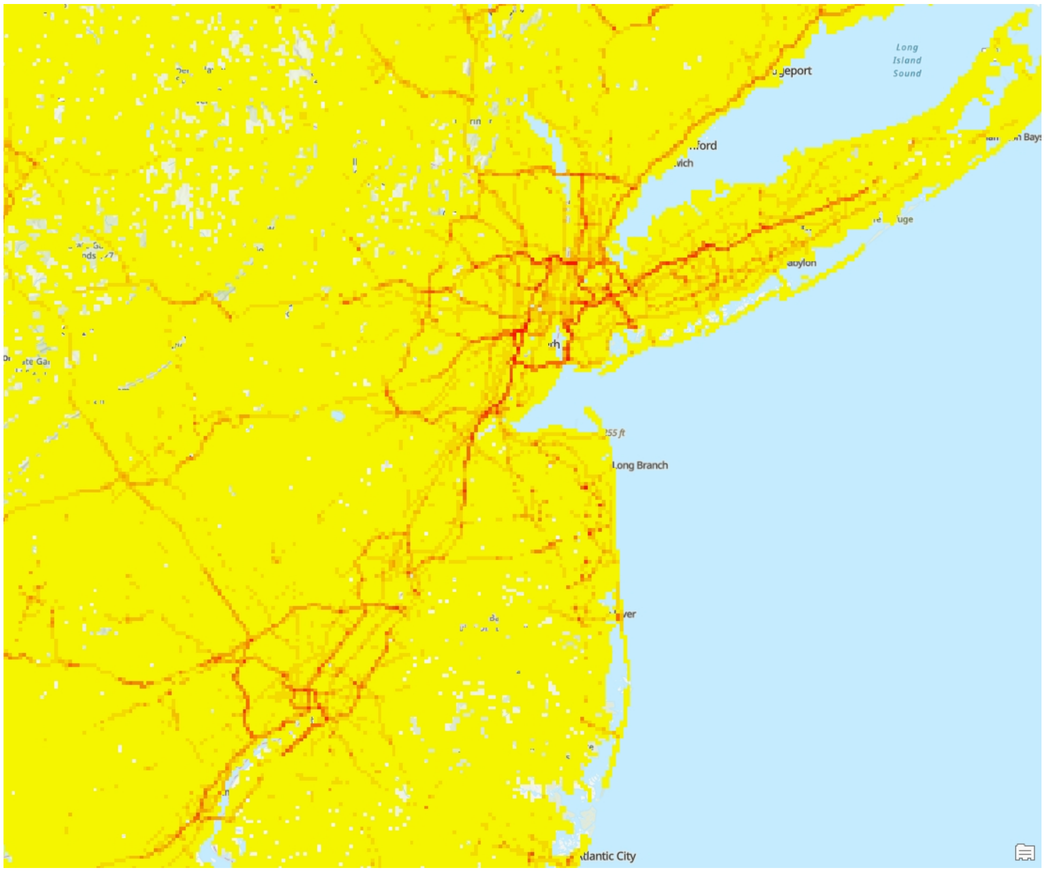
Table A.6 –The Impact of Pollution on Mental Health (using raw PHQ-4 as Outcome)

	1km			5km		
	(1) Noise Pollution	(2) Light Pollution	(3) All Sensory Pollutants	(4) Noise Pollution	(5) Light Pollution	(6) All Sensory Pollutants
Road Noise Pollution (1km)	0.0075**		0.0063*	0.0072**		0.0063*
	(0.0033)		(0.0033)	(0.0033)		(0.0033)
CO_2 emission (1km)	0.0111		0.0058			
	(0.0093)		(0.0100)			
$PM_{2.5}$ concentration (1km)	-0.0004		-0.0003			
	(0.0402)		(0.0404)			
ALAN (1km)		0.0310**	0.0074**		0.0310**	0.0050
		(0.0129)	(0.0034)		(0.0129)	(0.0037)
CO_2 emission (5km)				0.0327**		0.0298*
				(0.0146)		(0.0163)
$PM_{2.5}$ concentration (5km)				-0.0209		-0.0176
				(0.0410)		(0.0411)
Individual controls	✓	✓	✓	✓	✓	✓
Environmental controls	✓	✓	✓	✓	✓	✓
County-level Fixed Effect	✓	✓	✓	✓	✓	✓
Year Fixed Effect	✓	✓	✓	✓	✓	✓
Instrument Variable:						
County × wind direction	✓	-	✓	✓	-	✓
Nighttime Cloud Cover	-	✓	✓	-	✓	✓
Other Instruments	✓	✓	✓	✓	✓	✓
Observations	14,030	14,030	14,030	14,030	14,030	14,030

Notes: The dependent variable is the raw (non-standardized) PHQ-4 score. Other Instruments include the area ruggedness index, road ruggedness index, annual average temperature, wind speed, and maximum wind speed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

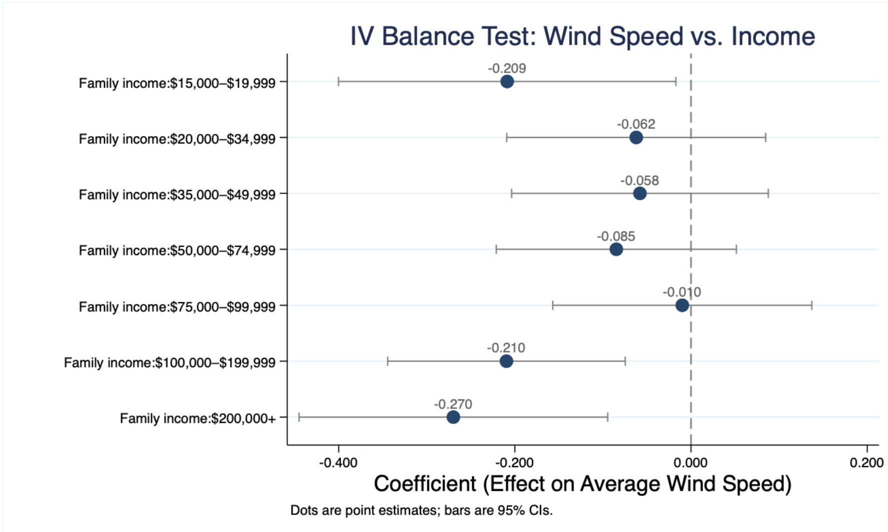
B Figures

FIGURE **B.1** –CO_2 EMISSION MAP

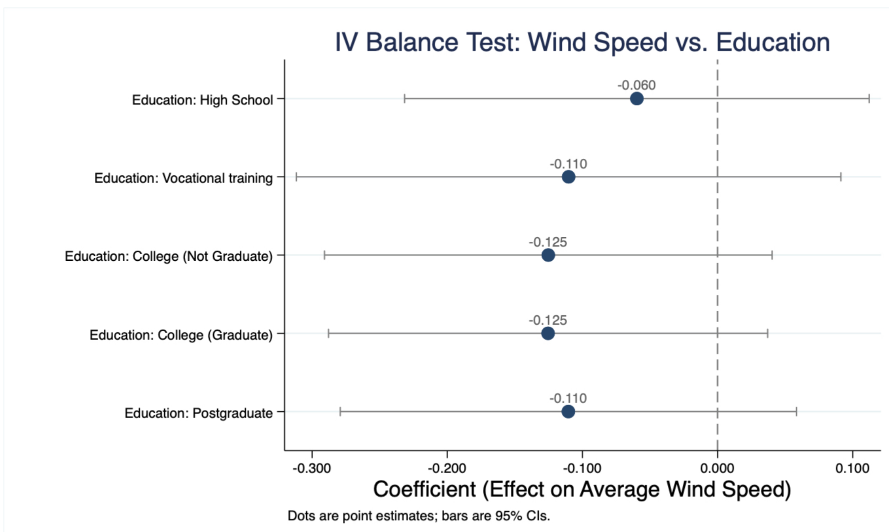


Note: We show the 2017 CO_2 emission map for New York City and its surrounding areas for brevity. The cells with a darker shade of red represent more traffic-generated CO_2 emissions. Notably, areas with detectable traffic-related CO_2 emissions tend to be fairly close to the highways.

Figure B.2 –IV balance test: wind speed, income, and education



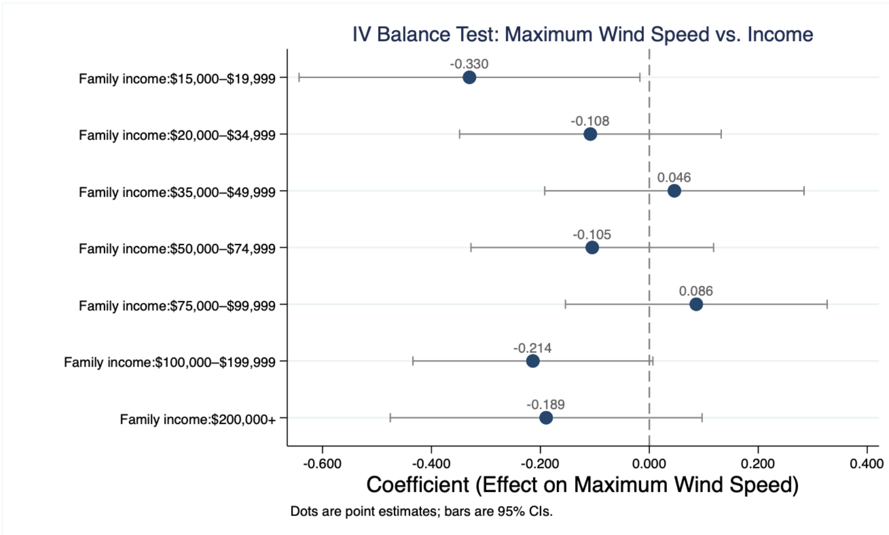
(a) IV balance test: wind speed vs. income.



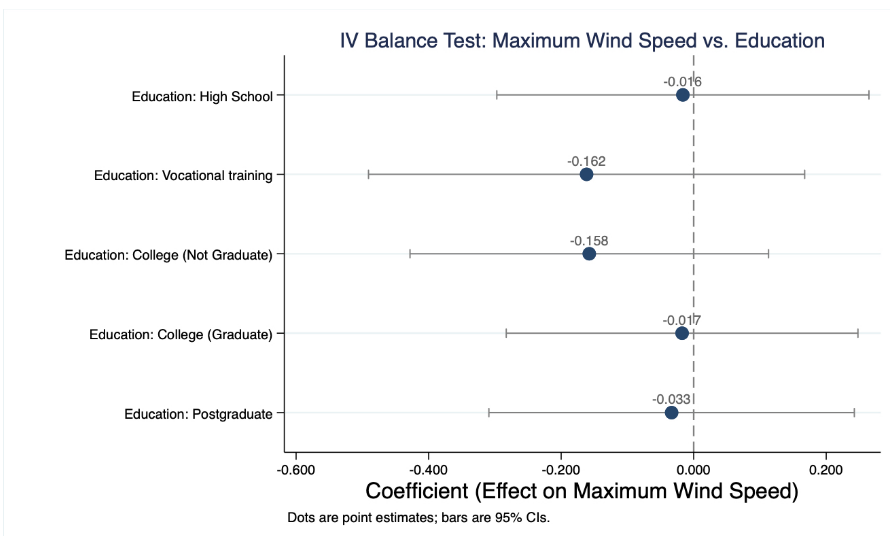
(b) IV balance test: wind speed vs. education.

Note: These are the estimated coefficients and their 95% CIs from the auxiliary regression of maximum wind speed on income/education range indicators.

FIGURE **B.3** –IV BALANCE TEST: MAXIMUM WIND SPEED, INCOME, AND EDUCATION



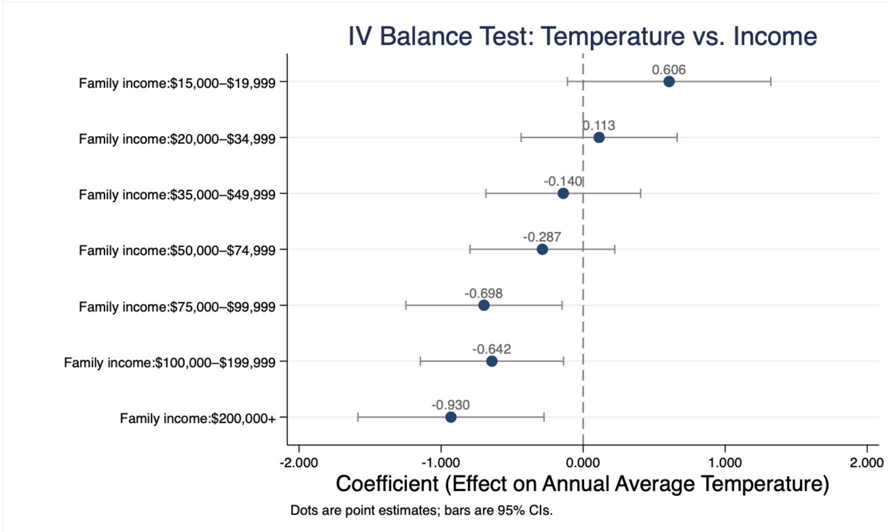
(A) IV BALANCE TEST: MAXIMUM WIND SPEED VS. INCOME.



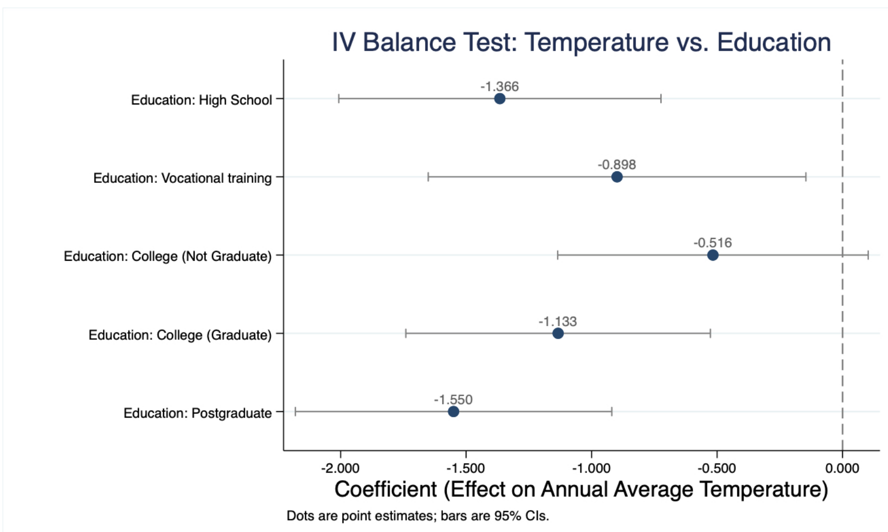
(B) IV BALANCE TEST: MAXIMUM WIND SPEED VS. EDUCATION.

Note: These are the estimated coefficients and their 95% CIs from the auxiliary regression of maximum wind speed on income/education range indicators.

Figure B.4 –IV balance test: annual temperature, income, and education



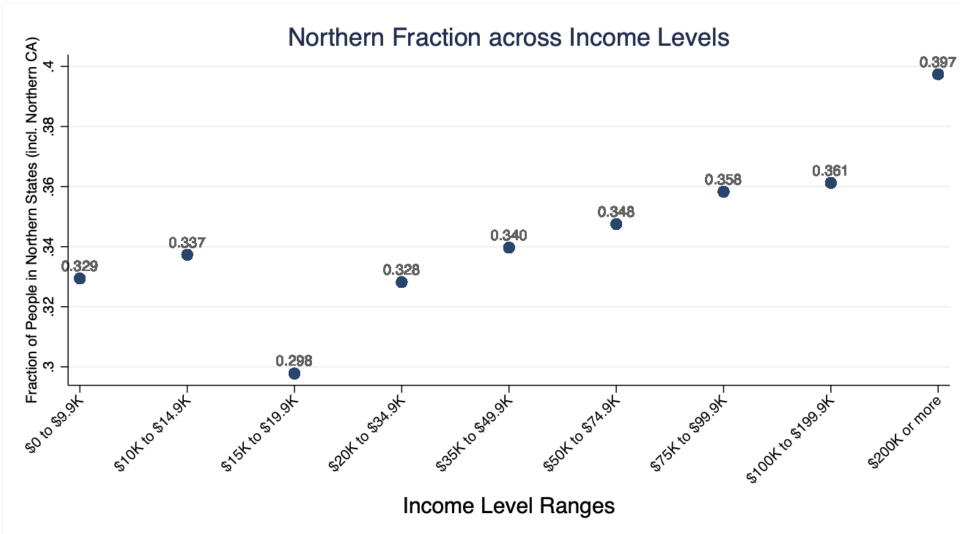
(a) IV balance test: annual temperature vs. income.



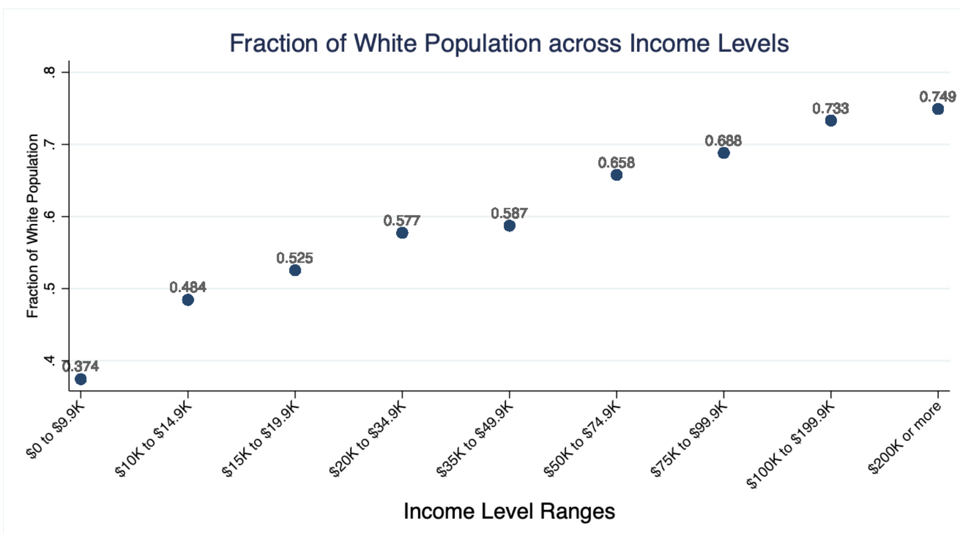
(b) IV balance test: annual temperature vs. education.

Note: These are the estimated coefficients and their 95% CIs from the auxiliary regression of annual average temperature on income/education range indicators. However, the temperature instrument tends to be negatively correlated with respondents' income and education. We believe there are two main reasons for this. First, the fraction of people living in the relatively cool northern US and northern California is increasing with income (see Figure B.5a). Second, the fraction of white people is increasing with income levels (see Figure B.5b). People of color, especially Hispanics and blacks, who tend to be less educated and with lower incomes (compared to whites), are more likely to live in southern areas and hotter areas (e.g. TX, FL, and southern CA). Once we condition on age, race, and gender, the temperature instrument is almost mean independent of income and education (see Figures B.6a and B.6b).

Figure **B.5** –Population composition across income levels

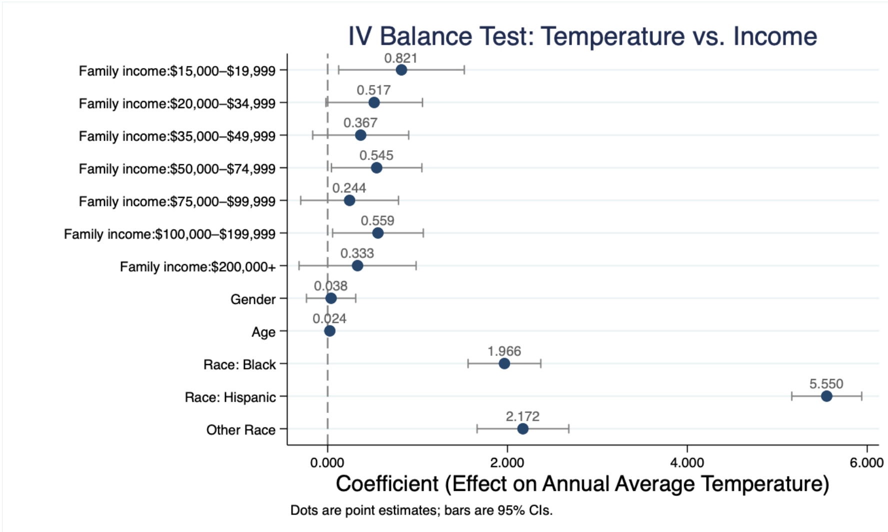


(a) Northern fraction across income levels.

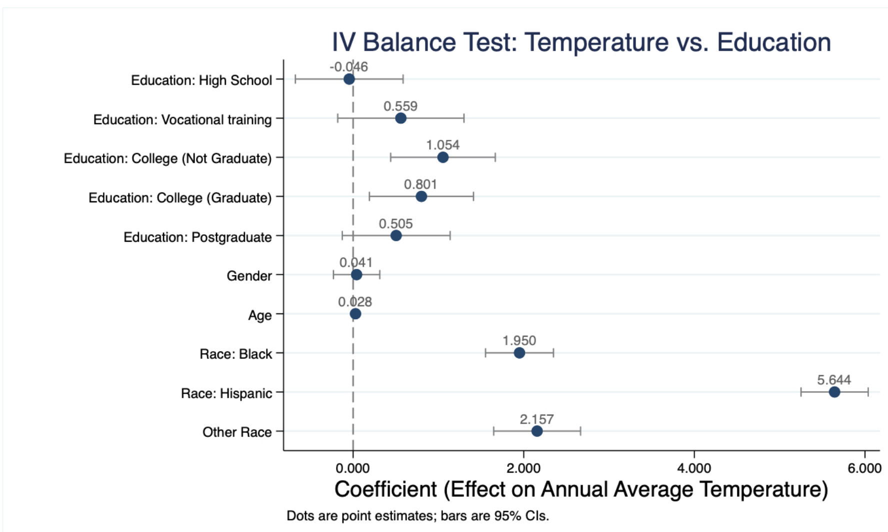


(b) Fraction of white population across income levels.

Figure **B.6** –IV balance test: temperature, income, and education



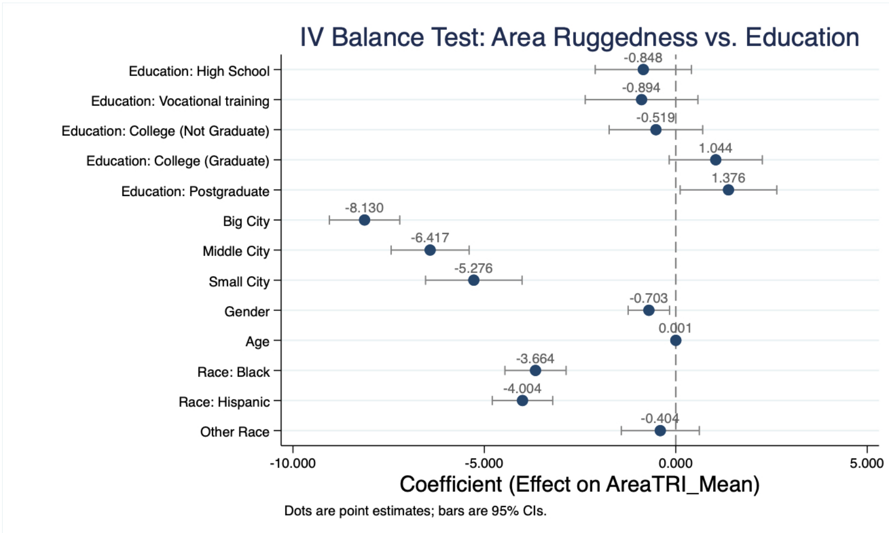
(a) IV balance test: temperature vs. income.



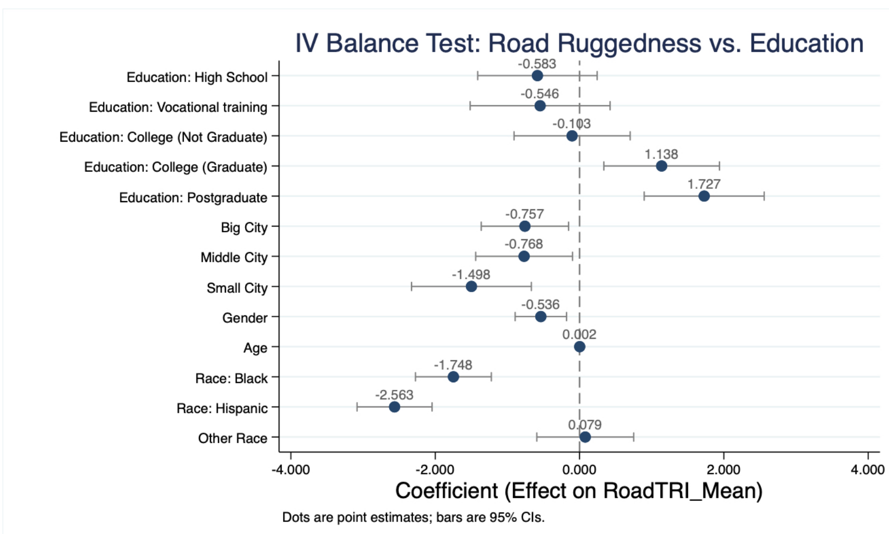
(b) IV balance test: temperature vs. education.

Note: These are the estimated coefficients and their 95% CIs from the auxiliary regression of respondents' annual average temperature on their income/education range indicators and three exogenous control variables (gender, age, and race).

Figure B.7 –IV balance test: area ruggedness, road ruggedness, and education.



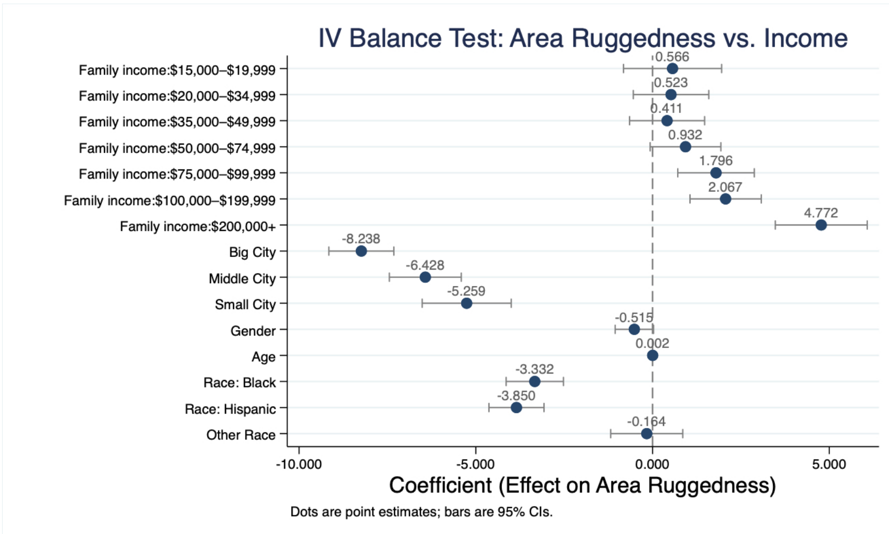
(a) IV balance test: area ruggedness vs. education.



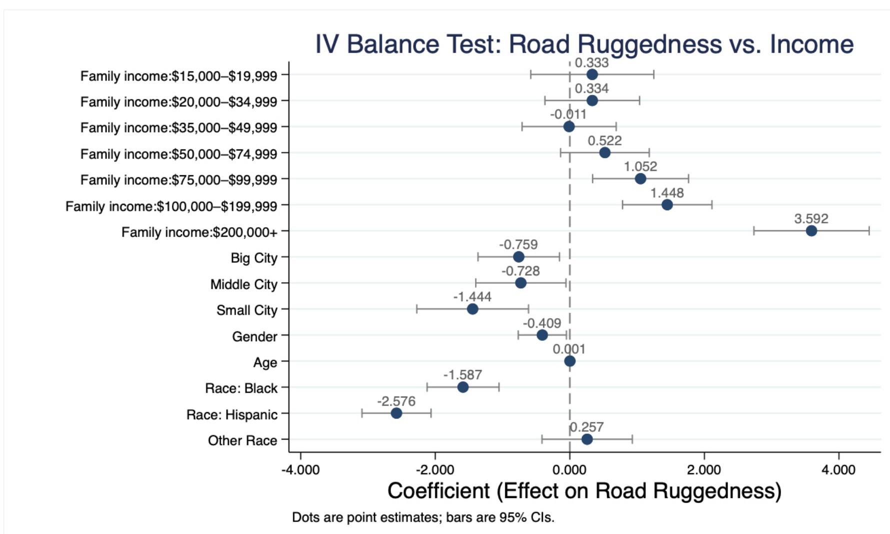
(b) IV balance test: road ruggedness vs. education.

Note: These are the estimated coefficients and their 95% CIs from the auxiliary regression of respondents' area/road ruggedness index on their education range indicators and three exogenous control variables (gender, age, and race), conditional on city levels. In Figures B.7a and B.7b, we find that even after conditioning on three exogenous variables (age, gender, race) and city-level fixed effects, the people with the highest income levels and education levels still tend to live in areas with higher Area and Road Ruggedness Index. However, we have no intuitive reason to believe that ruggedness will affect respondents' mental health through the channel of income or education.

Figure **B.8** –IV balance test: area ruggedness, road ruggedness, and income.



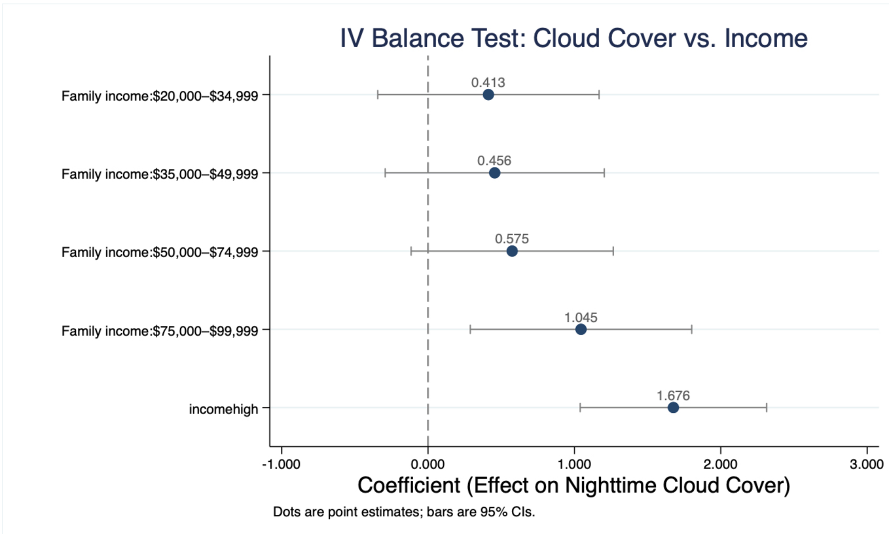
(a) IV balance test: area ruggedness vs. income.



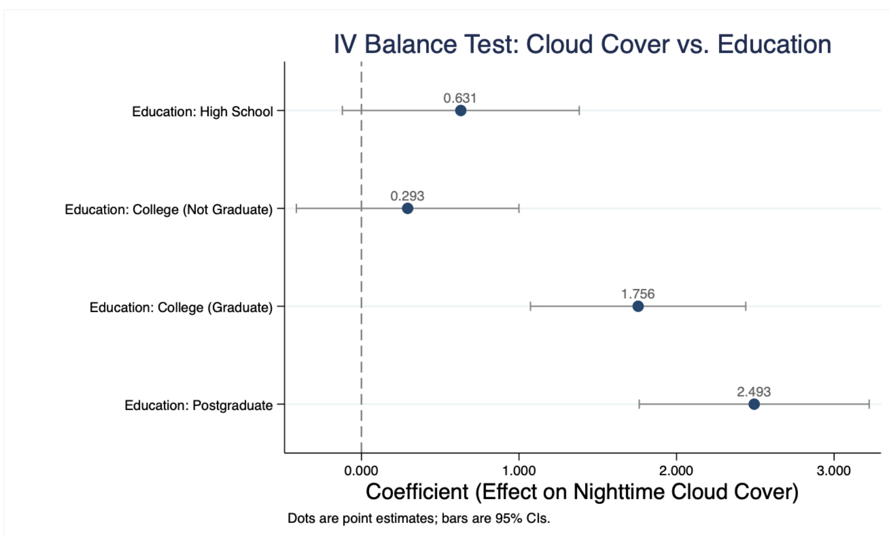
(b) IV balance test: road ruggedness vs. income.

Note: These are the estimated coefficients and their 95% CIs from the auxiliary regression of respondents' area/road ruggedness index on their income range indicators and three exogenous control variables (gender, age, and race), conditional on city levels. In Figures B.8a and B.8b, we find that even after conditioning on three exogenous variables (age, gender, race) and city-level fixed effects, the people with the highest income levels and education levels still tend to live in areas with higher Area and Road Ruggedness Index. However, we have no intuitive reason to believe that ruggedness will affect respondents' mental health through the channel of income or education.

Figure **B.9** –IV balance test: nighttime cloud cover, income, and education.



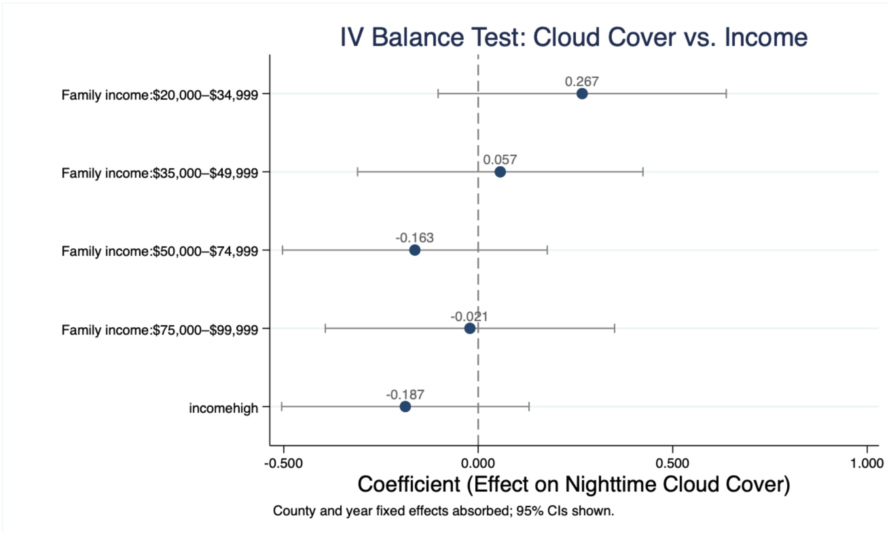
(a) IV balance test: nighttime cloud cover vs. income.



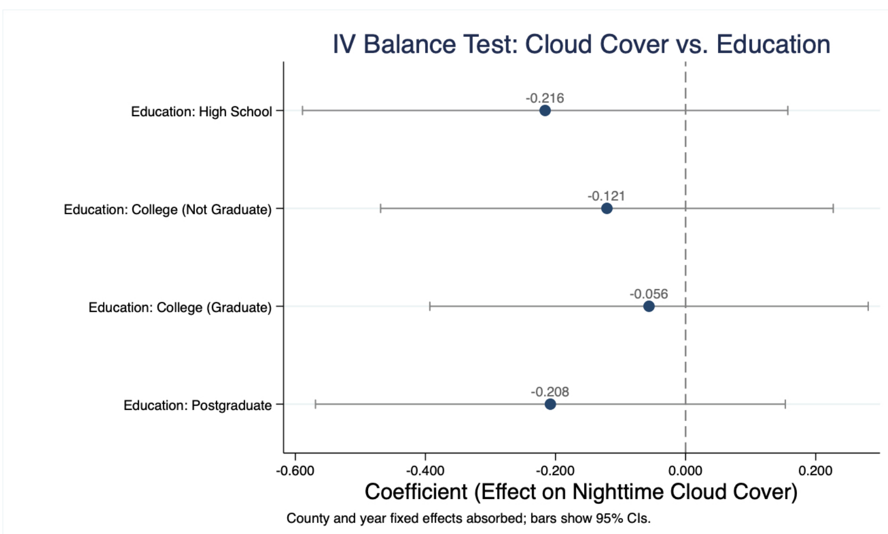
(b) IV balance test: nighttime cloud cover vs. education.

Note: These are the estimated coefficients and their 95% CIs from the auxiliary regression of respondents' during-survey nighttime cloud cover on their income/education range indicators.

Figure **B.10** –IV balance test: nighttime cloud cover, income, and education (county and year fixed effects).



(a) IV balance test: nighttime cloud cover vs. income (county and year fixed effects).



(b) IV balance test: nighttime cloud cover vs. education (county and year fixed effects).

Note: These are the estimated coefficients and their 95% CIs from the auxiliary regression of respondents' during-survey nighttime cloud cover on their income/education range indicators, conditional on county and year fixed effects.