Beyond the Haze of Air Pollution: Traffic Noise and Mental Health

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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. While the literature has linked several factors to poor mental health, the role of non-chemical environmental factors is unclear. Using restricted data on approximately 14,000 survey respondents, we estimate that road noise is associated with sleep deprivation and has a statistically significant, causal effect on mental health, equivalent to around 10.5% more of the respondents experiencing mild symptoms from little symptoms. This translates to an annual welfare loss as large as $13 billion for the US.

Keywords— Road noise; Mental health; Area and road ruggedness; Wind speed; Wind direction; HINTS

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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 influencing health) (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 poor mental health, poorer academic performance, more serious dementia, and even higher suicide rates (Zhang et al., 2017; Dzhambov et al., 2018; Ao et al., 2021; Heissel et al., 2022; Persico and Marcotte, 2022; Balakrishnan and Tsaneva, 2023; Bishop et al., 2023; Xie et al., 2023). However, the effect of non-chemical environmental triggers such as noise pollution has received scant attention.

For example, exposure to excessive noise can lead to symptoms such as anxiety, nervousness, and mental fatigue (Argys et al., 2020) which induces cognitive impairment in children and interferes with sleep (Svingos et al., 2018). In addition,

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

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. Still, the relationship between the effects of ambient noise on mental health and the underlying mechanism is not well-established in the literature. Zare et al. (2018) argue that the negative effects of noise on children's neurodevelopmental and mental health are heterogeneous and limited. Furthermore, the link could be weakened by large variations in individual noise exposure because of differences in occupational categories and modes of transportation (Ma et al., 2020). Thus, identifying and acknowledging the causal effects of noise pollution on mental health is both welfare and policy-relevant.[2]

We fill the gap in the literature by identifying a strong causal link between ambient noise pollution and mental health. 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 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. Meanwhile, American drivers spent more than 84 billion hours driving during 2015, on average, spending just under an hour driving every day (Filosa et al., 2017). Given the widespread roadway network in the US and the extensive usage of private vehicles for transportation, we determine if ambient road noise is a contributing factor to mental health problems in the US.

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

[2]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).

"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. However, none of the aforementioned studies establish a causal link between 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 have access to 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 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 transportation-related ambient noise relatively precisely. We also use information on chemical releases from the US Environmental Protection Agency's (EPA's) Toxics Release Inventory (TRI), satellite data measures traffic-generated CO_2 emissions from the National Aeronautics and Space Administration (NASA), and weather information from the National Centers for Environmental Information as control variables.

Our key outcome variable is a summary mental health index for each respondent in the HINTS data. 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.[3] 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

[3]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.8, we also present estimates using the raw (unstandardized) index values.

such as cloud cover and days with extreme temperature and air quality.

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 noise pollution is not randomly assigned, since respondents may sort themselves to live in areas with different levels of ambient roadway noise and air pollution based on their socioeconomic status. We overcome the challenge by exploiting variations in local topography, during-survey temperature, and annual wind speed and direction to extract exogenous variation in ambient noise and traffic-generated air pollution.

The identifying assumption for our instrumental variable approach is that topographic variation, wind conditions, and during-survey temperature only affect respondents' mental health through the channel of ambient roadway noise and air pollution. To isolate the variation in noise from air pollution, we control for local traffic-generated air pollution using data from NASA's Database of Road Transportation Emissions (DARTE) and use our instruments to address its endogeneity.[4] We argue that the variation in local topography and the number of days with different prevailing wind directions generate different ambient 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 during-survey temperature to extract the exogenous change in 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 to capture the direct effect on mental health, but also use during-survey temperature (which should not have a direct effect on mental health) as one of our instruments to address the endogeneity of ambient noise.

[4]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.

We estimate that the mental health of an average respondent worsens by 0.0026 standard deviations when ambient road noise increases by 1 dB (1.96% relative to the mean noise level). The effect is equivalent to 22 out of 3017 respondents (i.e. year 2020) with little mental health problems, beginning to have mild mental health symptoms. It means a 10.5% increase in people experiencing mild mental health symptoms from little symptoms. Although the effect of road noise on mental health is small, the results are robust and statistically significant under various model specifications and translate to an annual welfare loss as high as $13 billion due to lost earnings in the labor market. It is reassuring that we do not find any relationship between ambient noise and mental health for a sample of hearing-impaired respondents.

We also address the potential mechanism through which ambient 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 24 minutes/week when average road noise in the county increases by 10 dB.

The adverse mental health effects identified by our analysis imply huge welfare costs through lost earnings and workplace absenteeism. As the Biden administration makes substantial investments in updating the US 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 ambient noise from highways 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 have access to 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.[5] 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 respondent in the HINTS data. 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.[6] 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 communication, September 21st, 2022), we standardized this index by year to account for systemic trends across the years and to facilitate 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.

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[5] 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.

[6] 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, the 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.

The DoT's National Transportation Noise Maps provide spatially gridded nationwide 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 (Binghamton University). Appendix Figure A.1 shows the 2020 noise map for the contiguous US.[7]

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. 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 960 m.[8] 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. 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 highways. 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.[9]

Since mental health outcomes are correlated with exposure to chemical pollutants (e.g. see Ao et al. (2021)), we also control for ambient toxic pollution by leveraging

[7]Road noise is calculated by algorithms from the Federal Highway Administration's Traffic Noise Model version 2.5, which models road noise at a receptor height of 1.5m above ground level (DOT, 2020).

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

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

data from the TRI. The TRI records self-reported measurements of more than 700 chemicals released into the air, water and land annually by facilities in the chemical, manufacturing, metal mining, and electric power generation sectors across the US and is a widely used source for information on toxic pollution. Based on locational information for all facilities reporting to the TRI, we calculate the local emission of toxic chemicals within each 5-digit zip code area by summing up the total on-site releases for all TRI facilities within each zip code area.

In addition, we also use county-level Air Quality Index (AQI) data from the EPA to measure concentrations of the six Criteria Pollutants regulated under the Clean Air Act. One concern with using the county-level AQI data is that only about 1000 out of 3000 US counties have air quality monitors, which contributes to many missing AQI reports for the respondents in our sample. Areas without air quality monitors are known to have lower pollution and/or smaller populations. Thus we assume that areas without AQI reports have very limited air emissions and we assign a 0 AQI value to areas without these reports.[10]

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 focuses on on-road emissions based on roadway-level traffic data and state-specific emission factors for multiple vehicle types, which covers the conterminous US for 1980-2017 at a high resolution of 1km annually. 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, there is evidence that in general, traffic-related CO_2 is correlated with other pollutants like SO_2 and NO_X because of the existence of correlations between the emission patterns (Liang et al., 2024) 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.

[10] Cross-checking against the TRI, we find that 84.3% of our respondents from counties without AQI reports have zero or very limited (< 100 lbs) toxic air emissions, confirming our assumption that these are areas where air pollution is not a significant environmental concern. However, Zou (2021) uses satellite data to show that areas without monitors also have high levels of air (PM2.5) pollution. So, we also create a sub-sample by dropping areas without air pollution monitors (around 2000 respondents) rather than assigning them AQI values of zero. The estimates from this sub-sample are reported in Appendix Table A.9. Although the magnitudes of the estimates are similar to our main specification, the results are not significant given the rising standard errors.

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 spans 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.

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:

$$\begin{gathered}
S_{izt} = \beta_0 + \alpha_1 Roadnoise1km_{zt} + \alpha_2 CO_2 Emission1km_{zt} \\
+\beta_1 Female_{izt} + \beta_2 Married_{izt} + \beta_3 Age_{izt} + \beta_4 Age^2_{izt} \\
+\boldsymbol{\beta_5} Educ_{izt} + \beta_6 Hhnum_{izt} + \boldsymbol{\beta_7} Race_{izt} + \boldsymbol{\beta_8} Income_{izt} \\
+\lambda_1 DocVis_{izt} + \lambda_2 Cancer_{izt} + \lambda_3 CancerFam_{izt} \\
+\lambda_4 BMI_{izt} + \lambda_5 Diabetes_{izt} + \lambda_6 Hypertension_{izt} + \lambda_7 Exercise_{izt} + \lambda_8 Ownfrac_{zt} \\
+\boldsymbol{\gamma_1} ExtremeTem_{zt} + \gamma_2 Cloudcover_{zt} + \gamma_3 Solarenergy_{zt} \\
+\gamma_4 TE_{zt} + \gamma_5 avgAQI_{ct} + \theta_c + \eta_t + \epsilon_{izt}
\end{gathered} \tag{1}$$

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.

$Female$ 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.[11] $Race_{izt}$ 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 household income of individual respondent i from zip code area z in year t from

[11] 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 is "less than high school" in our specification.

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.[12] Joshi (2016) finds individuals tend to report worse mental health when local house prices decline, but this association is most significant for individuals who are least likely to be homeowners. 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.

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 year with daily maximum temperature below freezing or above $85°F$, respectively (Burton and Roach, 2022). 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 year 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 annual average solar energy, 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.[13]

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

[13]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

TE_{zt} is the total on-site emissions (air, water, and land emissions) of all 770 toxic chemicals from all facilities within 5-digit zip code area z in year t that report their emissions to the EPA's TRI. $avgAQI_{ct}$ captures the average annual ambient air quality at the county level due to the six criteria pollutants under the Clean Air Act (i.e. ground-level ozone, particulate matter, carbon monoxide, lead, sulfur dioxide, and nitrogen dioxide); these pollutants are not reported in the TRI and are therefore not included in total on-site emissions. $CO_2Emission1km_{zt}$ is the annual-average traffic-generated CO_2 emissions within a respondent's 1km buffer, which we use to approximate traffic-related air pollutants.

$Roadnoise1km_{zt}$ 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 it is 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),[14] 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 noise or air pollution may not be randomly assigned. Exposure to highway noise and corresponding traffic-generated air pollution may be endogenous 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 variations at the census tract level along with wind speed, wind direction, and during-survey temperature at the 5-digit zip code level to address this potential endogeneity between ambient noise or air pollution and mental health. We describe each of these instruments below,

on factors such as the type of clouds, the time of day, the season, and the geographical location. Partially cloudy skies and the contribution of diffuse radiation mean that even cloudy areas can still experience significant solar energy. This complexity is why we include both cloud cover fraction and solar energy in the same regression analysis.

[14]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.

followed by the estimating equations in our two-stage regression model.

Since road noise is generated 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.[15] 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 speeds and behaviors also impact the combustion efficiency of gasoline, which contributes to various traffic-generated air pollution levels.

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.

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,

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

depending on wind speed and direction. Thus, we exploit the daily variation in wind conditions to address the endogeneity of ambient noise and air pollution. We argue that the variation in wind speed and direction generates exogenous changes in ambient noise and 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.[16]

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 "lines" (for example, highways). We do not emphasize the idea of respondents being upwind or downwind of these pollution sources since a respondent who lives downwind from one highway (or one section of a highway) could also be living upwind from another highway (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.

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 (similar to our outcome variable) during the "last 30 days". Thus, we control for the number of days with extreme temperatures to capture the direct effect on mental health, but we also use the average temperature during each survey (which should not have a direct effect on mental health) to address the impact of seasonality and the associated variation in the propagation of noise.

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

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

$$
\begin{aligned}
Noise(CO_2Emission)_{izt} &= \alpha_0 + \alpha_1 \cdot RoadRI_z + \alpha_2 \cdot AreaRI_z + \\
\beta_1 \cdot windspeed_{zt} + \beta_2 \cdot maxwindspeed_{zt} &+ \sum_{c \in C} \sum_{k=0}^{2} \gamma_c \cdot Winddir_{zt}^{90k} \\
+\delta \cdot surveytemp_{zt} &+ X'_{izt}\sigma + W'_{zt}\eta + \theta_c + \eta_t + \epsilon_{izt}
\end{aligned} \tag{2}
$$

The dependent variable $Noise(CO_2emission)_{izt}$ represents either ambient road noise or air pollution (approximated by traffic-generated CO_2 emission) within a 1 km buffer of each individual i located in a 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, the average temperature during the time of survey for each HINTS survey wave.[17] $\gamma_c \cdot Winddir_{zt}^{90k}$, 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). The included instruments (control variables) at the individual or zip code area level are represented by the vectors X'_{izt} and W'_{zt}, respectively, and are the same as in Eq.(1).

We then utilize the predicted 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:

$$
\begin{aligned}
Stdphq4_{izt} = \alpha + \beta_1 \cdot Road\widehat{noise}1km_{izt} + \beta_2 \cdot Co_2E\widehat{mission}1km_{izt} \\
+X'_{izt}\sigma + W'_{zt}\eta + \theta_c + \eta_t + \epsilon_{izt}
\end{aligned} \tag{3}
$$

$Road\widehat{noise}1km_{izt}$ and $Co_2E\widehat{mission}1km_{izt}$ are the ambient road noise and traffic-generated CO_2 emissions jointly 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

[17] 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.

exposed to road noise. Figure 4 shows the distribution of ambient road noise within a 1 km buffer for our sample respondents.[18] Most respondents experience ambient road noise between 50 and 60 dB and only a very small fraction of respondents reside with undetectable ambient road noise; the average annual ambient road noise within a 1 km buffer of the sample respondents' 9-digit zip code centroids is 50.96 dB (53.81 dB for those with detectable road noise). The lowest detectable noise value reported in DoT data is 45 dB, and the minimum average ambient road noise recorded is 45.1 dB within the 1 km buffer. The maximum average ambient road noise is 60.83 dB, which is well above the 55 dB cutoff set by EPA for human health and welfare protection (EPA, 1974). The correlation among road noise within a 1 km buffer across years exceeds 95%.[19]

As for the outcome variable of interest, we focus on the summary index of mental health (PHQ-4). This index ranges from 0 to 12, and a larger value represents worse mental health. Nearly half of the respondents in our sample have a value of 0 for this 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.[20] People with diabetes or hypertension as well as those with a higher BMI are more likely to have poorer mental health.[21] 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'

[18]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.

[19]We describe our method for calculating the correlation in footnote 14.

[20]Our results are consistent with the report from the 2021 National Survey on Drug Use and Health, which indicates young adults aged 18-25 years had the highest prevalence of any mental illness (33.7%) compared to adults aged 26-49 years (28.1%) and aged 50 and older (15.0%). Also, the prevalence of serious mental illness among US adults (2021) for these three age groups are 11.4%, 7.1%, and 2.5%, respectively.

[21]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.

9-digit zip code centroids is negatively associated with 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 Bryson (2022), we find that women are generally unhappier than men and they have more days with poor mental health. 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 or 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 air quality or toxic emissions 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 air pollution directly affects individual-level mental health in the US.

Li et al. (2020) find that cool days reduce the probability that respondents report poor mental health but hot days increase the probability. Mullins and White (2019) also finds that cold temperatures reduce negative mental health outcomes while hot temperatures increase them. 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. However, the association between temperature and mental health is not significant in our sample. 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.

Similarly, we do not find any patterns to suggest that people who live in areas with worse air quality or higher total onsite emissions have higher ambient road noise either. We group the AQI variable into equal-sized bins (that is, each bin has an equal number of observations) and compute the mean of the AQI and road noise within each bin, then create a binned scatterplot of these data points in Appendix Figure A.4 Panel (a), after absorbing the county-fixed effect to control for the unobservable confounding factors across counties. The slight upward trend in this figure is mainly because of the outlier group with the highest AQI index. We also show the binned scatter plot between ambient road noise and total onsite emission (see Figure A.4 Panel (b)). The fitted line is quite flat in this figure which does not point to obvious sorting behavior across different emission levels. Additionally, we show the mean value and its corresponding 95% confidence interval for each emission bin in Figure A.5. This figure corroborates our previous finding and shows that ambient road noise is stable across different emission levels (most confidence intervals overlap with others).

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 during-survey 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.6. 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.7 to A.12 show and discuss 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.[22] 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.

Table 2 reports the IV estimates alongside the OLS results. Column 2 reports the results from a model that includes the AQI and onsite toxic emissions as control variables to account for the potential confounding of general air pollution with ambient noise. We also regard the traffic-generated CO_2 emissions as endogenous and use our instruments to address the approximated traffic-generated air pollution. We calculate the traffic-generated CO_2 emissions (unit: 1,000 tons) within a 1 and 5 km buffer around respondents' 9-digit zip code centroids, separately. We show the results using CO_2 emissions within 1 km in Panel A and those within 5 km in Panel B, respectively.

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. This is conditional on traffic-related air pollution, which also has a negative effect on mental health. In column 2 of Table 2, Panel A, we find each thousand-ton increment of traffic-generated CO_2 emissions worsens mental health by 0.0041 standard deviations. The negative effect becomes significant at a 5% level when we measure the traffic-generated CO_2 emissions using a 5 km buffer (see column 2 of Table 2, Panel B).

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

[22]The first-stage F-values are small which is expected given the large number of instruments relative to the sample size.

respondents' geographic areas, we also consider alternative specifications in which we interact wind directions with state or census division dummies. See columns (3) and (4), respectively in Table 2. The coefficient on road noise remains negative and significant/marginally significant. 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 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.4 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 to approximate other traffic-related 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.[23] 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.[24] 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.5 for the full specifications). We find that the approximated concomitant air pollution does not have any statistically significant effect on respondents' mental health, conditional on either way of measuring traffic-generated CO_2 emissions, and the

[23]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.

[24]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.

negative effect of road noise on mental health is still significant at the 5% level. 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 find a positive association between air pollutants 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.

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.6 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 given the limited statistical power and concerns regarding sample selection. 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.[25] 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.[26]

[25]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.

[26]The coefficients on income, education, gender, marital status, age, race, and some

Finally, we also extract a sub-sample of senior citizens (60+ years) from the general sample without any hearing impairment. While this group of respondents does not report hearing impairment, the National Institute on Aging reports that nearly one third of older adults have hearing loss and that many older adults are unaware or don't want to admit that they have a problem with hearing. We do not find road noise has a significantly negative effect on these respondents' mental health (see column 3 of Table 5).

6 Noise, Sleep Deprivation and Mental Health

In this section, we focus on the association between noise pollution and sleep duration in an attempt to identify a potential channel through which ambient 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.

Our key independent variable is still ambient noise. 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.[27] 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 to approximate general traffic-related air pollutants. The reduced-form specification

physical health indices are statistically significant for this sub-sample.

[27] 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.

is as follows:

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

We keep most of the individual-level variables from Eq.(1) though some physical health conditions are not available in these three waves (e.g. diabetes and hypertension). Also, 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 the respondents with higher education levels, more household members, higher BMI values, and older respondents, have significantly less sleep whereas female and married respondents have significantly more sleep (see Appendix Table A.7 for the full specifications).

Most notably, we find that average road noise in the county has a significantly negative impact on respondents' sleep duration. A respondent's sleep duration is reduced by around 24 minutes when the ambient road noise within their county of residence increases by 10 dB.[28] We also find that average traffic-generated CO_2 emissions are negatively associated with sleep duration, but the estimate is not statistically significant.

7 Conclusion

The welfare effect of non-chemical triggers on human health has received scant attention. Yet it is well established that the human stress response system is triggered by stimulants such as light and noise (Jariwala et al., 2017, Kumar et al., 2019). The 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,

[28] $0.040 \times 60 \times 10 = 24$ minutes.

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 big US 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 noise and the need for innovative policy, we focus on general vehicular noise from major roadways and its effect on mental health through the human stress response system and sleep deprivation. We exploit variations in topography, daily wind conditions, and during-survey 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.

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. Our findings in this study point to the bottom line of their stories. If noise pollution makes people engage in criminal activities or even commit suicide, the behavioral change can likely be explained through a change in their mental health. We believe our findings are consistent with these other studies and point to the first-level effect of noise pollution on human behavior.

Although the deleterious effects of noise pollution on mental health that we find are 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 22 out of 3017 respondents (i.e. year 2020) may go from having "little" to "mild" depressive symptoms because of each decibel of ambient road noise.[29] Using Germinario et al. (2022)'s estimates,

[29] First, we calculate the weighted average of the standardized mental health index for each year. Then, for any specific year, we change 0.74% (22/3017) of respondents whose raw phq4 index equals 2 to 3 (indicating the marginal change from none to mild mental health problems based on HINTS' data description, see details at 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

this is equivalent to an 11.51-12.95 billion dollar (in 2021 dollars) loss in welfare.[30] 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). But 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 Biden administration focuses on (re)building the US highway infrastructure, this potential welfare cost due to roadway noise should 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).

coefficient of ambient road noise in our main specification).

[30] $9720.96 \times 0.74\% \times 16\%(18\%) = 11.51(12.95)$

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Figures

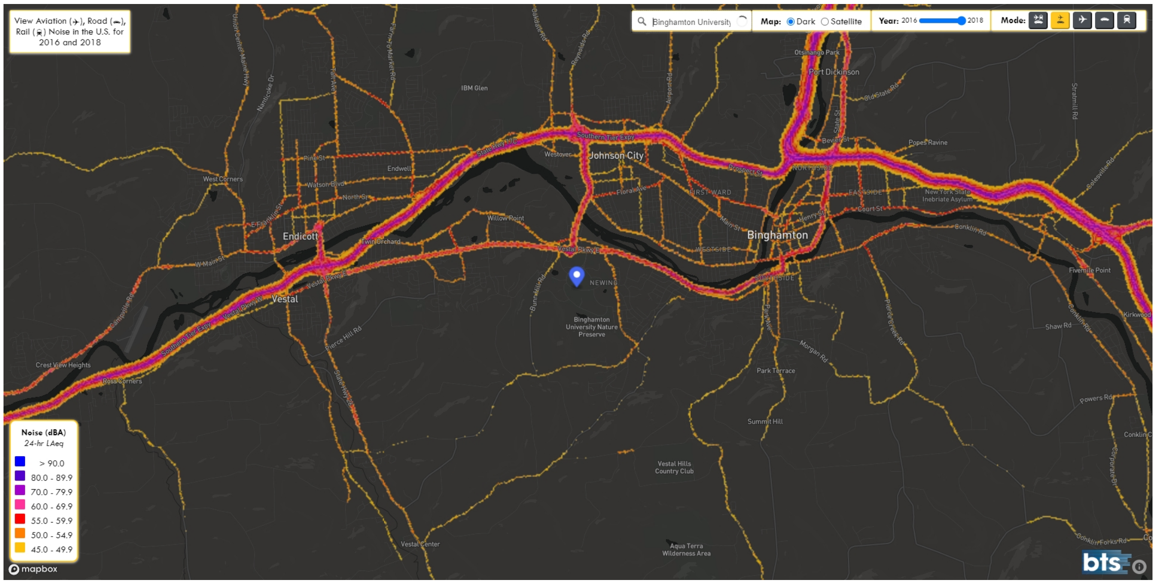


Figure 1: Binghamton University Noise Map

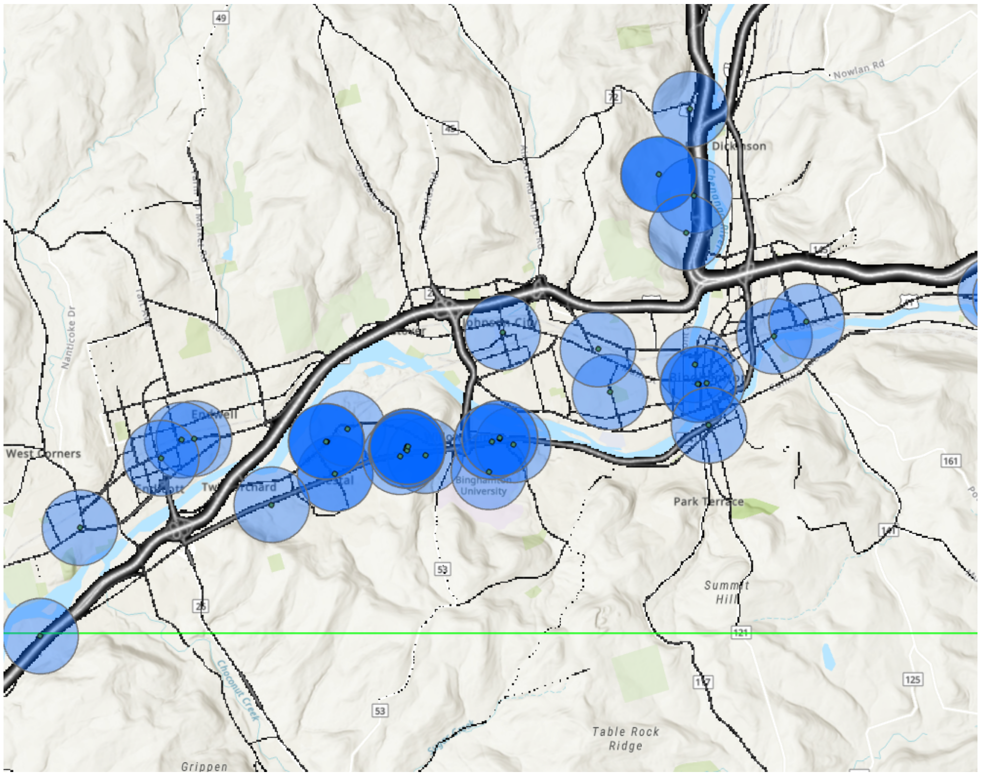
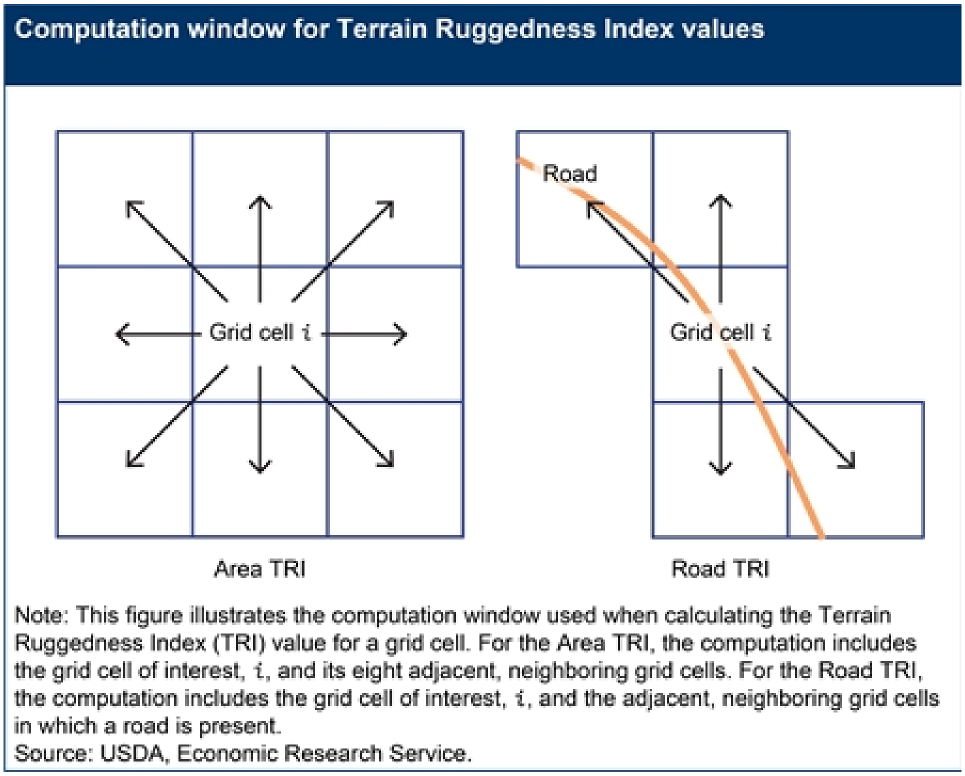


Figure 2: Noise Buffers for Hypothetical HINTS Respondents



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

Figure 3: Terrain Ruggedness Index Computation

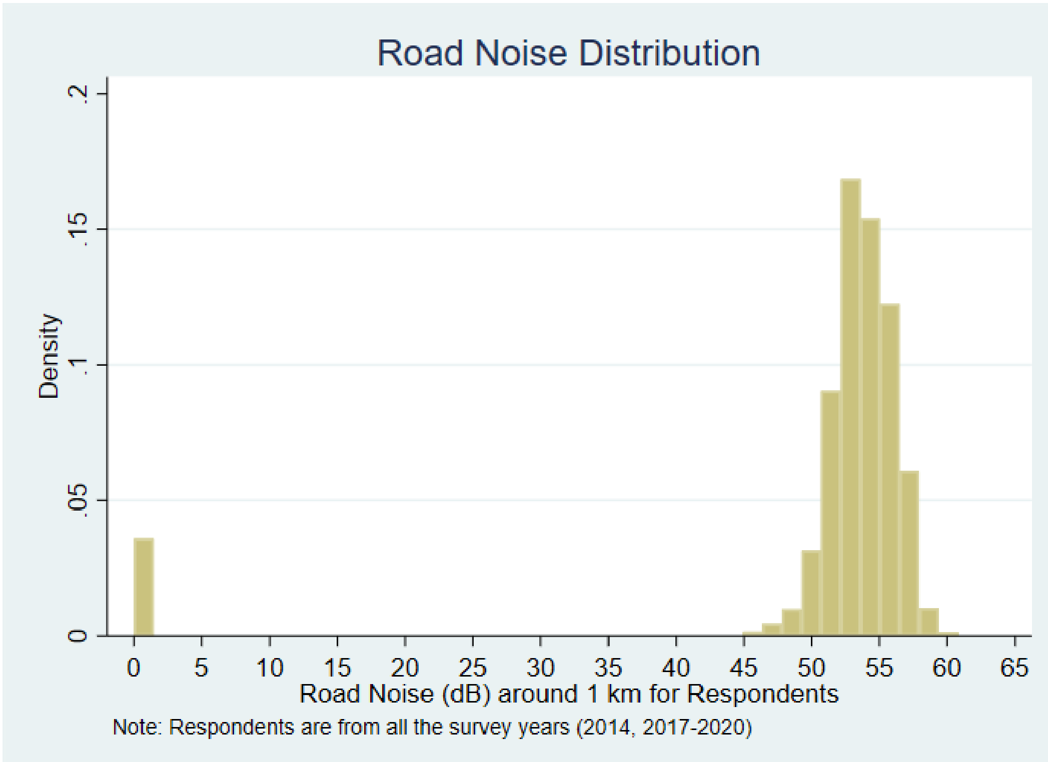


Figure 4: Ambient Road Noise Distribution

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)[31]	0.55	0.25
Household size (number of people)	2.43	1.45
College graduate (percentage)	0.28	0.45
Income ($50K-$75K) (percentage)	0.18	0.38
Mental health index		
PHQ-4 (raw index)	1.90	2.79
PHQ-4 (standardized)	-0.0045	0.99
Health indices		
Exercise (days/week)	2.75	2.24
BMI	28.44	6.59
Diabetes (percentage)	0.20	0.40
Hypertension (percentage)	0.43	0.50
Had cancer (percentage)	0.15	0.36
Family had cancer (percentage)	0.56	0.50
Environmental factors		
County Average AQI	39.81	20.47
Zip-5 Total onsite emission (lbs/year)	79373.11	826155.9
Zip-5 During-survey temp ($^{\circ}F$)	56.32	10.69
Zip-5 Cloud cover (%)	44.91	12.55
Zip-5 Solar energy (MJ/m^2)	15.16	4.14
Zip-9 CO_2 emissions (Kton/year)	4.99	9.61

Note: N=14,643

[31] 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: CO_2 emission within 1 km	(1)	(2)	(3)	(4)
Road noise[32]	0.0016**	0.0026**	0.0069+	0.0118*
	(0.0008)	(0.0012)	(0.0044)	(0.0066)
CO_2 emission	0.0002	0.0041	0.0070	0.0038
	(0.0009)	(0.0033)	(0.0083)	(0.0126)
Panel B: CO_2 emission within 5 km				
Road noise	0.0015*	0.0025**	0.0068	0.0115*
	(0.0008)	(0.0012)	(0.0044)	(0.0063)
CO_2 emission	0.0018	0.0111**	0.0089	0.0058
	(0.0023)	(0.0052)	(0.0095)	(0.0119)
Control Variables				
Demographics	X***	X***	X***	X***
Health indices	X***	X***	X***	X***
Weather	X	X	X	X
TRI emissions	X	X	X	X
AQI	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	0.116	0.111
R^2 (Panel B)	0.198	0.123	0.120	0.113
Observations[33]	14,033	14,033	14,033	14,033

Note: +p<0.15; *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.). Other Instruments include area ruggedness index, road ruggedness index, during-survey temperature, wind speed, and maximum wind speed.*

[32] Ambient noise in the 1km buffer surrounding the centroid of each respondent's 9-digit zip code area.

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

Table 3: Alternative Noise Measurement: 2SLS Estimates

	Dependent variable:
	Standardized mental health index
	(1)
Road noise	−0.00024
	(0.0009)
CO_2 emission 1km	0.0052
	(0.0033)
Demographics	X***
Health Indices	X***
Weather	X
TRI Emissions	X
AQI	X
County FE	X
Year FE	X
R^2	0.121
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.).*

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		0.0114**
		(0.0052)
CSwpd×Road noise	-0.0094	-0.0102
	(0.0171)	(0.0170)
Demographics	X***	X***
Health Indices	X***	X***
Weather	X	X
TRI Emissions	X	X
AQI	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.).*

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	-0.0022	0.0022*	0.0023	0.0041**
	(0.0075)	(0.0013)	(0.0018)	(0.0020)
CO_2 emission 1km	0.0056	0.0055*	-0.0002	0.0044
	(0.0070)	(0.0032)	(0.0038)	(0.0040)
Demographics	X***	X***	X***	X***
Health Indices	X***	X***	X***	X***
Weather	X	X	X	X
TRI Emissions	X	X	X	X
AQI	X	X	X	X
County FE	X	X	X	X
Year FE	X	X	X	X
R^2	0.162	0.122	0.100	0.116
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.).*

Table 6: Sleep Duration and Noise

	Dependent variable:
	Average sleep hours
Average road noise	-0.040^{*}
	(0.021)
Average CO_2 emission	-0.0025
	(0.0065)
Constant	11.167^{***}
	(1.144)
Demographics	X^{***}
Health Indices	X^{***}
City Level	X
Housing Ownership	X
R^2	0.036
Observations	8,726
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

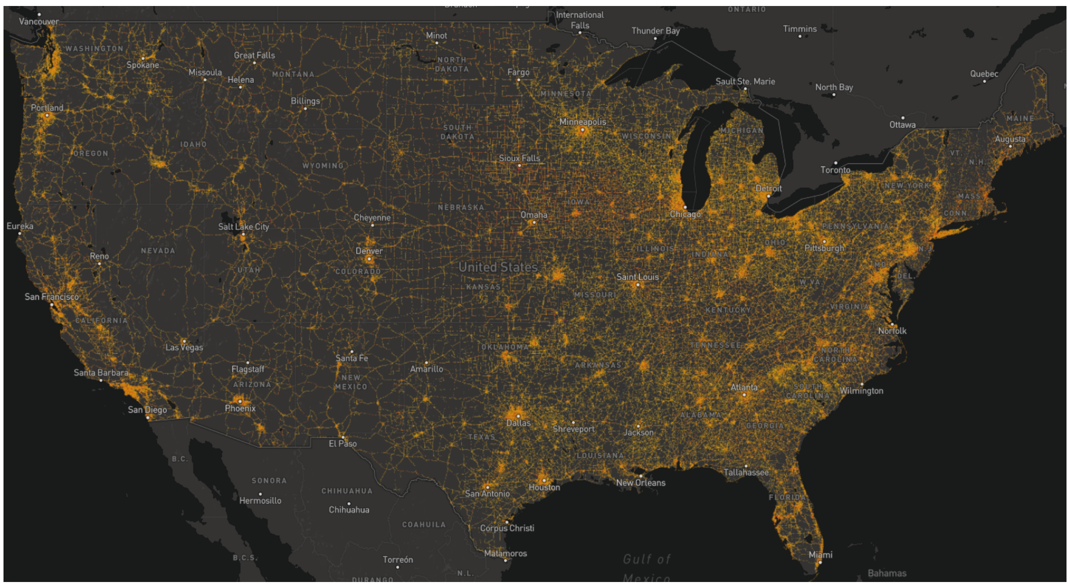


Figure A.1: DoT National Noise Map 2020

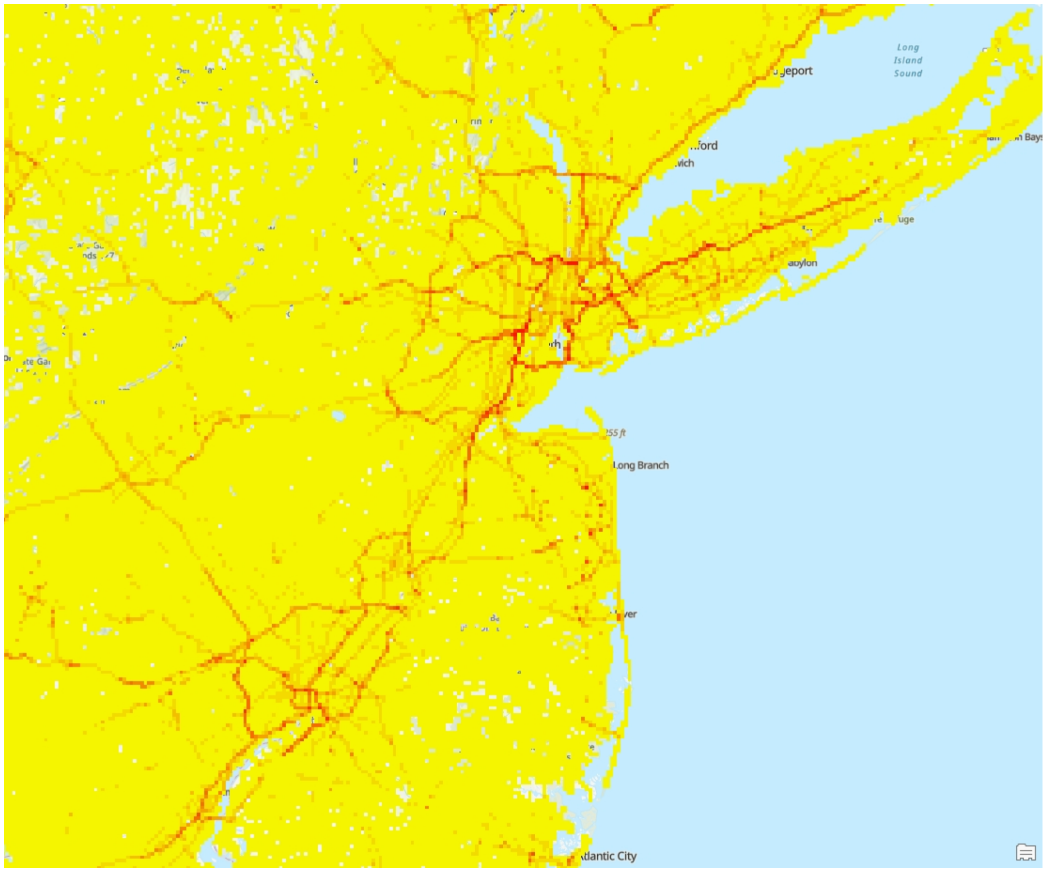
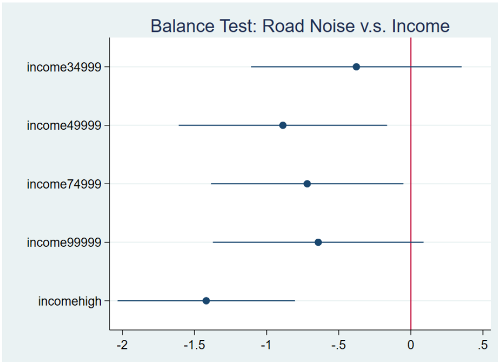
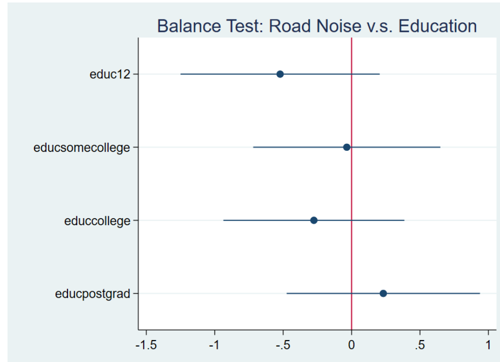


Figure A.2: CO_2 Emission Map

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.



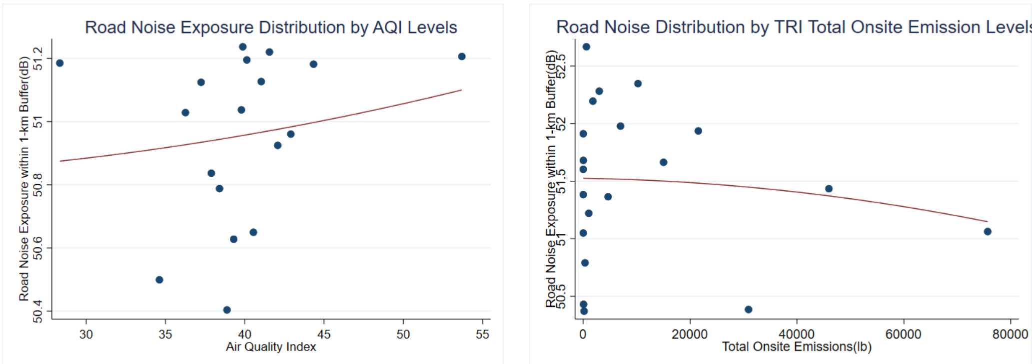
(a) Road Noise and Income



(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) Ambient Road Noise and Air Quality Index

(b) Ambient Road Noise and Total Onsite Emissions

Figure A.4: Ambient Road Noise v.s. Other Pollutants

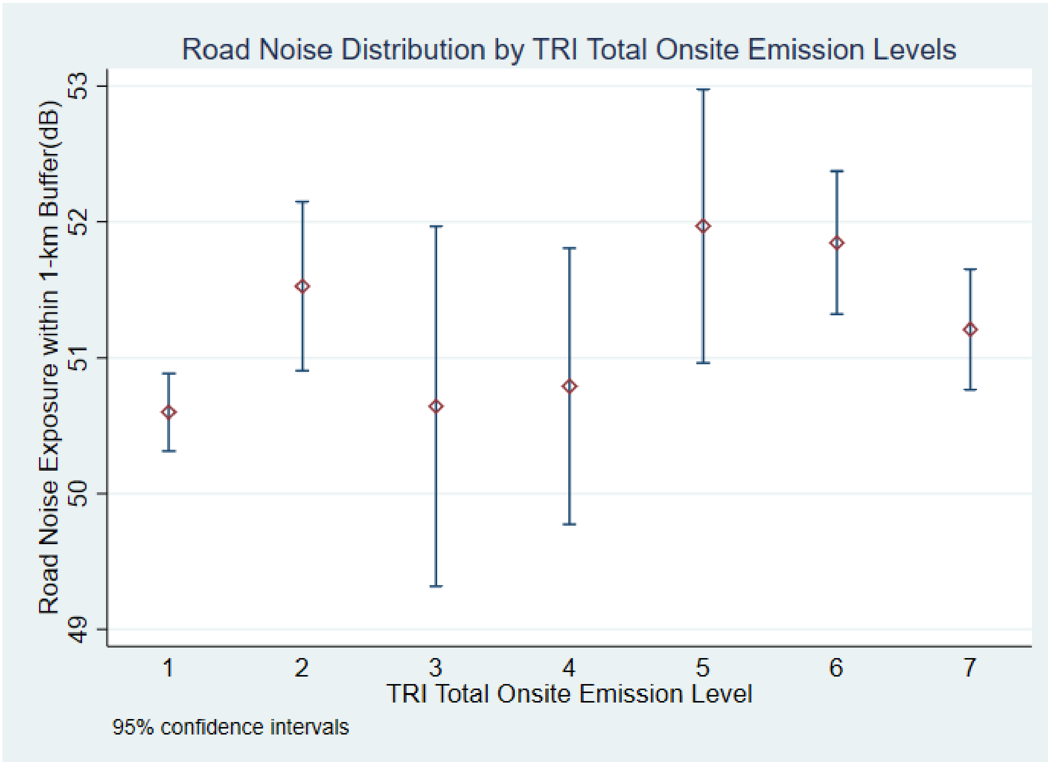
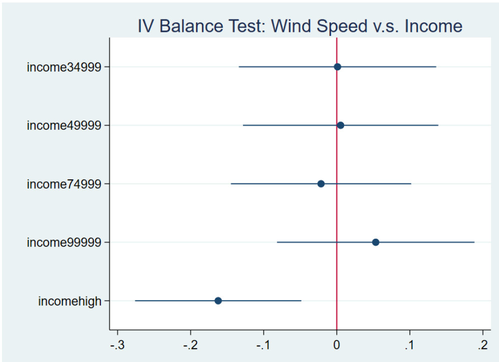
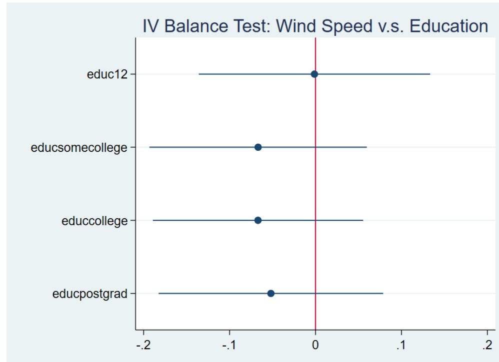


Figure A.5: Ambient Road Noise across Emission Levels

Note: We draw our sample with total onsite emissions between 0 and 100,000 lbs in this figure and it includes around 94% of all the respondents. To address the huge variation in total onsite emissions across facilities (the mean is 85918.36 with a standard deviation of 888631.1; the 50%, 75%, 90%, and 95% percentiles are 1600.99, 38078.2, 152543.3, and 1920724, respectively), we create total onsite emission level indicators based on the distribution of respondents' emission levels (level 1: 0 total onsite emission; level 2: 0-19.99 lbs; level 3: 20-99.99 lbs; level 4: 100-499.99 lbs; level 5: 500-999.99 lbs; level 6: 1,000-9,999.99 lbs; level 7: larger than 10,000 lbs).



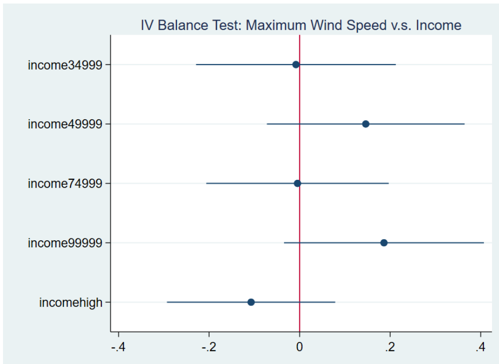
(a) Wind Speed v.s. Income



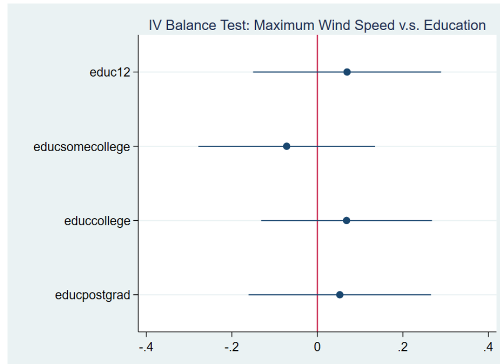
(b) Wind Speed v.s. Education

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.6: IV Balance Test for Wind Speed



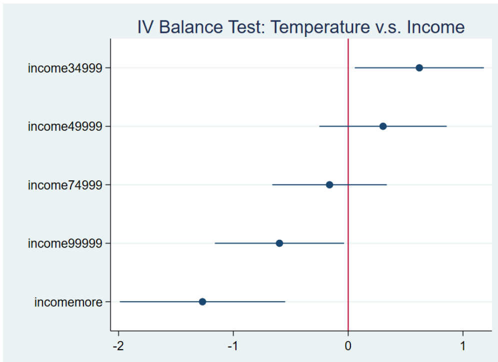
(a) Maximum Wind Speed v.s. Income



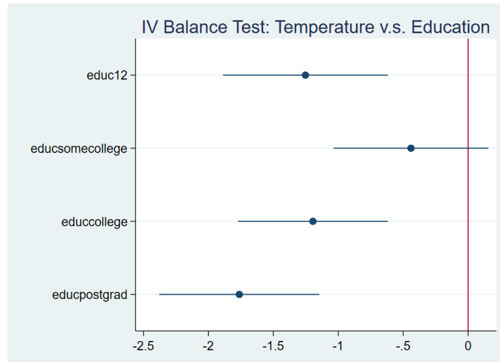
(b) Maximum Wind Speed v.s. Education

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.7: IV Balance Test for Maximum Wind Speed



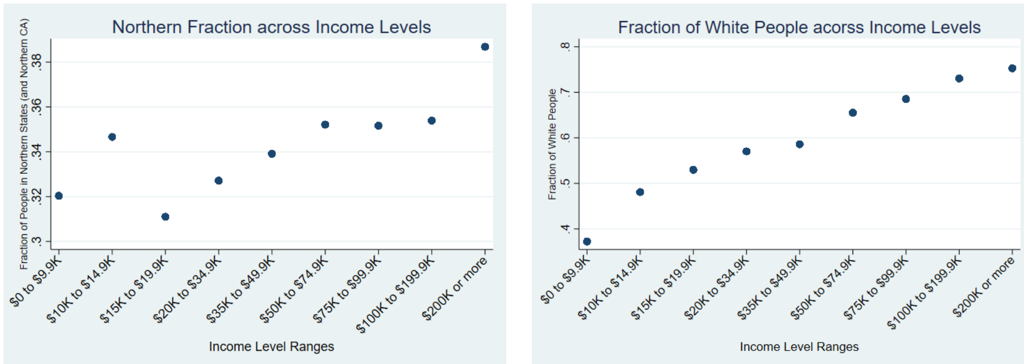
(a) Temperature v.s. Income



(b) Temperature v.s. Education

Note: These are the estimated coefficients and their 95% CIs from the auxiliary regression of during-survey 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.9 (a)). Second, the fraction of white people is increasing with income levels (see Figure A.9 (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 mean independent of income and education (see Figure A.10).

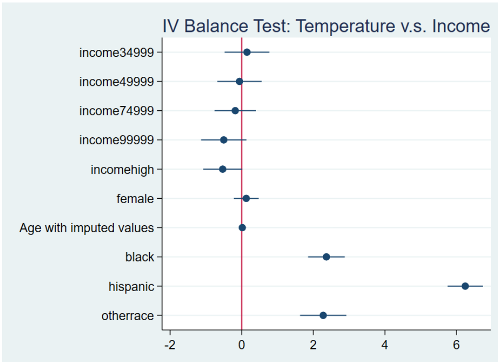
Figure A.8: IV Balance Test for Temperature



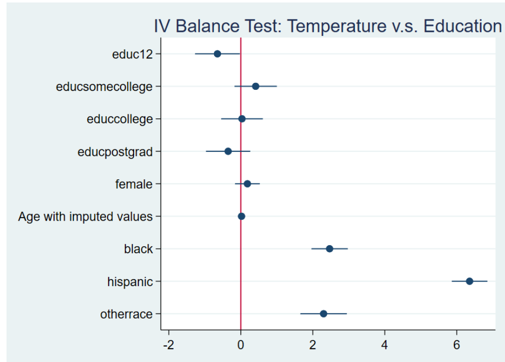
(a) The Fraction of Respondents in the Northern U.S across Income Levels

(b) The Fraction of White Respondents across Income Levels

Figure A.9: Respondents' Distribution across Areas and Income Levels



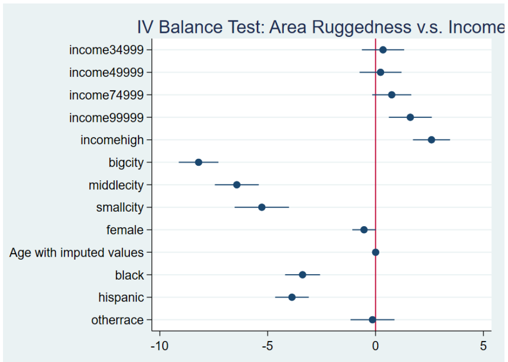
(a) Temperature v.s. Income



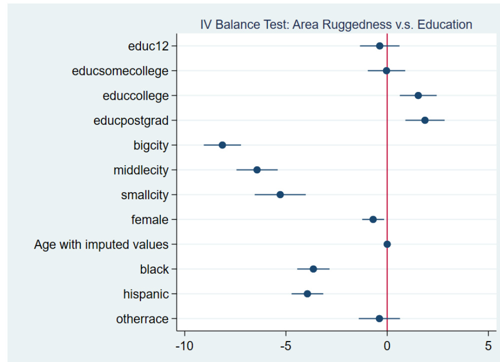
(b) Temperature v.s. Education

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

Figure A.10: IV Balance Test for Temperature



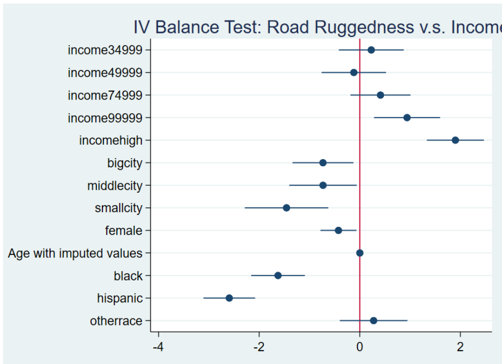
(a) Area Ruggedness v.s. Income



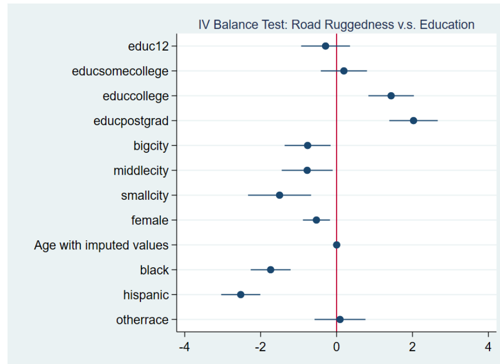
(b) Area Ruggedness v.s. Education

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.11 and A.12, 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.11: 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.11 and A.12, 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.12: IV Balance Test for Road Ruggedness

B Tables

Table A.1: Income Distribution

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	14,643	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***	−0.089***	−0.090***
	(0.029)	(0.029)	(0.029)
educpostgrad	−0.116***	−0.112***	−0.115***
	(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_i	−0.007**	−0.007**	−0.007**
	(0.003)	(0.003)	(0.003)
agesqr	−0.00005*	−0.00005*	−0.00005**
	(0.00003)	(0.00003)	(0.00003)
black	−0.228***	−0.229***	−0.231***
	(0.027)	(0.027)	(0.027)
hispanic	−0.051*	−0.055**	−0.056**
	(0.026)	(0.027)	(0.027)
otherrace	−0.017	−0.020	−0.019
	(0.032)	(0.032)	(0.032)
everhadcancer_i	0.022	0.023	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)

	Dependent variable:		
	Standardized mental health index		
	OLS	*IV Approach*	
income49999	−0.333***	−0.333***	−0.331***
	(0.031)	(0.031)	(0.031))
income74999	−0.406***	−0.407***	−0.404***
	(0.029)	(0.030)	(0.030)
income99999	−0.454***	−0.454***	−0.451***
	(0.033)	(0.033)	(0.033)
incomehigh	−0.484***	−0.482***	−0.480***
	(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***	0.146***	0.145***
	(0.022)	(0.022)	(0.022)
hypertension	0.089***	0.088***	0.088***
	(0.019)	(0.019)	(0.019)
ownfraction	−0.165***	−0.140***	−0.121***
	(0.036)	(0.039)	(0.040))
icyday	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)
hotday	0.0001	0.0001	0.0003
	(0.0006)	(0.0006)	(0.0006)
surveycloudcover	0.003**	0.003*	0.002
	(0.001)	(0.002)	(0.002)
surveysolarenergy	0.0007	0.0004	0.0002
	(0.003)	(0.003)	(0.003)
TotalEmi	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
avgAQI	−0.0006	−0.0007	−0.0008
	(0.0015)	(0.001)	(0.001)

	Dependent variable:		
	Standardized mental health index		
	OLS	*IV Approach*	
roadnoise1km	0.0016**	0.0026**	0.0025**
	(0.0008)	(0.0011)	(0.0012)
CO_2 emission1km	0.0002	0.0041	
	(0.0009)	(0.0033)	
CO_2 emission5km			0.0111**
			(0.0052)
Constant	0.655***		
	(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

	Dependent variable:	
	Main Sample	
	Road noise	*CO_2 emission 1km*
	(1)	(2)
Windspeed:	0.293***	0.145
	(0.129)	(0.153)
Windspeed Maximum:	-0.037	-0.067
	(0.080)	(0.095)
Surveytemp:	0.090	0.322***
	(0.062)	(0.073)
RoadTRI:	0.188***	0.065**
	(0.022)	(0.026)
AreaTRI:	-0.164***	-0.061***
	(0.015)	(0.018)
F Statistic	3.72	0.48
County FE	X	X
Year FE	X	X
R^2	0.612	0.233
Observations	14,033	14,033
Note:		*p<0.1; **p<0.05; ***p<0.01

We report the first stage results for our instruments except for the wind direction×county terms for brevity.

Table A.4: Alternative Noise Measurement: 2SLS Estimates with Full Model Specifications

	Dependent variable:
	Standardized mental health index
	(1)
educ12	−0.054*
	(0.031)
educsomecollege	−0.038
	(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_i	−0.007**
	(0.003)
agesqr	−0.00005**
	(0.00003)
black	−0.228***
	(0.027)
hispanic	−0.054**
	(0.027)
otherrace	−0.020
	(0.032)
everhadcancer_i	0.023
	(0.024)
familyeverhadcancer	0.065***
	(0.020)
income34999	−0.258***
	(0.030)

	Dependent variable:
	Standardized mental health index
income49999	-0.333^{***}
	(0.031))
income74999	-0.407^{***}
	(0.030)
income99999	-0.455^{***}
	(0.033)
incomehigh	-0.484^{***}
	(0.031)
freqgoprovider	0.038^{***}
	(0.003)
timesmoderateexercise	-0.043^{***}
	(0.004)
bmi	0.005^{***}
	(0.001)
diabetes	0.146^{***}
	(0.022)
hypertension	0.088^{***}
	(0.019)
ownfraction	-0.145^{***}
	(0.040))
icyday	−0.001
	(0.001)
hotday	0.0002
	(0.0006)
surveycloudcover	0.003^{*}
	(0.002)
surveysolarenergy	0.0004
	(0.003)
TotalEmi	0.000
	(0.000)
avgAQI	−0.0007
	(0.001)

	Dependent variable:
	Standardized mental health index
roadnoise1km	-0.00024
	(0.0009)
CO_2 emission1km	0.0052
	(0.0033)
County FE	X
Year FE	X
R^2	0.121
Observations	14,033
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A.5: 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	−0.038
	(0.029)	(0.029)
educcollege	−0.089***	−0.090***
	(0.029)	(0.029)
educpostgrad	−0.111***	−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_i	−0.007**	−0.007**
	(0.003)	(0.003)
agesqr	−0.00005*	−0.00005**
	(0.00003)	(0.00003)
black	−0.229***	−0.232***
	(0.027)	(0.027)
hispanic	−0.055**	−0.056**
	(0.027)	(0.027)
otherrace	−0.021	−0.019
	(0.032)	(0.032)
everhadcancer_i	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)

	Dependent variable:	
	Standardized mental health index	
	(1)	(2)
income49999	−0.333***	−0.330***
	(0.031)	(0.031))
income74999	−0.407***	−0.404***
	(0.030)	(0.030)
income99999	−0.454***	−0.451***
	(0.033)	(0.033)
incomehigh	−0.482***	−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***	0.145***
	(0.022)	(0.022)
hypertension	0.088***	0.088***
	(0.019)	(0.019)
ownfraction	−0.142***	−0.123***
	(0.039)	(0.040))
icyday	−0.001	−0.001
	(0.001)	(0.001)
hotday	0.0001	0.0003
	(0.0006)	(0.0006)
surveycloudcover	0.003*	0.002
	(0.002)	(0.002)
surveysolarenergy	0.0004	0.0002
	(0.003)	(0.003)
TotalEmi	0.000	0.000
	(0.000)	(0.000)
avgAQI	−0.0007	−0.0008
	(0.001)	(0.001)

	Dependent variable:	
	Standardized mental health index	
	(1)	(2)
roadnoise1km	0.0027**	0.0026**
	(0.0012)	(0.0012)
roadnoise1km×CSwpd	-0.0094	-0.0102
	(0.0171)	(0.0170)
CO_2 emission1km	0.0043	
	(0.0033)	
CO_2 emission5km		0.0114**
		(0.0052)
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.6: 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	−0.073	−0.054	−0.016	−0.064*
	(0.171)	(0.036)	(0.050)	(0.035)
educsomecollege	0.089	−0.012	−0.002	−0.041
	(0.169)	(0.034)	(0.048)	(0.033)
educcollege	−0.037	−0.082**	−0.031	−0.101***
	(0.189)	(0.034)	(0.050)	(0.033)
educpostgrad	−0.210	−0.086**	−0.067	−0.111***
	(0.200)	(0.037)	(0.053)	(0.036)
female	0.031	0.094***	0.094***	0.087***
	(0.110)	(0.020)	(0.030)	(0.019)
married	−0.233*	−0.151***	−0.078***	−0.135***
	(0.131)	(0.023)	(0.034)	(0.022)
totalhousehold	0.038	−0.002	0.001	0.002
	(0.052)	(0.008)	(0.014)	(0.007)
age_i	−0.063***	−0.005	−0.046	−0.008**
	(0.024)	(0.004)	(0.033)	(0.003)
agesqr	0.0003**	−0.0001**	0.0002	−0.00004
	(0.0002)	(0.00003)	(0.0002)	(0.00003)
black	−0.093	−0.232***	−0.233***	−0.240***
	(0.222)	(0.031)	(0.046)	(0.030)
hispanic	−0.016	−0.073**	0.009	−0.077***
	(0.160)	(0.030)	(0.052)	(0.029)
otherrace	0.284	−0.038	−0.031	−0.022
	(0.213)	(0.036)	(0.061)	(0.034)
everhadcancer_i	−0.045	0.012	0.015	0.013
	(0.126)	(0.028)	(0.033)	(0.027)
familyeverhadcancer	0.089	0.066***	0.051	0.069***
	(0.140)	(0.024)	(0.037)	(0.023)
income34999	−0.043	−0.239***	−0.340***	−0.244***
	(0.176)	(0.036)	(0.051)	(0.035)

	Dependent variable:			
	Standardized mental health index			
	HI	NHI	ENHI	Comparable sample
	(1)	(2)	(3)	(4)
income49999	−0.104	−0.289***	−0.387***	−0.315***
	(0.182)	(0.036)	(0.051)	(0.035)
income74999	−0.012	−0.368***	−0.380***	−0.386***
	(0.183)	(0.034)	(0.050)	(0.033)
income99999	0.091	−0.408***	−0.488***	−0.434***
	(0.220)	(0.038)	(0.058)	(0.037)
incomehigh	−0.355*	−0.441***	−0.453***	−0.463***
	(0.185)	(0.036)	(0.055)	(0.035)
freqgoprovider	0.027	0.037***	0.030***	0.036***
	(0.017)	(0.003)	(0.005)	(0.003)
timesmoderateexercise	−0.014	−0.042***	−0.038***	−0.040***
	(0.023)	(0.004)	(0.006)	(0.004)
bmi	0.012	0.005***	−0.005***	0.006***
	(0.009)	(0.002)	(0.003)	(0.002)
diabetes	0.161	0.127***	0.100***	0.116***
	(0.122)	(0.026)	(0.034)	(0.025)
hypertension	0.226*	0.074***	0.028	0.118***
	(0.122)	(0.022)	(0.031)	(0.022)
TotalEmi	−0.00000	0.000	−0.000	−0.000
	(0.00000)	(0.000)	(0.000)	(0.000)
avgAQI	0.001	−0.001	0.0014	−0.0003
	(0.011)	(0.002)	(0.003)	(0.002)
ownfraction	−0.291	−0.138***	−0.168***	−0.170***
	(0.221)	(0.044)	(0.065)	(0.045)
icyday	0.0098	0.0005	0.0027	0.0008
	(0.0139)	(0.0022)	(0.0035)	(0.0017)
hotday	−0.0046	−0.0005	−0.0008	0.0002
	(0.0033)	(0.0007)	(0.0010)	(0.0006)
surveycloudcover	−0.0005	0.0008	0.0043	0.0013
	(0.0106)	(0.0019)	(0.0029)	(0.0017)
surveysolarenergy	0.0074	0.0025	−0.0033	0.0008
	(0.0274)	(0.0032)	(0.0047)	(0.0033)

	Dependent variable:			
	Standardized mental health index			
	HI	NHI	ENHI	Comparable sample
	(1)	(2)	(3)	(4)
Road noise	−0.0022	0.0022*	0.0023	0.0041**
	(0.0075)	(0.0013)	(0.0018)	(0.0020)
CO_2 emission 1km	0.0056	0.0055*	−0.0002	0.0044
	(0.0070)	(0.0032)	(0.0038)	(0.0040)
R^2	0.162	0.122	0.100	0.116
Observations	583	10,469	3,906	10,690

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

Table A.7: Sleep Duration and Noise: Full Model Specification

	Dependent variable:
	Average sleep
educ12	−0.067
	(0.050)
educsomecollege	−0.163***
	(0.049)
educcollege	−0.107**
	(0.051)
educpostgrad	−0.049
	(0.056)
female	0.119***
	(0.031)
married	0.116***
	(0.035)
totalhousehold	−0.029***
	(0.009)
age_i	−0.048***
	(0.005)
agesqr	0.0005***
	(0.00005)
black	−0.076*
	(0.046)
hispanic	0.085*
	(0.046)
otherrace	−0.161***
	(0.060)
bigcity	−0.066
	(0.055)
middlecity	0.018
	(0.055)
smallcity	−0.067
	(0.063)
everhadcancer	−0.053*
	(0.029)
familyeverhadcancer	−0.052
	(0.032)

	Dependent variable:
	Average sleep
income34999	0.016
	(0.048)
income49999	−0.051
	(0.049)
income74999	−0.001
	(0.048)
income99999	−0.033
	(0.058)
incomehigh	−0.046
	(0.055)
freqgoprovider	0.004
	(0.005)
timesmoderateexercise	−0.004
	(0.007)
bmi	-0.012^{***}
	(0.002)
own	−0.027
	(0.037)
avgroadnoise	-0.040^{*}
	(0.021)
avgCO_2emission	−0.002
	(0.006)
Constant	11.167^{***}
	(1.144)
R^2	0.036
Observations	8,726
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A.8: 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	-0.110	-0.109
	(0.081)	(0.081)
educcollege	-0.251^{***}	-0.255^{***}
	(0.082)	(0.082)
educpostgrad	-0.316^{***}	-0.326^{***}
	(0.090)	(0.090))
female	0.225^{***}	0.222^{***}
	(0.048)	(0.048)
married	-0.412^{***}	-0.411^{***}
	(0.055)	(0.055)
totalhousehold	0.008	0.008
	(0.019)	(0.019)
age_i	-0.019^{**}	-0.018^{**}
	(0.008)	(0.008)
agesqr	-0.0001^{*}	-0.0002^{**}
	(0.00008)	(0.00008)
black	-0.645^{***}	-0.651^{***}
	(0.076)	(0.076)
hispanic	-0.154^{**}	-0.157^{**}
	(0.075)	(0.075)
otherrace	-0.058	-0.055
	(0.089)	(0.089)
everhadcancer_i	0.066	0.065
	(0.068)	(0.068)
familyeverhadcancer	0.182^{***}	0.179^{***}
	(0.057)	(0.057)
income34999	-0.732^{***}	-0.724^{***}
	(0.086)	(0.086)

	Dependent variable:	
	Raw mental health index	
	(1)	(2)
income49999	−0.943***	−0.936***
	(0.086)	(0.087))
income74999	−1.151***	−1.142***
	(0.083)	(0.083)
income99999	−1.285***	−1.277***
	(0.093)	(0.093)
incomehigh	−1.362***	−1.355***
	(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	0.412***	0.411***
	(0.063)	(0.063)
hypertension	0.249***	0.250***
	(0.055)	(0.055)
ownfraction	−0.397***	−0.341***
	(0.111)	(0.114)
icyday	−0.003	−0.002
	(0.004)	(0.004)
hotday	0.0005	0.0009
	(0.0016)	(0.0016)
surveycloudcover	0.008*	0.006
	(0.004)	(0.004)
surveysolarenergy	0.0010	0.0004
	(0.008)	(0.008)
TotalEmi	0.000	0.000
	(0.000)	(0.000)
avgAQI	−0.002	−0.002
	(0.004)	(0.004)

	Dependent variable:	
	Raw mental health index	
	(1)	(2)
roadnoise1km	0.0074**	0.0070**
	(0.0033)	(0.0033)
CO_2 emission1km	0.0113	
	(0.0093)	
CO_2 emission5km		0.0310**
		(0.0147)
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.9: Positive AQI Sample: 2SLS Estimates with Full Model Specifications

	Dependent variable:
	Standardized mental health index
	(1)
educ12	−0.040
	(0.032)
educsomecollege	−0.039
	(0.030)
educcollege	−0.080***
	(0.031)
educpostgrad	−0.108***
	(0.033)
female	0.080***
	(0.018)
married	−0.144***
	(0.020)
totalhousehold	0.002
	(0.007)
age_i	−0.006**
	(0.003)
agesqr	−0.00005*
	(0.00003)
black	−0.242***
	(0.028)
hispanic	−0.057**
	(0.027)
otherrace	−0.013
	(0.032)
everhadcancer_i	0.026
	(0.025)
familyeverhadcancer	0.060***
	(0.021)
income34999	−0.247***
	(0.032)

	Dependent variable:
	Standardized mental health index
income49999	−0.332***
	(0.032))
income74999	−0.394***
	(0.031)
income99999	−0.446***
	(0.034)
incomehigh	−0.466***
	(0.033)
freqgoprovider	0.037***
	(0.003)
timesmoderateexercise	−0.043***
	(0.004)
bmi	0.006***
	(0.001)
diabetes	0.137***
	(0.024)
hypertension	0.098***
	(0.020)
ownfraction	−0.154***
	(0.041))
icyday	−0.001
	(0.001)
hotday	−0.00001
	(0.0006)
surveycloudcover	0.002
	(0.002)
surveysolarenergy	−0.00004
	(0.003)
TotalEmi	0.000
	(0.000)
avgAQI	−0.0005
	(0.002)

	Dependent variable:
	Standardized mental health index
roadnoise1km	0.0022^{+}
	(0.0016)
CO_2 emission1km	0.0037
	(0.0034)
County FE	X
Year FE	X
R^2	0.121
Observations	12,393
Note:	$^{+}$p<0.2; *p<0.1; **p<0.05; ***p<0.01