Neglected Hazard: Mental Health and Roadway Noise

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Abstract

Poor mental health triggers serious labor market penalties and is a growing cause for concern among health professionals and economists. Using restricted data on approximately 14,000 survey respondents combined with spatially detailed national noise maps, we estimate that road noise is associated with sleep deprivation and has a statistically significant, causal effect on mental health, equivalent to a 12.7% increase in the number of respondents experiencing mild symptoms. This translates to an annual welfare loss as large as $12.8 billion for the US.

Keywords— Road noise; Air pollution; Mental health; Area and road ruggedness; Wind speed; Wind direction; HINTS; DARTE; $PM_{2.5}$

JEL codes: Q53, I12

1 Introduction

According to the 2021 National Survey on Drug Use and Health,[1] approximately one-fifth of US adults (57.8 million in 2021) experience mental illness, more than three times the number reported in 2011 (15.2 million adults aged 18 years or older) (Peng et al., 2016). This is relatively high compared to the incidence of mental illness in other developed countries. For example, 1 in 6 people in England and Switzerland and 1 in 7 people in France are reported to suffer from mental illness (Hämmig et al., 2009; Leray et al., 2011; McManus et al., 2016). The prevalence of any mental illness, which is defined as a mental, behavioral, or emotional disorder, is more frequent among females (27.2%) than males (18.1%); young adults aged 18-25 years old (33.7%) than adults aged 26-49 years old (28.1%) or aged 50 and older (15.0%); and multi-racial individuals (34.9%) than individuals identifying with a single race or ethnic group. Furthermore, 14.1 million individuals (or 5.5% of US adults in 2021) are reported to suffer from serious mental illness that results in serious functional impairment interfering with or limiting one or more major life activities. The high and rising incidence of mental illness in the US is an increasing cause for concern since it harms educational outcomes for children and brings large productivity and earning penalties for adults (Cornaglia et al., 2015; Biasi et al., 2021), which impacts social mobility (Goodman et al., 2011) and imposes a multi-billion dollar burden on the economy every year (Rice and Miller, 1998).

The medical literature has identified a multitude of factors that are associated with poor mental health outcomes, including genetic markers and social determinants (e.g. economic opportunities, living conditions, or other nonmedical factors) (Gatt et al., 2015; Alegría et al., 2018). A common thread among these factors is that they trigger the human stress response system. The economics literature has further identified links between demographic, education, unemployment, retirement, and migration effects and mental health (Bartel and Taubman, 1986; Kennedy and McDonald, 2006; Dave et al., 2008; Farré et al., 2018; Jiang et al., 2020; Picchio and Ours, 2020). Environmental factors, such as chemical air pollution, are also known to trigger the human stress response system and are associated with degraded physical and mental health, poorer academic performance, more

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

serious dementia, and even higher suicide rates (Zhang et al., 2017; Dzhambov et al., 2018; Ao et al., 2021; Gillingham and Huang, 2021; Heissel et al., 2022; Persico and Marcotte, 2022; Balakrishnan and Tsaneva, 2023; Bishop et al., 2023; Xie et al., 2023).

Non-chemical environmental triggers are also known to affect mental health. For example, exposure to excessive noise can lead to symptoms of anxiety, nervousness, and mental fatigue (Argys et al., 2020) which induces cognitive impairment in children and interferes with sleep (Svingos et al., 2018).[2] The link between ambient noise and mental health is increasingly recognized as a critical public health concern. Chronic exposure to environmental noise (e.g. traffic noise) is associated with heightened risks of depression, anxiety, and behavioral disorders, as well as cognitive impairment and emotional distress (Basner et al., 2014; Clark and Paunovic, 2018; Hahad et al., 2024). Mechanistically, noise-induced neuroinflammation, oxidative stress, and circadian rhythm disruptions directly impact the brain, while systemic effects, such as immune dysregulation and feedback from organ damage, further exacerbate mental health risks (Hahad et al., 2024). These findings align with prior research showing that noise exposure elevates stress hormones, disrupts sleep, and disproportionately affects vulnerable groups, including children and socioeconomically disadvantaged populations (Stansfeld and Clark, 2015; Beutel et al., 2016). Collectively, these studies underscore the need for integrated noise mitigation strategies in urban planning and public health policy to address its pervasive mental health impacts.[3]

With the singularly ubiquitous network of roadways in the United States, we focus on the mental health effects of roadway noise on a random sample of individuals surveyed by the National Cancer Institute (NCI). At approximately 3 million kilometers, the US has the largest road network in

[2]In addition, the likelihood of cardiovascular disease, tinnitus, and stroke also increases with greater exposure to noise pollution (Münzel et al., 2014). Hammer et al. (2014) estimate that 104 million individuals in the US are exposed to a continuous average noise level above 70 dB which may increase their risk of noise-induced hearing loss.

[3]Noise pollution, defined as unwanted or excessive sound, is regulated in the United States under the Clean Air Act-Title IV, the Noise Control Act (NCA) of 1972 and the Quiet Communities Act (QCA) of 1978. However, due to a lack of federal funding, the Office of Noise Abatement and Control was closed in 1982 and the primary responsibility for regulating noise pollution was shifted to state and local governments. While the NCA and QCA remain in effect they are unfunded (https://www.epa.gov/history/epa-history-noise-and-noise-control-act) and the EPA was sued in June 2023 for failing to regulate noise pollution (see InsideEPA.com).

the world, nearly double that of China (1.7 million km) and three times that of India (1 million km), the countries with the second and third largest road networks, respectively. Compared to the European Union, which has 0.14 million km of motorways, the length of motorways in the US is nearly 21 times higher. It is estimated that more than 11 million Americans live within 500 feet of a major US highway that has an average annual daily traffic of at least 125,000 vehicles per day. The traffic on these highways jointly contributes to local noise pollution and traffic related air pollution. We determine if ambient road noise is a contributing factor to mental health problems in the US, isolating the effect of roadway noise from traffic related air pollution.

Lan et al. (2020) support the hypothesis of an association between traffic noise and more severe anxiety through a systematic literature review and meta-analysis, but they suggest that more high-quality studies are needed to confirm the association and recommend an investigation of the mechanisms behind that association. Heissel et al. (2022) find traffic pollution leads to worse academic performance, but the study conflates the effects of noise and air pollution using schools located "upwind/downwind" of highways for identification. To the best of our knowledge, the only studies in the economics literature that directly link noise pollution to human health are Argys et al. (2020) and Hener (2022). They find that mothers who are exposed to more aviation noise are more likely to have babies with low birth weight and an increase in ambient noise contributes to more violent crime activities, respectively. Notably, Dean (forthcoming) finds noise reduces workers' productivity in an experiment setting in Kenya. However, none of the aforementioned studies establish a causal link between roadway noise pollution and human mental health.

We utilize novel data that measure ambient roadway noise at the residences of approximately 14,000 individuals between 2014 and 2020. A unique feature of our data is that we can link individual mental health outcomes to highway noise pollution through relatively precise residential addresses. Under a data use agreement, we access the restricted version of the NCI's Health Information National Trend Survey (HINTS) which includes detailed information on individual respondents' mental health status, demographic and physical characteristics, and the 9-digit zip code for their residence.

We obtain annual noise data from the Department of Transportation's National Transportation Noise Maps for 2016, 2018 and 2020, focusing on road noise. These data are available on a 30-meter grid which allows us to measure annual transportation-related ambient noise relatively precisely. To isolate the effect of roadway noise from that of concomitant, traffic-related air pollution, we also use high-resolution satellite-based annual $PM_{2.5}$ concentrations from Shen et al. (2024), satellite data measuring annual traffic-generated CO_2 emissions from the National Aeronautics and Space Administration (NASA), and weather information from the National Centers for Environmental Information as additional environmental control variables.

Our key outcome variable is a summary mental health index for each respondent in the HINTS survey. The index ranges from 0 to 12 with a larger number indicating worse mental health. While nearly half the respondents don't report any mental health issues in the two weeks immediately preceding the survey (an index value of zero), nearly 25% report experiencing symptoms of anxiety or depression on some days (an index value between 1 and 4). Since our sample includes respondents from multiple waves of the HINTS survey, we standardize this index by year to facilitate comparison across survey years.[4] Our key independent variable is local road noise at the 9-digit zip code level, which measures ambient noise at a "several households" or "street" level. We control for individual demographic information like gender, race, education, and income. Based on the mental health literature, we also include detailed controls for individual physical health and local environmental conditions such as cloud cover and days with extreme temperature.

We then conduct the first national-level, quasi-experimental study to investigate the causal effect of roadway noise pollution on adulthood mental health. The most challenging part of this study is that roadway noise pollution is not randomly assigned, since respondents may sort themselves to live in areas with different levels of ambient roadway noise and associated air pollution based on

[4]This was recommended by NCI staff when reviewing our application for access to the restricted HINTS data which included a description of our proposed study and research design (Richard Moser, personal communication, September 21st, 2022). In the online appendix Table A.10, we also present estimates using the raw (unstandardized) index values.

their socioeconomic status. We overcome the challenge by exploiting variations in local topography, annual average temperature, and annual wind speed and direction to extract exogenous variation in annual ambient roadway noise and the associated traffic-generated air pollution.

The identifying assumption for our instrumental variable approach is that topographic variation, wind conditions, and annual average temperature only affect respondents' mental health through the channel of ambient roadway noise and air pollution.[5] We argue that the variation in local topography and the number of days with different prevailing wind directions generate different ambient roadway noise and traffic-related air pollution for respondents given that the distribution of highways surrounding respondents is not uniform. In other words, some areas usually have heavier traffic than other areas and differences in local topography, wind speeds, and wind direction generate exogenous variation in ambient noise and air pollution for the respondents in our sample. Furthermore, air is less dense at higher temperatures which increases the speed at which sound waves travel through it. This means that ambient noise pollution will be reinforced under higher temperatures, *ceteris paribus*. We rely on this mechanism and use annual average temperature to extract the exogenous change in annual ambient noise as well. We note that Mullins and White (2019) investigate the causal effect of temperature on mental health. However, their findings suggest the strongest impacts occur only at the most extreme temperature bins for emergency department visits and suicide rates, which are very serious mental health outcomes. They do not find significant effects of temperature on self-reported mental health during the "last 30 days" (similar to our outcome variable). Thus, we control for the number of days with extreme temperatures during each survey period to capture the direct effect on mental health, but also use annual average temperature (which should not have a direct effect on mental health) as one of our instruments to address the endogeneity of ambient noise.

We estimate that the mental health of an average respondent worsens by 0.0026 standard deviations

[5] The literature has documented an association between wind direction and air pollution using mainly within area temporal variation (see, for example, Deryugina et al., 2019; Heissel et al., 2022). In the absence of high frequency information on ambient noise, combined with the pooled format of our mental health data, we rely on cross-sectional variation.

when ambient road noise increases by 1 dB (1.96% relative to the mean noise level). The effect is equivalent to 18 out of 2528 respondents in a typical survey year (i.e. year 2018) with little mental health problems reporting mild mental health symptoms instead. This is equivalent to a 12.7% increase in the number of respondents experiencing mild mental health symptoms. These results are robust and statistically significant under various model specifications and translate to an annual welfare loss as high as $12.8 billion due to lost earnings in the labor market. It is reassuring that we do not find any relationship between ambient roadway noise and mental health for a sample of hearing-impaired respondents.

We also address the potential mechanism through which ambient roadway noise may affect mental health. Using county-level data we find that road noise has a significant negative association with respondents' sleep duration, reducing it by around 25 minutes/week when average road noise in the county increases by 10 dB.

The adverse mental health effects of roadway noise identified by our analysis imply huge welfare costs through lost earnings and workplace absenteeism. As the US makes substantial investments in updating its transportation and housing infrastructure, our results point to the need for concomitant investments in roadway noise abatement strategies. This is underscored by the June 2023 legal action by Quiet Communities, Inc., a citizen action group, in which the EPA has been cited for failure to act upon the Noise Control Act.

The rest of the paper is organized as follows: Section II describes our data. Section III illustrates our empirical strategy. We report our main results in Section IV and assess the robustness of these results in Section V. Section VI addresses the potential mechanism through which noise affects mental health. Section VII concludes.

2 Data

We exploit data that measure annual ambient noise from roadways at the residential location of approximately 14,000 individuals in the continental US over 5 years (2014, 2017-2020). A unique feature of our data is that we can link individual mental health outcomes to ambient roadway noise through relatively precise residential addresses. Under a data use agreement, we access the restricted version of the NCI's Health Information National Trend Survey (HINTS) which includes detailed information on individual respondents' mental and physical health conditions, demographic characteristics, and the 9-digit zip code area for their residence. HINTS collects nationally representative data to evaluate the American public knowledge of, attitudes toward, and use of cancer- and health-related information.[6] It is suited to our analysis since it provides both physical and mental health information for each respondent along with relatively precise residential location, and the information is gathered without reference to ambient noise levels.

Our key outcome variable is a summary mental health index for each HINTS respondent. This summary index is based on the answers to four separate mental health-related questions: over the past 2 weeks, how often have you been bothered by any of the following problems? 1. Little interest or pleasure in doing things; 2. Feeling down, depressed or hopeless; 3. Feeling nervous, anxious, or on edge; 4. Not being able to stop or control worrying. The index ranges from 0 to 12 with a larger number indicating worse mental health.[7] While nearly half the respondents don't report any mental health issues in the two weeks immediately preceding the survey (an index value of zero), nearly 25% report experiencing symptoms of anxiety or depression on some days (an index value between 1 and 4). Since our sample includes respondents from multiple waves of the HINTS survey, and following the recommendation from the NCI (Richard Moser, personal commu-

[6]HINTS uses survey weights to allow researchers to generalize their analysis to the national US population. The first step to create these weights is an adjustment to reflect the selection probabilities. To compensate for non-response and coverage error, the selection weights are calibrated using data from the American Community Survey conducted by the US Census Bureau. For more details about the sampling and weighting process, see https://hints.cancer.gov/about-hints/frequently-asked-questions.aspx.

[7]For each mental health-related question, the answers "not at all"; "several days"; "more than half the days"; "nearly every day" are assigned to values from 0 to 3, respectively. 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.

nication, September 21st, 2022), we standardized this index by year to account for systemic trends across the years and pooled a cross-sectional data set that facilitates comparison across survey years.

One of the most valuable characteristics of the restricted version of HINTS is that it offers geographic and detailed demographic and health information for each respondent. The geographic information provides residential location including rural/urban designation, county FIPS code, and 9-digit zip code. We use the 9-digit zip code to locate the respondents on the DoT's National Transportation noise maps. 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: 2014 and 2017-2020. But, in Section 6, we use the respondents from the first three waves as a separate sample to disentangle the mechanism through which noise pollution affects mental health.

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 1 shows the ambient noise surrounding our institution. Appendix Figure A.1 shows the 2020 noise map for the contiguous US.

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). If speed data is missing, a default value of 35 mph is used. 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.

Key assumptions in road noise modeling include using 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 types. The AADT values are assumed to be evenly distributed over 24 hours. 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. The data used has some inherent uncertainties, especially over longer distances due to factors like atmospheric conditions or variations in terrain that are not fully accounted for in this simplified modeling.

Importantly for us, the noise data are available on a fine spatial grid of 30-meter square. Since ambient noise is highly localized, we utilize the 9-digit zip code for each respondent's street address, which is a relatively precise indicator of location and may be interpreted as identifying the location within a few houses or at the street level.[8] We assume that each respondent resides at the centroid of the zip-9 area and use data from GeoLytics, 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 noise maps.

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). In other words, 78 dB ambient noise at 15 m from the noise source will be equivalent to 42 dB at a distance of

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

960 m.[9] 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.[10] Figure 2 depicts the zip-9 centroids for a sample of hypothetical HINTS respondents near our institution. 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.[11]

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 high 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, Liang et al. (2024) report that traffic-related CO_2 is correlated with other pollutants like SO_2 and NO_X and we use on-road CO_2 emissions to approximate traffic-related air pollution. Appendix Figure A.2 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 calculate a respondent's surrounding on-road air pollutants (approximated by CO_2 emissions) as the average across all pixels in the 1km buffer that have detectable CO_2 emissions. To further address the concern that traffic-generated CO_2 emissions cannot fully capture respondents' surrounding traffic-related air pollution, we estimate $PM_{2.5}$ concentrations in the 1 km buffer surrounding their place of residence 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 × 1 km) estimate of local air pollution (Kayastha et al., 2024).

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

[10] 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).

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

Mullins and White (2019) show that higher temperatures (relative to the mean values) are associated with poorer mental health outcomes. Thus, we account for temperature anomalies by including the number of days within a 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 (NCEI). We also get the 5-digit zip code level average daily temperature during the survey year for each HINTS wave.

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 exploit it directly at the 5-digit zip code level.

We also innovatively use Area and Road Ruggedness Scales data from the US Department of Agriculture (USDA). These data provide measures of topographic variation, or "ruggedness", for census tracts across all 50 states and Washington, DC. These data are especially valuable to our study since they have nationwide coverage and are the first to provide a road-only measure of ruggedness that helps us link local topographic variation with ambient road noise.

Our key independent variable is local road noise pollution at the 9-digit zip code level, which measures noise at a "several households" or "street" level. We control for individual demographic characteristics like gender, race, education, and income. Based on the mental health literature as aforementioned, we also include detailed controls for individual physical health conditions, housing ownership status, marital status, and access to health care.

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 14,643) 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.

3 Identification Strategy

3.1 Basic Model: OLS

To obtain a basic description of the association between mental health and the various correlates that have been identified from the literature, we begin with a simple OLS regression. We address the potential endogeneity issues between mental health and our key regressors (ambient road noise/air pollution) through an instrumental variable approach in the following sub-section.

The reduced-form model describing the relationship between human mental health and ambient road noise is as follows:

$$
\begin{gathered}
S_{izt} = \beta_0 + \alpha_1 Roadnoise1km_{zt} + \alpha_2 CO_2 Emission1km_{zt} + \alpha_3 PM_{2.5}1km_{zt} \\
+\beta_1 Female_{izt} + \beta_2 Married_{izt} + \beta_3 Age_{izt} + \beta_4 Age^2_{izt} \\
+\boldsymbol{\beta_5} Educ_{izt} + \beta_6 Hhnum_{izt} + \boldsymbol{\beta_7} Race_{izt} + \boldsymbol{\beta_8} Income_{izt} \\
+\lambda_1 DocVis_{izt} + \lambda_2 Cancer_{izt} + \lambda_3 CancerFam_{izt} \\
+\lambda_4 BMI_{izt} + \lambda_5 Diabetes_{izt} + \lambda_6 Hypertension_{izt} + \lambda_7 Exercise_{izt} + \lambda_8 Ownfrac_{zt} \\
+\boldsymbol{\gamma_1} ExtremeTem_{zt} + \gamma_2 Cloudcover_{zt} + \gamma_3 Solarenergy_{zt} + \theta_c + \eta_t + \epsilon_{izt}
\end{gathered}
\tag{1}
$$

where S_{izt} represents the standardized mental health summary index (PHQ-4) for an individual respondent i from zip code area z (5 or 9 digit) in year t. We standardize the PHQ-4 measure for each respondent by subtracting the mean value of PHQ-4 for that survey year and dividing it by the corresponding standard deviation so that each respondent is compared with the "general" respondent from the same survey year. By standardizing the PHQ-4 measure, we address the concern that our outcome of interest may have changed systematically over time. A higher standardized

PHQ-4 index indicates a worse mental health for the respondent. θ_c and η_t represent the county and year-of-survey fixed effects, respectively.

$Female$ 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. β_3, β_4 and $\boldsymbol{\beta_5}$ (a vector for different educational levels) 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 of individual respondent i from zip code area z in year t from HINTS data. Annual income is potentially an endogenous variable since it could be determined simultaneously with or be related to other 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

[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".

[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

house prices decline, but this association is most significant for individuals who are least likely to be homeowners. λ_8 captures the association between home ownership and mental health.

It is well established that physical health also 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. Mikkelsen et al. (2017) find positive effects of exercise on mood states such as anxiety, stress, and depression. So, we control for "Exercise" which counts how many days a respondent does any physical activity or exercise of at least moderate intensity in a typical week.[14]

We include several environmental factors that are known to contribute to mental health conditions. $ExtremeTem_{zt}$ includes two controls for the number of days during the survey period with daily maximum temperature below freezing or above $85°F$, respectively (Burton and Roach, 2022).[15] Intraday weather conditions may also affect respondents' mental health. Xu et al. (2020) find that depression symptoms peak on cloudy days, so we include the average cloud cover fraction (%) within a day across each survey period at the 5-digit zip code level. People's moods may also be affected by seasonality and Molin et al. (1996) argue that lack of light is a driving factor for the development of winter depression. Therefore, we include the average solar energy during each survey period, which indicates the total energy from the sun that builds up a day at the 5-digit zip code level, as a correlate that is independent of cloud cover.[16]

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]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.

[16]While most people may think that cloudier places will have less solar energy, the relationship is more intricate. The relationship between cloud cover and solar energy depends on factors such as the type of clouds, the time of day, the season, and the geographical location. Partially cloudy skies and the contribution

$CO_2Emission1km_{zt}$ is the annual-average traffic-generated CO_2 emissions within a 1 km radius circular buffer anchored to the centroid of the 9-digit zip code for the respondent's residence. We use this to approximate local traffic-related air pollutants, along with $PM_{2.5}1km_{zt}$ which records the annual average $PM_{2.5}$ concentrations within the same 1km buffer.[17]

$Roadnoise1km_{zt}$ represents the annual-average ambient road noise in year t within a buffer of 1 km radius located at the centroid of the 9-digit zip code of each respondent's street address. One limitation of the DoT data is that they are not available annually. We assign 2016 noise data to respondents from the 2014 HINTS wave, 2018 noise data to respondents from the 2017 and 2018 HINTS waves, and 2020 noise data to respondents from the 2019 and 2020 HINTS waves as approximations. Local noise pollution is very strongly correlated over time (the correlation coefficient exceeds 0.95),[18] so we anticipate that this approximation has minimal measurement error.

3.2 Instrumental Variable Approach

The biggest challenge in identifying the causal effect of noise pollution on mental health is that roadway noise and traffic-related 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, the current literature on environmental justice has clear evidence to show that less privileged people are disproportionately exposed to higher pollution (Banzhaf et al., 2019). We innovatively utilize local topographic variation at the census tract level along with wind speed, wind direction, and annual average temperature at the 5-digit zip code level to address this

of diffuse radiation mean that even cloudy areas can still experience significant solar energy.

[17]We also calculate both air pollutants within a 5 km radius circular buffer to capture air pollution within a larger area as a robustness check.

[18]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.

potential endogeneity between ambient noise or air pollution and mental health. We describe each of these instruments below, followed by the estimating equations in our two-stage regression model.

Since road noise is generated primarily through the friction between the vehicle tires and the surface of the road, slower-moving vehicles generate lower noise. Combined with the fact that drivers drive relatively slowly in areas with greater topographic variation, we anticipate that road noise is generally lower in such areas. The USDA recently released the Area and Road Ruggedness Scales which includes the Area Terrain Ruggedness Index and the Road Ruggedness Index, both at the census tract level.[19] The ruggedness index is the sum change in elevation between each grid cell and its neighboring cells, with lower values indicating smaller changes in elevation and higher values indicating larger changes. 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 3). 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 different driving behaviors also impact the fuel efficiency of vehicles, which contributes to variation in traffic-generated air pollution.

Wind direction and wind speed have been used in the recent literature as instrumental variables given their naturally exogenous characteristics. However, most of the current research using wind-related instrumental variables focuses on the endogeneity of air pollution (Deryugina et al., 2019; Burton and Roach, 2022; Persico and Marcotte, 2022). A handful of recent studies have linked wind-related variables to noise exposure. Hener (2022) exploits the exogenous change in daily wind speed and wind direction to investigate the effect of aviation noise on local crime rates. Zou (2017) establishes the link between wind farms and suicide rates by investigating how wind direction changes exposure to low-frequency noise.

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

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. 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.[20]

Furthermore, roadway noise and, likewise, traffic-related air pollution, is not a point source pollutant (unlike, for example, toxic emissions from a TRI facility). Rather we think of them as being generated along "line segments" (for example, highways). Thus, we do not emphasize the idea of respondents being upwind or downwind of 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. We argue that the variation in the prevailing wind directions generates exogenous variation in ambient noise and traffic-related air pollution exposure for respondents because highway distribution surrounding respondents is unlikely to be uniform. That is, some areas usually have heavier traffic (and therefore higher roadway noise and air pollution) than other areas, and 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.

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

The propagation of noise is not only affected by wind but also by ambient temperature. The density of air is lower at higher temperatures which refracts noise away from the ground and reduces ambient noise. Although Mullins and White (2019) investigate the causal effect of temperature on mental health, their findings suggest the strongest impacts occur only at the most extreme temperature bins for emergency department visits and suicide rates, which are very serious mental health outcomes. They do not find significant effects of temperature on self-reported mental health during the "last 30 days" (similar to our outcome variable). Thus, we control for the number of days during each survey period with extreme temperatures to capture the direct effect on mental health, but we also use the average daily temperature during each survey year (which should not have a direct effect on mental health) to address the impact of associated variation in the propagation of noise.[21]

The first-stage equation for our baseline two-stage least squares regression model is:

$$
\begin{gathered}
Noise(CO_2Emission/PM_{2.5})_{izt} = \alpha_0 + \alpha_1 \cdot RoadRI_z + \alpha_2 \cdot AreaRI_z + \\
\beta_1 \cdot windspeed_{zt} + \beta_2 \cdot maxwindspeed_{zt} + \sum_{c \in C} \sum_{k=0}^{2} \gamma_c \cdot Winddir_{zt}^{90k} \\
+\delta \cdot averagetemp_{zt} + X_{izt}^{'}\sigma + W_{zt}^{'}\eta + \theta_c + \eta_t + \epsilon_{izt}
\end{gathered} \tag{2}
$$

The dependent variable $Noise(CO_2Emission/PM_{2.5})_{izt}$ represents either annual ambient road noise or annual average air pollution 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.[22] $Winddir_{zt}^{90k}$, 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).[23] The included instruments (control variables) at the

[21] 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.

[22] 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.

[23] We interact wind directions with county fixed effects rather than 5- or 9-digit zip code fixed effects for

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 ambient noise and air pollution from Eq.(2) to estimate the causal effect of noise and air pollution on mental health using the following second-stage regression:

$$\begin{aligned} Stdphq4_{izt} = \alpha + \beta_1 \cdot Road\widehat{noise}1km_{izt} + \beta_2 \cdot CO_2E\widehat{mission}1km_{izt} + \beta_3 \cdot PM\widehat{_{2.5}1}km_{izt} \\ +X_{izt}^{'}\sigma + W_{zt}^{'}\eta + \theta_c + \eta_t + \epsilon_{izt} \end{aligned} \tag{3}$$

$Road\widehat{noise}1km_{izt}$, $CO_2E\widehat{mission}1km_{izt}$, and $PM\widehat{_{2.5}1}km_{izt}$ are the ambient road noise, traffic-generated CO_2 emissions, and local $PM_{2.5}$ concentrations predicted by the excluded instruments from Eq.(2). All the other control variables are the same in Eq.(1).

4 Main Results

4.1 Summary Statistics

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. Figure 4 shows the distribution of ambient road noise within a 1 km buffer for our sample respondents.[24] 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

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.

[24] 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.

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).

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, which means 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.[25] People with diabetes or hypertension as well as those with a higher BMI are more likely to have poorer mental health.[26] Table 1 summarizes our data separated into demographic, health, and environmental variables, respectively.

4.2 OLS Results

The results from the basic OLS model fit well with our expectations and intuition. Table 2 column 1 shows that road noise within a 1 km buffer around respondents' 9-digit zip code centroids is negatively associated with mental health (recall, a higher value for the PHQ-4 index indicates worse mental health), and that the mental health of respondents worsens by 0.0016 standard deviations when ambient road noise increases by 1 dB.

The first column of Table A.2 reports all the coefficients from the basic OLS model. 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

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

[26] 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.

Bryson (2022), 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.

As for differences by population sub-group, we find that 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.

The current literature shows a strong association between physical health and mental health (Goodman et al., 2011; Kristiansen, 2021; Kesavayuth et al., 2022). We find that the respondents who visit doctors more frequently, have larger BMI, and ever had diabetes or hypertension have significantly worse mental health. We also find a positive relationship between exercise and respondents' mental health, which fits with the evidence from the literature (Windle et al., 2010).

We report the association of several environmental factors with mental health. First, we do not find significant associations between 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). China 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), and the pronounced effects found in China may not apply to the US. Persico and Marcotte (2022) focus on the US and find that air pollution is positively associated with the suicide rate, but the evidence is at the aggregated (county) level. 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.

Li et al. (2020) and Mullins and White (2019) report a negative association between temperature and mental health. We find similar results in our sample– respondents' mental health is positively associated with the number of days when the maximum daily temperature is below freezing, conditional on other environmental factors. Meanwhile, the number of days with a maximum daily temperature above $85°F$ is negatively associated with mental health and the association is statistically significant at the 10% level. We also find a higher fraction of cloud cover predicts worse mental health and the result is significant at a 5% significance level. But, we do not find any significant association between solar energy and mental health.

4.3 IV Results

To assess the prevalence of sorting behavior with respect to ambient noise, we plot the coefficients from the regression of ambient road noise on each confounding factor (income/education) separately in Appendix Figure A.3. While there is some evidence suggesting people with higher income levels ($> 100K$) tend to live in areas with less ambient road noise, we do not observe a similar pattern with respect to education.

Although we do not find unconditional evidence of sorting behavior among the respondents in our sample, we still allow for the possibility that ambient noise pollution is not random given the evidence from the environmental justice literature on the greater pollution exposure experienced by marginalized communities (Banzhaf et al., 2019). We utilize an instrumental variables approach in which we assume ambient road noise (as well as the concomitant traffic-related air pollution) is endogenous to mental health, using local topography, wind speed, wind direction, and annual average temperature to extract the exogenous variation in ambient noise pollution. To assess whether our instruments are randomly assigned or confounded with demographic variables, we estimate separate sets of regressions for each instrument (except for wind direction × county fixed effects) on only one potentially confounded variable at a time and plot the estimated coefficients and their standard errors for each IV separately. For instance, we estimate a regression of wind speed on all income/education level indicators and plot the coefficients in Figure A.4. 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 A.5 to A.10 show the plots for other instruments. 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 are shown in Appendix Table A.3. 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, as demonstrated in columns 1-3. 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.[27]

Table 2, columns 2-4, report the IV estimates where we regard ambient road noise and the two measures of traffic related air pollution as endogenous. The effect of ambient road noise within a 1 km buffer around respondents' 9-digit zip code centroids on their mental health is estimated to be larger in column 2 as compared to column 1, albeit less precisely estimated. The 2SLS estimates suggest that the mental health of respondents worsens by 0.0026 standard deviations when their ambient road noise increases by 1 dB, or that around 18 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. This is equivalent to a 12.7% increase in the number of respondents experiencing mild mental health symptoms.[28] This is conditional on traffic-related

[27]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, Appendix Table A.4 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. The second-stage results using the three instruments are reported in Appendix Table A.5, we still find significantly negative effects of ambient road noise on mental health albeit the magnitude of the estimated coefficient is about 10 times larger than the coefficients reported in Table 2.

[28]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 0.0026 (the coefficient on ambient road noise in our main specification). The 12.7% increase in the number of respondents experiencing mild symptoms is calculated as 18/142, see Appendix Table A.1 Panel B for mental health distribution of the survey year 2018.

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 column 2 of Table 2, Panel B). This is consistent with the evidence in the literature. Ventriglio et al. (2021) investigate the association between major environmental pollutants and various mental health disorders, and they find the evidence is inconclusive. Although some studies report a positive association between air pollution and mental health (for example, Pun et al., 2017 and King et al., 2022), the complexity of confounders and pollutant measurements prevent any conclusion on a causal relationship between ambient air pollution and mental health.

Although our main specification (column 2 of Table 2) uses wind direction×county fixed effects as instruments to allow for the most flexible wind instruments across respondents' geographic areas, in columns 3 and 4 of Table 2 we also consider alternative specifications in which we interact wind direction with state or census division dummies. The coefficient on road noise remains negative and significant. 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.

The association between most control variables and mental health is quite similar to the results from the OLS model. For example, education, marriage, and income are associated with significant improvements in mental health. Younger respondents and females tend to have significantly worse mental health. Black and Hispanic respondents have significantly better mental health compared to White respondents.

5 Robustness Checks

5.1 Measurement Error

In our baseline analysis, we estimate the ambient noise in the 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 3 summarizes the 2SLS estimates using the point noise measurement (see Appendix Table A.8 for the full specifications). 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.

5.2 Potentially Confounding Traffic Related Air Pollution

Although we use locally precise traffic-generated CO_2 emissions and $PM_{2.5}$ concentrations to account for local air pollutants, we still worry that this approximation may not adequately capture traffic-related air pollution that is concomitant with noise pollution. So, in an alternative specification, we attempt to disentangle the effect of concomitant air pollution from the effect of noise pollution by exploiting variations in local clean energy usage. The EPA's Green Vehicle Guide notes that electric vehicles (EVs) produce no tailpipe emissions and the total emissions produced by EVs are typically less than gasoline-powered vehicles. Likewise, other alternative fuel vehicles, for example, those powered by biodiesel and E95 (95% ethanol blend), also produce lower 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.[29] 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.[30] Next, we create an interaction term between *roadnoise1km* and *CSperwpd*. This interaction term disentangles the impact of air pollution (as approximated by local clean energy usage), conditional on the ambient noise level.

We report our results in columns 1 and 2 of Table 4 (see Appendix Table A.7 for the full specifications). We find that the additional control for concomitant air pollution does not have any statistically significant effect on respondents' mental health, conditional on $PM_{2.5}$ concentrations, and either way of measuring traffic-generated CO_2 emissions, and the negative effect of road noise on mental health is still significant at the 5% level.

[29]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.

[30]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 Sub-sample of Hearing Impaired Respondents

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 5 (see Appendix Table A.8 for the full specifications). 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.[31] 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 5). 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

[31] Note that the number of observations in columns 1 and 2 of Table 5 does not add up to our full sample size of 14,033 because the question on hearing impairment is not surveyed in 2014.

do not find road noise has a significantly negative effect on these respondents' mental health (see column 3 of Table 5).

6 Noise, Sleep Deprivation and Mental Health

In this section, we focus on the association between roadway noise pollution and sleep duration in an attempt to identify a potential channel through which ambient roadway noise has a deleterious effect on mental health. There is evidence in the epidemiology literature that 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 contribute to sleep disturbance and lead to the release of stress hormones (Argys et al., 2020).

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.[32] 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

[32]We reiterate that noise pollution is a very local pollution source, so there might be some measurement errors when we utilize the average noise exposure in a relatively large area.

i residing in county c in survey year t is as follows:

$$\begin{gathered}Avgsleep_{ict} = \beta_0 + \gamma_1 Roadnoise_{ct} + \gamma_2 CO_2 Emission_{ct} + \gamma_3 PM_{2.5} Concentration_{ct} \\ +\beta_1 Female_{ict} + \boldsymbol{\beta_2} Urban_{ict} + \beta_3 Married_{ict} \\ +\beta_4 Age_{ict} + \beta_5 Age^2_{ict} + \boldsymbol{\beta_6} Educ_{ict} + \beta_7 Hhnum_{ict} + \boldsymbol{\beta_8} Race_{ict} + \boldsymbol{\beta_9} Income_{ict} \\ +\lambda_1 DocVis_{ict} + \lambda_2 Cancer_{ict} + \lambda_3 CancerFam_{ict} \\ +\lambda_4 BMI_{ict} + \lambda_5 Exercise_{ict} + \lambda_6 Own_{ict} + \epsilon_{ict}\end{gathered} \tag{4}$$

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 (see Table 6). 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 (see Appendix Table A.9 for the full specification).

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 25 minutes when the ambient road noise increases by 10 dB.[33] We also find that average traffic-generated CO_2 emissions and PM$_{2.5}$ concentrations are negatively associated with sleep duration, but the estimates are not statistically significant.

[33] $0.041 \times 60 \times 10 = 25$ minutes.

7 Conclusion

It is well established that the human stress response system is triggered by non-chemcial stimulants such as light and noise (Jariwala et al., 2017, Kumar et al., 2019). The resulting release of stress hormones can cause fragmentation and disruption of sleep, increase oxidative stress in the vasculature and brain, and ultimately affect mental health (Münzel et al., 2021). The US is singular among developed nations in terms of its high rates of mental health disease. At the same time, the US is also characterized by one of the highest rates of private vehicle ownership and the most extensive network of roadways. Not surprisingly, the regulation of noise pollution has emerged as a policy goal in recent years. The Quiet Communities Act of 2021, which was introduced in the US House of Representatives in June 2021, requires the EPA to reestablish the Office of Noise Abatement and Control to assist in the development of local noise control programs, research, and education. Also, the extensive use of personal vehicles contributes to frequent traffic congestion in large cities. However, the lack of high-frequency noise and congestion data at a national level means that the effect of ambient road noise from traffic congestion (e.g. vehicle horns) and its deleterious effects on human health is understudied and remains a gap in the literature. Until policymakers at the EPA/DoT gather and report the necessary data, we cannot answer these questions at a granular level.

Nonetheless, recognizing the importance of ambient roadway noise and the need for innovative policy, we focus on general vehicular noise from major roadways and its potential role as a contributing factor to the high incidence of mental health issues in the US. We exploit variations in topography, daily wind conditions, and annual average temperature to extract exogenous variation in ambient roadway noise. We find robust causal evidence of the negative effects of road noise on the mental health of about 14,000 respondents surveyed by the NCI, conditional on the effects of co-generated vehicular air pollution.

Zou (2017) argues that low-frequency noise from wind farms may be the driving factor behind increasing suicide rates observed near wind farms and Hener (2022) finds noise pollution increases local crime rates. Similarly, Boes and Nüesch (2011) demonstrate that aircraft noise reduces apartment rents, reflecting residents' willingness to pay to avoid noise-related disturbances, while Pope (2008) highlights that information disclosure about airport noise leads to stronger depreciation in property values, revealing the significant perceived disamenity of noise. Von Graevenitz (2018) further quantifies the amenity cost of road noise, showing its substantial negative impact on housing markets. Our findings in this study point to the bottom line of these stories. If noise pollution drives behavioral changes, such as avoidance in the housing market, engagement in criminal activities, or even suicide, these behaviors can likely be explained by noise-induced changes in mental health. By demonstrating the first-level effects of noise pollution on mental well-being, our study provides a consistent and complementary perspective to these earlier findings, linking environmental noise to broader social and behavioral outcomes.

Although the deleterious effect of roadway noise pollution on mental health that we find is relatively mild, even mild deterioration in mental health can contribute to large penalties in the labor market. Germinario et al. (2022) find that respondents' earnings decrease by 16%-18% and the employment rate decreases by at most 4% when going from having "no" to "little" or "little" to "mild" depressive symptoms. The Federal Reserve reports that the total wages and salaries in the US are 9720.96 billion dollars in 2021. Our findings suggest that around 18 out of 2528 respondents (in the survey year 2018) may go from having "little" to "mild" depressive symptoms because of each decibel increase in ambient road noise. Using Germinario et al. (2022)'s estimates, this is equivalent to an 11.35-12.77 billion dollar (in 2021 dollars) loss in welfare.[34] Similarly, Peng et al. (2016) find the presence of mild (the most severe) depressive symptoms (relative to no depressive symptoms) increases work loss days by 1.9 (4.5) days and contributes to an annual total cost of workplace absenteeism ranging from 0.9-1.9 billion dollars (in 2009 dollars). Our back-of-the-envelope calculation implies the potential labor market penalties from the deleterious effect of ambient roadway noise could be even larger than those from workplace absenteeism. As the US focuses on (re)building its highway infrastructure, this potential welfare cost due to roadway noise should

[34] $9720.96 \times 0.73\% \times 16\%(18\%) = 11.35(12.77)$. 0.73% is calculated as 18/2528, see Appendix Table A.1 Panel B.

drive co-investment in noise abatement strategies such as required noise insulation in new and retrofitted homes and minimum setbacks from major roadways. Likewise, major urban areas might take a cue from New York City's Department of Environmental Protection which recently installed "noise cameras" to detect and ticket vehicles generating noise above 85 dB (Nolan, 2023).

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Figures

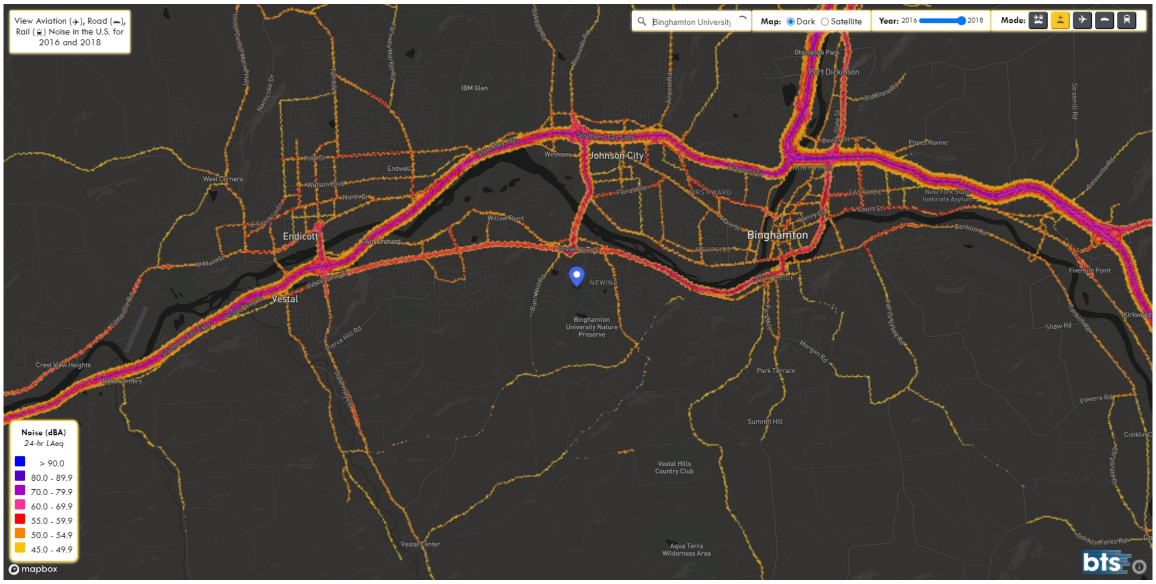


Figure 1: Binghamton University Noise Map

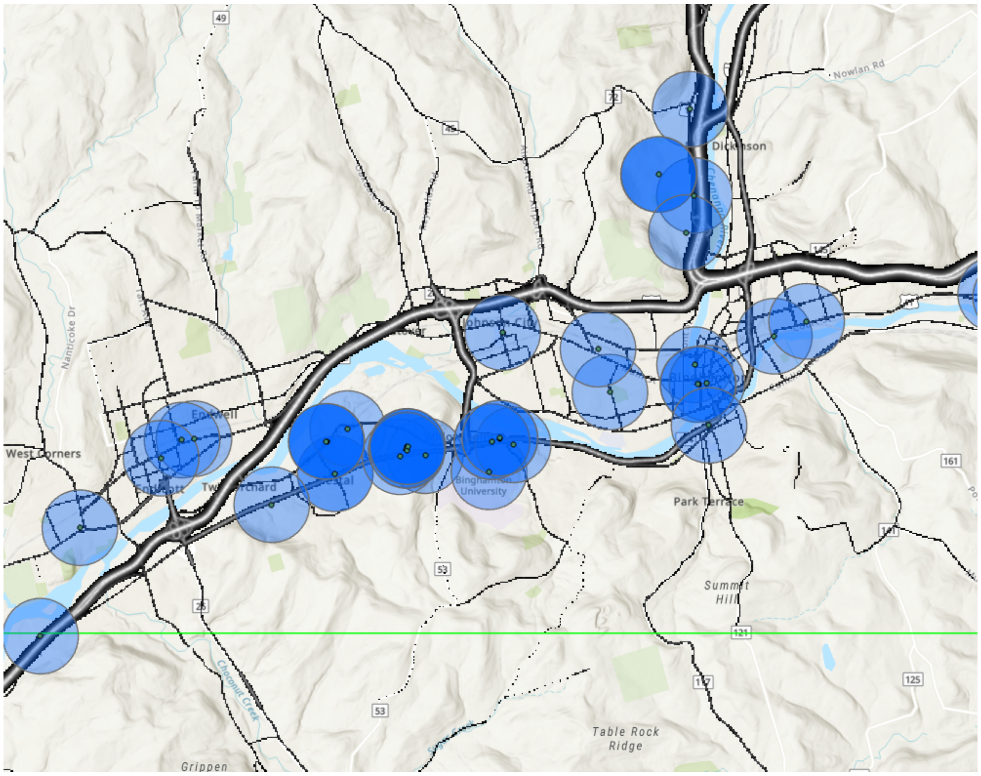
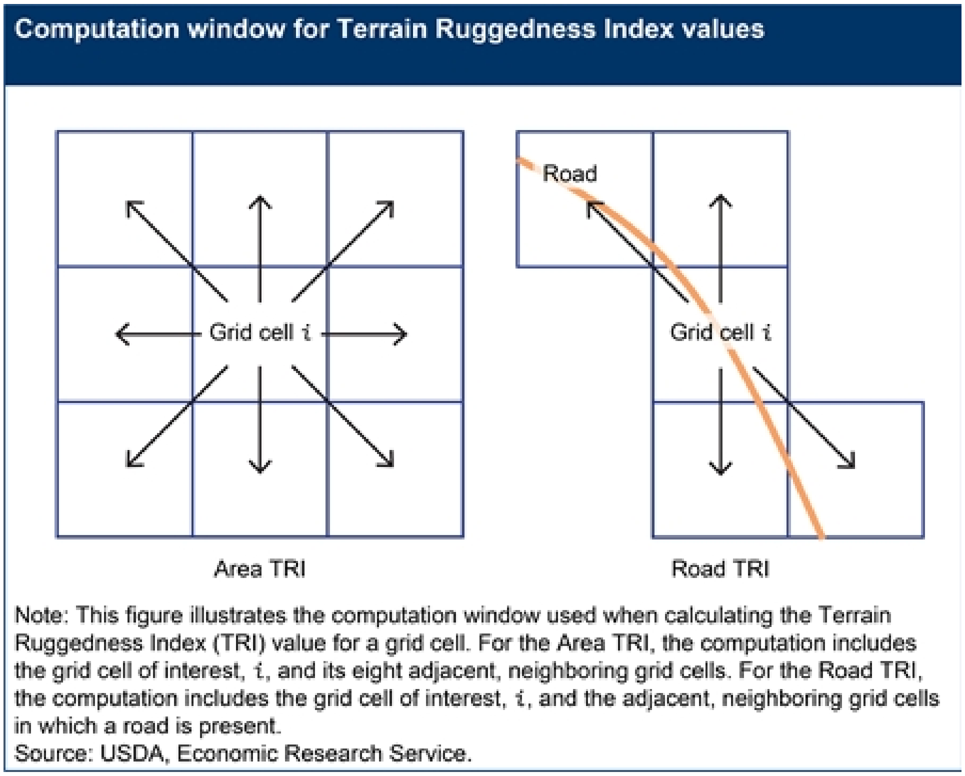


Figure 2: Noise Buffers for Hypothetical HINTS Respondents



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

Figure 3: Terrain Ruggedness Index Computation

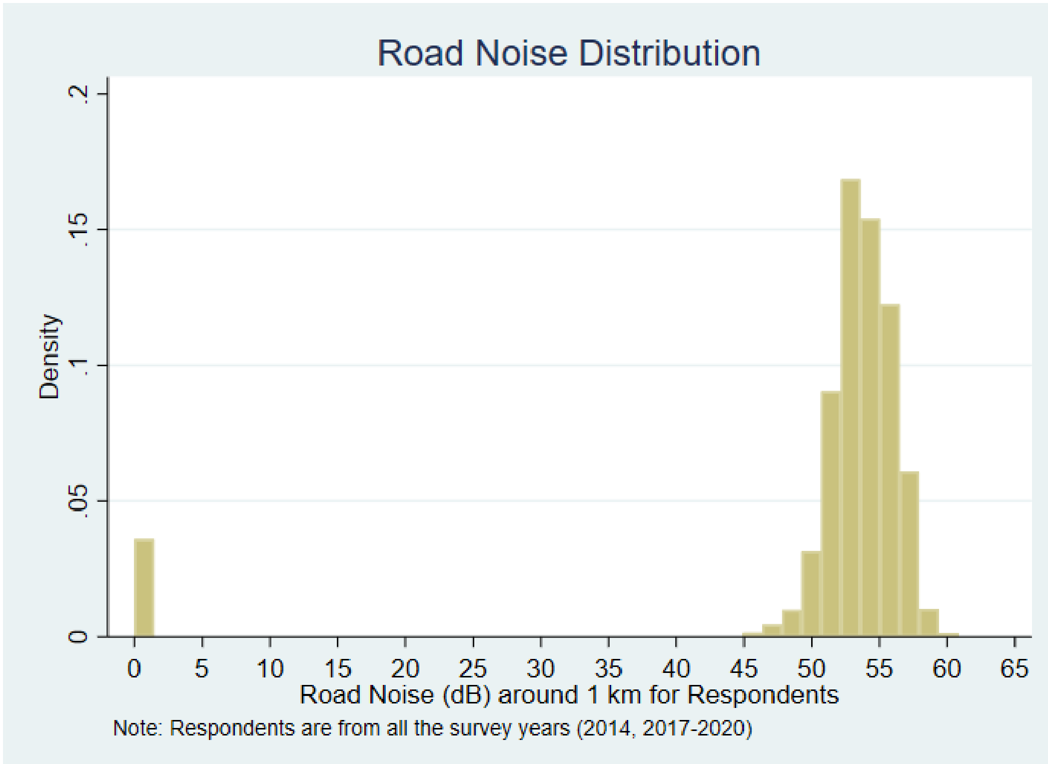


Figure 4: Ambient Road Noise Distribution

Tables

Table 1: Descriptive Statistics

	Mean	SD
Demographics		
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)[35]	0.55	0.25
Household size (number of people)	2.43	1.45
College graduate (percentage)	0.28	0.45
Income ($50K-$75K) (percentage)	0.18	0.38
Mental health index		
PHQ-4 (raw index)	1.90	2.79
PHQ-4 (standardized)	-0.0045	0.99
Health indices		
Exercise (days/week)	2.75	2.24
BMI	28.44	6.59
Diabetes (percentage)	0.20	0.40
Hypertension (percentage)	0.43	0.50
Had cancer (percentage)	0.15	0.36
Family had cancer (percentage)	0.56	0.50
Environmental factors		
Zip-5 Annual average temp ($^{\circ}F$)	60.13	8.46
Zip-5 During-survey cloud cover (%)	44.91	12.55
Zip-5 During-survey solar energy (MJ/m^2)	15.16	4.14
Zip-9 CO_2 emissions (Kton/year)	4.99	9.61
Zip-9 $PM_{2.5}$ concentration (μg/m^3)	7.65	1.76

Note: N=14,643

[35] It measures the fraction of people in the respondents' block group who own their residence.

Table 2: OLS/2SLS Results

	Dependent variable:			
	Standardized mental health index			
	OLS	*IV Approach*		
Panel A: Air pollution within 1 km	(1)	(2)	(3)	(4)
Road noise	0.0016**	0.0026**	0.0077*	0.0117*
	(0.0008)	(0.0012)	(0.0045)	(0.0067)
CO_2 emission	0.0002	0.0042	0.0110	0.0103
	(0.0009)	(0.0033)	(0.0085)	(0.0129)
$PM_{2.5}$ concentration	-0.0022	0.0033	-0.0371	-0.0318
	(0.0093)	(0.0142)	(0.0277)	(0.0365)
Panel B: Air pollution within 5 km				
Road noise	0.0016*	0.0025**	0.0077*	0.0121*
	(0.0008)	(0.0012)	(0.0044)	(0.0065)
CO_2 emission	0.0019	0.0120**	0.0134	0.0115
	(0.0023)	(0.0053)	(0.0095)	(0.0118)
$PM_{2.5}$ concentration	-0.0032	-0.0042	-0.0347	-0.0320
	(0.0098)	(0.0144)	(0.0270)	(0.0349)
Control Variables				
Demographics	X***	X***	X***	X***
Health indices	X***	X***	X***	X***
Weather	X	X	X	X
Instrument Variables				
County × wind direction		X		
State × wind direction			X	
Census Division × wind direction				X
Other instruments		X	X	X
County FE	X	X	X	X
Year FE	X	X	X	X
R^2 (Panel A)	0.198	0.122	0.108	0.101
R^2 (Panel B)	0.198	0.123	0.118	0.110
Observations[36]	14,033	14,033	14,033	14,033
Note:		*p<0.1; **p<0.05; ***p<0.01		

*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 also report the joint significance test (F-test) for control variables (i.e. *** on Demographics, Health Indices, etc.). Other Instruments include area ruggedness index, road ruggedness index, annual average temperature, wind speed, and maximum wind speed. Note that a higher value for the standardized mental health index indicates worse mental health.*

[36] There are 610 counties with only one observation each and we exclude them in our model with county fixed effect.

Table 3: Alternative Point Noise Measurement: 2SLS Estimates

	Dependent variable:
	Standardized mental health index
	(1)
Road noise	−0.00015
	(0.0009)
CO_2 emission 1km	0.0052
	(0.0033)
$PM_{2.5}$ concentration 1 km	0.0057
	(0.0141)
Demographics	X***
Health Indices	X***
Weather	X
County FE	X
Year FE	X
R^2	0.122
Observations	14,033
Note:	*p<0.1; **p<0.05; ***p<0.01

*Ambient noise is measured at the zip-9 centroid from each respondent's residence. We also report the joint significance test (F-test) for control variables (i.e. *** on Demographics, Health Indices, etc.). Note that a higher value for the standardized mental health index indicates worse mental health.*

Table 4: Robustness Check for Confounding Air Pollution: 2SLS Estimates

	Dependent variable:	
	Standardized mental health index	
	(1)	(2)
Road noise	0.0027**	0.0026**
	(0.0012)	(0.0012)
CO_2 emission 1km	0.0043	
	(0.0033)	
CO_2 emission 5km		0.0122**
		(0.0053)
$PM_{2.5}$ concentration 1km	0.0032	
	(0.0142)	
$PM_{2.5}$ concentration 5km		-0.0044
		(0.0144)
CSwpd×Road noise	-0.0083	-0.0095
	(0.0171)	(0.0170)
Demographics	X***	X***
Health Indices	X***	X***
Weather	X	X
County FE	X	X
Year FE	X	X
R^2	0.122	0.123
Observations	14,033	14,033
Note:		*p<0.1; **p<0.05; ***p<0.01

*We also report the joint significance test (F-test) for control variables (i.e. *** on Demographics, Health Indices, etc.). Note that a higher value for the standardized mental health index indicates worse mental health.*

Table 5: Hearing impaired/Non-hearing impaired Sub-sample: 2SLS Estimates

	Dependent variable:			
	Standardized mental health index			
	HI	NHI	ENHI	Comparable sample
	(1)	(2)	(3)	(4)
Road noise	−0.0033	0.0023*	0.0021	0.0044**
	(0.0076)	(0.0013)	(0.0018)	(0.0020)
CO_2 emission 1km	0.0026	0.0061*	0.0007	0.0044
	(0.0071)	(0.0032)	(0.0038)	(0.0040)
$PM_{2.5}$ concentration 1km	0.0221	−0.0003	−0.0183	0.0106
	(0.0647)	(0.0160)	(0.0238)	(0.0169)
Demographics	X***	X***	X***	X***
Health Indices	X***	X***	X***	X***
Weather	X	X	X	X
County FE	X	X	X	X
Year FE	X	X	X	X
R^2	0.159	0.121	0.100	0.117
Observations	583	10,469	3,906	10,690
Note:				*p<0.1; **p<0.05; ***p<0.01

*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. We also report the joint significance test (F-test) for control variables (i.e. *** on Demographics, Health Indices, etc.). Note that a higher value for the standardized mental health index indicates worse mental health.*

Table 6: Sleep Duration and Noise

	Dependent variable:
	Average sleep hours
Average road noise	-0.041^{*}
	(0.021)
Average CO_2 emission	-0.0014
	(0.0067)
Average $PM_{2.5}$ concentration	-0.0061
	(0.0097)
Constant	11.215^{***}
	(1.152)
Demographics	X***
Health Indices	X***
City Level	X
Housing Ownership	X
R^2	0.036
Observations	8,628
Note:	*p<0.1; **p<0.05; ***p<0.01

*We also report the joint significance test (F-test) for control variables (i.e. *** on Demographics, Health Indices, etc.).*

For Online Publication

Appendix

A Figures

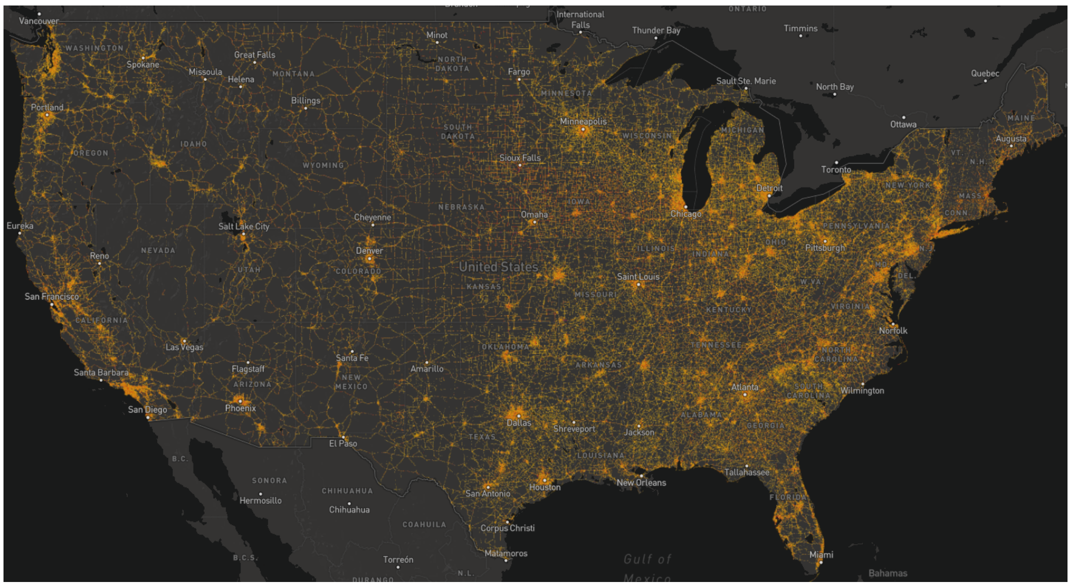


Figure A.1: DoT National Noise Map 2020

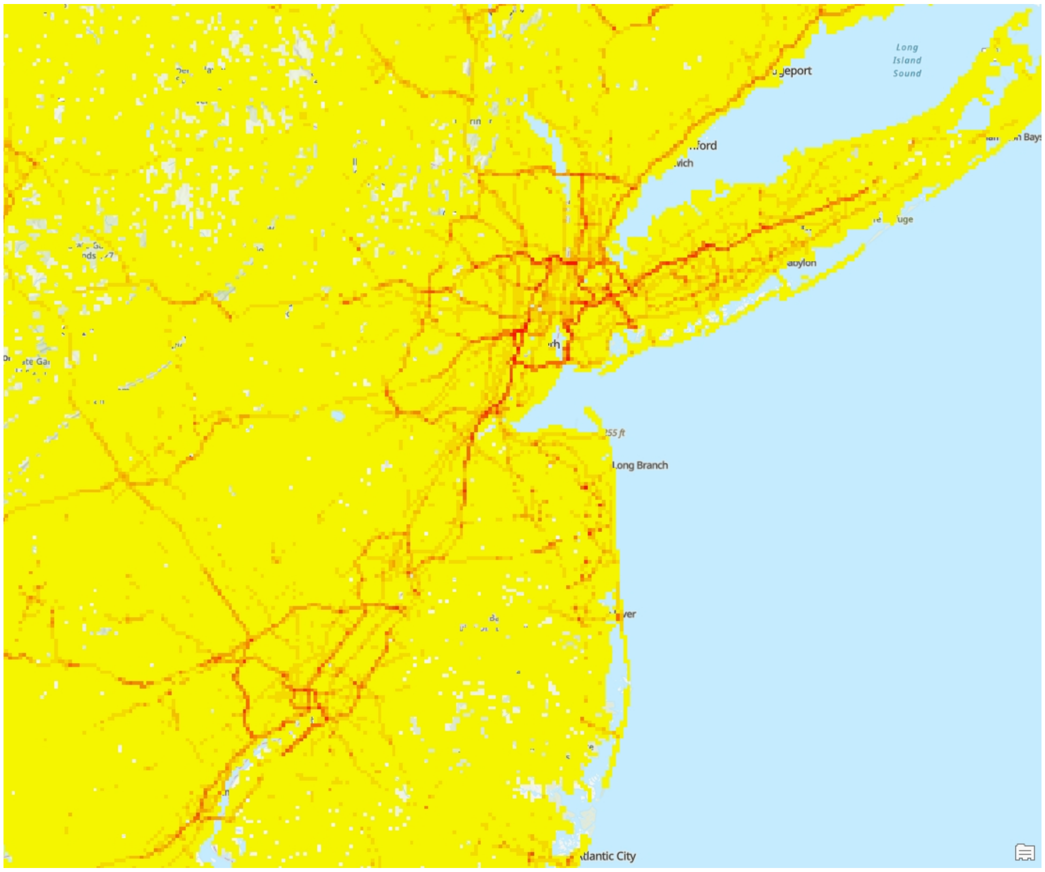
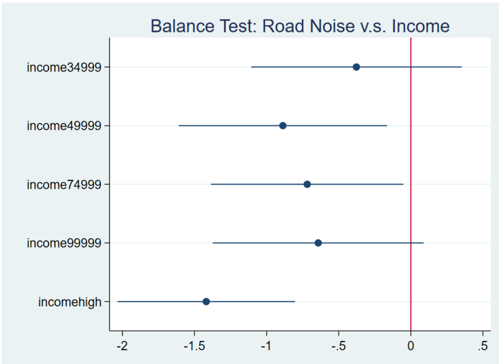
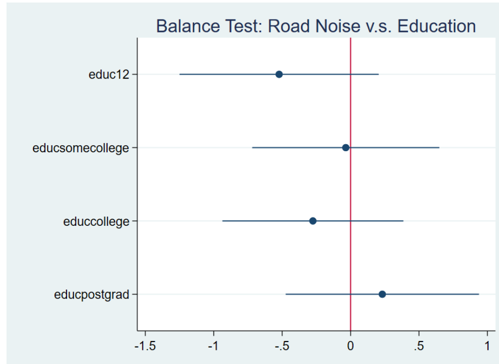


Figure A.2: CO_2 Emission Map

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.



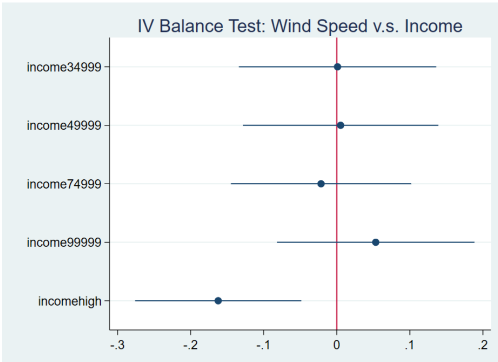
(a) Road Noise and Income



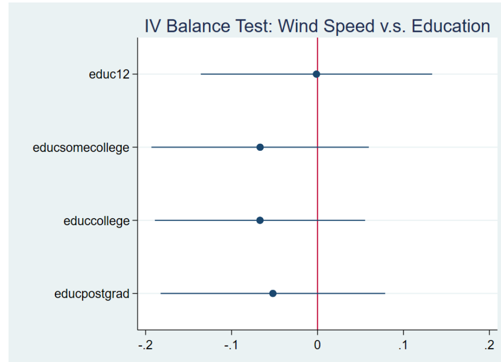
(b) Road Noise and Education

Figure A.3: Road Noise across Income/Education Levels

Note: These are the estimated coefficients and their 95% CIs from the auxiliary regression of respondents' ambient road noise within the 1-km buffer on their income/education range indicators.



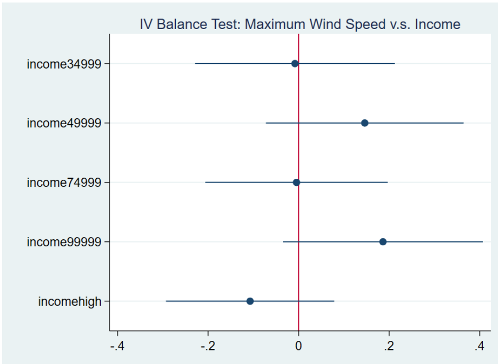
(a) Wind Speed v.s. Income



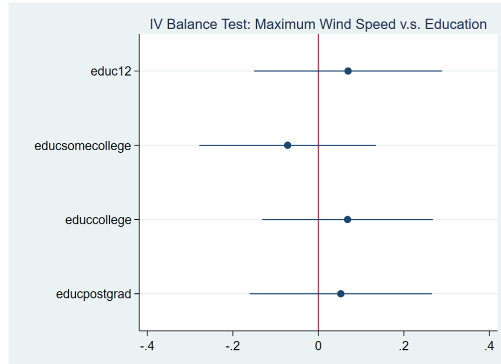
(b) Wind Speed v.s. Education

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

Figure A.4: IV Balance Test for Wind Speed



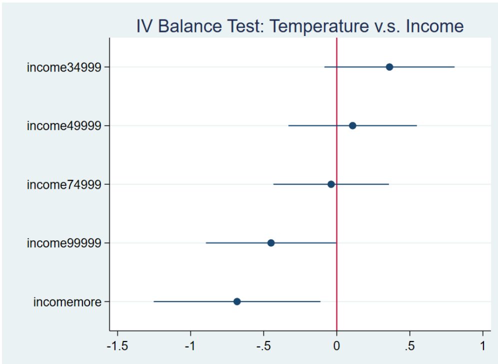
(a) Maximum Wind Speed v.s. Income



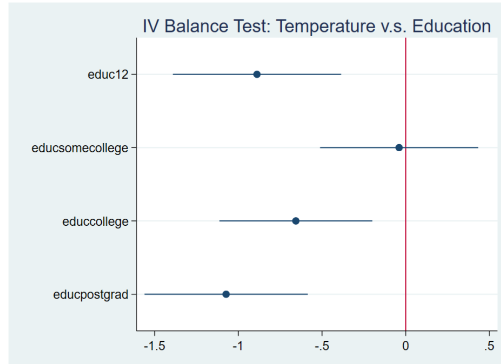
(b) Maximum Wind Speed v.s. Education

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

Figure A.5: IV Balance Test for Maximum Wind Speed



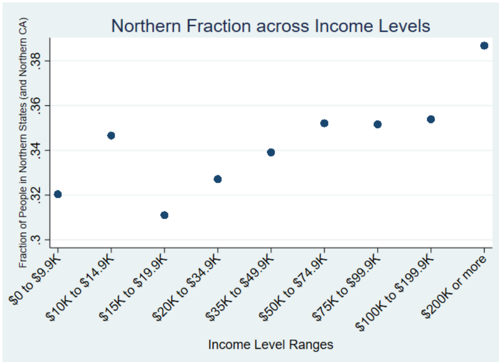
(a) Temperature v.s. Income



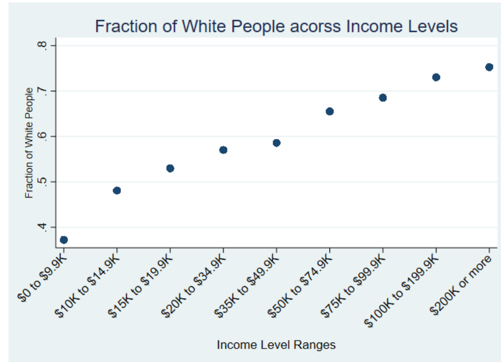
(b) Temperature v.s. Education

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 A.7 (a)). Second, the fraction of white people is increasing with income levels (see Figure A.7 (b)). 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 Figure A.8).

Figure A.6: IV Balance Test for Temperature

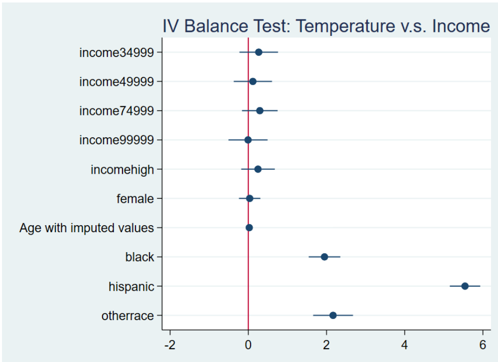


(a) The Fraction of Respondents in the Northern U.S across Income Levels

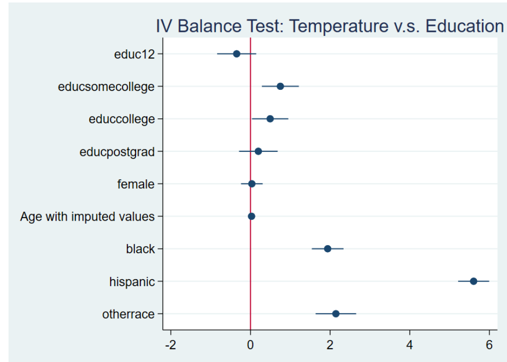


(b) The Fraction of White Respondents across Income Levels

Figure A.7: Respondents' Distribution across Areas and Income Levels



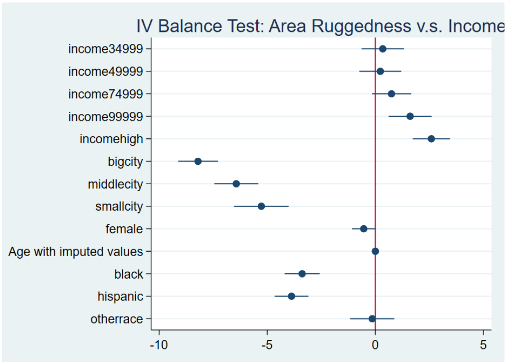
(a) Temperature v.s. Income



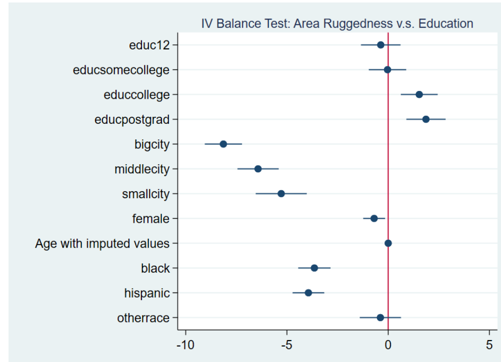
(b) Temperature v.s. Education

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 A.8: IV Balance Test for Temperature



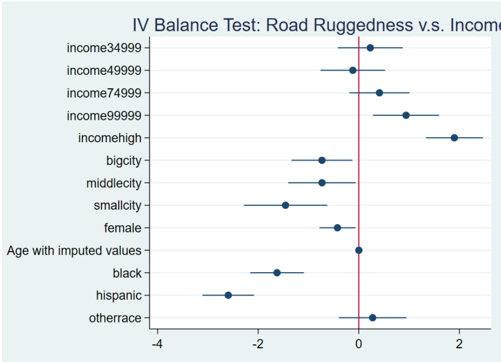
(a) Area Ruggedness v.s. Income



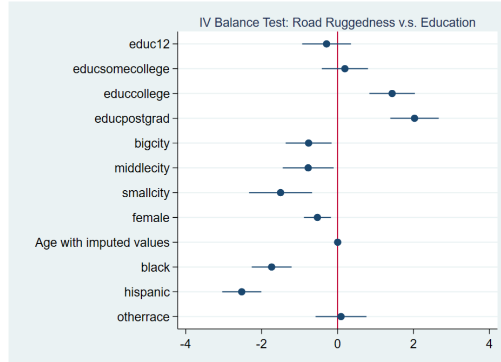
(b) Area Ruggedness v.s. Education

Note: These are the estimated coefficients and their 95% CIs from the auxiliary regression of respondents' area ruggedness index on their income/education range indicators and three exogenous control variables (gender, age, and race), conditional on city levels. In Figures A.9 and A.10, 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 A.9: IV Balance Test for Area Ruggedness



(a) Road Ruggedness v.s. Income



(b) Road Ruggedness v.s. Education

Note: These are the estimated coefficients and their 95% CIs from the auxiliary regression of respondents' road ruggedness index on their income/education range indicators and three exogenous control variables (gender, age, and race), conditional on city levels. In Figures A.9 and A.10, 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 A.10: IV Balance Test for Road Ruggedness

B Tables

Table A.1: Income and Mental Health Distribution

Panel A: Income		
Income Ranges	Freq.	Percent
$0 to $19,999	2,537	17.32
$20,000 to $34,999	1,874	12.80
$35,000 to $49,999	1,943	13.27
$50,000 to $74,999	2,633	17.98
$75,000 to $99,999	1,870	12.77
$100,000 or more	3,786	25.86
Total (Whole Sample)	14,643	100.00

Panel B: Mental Health			
Raw PHQ-4 Index	Standardized PHQ-4 Index	Freq.	Percent
0	-0.665	1,265	50.04
1	-0.307	315	12.46
2	0.051	285	11.27
3	0.408	142	5.62
4	0.766	200	7.91
5	1.124	67	2.65
6	1.481	41	1.62
7	1.839	48	1.90
8	2.197	42	1.66
9	2.554	32	1.27
10	2.912	29	1.15
11	3.270	22	0.87
12	3.627	40	1.58
Total (2018 Sub-sample)		2,528	100.00

Table A.2: Full Model Specifications

	Dependent variable:		
	Standardized mental health index		
	OLS	*IV Approach*	
	(1)	(2)	(3)
educ12	-0.056^{*}	-0.054^{*}	-0.054^{*}
	(0.030)	(0.030)	(0.030)
educsomecollege	-0.040	-0.038	-0.038
	(0.029)	(0.029)	(0.029)
educcollege	-0.092^{***}	-0.088^{***}	-0.090^{***}
	(0.029)	(0.029)	(0.029)
educpostgrad	-0.116^{***}	-0.112^{***}	-0.116^{***}
	(0.032)	(0.032)	(0.032)
female	0.079^{***}	0.079^{***}	0.078^{***}
	(0.017)	(0.017)	(0.017)
married	-0.149^{***}	-0.146^{***}	-0.146^{***}
	(0.019)	(0.020)	(0.020)
totalhousehold	0.002	0.003	0.003
	(0.007)	(0.007)	(0.007)
age	-0.007^{**}	-0.007^{**}	-0.007^{**}
	(0.003)	(0.003)	(0.003)
age^2	-0.00005^{*}	-0.00005^{*}	-0.00005^{**}
	(0.00003)	(0.00003)	(0.00003)
black	-0.228^{***}	-0.229^{***}	-0.232^{***}
	(0.027)	(0.027)	(0.027)
hispanic	-0.052^{*}	-0.057^{**}	-0.057^{**}
	(0.027)	(0.027)	(0.027)
otherrace	-0.017	-0.021	-0.019
	(0.032)	(0.032)	(0.032)
everhadcancer	0.022	0.022	0.023
	(0.024)	(0.024)	(0.024)
familyeverhadcancer	0.066^{***}	0.065^{***}	0.064^{***}
	(0.020)	(0.020)	(0.020)
income34999	-0.258^{***}	-0.259^{***}	-0.256^{***}
	(0.030)	(0.030)	(0.030)
income49999	-0.332^{***}	-0.333^{***}	-0.330^{***}
	(0.031)	(0.031)	(0.031)
income74999	-0.405^{***}	-0.406^{***}	-0.403^{***}
	(0.029)	(0.029)	(0.030)
income99999	-0.454^{***}	-0.454^{***}	-0.451^{***}
	(0.033)	(0.033)	(0.033)

	Dependent variable:		
	Standardized mental health index		
	OLS	*IV Approach*	
incomehigh	−0.483***	−0.482***	−0.479***
	(0.031)	(0.031)	(0.031)
freqgoprovider	0.038***	0.038***	0.038***
	(0.003)	(0.003)	(0.003)
timesmoderateexercise	−0.043***	−0.043***	−0.043***
	(0.004)	(0.004)	(0.004)
bmi	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)
diabetes	0.146***	0.147***	0.146***
	(0.022)	(0.022)	(0.022)
hypertension	0.089***	0.088***	0.088***
	(0.019)	(0.019)	(0.019)
ownfraction	−0.165***	−0.139***	−0.117***
	(0.036)	(0.039)	(0.040))
surveyicyday	−0.0003	−0.0003	−0.0002
	(0.002)	(0.002)	(0.002)
surveyhotday	0.0017*	0.0017*	0.0017*
	(0.0010)	(0.0010)	(0.0010)
surveycloudcover	0.0036**	0.0032**	0.0025
	(0.0015)	(0.0015)	(0.0016)
surveysolarenergy	0.0006	0.0003	0.0002
	(0.003)	(0.003)	(0.003)
roadnoise1km	0.0016**	0.0026**	0.0025**
	(0.0008)	(0.0012)	(0.0012)
CO_2 emission1km	0.0002	0.0042	
	(0.0009)	(0.0033)	
CO_2 emission5km			0.0120**
			(0.0053)
$PM_{2.5}$ concentration1km	-0.0022	0.0033	
	(0.0093)	(0.0142)	
$PM_{2.5}$ concentration5km			-0.0042
			(0.0144)
Constant	0.587***		
	(0.157)		
County FE	X	X	X
Year FE	X	X	X
R^2	0.198	0.122	0.123
Observations	14,033	14,033	14,033

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.3: First Stage Results

Panel A	Dependent variable: Road noise (1)	(2)	(3)
Windspeed	0.303**	0.423***	0.346***
	(0.128)	(0.117)	(0.114)
Windspeed Maximum	-0.061	-0.115*	-0.099
	(0.079)	(0.069)	(0.066)
Averagetemp	0.264***	0.170*	0.174
	(0.094)	(0.089)	(0.087)
RoadTRI	0.189***	0.237***	0.233***
	(0.022)	(0.023)	(0.023)
AreaTRI	-0.165***	-0.211***	-0.210***
	(0.015)	(0.016)	(0.015)
F Statistic	3.73	3.87	7.65
R^2	0.612	0.303	0.291
County × wind direction	X		
State × wind direction		X	
Census Division × wind direction			X

	Dependent variable: CO_2 Emission					
	1km Buffer			5km Buffer		
Panel B	(1)	(2)	(3)	(4)	(5)	(6)
Windspeed	0.145	-0.060	-0.063	0.097*	-0.059	-0.088
	(0.152)	(0.107)	(0.103)	(0.054)	(0.040)	(0.038)
Windspeed Maximum	-0.108	-0.022	-0.0005	-0.113***	0.002	0.023
	(0.094)	(0.063)	(0.060)	(0.033)	(0.023)	(0.022)
Averagetemp	0.394***	0.308***	0.310***	0.399***	0.335***	0.331***
	(0.111)	(0.081)	(0.079)	(0.039)	(0.030)	(0.029)
RoadTRI	0.066**	0.073***	0.076***	0.074***	0.073***	0.073***
	(0.026)	(0.021)	(0.021)	(0.009)	(0.008)	(0.008)
AreaTRI	-0.062***	-0.063***	-0.064***	-0.059***	-0.058***	-0.059***
	(0.018)	(0.014)	(0.014)	(0.006)	(0.005)	(0.005)
F Statistic	0.48	3.43	8.87	1.64	14.30	37.29
R^2	0.232	0.183	0.178	0.651	0.596	0.587
County × wind direction	X			X		
State × wind direction		X			X	
Census Division × wind direction			X			X

	Dependent variable: $PM_{2.5}$					
	1km Buffer			5km Buffer		
Panel C	(1)	(2)	(3)	(4)	(5)	(6)
Windspeed	-0.035***	-0.046***	-0.042***	-0.024**	-0.037***	-0.032***
	(0.011)	(0.010)	(0.009)	(0.010)	(0.009)	(0.009)
Windspeed Maximum	-0.146***	-0.090***	-0.082***	-0.153***	-0.096***	-0.088***
	(0.007)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)
Averagetemp	0.035***	0.037***	0.028***	0.034***	0.042***	0.032***
	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)
RoadTRI	0.005**	0.005***	0.006***	0.007***	0.006***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
AreaTRI	-0.012***	-0.012***	-0.012***	-0.013***	-0.013***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
F Statistic	3.36	12.18	23.68	3.89	14.48	28.50
R^2	0.871	0.801	0.791	0.889	0.822	0.811
County × wind direction	X			X		
State × wind direction		X			X	
Census Division × wind direction			X			X

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) and (4) 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.

Table A.4: First Stage Results without Wind-related Instruments

	Dependent variable:		
	Road noise	*CO_2 emission 1km*	*$PM_{2.5}$ concentration 1km*
	(1)	(2)	(3)
Averagetemp:	0.197**	0.345***	0.015***
	(0.084)	(0.076)	(0.007)
RoadTRI:	0.232***	0.079***	0.007***
	(0.023)	(0.021)	(0.002)
AreaTRI:	-0.212***	-0.068***	-0.013***
	(0.015)	(0.014)	(0.001)
F Statistic	69.31	15.22	68.08
County FE	X	X	X
Year FE	X	X	X
R^2	0.288	0.177	0.794
Observations	14,033	14,033	14,033
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.5: Robustness Check: 2SLS Estimates with Ruggedness and Average Temperature Instruments (without Wind-related Instruments)

	Dependent variable:
	Standardized mental health index
	(1)
educ12	−0.046
	(0.036)
educsomecollege	−0.032
	(0.033)
educcollege	−0.076
	(0.036)
educpostgrad	−0.113***
	(0.044)
female	0.069***
	(0.020)
married	−0.128***
	(0.024)
totalhousehold	0.002
	(0.008)
age	−0.007
	(0.004)
age^2	−0.00005*
	(0.00003)
black	−0.231***
	(0.030)
hispanic	−0.024
	(0.042)
otherrace	−0.025
	(0.039)
everhadcancer	0.030
	(0.028)
familyeverhadcancer	0.056**
	(0.022)
income34999	−0.274***
	(0.034)
income49999	−0.329***
	(0.034))
income74999	−0.423***
	(0.033)

	Dependent variable:
	Standardized mental health index
income99999	−0.462***
	(0.036)
incomehigh	−0.468***
	(0.035)
freqgoprovider	0.037***
	(0.004)
timesmoderateexercise	−0.043***
	(0.004)
bmi	0.004***
	(0.002)
diabetes	0.140***
	(0.025)
hypertension	0.087***
	(0.022)
ownfraction	−0.088
	(0.132)
surveyicyday	0.004
	(0.003)
surveyhotday	0.002
	(0.001)
surveycloudcover	0.005*
	(0.003)
surveysolarenergy	0.005
	(0.005)
roadnoise1km	0.036**
	(0.018)
CO_2 emission1km	−0.0010
	(0.030)
$PM_{2.5}$ concentration1km	−0.263
	(0.165)
County FE	X
Year FE	X
R^2	−0.05
Observations	14,033
Note:	+p<0.2; *p<0.1; **p<0.05; ***p<0.01

Table A.6: Alternative Point Noise Measurement: 2SLS Estimates with Full Model Specifications

	Dependent variable:
	Standardized mental health index
	(1)
educ12	−0.054*
	(0.030)
educsomecollege	−0.039
	(0.029)
educcollege	−0.089***
	(0.029)
educpostgrad	−0.111***
	(0.032)
female	0.080***
	(0.017)
married	−0.148***
	(0.020)
totalhousehold	0.003
	(0.007)
age	−0.007**
	(0.003)
age^2	−0.00005*
	(0.00003)
black	−0.228***
	(0.027)
hispanic	−0.056**
	(0.027)
otherrace	−0.020
	(0.032)
everhadcancer	0.023
	(0.024)
familyeverhadcancer	0.065***
	(0.020)
income34999	−0.258***
	(0.030)
income49999	−0.333***
	(0.031))
income74999	−0.406***
	(0.030)
income99999	−0.454***
	(0.033)

	Dependent variable:
	Standardized mental health index
incomehigh	-0.483^{***}
	(0.031)
freqgoprovider	0.038^{***}
	(0.003)
timesmoderateexercise	-0.043^{***}
	(0.004)
bmi	0.005^{***}
	(0.001)
diabetes	0.147^{***}
	(0.022)
hypertension	0.088^{***}
	(0.019)
ownfraction	-0.143^{***}
	(0.040))
surveyicyday	-0.0003
	(0.002)
surveyhotday	0.0017^{*}
	(0.0010)
surveycloudcover	0.0032^{**}
	(0.0015)
surveysolarenergy	0.0002
	(0.003)
roadnoise1km	-0.00015
	(0.0009)
CO_2 emission1km	0.0052
	(0.0033)
$PM_{2.5}$ concentration1km	0.0057
	(0.0141)
County FE	X
Year FE	X
R^2	0.122
Observations	14,033
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A.7: Robustness Check for Confounding Air Pollution: 2SLS Estimates with Full Model Specifications

	Dependent variable:	
	Standardized mental health index	
	(1)	(2)
educ12	-0.055^{*}	-0.055^{*}
	(0.030)	(0.030)
educsomecollege	-0.039	-0.039
	(0.029)	(0.029)
educcollege	-0.088^{***}	-0.090^{***}
	(0.029)	(0.029)
educpostgrad	-0.112^{***}	-0.115^{***}
	(0.032)	(0.032)
female	0.079^{***}	0.078^{***}
	(0.017)	(0.017)
married	-0.146^{***}	-0.146^{***}
	(0.020)	(0.020)
totalhousehold	0.003	0.003
	(0.007)	(0.007)
age	-0.007^{**}	-0.007^{**}
	(0.003)	(0.003)
age^2	-0.00005^{*}	-0.00005^{**}
	(0.00003)	(0.00003)
black	-0.230^{***}	-0.232^{***}
	(0.027)	(0.027)
hispanic	-0.058^{**}	-0.057^{**}
	(0.027)	(0.027)
otherrace	-0.021	-0.020
	(0.032)	(0.032)
everhadcancer	0.023	0.023
	(0.024)	(0.024)
familyeverhadcancer	0.065^{***}	0.064^{***}
	(0.020)	(0.020)
income34999	-0.259^{***}	-0.256^{***}
	(0.030)	(0.030)
income49999	-0.332^{***}	-0.329^{***}
	(0.031)	(0.031)
income74999	-0.406^{***}	-0.403^{***}
	(0.030)	(0.030)
income99999	-0.454^{***}	-0.451^{***}
	(0.033)	(0.033)

	Dependent variable:	
	Standardized mental health index	
	(1)	(2)
incomehigh	−0.481***	−0.479***
	(0.031)	(0.031)
freqgoprovider	0.038***	0.038***
	(0.003)	(0.003)
timesmoderateexercise	−0.043***	−0.043***
	(0.004)	(0.004)
bmi	0.005***	0.005***
	(0.001)	(0.001)
diabetes	0.146***	0.146***
	(0.022)	(0.022)
hypertension	0.088***	0.089***
	(0.019)	(0.019)
ownfraction	−0.140***	−0.119***
	(0.040)	(0.041)
surveyicyday	−0.0003	−0.0002
	(0.0018)	(0.0018)
surveyhotday	0.0017*	0.0017*
	(0.0010)	(0.0010)
surveycloudcover	0.0032**	0.0025
	(0.0015)	(0.0016)
surveysolarenergy	0.0003	0.0002
	(0.003)	(0.003)
roadnoise1km	0.0027**	0.0026**
	(0.0012)	(0.0012)
roadnoise1km×CSwpd	-0.0083	-0.0095
	(0.0171)	(0.0170)
CO_2 emission1km	0.0043	
	(0.0033)	
CO_2 emission5km		0.0122**
		(0.0053)
$PM_{2.5}$ concentration1km	0.0032	
	(0.0142)	
$PM_{2.5}$ concentration5km		-0.0044
		(0.0144)
County FE	X	X
Year FE	X	X
R^2	0.122	0.123
Observations	14,033	14,033
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.8: Hearing impaired/Non-hearing impaired Sub-sample: 2SLS Estimates with Full Model Specifications

	Dependent variable:			
	Standardized mental health index			
	HI	NHI	ENHI	Comparable sample
	(1)	(2)	(3)	(4)
educ12	−0.066	−0.054	−0.013	−0.065*
	(0.172)	(0.036)	(0.050)	(0.035)
educsomecollege	0.080	−0.012	−0.002	−0.041
	(0.167)	(0.034)	(0.048)	(0.033)
educcollege	−0.061	−0.080**	−0.029	−0.100***
	(0.190)	(0.034)	(0.050)	(0.033)
educpostgrad	−0.210	−0.084**	−0.066	−0.111***
	(0.201)	(0.037)	(0.052)	(0.036)
female	0.034	0.094***	0.093***	0.087***
	(0.111)	(0.020)	(0.030)	(0.019)
married	−0.221*	−0.150***	−0.078***	−0.135***
	(0.132)	(0.023)	(0.034)	(0.022)
totalhousehold	0.035	−0.002	0.001	0.002
	(0.052)	(0.008)	(0.014)	(0.007)
age	−0.064***	−0.005	−0.048	−0.008**
	(0.024)	(0.004)	(0.033)	(0.003)
age^2	0.0004**	−0.0001**	0.0003	−0.00004
	(0.0002)	(0.00003)	(0.0002)	(0.00003)
black	−0.089	−0.232***	−0.230***	−0.241***
	(0.221)	(0.031)	(0.046)	(0.030)
hispanic	−0.035	−0.075**	0.006	−0.081***
	(0.160)	(0.031)	(0.052)	(0.029)
otherrace	0.271	−0.040	−0.031	−0.023
	(0.212)	(0.036)	(0.061)	(0.034)
everhadcancer	−0.034	0.012	0.017	0.013
	(0.126)	(0.028)	(0.033)	(0.027)
familyeverhadcancer	0.076	0.065***	0.051	0.069***
	(0.139)	(0.024)	(0.037)	(0.023)
income34999	−0.038	−0.239***	−0.342***	−0.244***
	(0.174)	(0.036)	(0.050)	(0.034)
income49999	−0.117	−0.289***	−0.388***	−0.315***
	(0.183)	(0.036)	(0.051)	(0.035)
income74999	−0.027	−0.367***	−0.380***	−0.385***
	(0.183)	(0.034)	(0.050)	(0.033)

	Dependent variable:			
	Standardized mental health index			
	HI	NHI	ENHI	Comparable sample
	(1)	(2)	(3)	(4)
income99999	0.057	−0.408***	−0.487***	−0.434***
	(0.220)	(0.038)	(0.058)	(0.037)
incomehigh	−0.371*	−0.442***	−0.453***	−0.461***
	(0.184)	(0.036)	(0.055)	(0.035)
freqgoprovider	0.027	0.037***	0.030***	0.036***
	(0.017)	(0.003)	(0.005)	(0.003)
timesmoderateexercise	−0.015	−0.042***	−0.038***	−0.040***
	(0.023)	(0.004)	(0.006)	(0.004)
bmi	0.013	0.005***	−0.005**	0.006***
	(0.009)	(0.002)	(0.003)	(0.002)
diabetes	0.159	0.127***	0.099***	0.116***
	(0.121)	(0.026)	(0.034)	(0.025)
hypertension	0.215*	0.074***	0.027	0.118***
	(0.122)	(0.022)	(0.031)	(0.022)
ownfraction	−0.318	−0.135***	−0.169***	−0.167***
	(0.220)	(0.044)	(0.065)	(0.045)
surveyicyday	0.010	−0.0006	0.0027	0.0012
	(0.0147)	(0.0023)	(0.0038)	(0.0022)
surveyhotday	−0.0063	0.0007	0.0015	0.0021*
	(0.0065)	(0.0013)	(0.0020)	(0.0011)
surveycloudcover	−0.0014	0.0014	0.0050*	0.0022
	(0.0106)	(0.0019)	(0.0029)	(0.0017)
surveysolarenergy	0.0078	0.0024	−0.0034	0.0008
	(0.0275)	(0.0032)	(0.0047)	(0.0033)
Road noise	−0.0033	0.0023*	0.0021	0.0044**
	(0.0076)	(0.0013)	(0.0018)	(0.0020)
CO_2 emission1km	0.0026	0.0061*	0.0007	0.0044
	(0.0071)	(0.0032)	(0.0038)	(0.0040)
$PM_{2.5}$ concentration1km	0.0221	−0.0003	−0.0183	0.0106
	(0.0647)	(0.0160)	(0.0238)	(0.0169)
R^2	0.159	0.121	0.100	0.117
Observations	583	10,469	3,906	10,690
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.9: Sleep Duration and Noise: Full Model Specification

	Dependent variable:
	Average sleep
educ12	−0.055
	(0.050)
educsomecollege	−0.155***
	(0.050)
educcollege	−0.100**
	(0.051)
educpostgrad	−0.044
	(0.056)
female	0.117***
	(0.031)
married	0.122***
	(0.035)
totalhousehold	−0.029***
	(0.009)
age	−0.048***
	(0.005)
age^2	0.0005***
	(0.00005)
black	−0.076
	(0.046)
hispanic	0.081*
	(0.047)
otherrace	−0.163***
	(0.061)
bigcity	−0.065
	(0.055)
middlecity	0.017
	(0.056)
smallcity	−0.069
	(0.063)
everhadcancer	−0.052*
	(0.029)
familyeverhadcancer	−0.058*
	(0.032)

	Dependent variable:
	Average sleep
income34999	0.019
	(0.048)
income49999	−0.046
	(0.049)
income74999	−0.002
	(0.049)
income99999	−0.025
	(0.058)
incomehigh	−0.049
	(0.055)
freqgoprovider	0.005
	(0.005)
timesmoderateexercise	−0.003
	(0.007)
bmi	−0.011***
	(0.002)
own	−0.027
	(0.038)
avgroadnoise	−0.041*
	(0.021)
avgCO_2emission	−0.001
	(0.007)
avg$PM_{2.5}$concentration	−0.006
	(0.010)
Constant	11.215***
	(1.152)
R^2	0.036
Observations	8,628
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A.10: Robustness Check using Raw Mental Health Index: 2SLS Estimates with Full Model Specifications

	Dependent variable:	
	Raw mental health index	
	(1)	(2)
educ12	−0.153*	−0.153*
	(0.086)	(0.086)
educsomecollege	−0.111	−0.110
	(0.081)	(0.081)
educcollege	−0.250***	−0.254***
	(0.082)	(0.082)
educpostgrad	−0.317***	−0.327***
	(0.090)	(0.090)
female	0.224***	0.221***
	(0.048)	(0.048)
married	−0.412***	−0.411***
	(0.055)	(0.055)
totalhousehold	0.008	0.009
	(0.019)	(0.019)
age	−0.019**	−0.018**
	(0.008)	(0.008)
age^2	−0.0001*	−0.0002**
	(0.00008)	(0.00008)
black	−0.647***	−0.653***
	(0.076)	(0.076)
hispanic	−0.159**	−0.158**
	(0.075)	(0.075)
otherrace	−0.059	−0.055
	(0.089)	(0.089)
everhadcancer	0.065	0.065
	(0.068)	(0.068)
familyeverhadcancer	0.181***	0.179***
	(0.057)	(0.057)
income34999	−0.732***	−0.723***
	(0.086)	(0.086)
income49999	−0.941***	−0.933***
	(0.086)	(0.087))
income74999	−1.148***	−1.140***
	(0.083)	(0.083)

	Dependent variable:	
	Raw mental health index	
	(1)	(2)
income99999	−1.285***	−1.276***
	(0.093)	(0.093)
incomehigh	−1.361***	−1.354***
	(0.088)	(0.088)
freqgoprovider	0.107***	0.108***
	(0.008)	(0.008)
timesmoderateexercise	−0.120***	−0.120***
	(0.011)	(0.011)
bmi	0.013***	0.013***
	(0.004)	(0.004)
diabetes	0.414***	0.413***
	(0.063)	(0.063)
hypertension	0.249***	0.250***
	(0.055)	(0.055)
ownfraction	−0.393***	−0.331***
	(0.111)	(0.114)
surveyicyday	−0.0007	−0.0004
	(0.005)	(0.005)
surveyhotday	0.0050*	0.0049*
	(0.0028)	(0.0028)
surveycloudcover	0.0093**	0.0072
	(0.004)	(0.004)
surveysolarenergy	0.0006	0.0004
	(0.009)	(0.009)
roadnoise1km	0.0074**	0.0071**
	(0.0033)	(0.0033)
CO_2 emission1km	0.0115	
	(0.0093)	
CO_2 emission5km		0.0335**
		(0.0148)
$PM_{2.5}$ concentration1km	0.0082	
	(0.040)	
$PM_{2.5}$ concentration5km		−0.0131
		(0.041)
County FE	X	X
Year FE	X	X
R^2	0.123	0.123
Observations	14,033	14,033
Note:	*p<0.1; **p<0.05; ***p<0.01	