Too Shiny to Handle: Nighttime Light and Mental Health

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Abstract

Poor mental health imposes significant labor market penalties and is a growing concern among health professionals and economists. While several factors are linked to poor mental health, the role of non-chemical environmental factors remains unclear. Meanwhile, the average night sky has become brighter by 9.6% per year since 2011. This excessive light usage results in substantial welfare losses and health problems. We conduct the first study to establish a causal relationship between light pollution and mental health in the US. Using restricted data on approximately 14,000 survey respondents and granular nighttime light data from NASA, we exploit variations in local cloud cover to establish the exogenous change in nighttime light pollution. Our findings demonstrate that 2.7% of respondents who previously reported minimal mental health concerns are now showing mild symptoms of mental health issues. This translates to an annual welfare loss of up to $47 billion attributed to lost earnings in the labor market.

***Keywords*—** Light Pollution; Mental health; Cloud Cover; HINTS

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1 Introduction

Mental health issues have become a pressing concern in the United States, with significant implications for individual well-being and societal productivity. Recent studies indicate that mental health disorders are widespread, with the National Institute of Mental Health reporting that nearly 1 in 5 US adults live with a mental illness each year (National Institute of Mental Health, 2021). This prevalence is higher compared to other developed countries. For instance, the World Health Organization (WHO) highlights that the burden of mental disorders in the US is greater than in countries such as Japan, Italy, and Spain, where mental health issues are less pervasive (Organization, 2017; De Graaf et al., 2008). The rising incidence of mental health problems in the US has drawn increasing attention from policymakers, healthcare providers, and economists due to its far-reaching consequences.

There is a substantial economic impact of mental health disorders. Mental health issues contribute to reduced productivity, increased absenteeism, and significant healthcare costs. The Global Burden of Disease Study estimates that mental and substance use disorders are among the leading causes of disability worldwide, with a particularly high impact in high-income countries, including the United States (Whiteford et al., 2013). The economic burden in the US is profound, with mental health disorders costing the economy billions of dollars annually in lost productivity and healthcare expenditures (Oeconomics et al., 2020). This economic impact underscores the importance of addressing mental health issues through effective policies and interventions.

Environmental factors, including chemical air pollution, have been widely studied for their adverse effects on mental health, activating the human stress response system and leading to various negative outcomes (Zhang et al., 2017; Dzhambov et al., 2018). However, the impact of non-chemical environmental factors, such as noise and light pollution, remains underexplored. Wen and Khanna (2024) find ambient road noise has a significant causal effect on human mental health. We build on the work of Wen and Khanna (2024), and focus on another prevalent but understudied non-chemical environmental concern, light pollution.

Light pollution, defined as excessive or misdirected artificial light, has been shown to disrupt natural circadian rhythms, leading to sleep disturbances and other health problems (Cajochen et al., 2011; Falchi et al., 2016). Despite its prevalence, the link between light pollution and mental health has received scant attention in the literature. In this study, we address this gap by investigating the causal relationship between nighttime light and mental health. Excessive exposure to artificial light at night disrupts natural circadian rhythms, leading to sleep disturbances, reduced melatonin production, and an increased risk of various health problems such as obesity, diabetes, and cardiovascular diseases (Cajochen et al., 2011; Falchi et al., 2016). Additionally, there is evidence linking light pollution to a higher prevalence of mood disorders and depression among individuals residing in brightly illuminated urban areas (Juda et al., 2013).

Studies on ambient light or light pollution are emerging in the economic literature. It is recognized that stimuli such as light and noise can activate the human stress response system (Jariwala et al., 2017, Kumar et al., 2019). Gallaway et al. (2010) analyze the economic factors of global light pollution and quantify its economic causes. Doleac and Sanders (2015) show that ambient light can decrease criminal activities, while Brei et al. (2016) find nighttime light has a deleterious effect on biodiversity, based on evidence of sea turtles in the Caribbean. Argys et al. (2021) find light pollution negatively affects infant health. Notably, Boslett et al. (2021) find shale gas development significantly increases nighttime light pollution in rural areas, which is associated with sleep deprivation and poor physical or mental health. However, none of the aforementioned studies establish a direct causal link between ambient nighttime light pollution and human mental health.

In the US, light pollution is a significant environmental issue, particularly in densely populated urban areas and regions with high levels of industrial activity. Cities such as Los Angeles, New York City, and Chicago are known for their intense artificial illumination, which casts a pervasive glow that obscures the natural night sky and disrupts ecosystems (Falchi et al., 2016). The widespread use of inefficient lighting fixtures, such as high-pressure sodium and mercury vapor lamps, contributes to the problem, as does the excessive use of brightly lit signage and outdoor advertising (Davies et al., 2013). Additionally, the rapid expansion of urban areas and suburban sprawl exacerbates light pollution by increasing the overall intensity and spatial extent of artificial lighting (Bogard, 2013). These factors combine to create a situation where much of the US population resides in areas where the night sky is rarely truly dark, impacting both human health and wildlife (Gaston et al., 2015; Falchi et al., 2016).

Beyond its impact on human health, excessive artificial lighting can disrupt the behavior and habitats of nocturnal wildlife, including birds, insects, and mammals (Longcore and Rich, 2004; Davies et al., 2013). For example, light pollution can interfere with migration patterns, alter predator-prey dynamics, and disrupt reproductive cycles, ultimately threatening biodiversity and ecosystem functioning (Gaston et al., 2015). Therefore, addressing light pollution through the implementation of lighting regulations and adopting more energy-efficient lighting practices is crucial for safeguarding both human well-being and the natural environment.

In this paper, we leverage novel data that capture ambient nighttime light levels at the residences of approximately 14,000 individuals aged 18 and above, spanning the years from 2014 to 2020.[1] A unique aspect of our dataset is the ability to connect individual mental health outcomes directly to

[1]We do not include any survey years after 2020 since we are concerned about any systemic change in respondents' mental health or lifestyle after COVID-19.

nighttime light pollution levels via relatively precise residential addresses. Through a data use agreement, we have access to the restricted version of the NCI's Health Information National Trend Survey (HINTS), which provides comprehensive details on individual respondents' mental health status, demographic and physical attributes, along with the 9-digit zip code corresponding to their residence.

We acquire light pollution data from NASA's VIIRS/NPP Lunar BRDF-Adjusted Nighttime Lights Yearly maps. These datasets are accessible on a 500-meter grid, enabling us to gauge each respondent's ambient nighttime light pollution with relative precision. Additionally, we utilize skyglow data from Loss of the Night (LON) to validate the robustness of our light pollution measurements.[2] Furthermore, we incorporate information on chemical releases from the US Environmental Protection Agency's (EPA's) Toxics Release Inventory (TRI) and weather data from the National Centers for Environmental Information as control variables.

We conduct the first national-level, quasi-experimental study to investigate the causal effect of ambient nighttime light pollution on adulthood mental health. Our primary outcome variable is a composite mental health index assigned to each respondent in the HINTS data. This index spans from 0 to 12, where a higher value signifies poorer mental health. Notably, approximately half of the respondents do not report any mental health concerns in the two weeks leading up to the survey, reflected by an index value of zero. Conversely, nearly 25% of respondents indicate experiencing symptoms of anxiety or depression on some days, denoted by an index value falling 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 primary independent variable is the level of local nighttime light pollution at the 9-digit zip code level, capturing ambient light at a "several household" or "street" level. We incorporate controls for individual demographic characteristics such as gender, race, education, and income. Additionally, drawing from the mental health literature, we include comprehensive controls for individual physical health and local environmental conditions, including factors such as solar energy exposure and occurrences of extreme temperature and air quality fluctuations.

The primary challenge of this study lies in the non-random assignment of light pollution, as respondents may self-select into areas with varying levels of ambient nighttime light and associated pollutants based on their socioeconomic status. To address this challenge, we employ variations in

[2]See more details about the LON project at http://www.myskyatnight.com/#map.

[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.2), we also present estimates using the raw (unstandardized) index values.

local cloud cover to extract exogenous variation in ambient nighttime light. Firstly, the cloud cover must correlate with nighttime light pollution. Kyba et al. (2011) find that cloud cover serves as an amplifier for light pollution, which is because clouds can reflect and scatter artificial light emitted from the ground, causing an increase in the brightness of the sky.

Second, the instrumental variable approach relies on the assumption that variations in local cloud cover only influence respondents' mental health outcomes through the pathway of ambient nighttime light. Specifically, we exploit nighttime cloud cover as our instrument. While daytime cloud cover might affect mental health directly by blocking sunlight, which can influence mood and well-being, nighttime cloud cover does not present the same issue. People do not expect sunlight during the night, and therefore, the absence or presence of clouds at night should not directly affect their mental health. Hence, the average nighttime cloud cover during each survey year can generate cross-sectional exogenous variation in nighttime light, serving as a valid instrumental variable in this study.

In this study, we find that the mental health of an average respondent worsens by 0.0095 standard deviations when ambient nighttime light radiance increases by 1 unit. The effect is equivalent to 81 out of 3017 respondents in a typical survey year (i.e. year 2020) with little mental health problems reporting mild mental health symptoms instead. This is equivalent to a 2.8% increase in the number of respondents experiencing mild mental health symptoms.

These findings remain robust and statistically significant across different model specifications, indicating an annual welfare loss of up to $47 billion attributed to lost earnings in the labor market. Additionally, it is reassuring to observe a consistent relationship between ambient nighttime light and mental health outcomes, confirmed by a robustness check using an alternative light pollution measurement. This alternative measurement is based not on satellite data but on human observations. Specifically, it relies on the subjective assessment of how visible certain stars are, with human reporters documenting the brightness of the night sky to determine the level of light pollution. This human-eye-captured data provides an independent verification of our findings, strengthening the validity of our results.

Furthermore, we delve into the potential mechanism underlying the impact of ambient nighttime light on mental health. Analyzing respondents' data on sleep duration and quality, we observe that a one-unit increase in light pollution correlates with a 0.24% reduction in sleep duration across all samples. Notably, among individuals aged 55 and above, this effect is more pronounced, leading to a 0.80% decrease in sleep duration. Additionally, we find that older respondents generally experience poorer sleep quality as nighttime light increases.

The adverse mental health effects identified by our analysis imply huge welfare costs through lost earnings and workplace absenteeism. Given the multifaceted impacts of light pollution, effective policy interventions are paramount. Policymakers must lead initiatives aimed at promoting the adoption of energy-efficient lighting technologies and reducing unnecessary outdoor lighting. Simultaneously, efforts to raise public awareness about the importance of preserving natural darkness for both human well-being and scientific progress are essential.

The rest of the paper is organized as follows: Section (2) describes our data. Section (3) illustrates our empirical strategy. We report our main results in Section (4) and assess the robustness of these results in Section (5). Section (6) addresses the potential mechanism through which nighttime light affects mental health. Section (7) concludes.

2 Data

2.1 Data Description

We exploit data that measure ambient nighttime light 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 nighttime light through relatively precise residential addresses. Notably, we use the same mental health data as Wen and Khanna (2024), which enhances the comparability and robustness of our findings in the context of existing research.

The Health Information National Trends Survey (HINTS) - Under a data use agreement, we have access to the restricted version of the NCI's Health Information National Trend Survey (HINTS) over five years (2014, 2017, 2018, 2019, 2020) 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.[4] It is suited to our analysis since it provides both physical and mental health information for each respondent along with a relatively precise residential location, and the information is gathered without reference to ambient nighttime light pollution levels.

[4]HINTS uses survey weights to allow researchers to generalize their analysis to the national US population. The first step in creating these weights is to adjust them 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.

Our key outcome variable is a summary of the mental health index (PHQ-4[5]) 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 NASA's VIIRS/NPP Lunar BRDF-Adjusted Nighttime Lights Yearly 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 following five waves: 2014 and 2017-2020.

NASA's VIIRS/NPP Lunar BRDF-Adjusted Nighttime Lights Yearly maps - Light pollution, as measured through instruments like VIIRS, refers to the excess or misdirected artificial illumination emitted into the atmosphere, disrupting the natural darkness of the nighttime environment. NASA's VIIRS/NPP Lunar BRDF-Adjusted Nighttime Lights Yearly maps provide spatially gridded nationwide nighttime light pollution data since 2012. The maps are updated annually and offer us the opportunity to utilize cross-sectional variations in nighttime light across our HINTS survey years. In the VIIRS data, light pollution is quantified in terms of radiance, which represents the amount of light emitted or reflected from the Earth's surface and atmosphere. This radiance measurement encompasses various sources of artificial light, including urban areas, industrial sites, and transportation networks, etc. High levels of radiance captured by VIIRS indicate areas with significant light pollution, which can lead to adverse effects such as skyglow, glare, and light

[5]The Patient Health Questionnaire-4 (PHQ-4) was developed and validated by Löwe et al. (2010) in order to address the fact that anxiety and depression are two of the most prevalent illnesses among the general population.

[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, 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.

trespass. Understanding and monitoring light pollution using the VIIRS data are crucial for assessing its impact on ecosystems, human health, astronomical observations, and energy consumption, guiding efforts to mitigate its effects, and promoting more sustainable lighting practices. Figure (1) displays the ambient nighttime light across the United States in 2018.

The Measurement of Light Pollution Exposure for Each Respondent - The nighttime light data are available on a fine spatial grid of 500-meter square. Since ambient nighttime light 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 of a building 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 NASA's national nighttime light maps.

The brightness of the night sky is not limited to urban areas. National Park Service documents that the glow from cities can be observed even at distances over 200 miles from national parks. However, we believe that local nighttime light is the key light pollution source that plays a significant role in affecting the human central response system and mental health. To estimate respondents' ambient nighttime light, we create a circular buffer with a radius of 1 km around each respondent's 9-digit zip code centroid. Although the light data are available on a 500 m pixel, we chose a 1 km radius buffer to capture a broader and more representative measure of ambient nighttime light exposure around each respondent's residence. This choice is justified by the need to account for variations in light pollution within a larger area that individuals are likely to traverse in their daily activities, such as walking after dinner. A 1 km buffer better reflects the typical range of human movement and interactions with their environment, thereby providing a more realistic measure of light exposure. Figure (4) depicts the zip-9 centroids for a sample of hypothetical HINTS respondents near one of our institutions (University at Buffalo). The blue circles are the 1-km light buffers, and the orange to purple cells represent weak to substantial ambient nighttime light pollution. Within a buffer, each 500 m^2 pixel area has a unique value for ambient nighttime light. We calculate a respondent's ambient nighttime light pollution as the average across all pixels in the buffer that have detectable light.

Naked Eye Limiting Magnitude (NELM) - NASA's light maps offer us a comprehensive evaluation of the nighttime light pollution captured by satellites. However, we are concerned whether the light pollution that human eyes capture is consistent with that captured by satellites. We utilize the skyglow data from Loss of the Night (LON), which is a web application using citizen science, and provide some tools to help citizen participants visualize and collect the skyglow data. The LON project is also exploited by Argys et al. (2021) to investigate the effect of light pollution on infant health. The data quality is approved to be reliable and accurate in their study. The LON collects its nighttime light data based on Naked Eye Limiting Magnitude (NELM), which is defined as the faintest star that a naked human eye can see. Higher values of the NELM mean more stars are captured by the naked eyes, which indicate less skyglow and darker sky. We discuss more details in constructing this measurement for our respondents in Section (5.1).

The Toxics Release Inventory (TRI) - Since mental health outcomes are correlated with exposure to chemical pollutants (e.g. Ao et al. (2021)), we also control for ambient toxic pollution by leveraging data from the Toxics Release Inventory (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.

$PM_{2.5}$ Measurement - To measure $PM_{2.5}$ concentrations, we rely on satellite-derived estimates from the Atmospheric Composition Analysis Group at Washington University in St. Louis. These data provide global and regional ground-level $PM_{2.5}$ estimates by integrating information from satellite observations, chemical transport models, and ground-based monitoring. Specifically, aerosol optical depth (AOD) measurements are collected from multiple satellite instruments, including NASA's MODIS, MISR, SeaWiFS, and VIIRS, using retrieval algorithms such as Dark Target, Deep Blue, and MAIAC. These AOD estimates are further refined using simulations from the GEOS-Chem chemical transport model and calibrated against ground-based sun photometer data from AERONET. This comprehensive approach enables the generation of highly accurate $PM_{2.5}$ estimates that closely align with ground-based measurements (Van Donkelaar et al., 2016). While regulatory monitoring networks offer direct measurements, their spatial coverage is limited; in the United States, only about 1,000 monitors exist, predominantly in urban areas. Consequently, nearly a quarter of respondents in our sample reside in locations without an EPA $PM_{2.5}$ monitor, making satellite-derived estimates a crucial alternative for assessing air pollution exposure. We calculate the average $PM_{2.5}$ concentrations within each respondent's county to account for any potential air pollution impacts on mental health.

Air Quality Index (AQI) Data - In addition, we also use county-level Air Quality Index (AQI) data from the US for a robustness check. Environmental Protection Agency (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 minimal air emissions and we assign a 0 AQI value to areas without these reports.[7]

Weather Data from the National Centers for Environmental Information - 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 obtain daily information on other environmental factors from Visual Crossing, which offers rich historical data on weather conditions like temperature, precipitation, solar energy, and cloud cover. 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.

2.2 Summary Statistics

Our key independent variable is local ambient nighttime light pollution at the 9-digit zip code level, which measures noise at a "building" or "street" level. The statistic summary of the measurement of light pollution is reported in Table (1). The average radiance value is 29.29 W/cm^2sr. To put this in perspective, this level of brightness is similar to what you would experience in a suburban area with moderate street lighting. Radiance in this context measures the amount of light emitted in a particular direction per unit area, with higher values indicating brighter light.

More than 19,000 respondents have 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 14,030 individuals across all the survey years.

Table (1) and (2) provide a summary of statistics for mental health scores (PHQ-4), light pollution (average radiance within 1 km of each respondent), NELM, and individual-level demographic controls. The detailed statistics of PHQ-4 scores are shown in Table (A.1). The average PHQ-4

[7] 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. We report the results using AQI instead of $PM_{2.5}$ concentrations in the Appendix.

score across all samples is 1.90. The PHQ-4 scores are rated as normal (0-2), mild (3-5), moderate (6-8), and severe (9-12). A higher PHQ-4 index indicates worse mental health for the respondent.

Following Wen and Khanna (2024), we control for individual demographic characteristics such as age, age squared, marital status, household size, gender, race, education, and family income level. Table (1) provides a statistical summary of demographic controls. Specifically, gender and marital status are represented as dummy variables, which equal 1 if an individual respondent is female or married, respectively. The education indicators consist of four dummy variables to delineate the respondent's education level.[8] The race indicators are also represented as dummy variables to indicate non-Hispanic black, Hispanic, and non-Hispanic other race categories.

Table (2) displays detailed controls for individual physical health conditions, access to healthcare, physical activity or exercise every week and family history of cancer. Specifically, we include the number of times a respondent visits a doctor, nurse, or other health professional during the past 12 months. Family history of cancer is represented as a dummy variable, where 1 indicates that a respondent or their family members had cancer. Additionally, individual physical health conditions include Body Mass Index (BMI) and the occurrence of two common diseases, diabetes and hypertension. The respondents engage in physical activity or exercise around 3 times per week.

Table (2) also includes the statistical summary of environmental level controls. The AQI (Air Quality Index) is based on the concentrations of the 6 criteria gases (i.e. CO, O_3, NO_2, PM, SO_2, and Pb) covered under the Clean Air Act, with the county average value of AQI being 40.07. A higher AQI value indicates greater levels of air pollution and increased health concerns. Additionally, there are approximately 12 days per year with daily maximum temperatures below freezing and 83 days per year with daily maximum temperatures above 85°F. The variable "Zip-9 level fraction of people owning/renting a home" represents the fraction of residents owning/renting a house at the zip-9 level. [9]

[8]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" according to our specifications.

[9]Specifically, 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.

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 in the current literature, we begin with a simple OLS regression. We address the potential endogeneity issues between mental health and our key regressor (light pollution) through an instrumental variable approach in the following sub-section.

The OLS model describing the relationship between human mental health and nighttime light pollution is as follows:

$$\text{PHQ-4(STD)}_{izct} = \beta \text{Light Pollution(1 km)}_{zct} + \alpha X'_{izct} + \gamma Z'_{zct} + \pi W'_{ct} + \theta_c + \eta_t + \epsilon_{izct} \tag{1}$$

where $PHQ-4(STD)_{izct}$ represents the standardized mental health summary index (PHQ-4) for an individual respondent i from zip code area z (9 digit/5 digit) at county c 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 worse mental health for the respondent.

$Light\ Pollution(1km)_{zct}$ is the average radiance within the 1 km buffer at the 9 digit zip code area z in county c in year t. X'_{izct} is a vector of individual-level controls. It is well established that physical health also plays a significant direct and indirect role in explaining mental health (Kristiansen, 2021; Kesavayuth et al., 2022). Therefore, we include not only age, age squared, marital status, household size, gender, race, education, and family income level but also physical health condition and family cancer history.

Specifically, we include the total number of people living in the respondent's household as a control variable. 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 county c in year t from HINTS data. [10] Mikkelsen et al. (2017) find positive effects of exercise on mood states such as anxiety,

[10] Annual income is potentially an endogenous control variable since it could be determined simultaneously

stress, and depression. Therefore, we control for the number of days a respondent engages in any physical activity or exercise of at least moderate intensity in a typical week.

There are two types of environmental level control variables: zip code (5 digit) level and county level. Z'_{zct} represents a vector of covariates that vary at the zip code and year level, while W'_{ct} denotes environmental controls at the county level. At the zip code level, controls include the number of days during the survey year with daily maximum temperature below freezing or above 85°F, as these conditions can affect mental health (Burton and Roach, 2022). Additionally, total on-site emissions (air, water, and land emissions) of all 770 toxic chemicals from all facilities are accounted for. Molin et al. (1996) argue that lack of light is a driving factor for the development of winter depression. Thus, we also account for the annual average solar energy at the 5 digit zip code level. Another control factor is the fraction of residents owning a house at the block group level, as individuals tend to report worse mental health when local house prices decline (Joshi, 2016).

At the county level, controls include the average $PM_{2.5}$ concentrations (or annual ambient air quality in the robustness check).[11] County and year fixed effects are denoted by θ_c and η_t, and ϵ_{ict} is an error term.

A critical issue in implementing this approach is addressing the possibility that each respondent's locations with higher light pollution are not randomly assigned. 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 doubt the same situation may also apply to this new pollution source (i.e. nighttime light). To mitigate this concern, we incorporate county-level fixed effects in our regression models to account for time-invariant differences across counties. However, there may still be concerns about unobserved time-varying differences across individuals or counties that are correlated with both light pollution and mental health scores.

For instance, it's possible that areas with higher light pollution are more appealing to individuals due to proximity to main roads, public facilities, central business districts (CBD), and well-developed regions. In addition, these areas may offer better amenities and public services, which could have a positive impact on people's mental health and potentially lead to a decrease in the PHQ-4 score. If this were the case, the estimated relationship of interest in an OLS model, even with

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.

[11] 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.

fixed effects, could have a downward bias. This highlights the importance of carefully considering and addressing potential confounding factors in the analysis. To address this issue, we employ the instrumental variable (IV) approach.

3.2 Instrumental Variable Approach

We innovatively utilize local cloud cover variations at the 5-digit zip code level to address this potential endogeneity between ambient nighttime light pollution and mental health. We describe the mechanism of our instrument below, followed by the estimating equations in our two-stage regression model.

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

$$\text{Light Pollution(1km)}_{zct} = \rho \text{Nighttime Cloud Cover}_{zct} + \phi X'_{izct} + \chi Z'_{zct} + \psi W'_{ct} + \theta_c + \eta_t + \epsilon_{izct} \quad (2)$$

The dependent variable $Light\ Pollution(1km)_{izct}$ represents light pollution within a 1 km buffer of each individual i located in a 9-digit zip code area z in county c in year t. The instrument variable $Nighttime\ Cloud\ Cover_{zct}$ represents the zip-5 level annual average Nighttime cloud cover in county c in year t.[12] We then utilize the predicted ambient nighttime light pollution from Eq.(2) to estimate the causal effect of light pollution on mental health using the following second-stage regression:

$$\text{PHQ-4(STD)}_{izct} = \beta \widehat{\text{Light Pollution}}(1\text{ km})_{zct} + \alpha X'_{izct} + \gamma Z'_{zct} + \pi W'_{ct} + \theta_c + \eta_t + \epsilon_{izct} \quad (3)$$

$\widehat{Light\ Pollution}(1km)_{zct}$ is the ambient nighttime light pollution predicted by the excluded instrument from Eq.(2). All the other control variables are the same in Eq.(1).

For an instrument to be valid, it must satisfy two key conditions - relevance and exogeneity. Natural events or exogenous changes that impact light pollution levels but are unrelated to mental health outcomes can ideally serve as instruments. We propose that average cloud cover during each survey year, being a meteorological phenomenon, could generate cross-sectional exogenous variation in nighttime light and serve as a valid instrumental variable.

Nighttime Cloud cover can influence the observed levels of light pollution from satellites in various ways. Firstly, clouds can reflect and scatter artificial light emitted from the ground, causing an increase in the brightness of the sky when viewed from above. Kyba et al. (2011) find that cloud cover acts as an amplifier for light pollution in urban ecosystems. This scattering effect can lead to

[12] We obtained hourly cloud cover data and daily sunrise/sunset times from Visual Crossing to calculate the annual nighttime cloud cover data. The summary statistics for nighttime cloud cover are reported in Table 1. For more details, visit https://www.visualcrossing.com/weather/weather-data-services.

higher observed levels of light pollution, particularly in areas with significant cloud cover. Figure (3) shows the correlation between the nighttime light pollution(1km buffer) and the nighttime cloud cover Secondly, the absorption of light by clouds can also reduce observed light pollution. However, Hakuba et al. (2017) find the absorption effect appears most distinctly at desert-like locations, where overall have little occurrence of clouds.

Although the literature suggests that the effects of nighttime cloud cover on observed nighttime light pollution levels from satellite imagery are complex and can involve a combination of scattering, reflection, and absorption processes, we believe that the scattering and reflection (amplifying) effect by clouds plays a dominant role in affecting light pollution in urban settings. Additionally, some researchers utilize cloud layers to model cloud cover as an approximation for the propagation of light pollution (Cinzano and Falchi, 2012).

Nighttime cloud cover is an exogenous meteorological phenomenon[13] and should be independent of local economic activity, demographic characteristics, pollution patterns, and other unobserved variables in the error term. Although nighttime cloud cover does not directly affect daytime solar energy, there is concern about a potential correlation between cloud cover identification and solar energy. Nighttime cloud cover might correlate with solar energy and serve as an approximate measure for intra-day cloud conditions. To mitigate potential bias from this correlation, we control for average solar energy during each survey year.

Notably, while our key independent endogenous variable is nighttime light, the control of solar energy only captures the approximated cloud cover conditions during the daytime. Our use of solar energy control helps to mitigate potential bias arising from daytime cloud cover effects. Meanwhile, our direct measure of nighttime cloud cover serves as an instrument to generate exogenous variation in nighttime light. This approach allows us to address concerns regarding potential endogeneity and obtain more reliable estimates of the impact of nighttime light on mental health outcomes. We notice that Wen and Khanna (2024) argue cloud cover and solar energy might affect mental health separately. We do not control for daytime cloud cover because it is highly correlated with nighttime cloud cover. If we were to control for daytime cloud cover, it could compromise the validity of our instrument (nighttime cloud cover) by introducing another pathway through which it could affect our outcome variable (mental health). By focusing on nighttime cloud cover, we ensure that our instrument impacts mental health primarily through its effect on nighttime light, thereby maintaining the robustness of our causal estimates.

Furthermore, if there exists a relationship between nighttime cloud cover and nighttime light

[13] Because it is influenced by factors external to the atmosphere, such as changes in temperature, humidity, and air pressure.

pollution, then it is expected that a reduced-form relationship between the cloud cover and the mental scores would emerge. The concept of the IV approach is apparent in the reduced-form specification:

$$\text{PHQ-4(STD)}_{izct} = \zeta \text{Nighttime Cloud Cover}_{zct} + \xi X'_{izct} + \kappa Z'_{zct} + \lambda W'_{ct} + \theta_c + \eta_t + \epsilon_{izct} \quad (4)$$

4 Main Results

Panel (A) in Table (3) displays the OLS and IV results without individual-level and environmental-level controls. Column (1) presents the OLS result, while Column (2) presents the IV result. Both indicate that nighttime light pollution increases standardized PHQ-4 score, indicating worse mental health.

Column (5) in Table (3) presents the main OLS estimates of the impact of light pollution on mental health using the full sample with all controls, as described by Equation (1). The dependent variable in Table (3) is the standardized mental health score (PHQ-4). A higher score indicates more severe mental health issues. It reports the estimated impact as 0.0014, which is statistically significant at the 1% level. However, as mentioned previously, it is likely that OLS estimates are biased due to the endogeneity issue associated with light pollution. Therefore, the instrumental variable (IV) results are represented in Column (6), and the first-stage estimates, represented by Equation (2), are shown in Column (8).

Specifically, the first-stage estimates reveal a positive and significant relationship (denoted as ρ in Equation (2)) between cloud cover and light pollution. This finding supports the hypothesis that cloud cover acts as an amplifier of light pollution. In other words, locations with higher levels of cloud cover tend to experience higher levels of light pollution. Column (6) presents the regression results for the second stage of instrumental variable (IV) estimation, where the estimated coefficient, denoted as β, equals 0.0095. This indicates that respondents' mental health deteriorates by 0.0095 standard deviations with a one-unit increase in ambient light pollution. This effect translates to approximately 2.7% of respondents who previously reported minimal mental health issues exhibiting mild mental health symptoms.[14]

[14]First, we calculate the weighted average of the standardized mental health index for each year in our sample. Then, for any specific year, such as 2020, we adjust the data by decreasing the number of respondents with a raw PHQ-4 score of 2 and increasing the number of respondents with a score value of 3. This manipulation reflects a marginal change from no mental health problems to mild mental health problems, based on the data from HINTS (see https://hints.cancer.gov). After adjusting the data, we calculate the new corresponding weighted average standardized mental health score. The difference between the original weighted average index and the manipulated weighted average index equals 0.0095 (the coefficient on ambient light pollution in our main specification). The 2.7% increase in the number of respondents experiencing mild symptoms is calculated as 6 out of 213.

In addition, the first-stage effective F-statistic, accounting for non-homoskedasticity, is 131.067, exceeding the conventional weak instrument threshold of 10. This indicates that our IV estimate is not subject to weak instrument bias. Nevertheless, we also subject the estimate to the Anderson-Rubin weak IV robust test, assessing the null hypothesis of no effect of light pollution on mental health. With a p-value of 0.037, we could reject the null hypothesis. This suggests that the main finding of this study remains robust even when considering the strength of the instrument.[15]

Column (7) presents reduced-form estimates as depicted by Equation (4). The estimation results reveal a statistically significant positive relationship between nighttime cloud cover and the mental score. Specifically, respondents residing in areas with relatively higher levels of nighttime cloud cover tend to exhibit higher mental scores, indicating worse mental issues. When comparing the OLS estimate with the IV estimate, it suggests that OLS estimates are likely to be downward biased. The reason behind the downward bias in the OLS estimates could be attributed to unobserved time-varying differences among respondents during the survey period that are correlated with both the PHQ-4 score and the light pollution. If the presence of omitted variables like local amenities is the case, the estimated relationship of interest in an OLS model suffers from a downward bias.

5 Robustness Check

5.1 Light Measurement

While NASA's nighttime light maps provide a comprehensive top-to-bottom view of national light pollution, individuals' experiences of light pollution may vary when viewed from a bottom-to-top perspective. Therefore, we utilize skyglow data from Loss of the Night (LON), a web application that leverages citizen science. LON provides tools to help citizen participants visualize and collect skyglow data, offering a more nuanced understanding of light pollution from ground-level observations.

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

Argys et al. (2021) also utilises the NELM measurement from the LON project and highlights two

[15] See Andrews et al. (2019)

advantages of using this metric. Firstly, they note that the bottom-to-top view provided by LON users may offer a more accurate reflection of how humans perceive light pollution. Secondly, Argys et al. (2021) point out that satellites cannot sensitively capture the blue part of the visible spectrum of light, such as nighttime light emitted by LED streetlights (Kyba et al., 2017). Therefore, the NELM measurement, which relies on human eyes as sensors, can more efficiently capture this aspect of light pollution compared to satellite-based measurements.

Notably, while our primary nighttime light measurement relies on satellite data, we focus on a national sample rather than a local urbanized area, as in Argys et al. (2021). Our dataset comprises some rural areas with few LON users, as well as a large number of LON records for several big cities. To mitigate measurement errors in reporting to the LON project and avoid sample selection issues among LON users between rural and urban areas, we prefer to use satellite data, which provides a comprehensive and consistent measurement of nighttime light across different regions. However, to ensure the robustness of our empirical strategy and incorporate a different light measurement, we also leverage the NELM measurement from the LON project.

A simple rule of thumb suggests that an increase in the NELM by one unit indicates that approximately three to four times as many stars could be seen with the naked eye. For example, a NELM of 2 suggests that approximately 25 stars can be seen, while a NELM of 3 indicates that approximately 75-100 stars can be seen with the naked eye. The increase in the number of visible stars suggests a reduction in skyglow and decreased light pollution.

The LON project provides precise geographic locations for each observation record. We utilize this information by drawing a buffer with a radius of 50 km centered at the zip-9 centroid of each HINTS respondent. While a 50 km buffer is larger than our baseline 1 km radius, this choice is justified by several factors. First, the LON project offers user-reported observations of stars, and a smaller 1 km buffer would result in very limited matched respondents with star observations surrounding their residences. By expanding the buffer to 50 km, we assume the level of star observation is relatively uniform within this area, allowing us to obtain a sufficient number of observations for most respondents. This approach ensures that we have enough data to make reliable inferences. Additionally, this approach aligns with studies such as Falchi et al. (2016) and Kyba et al. (2017) that document how light pollution from urban areas can impact regions up to tens of kilometers away. By using a larger buffer, we aim to capture the extended influence of light pollution, providing a comprehensive assessment of its impact on mental health.

Within this buffer, we calculate the average NELM values from all observation records for each respondent's survey year. This average NELM value is then assigned as the respondent's NELM measurement. We use each respondent's NELM value as the measurement of nighttime light and proceed to run our 2SLS specification as follows:

$$\text{NELM}_{zct} = \rho_1 \text{Nighttime Cloud Cover}_{zct} + \phi_1 X'_{izct} + \chi_1 Z'_{zct} + \psi_1 W'_{ct} + \theta_c + \eta_t + \epsilon_{izct} \quad (5)$$

The dependent variable $NELM_{izt}$ represents ambient nighttime light pollution within a 50 km buffer of each individual i located in a 9-digit zip code area z in county c in year t. The excluded instrument in Equation (5) is the zip-5 level annual average nighttime cloud cover ($Cloud\ cover_{zct}$) for each HINTS survey wave, as the same as that in Equation (2). We then utilize the predicted ambient nighttime light pollution from Equation (5) to estimate the causal effect of light pollution on mental health using the following second-stage regression:

$$\text{PHQ-4(STD)}_{izct} = \beta_1 \widehat{\text{NELM}}_{zct} + \alpha_1 X'_{izct} + \gamma_1 Z'_{zct} + \pi_1 W'_{ct} + \theta_c + \eta_t + \epsilon_{izct} \quad (6)$$

$\widehat{NELM}_{zct}$ is the ambient nighttime light pollution predicted by the excluded instrument from Equation (5). All the other control variables are the same in Equation (1).

Table (4) displays both the OLS and IV results regarding the impact of light pollution on mental health, utilizing NELM as a measure of light pollution. Notably, higher NELM values indicate lower levels of light pollution. Column (2) presents the estimation of the causal relationship between light pollution and mental health, denoted as β_1 in Equation (6), which equals -0.5947. The results indicate that the PHQ-4 score of respondents improves by 0.5947 standard deviations when their NELM increases by 1 unit.

Column (4) displays the first-stage result of the IV estimation based on Equation (5). It indicates that cloud cover has a significant and negative impact on the NELM index. This finding suggests that cloud cover increases skyglow, resulting in fewer stars being visible to the naked eye. This aligns with our hypothesis that cloud cover acts as an amplifier of nighttime light pollution. The first-stage effective F-statistic is greater than the conventional weak instrument threshold of 10, indicating that the instrument is sufficiently strong. Additionally, the Anderson-Rubin weak IV robust test suggests a significant effect of NELM on PHQ-4 (standardized) score.

5.2 Walker's Law

Argys et al. (2021) employ an instrumental variable approach based on an empirical physics regularity known as Walker's law to predict skyglow using a city's population and distance to the city's center. Walker's law is based on the observation that skyglow, the diffuse brightness of the night sky over populated areas, increases with the population size and decreases with the distance from the city center. This relationship provides a predictable pattern of light pollution. However, it is worth noting that Walker's law may not be directly applicable to our sample, as it was discovered in California and is more suited for predicting skyglow in areas with relatively high urbanization (Walker, 1977). Nevertheless, we consider this instrumental variable as a robustness check in our study, given the external validity of Walker's law in predicting skyglow. Following the methodology of Argys et al. (2021), we construct an instrumental variable (Walker's Law) indicating predicted skyglow as follows:

$$\text{Walker's Law} = k \times \frac{1}{\text{distance}^{2.5}} \times \text{city's population} \tag{7}$$

where *Walker's Law* represents the predicted skyglow using Walker's law, *distance* is the distance (unit: km) between the zip-9 centroid of each respondent's residence and the centroid of the city to which the zip-9 belongs,[16] and k is a positive constant. We choose k to be 0.000001 in order to ensure that our instrumental variable measurement is comparable to our NELM light pollution.

Although the two components used in Walker's law (i.e., city's population and distance) can be argued to correlate with respondents' socioeconomic conditions, and residential sorting behavior may affect respondents' light pollution exposure, Argys et al. (2021) argue that residential choice appears not to be dependent on the exact distance between the zip code centroid and the geographic center of the corresponding residential city. We utilize their instrumental variable constructed by Walker's law and proceed to run the 2SLS as follows:

$$\text{Light Pollution(1 km)}_{zct} = \rho_2 \text{Walker's Law}_{zct} + \phi_2 X'_{izct} + \chi_2 Z'_{zct} + \psi_2 W'_{ct} + \theta_c + \eta_t + \epsilon_{izct} \tag{8}$$

The dependent variable $LightPollution_{zct}$ represents ambient nighttime light pollution within a 1 km buffer of each individual located in a 9-digit zip code area z in year t. The excluded instrument in Equation (8) is the IV constructed from Equation (7) at the individual-zip-9-year level. We then utilize the predicted ambient nighttime light pollution from Equation (8) to estimate the causal effect of light pollution on mental health using the following second-stage regression:

$$\text{PHQ-4(STD)}_{izct} = \beta_2 \text{Light Poll}\widehat{\text{ution}}\text{(1 km)}_{zct} + \alpha_2 X'_{izct} + \gamma_2 Z'_{zct} + \pi_2 W'_{ct} + \theta_c + \eta_t + \epsilon_{izct} \tag{9}$$

$Light\ Pol\widehat{lution}(1\ km)_{izct}$ is the ambient nighttime light pollution predicted by the excluded instrument from Equation (8). All the other control variables are the same in Equation (1).

Table (5) presents the OLS and IV results using Walker's law as the instrumental variable. In Panel A, we restrict the respondents' location to the closest CBD, no greater than 20 km away. The OLS estimates in Column (1) indicate a positive and statistically significant impact on the standardized PHQ-4 score, suggesting a worsening of the respondents' mental health. However, we do not

[16]We follow Argys et al. (2021) and use Centers for Disease Control and Prevention (CDC)'s 500 Cities Project, which offers us the latitude and longitude of each city's centroid as well as city population among the 500 largest US cities. We search for these 500 "large cities" centered at our HINTS respondent's residence with a radius of 20 or 50 km, respectively.

observe statistically significant coefficients based on the IV approach in Column (2) of Panel A. Specifically, in Column (4), the coefficient estimation, ρ_2, of the first stage equals 0.00082. The positive sign is consistent with Walker's law, indicating that the value of $Walker's\ law$ is positively related to skyglow.

However, Walker's law depends on the distance to the CBD, which only captures the impact of people living in urban areas. Therefore, the observations in Panel A are only 8,787, which is only half of all samples. To address this limitation and capture a broader range of respondents, we increase the range of the distance to the CBD from 20 km to 50 km. Panel B in Table (5) displays the regression results for respondents living within 50 km of the nearest CBD. Although the OLS estimates in Column (5) show a significant impact of light pollution worsening people's mental health, the IV results in Column (6) still indicate no significant impact.

Moreover, the first-stage effective F-statistic is not greater than the threshold of 10 for the samples living within 20 km of the CBD. Additionally, the AR weak IV robust test is only significant at the 10% level. This indicates our concern that although Walker's Law is based on a nonlinear transformation of the city's population and distance, it is still possible that it is correlated with other economic activities that may impact mental health. We argue that the nonlinear IV (described by Equation (7)), being predictive of light pollution, could not be orthogonal to unobserved factors determining mental health outcomes. In summary, the positive sign of the impact on mental health in both the OLS and IV results still provides marginal evidence that light pollution increases the PHQ-4 score, worsening mental health.

6 Potential Mechanisms

In this section, we delve into the association between light pollution and sleep duration, aiming to identify a potential pathway through which ambient nighttime light may negatively impact mental health.

Sleep Disorder - Evidence from the epidemiology literature suggests that artificial outdoor nighttime light is linked to altered sleep behavior in the US general population (Ohayon and Milesi, 2016). Cao et al. (2023) underscore the toxicological mechanism of light pollution through circadian disruption. They emphasize that light pollution directly interferes with natural light-dark cycles and disrupts the circadian photoentrainment of organisms, leading to adverse effects. Individuals living in regions with elevated nighttime light levels typically encounter delayed bedtime and wake-up times, shortened sleep durations, and heightened daytime sleepiness.

On the other side, sleep issues are frequently observed in individuals with mental health disorders.

Freeman et al. (2017) offer strong evidence suggesting that insomnia plays a causal role in the development of psychotic experiences and other mental health challenges. Further investigation is needed to determine if these findings extend beyond a student population. Addressing disrupted sleep may need to be given greater importance in mental health care provision.

In the HINTS surveys, respondents were asked the following questions in 2019: "During the past 7 days, how many hours of sleep did you get on average per night?"; "In the past 7 days, how would you rate your sleep quality overall?". We utilize the responses to these questions to gauge the effect of light pollution on both sleep duration and sleep quality. Table (6) displays the IV[17] results regarding the influence of nighttime light pollution on sleep duration and sleep quality. In Column (1), the estimated effect of light pollution on sleep duration is presented, with a negative coefficient signifying a decrease, although statistically insignificant.

As individuals age, they often experience increased difficulty both falling asleep initially and maintaining sleep throughout the night. Older adults typically spend more time in lighter stages of sleep compared to deep sleep. Additionally, the efficiency of the circadian rhythm tends to diminish with age, resulting in a forward shift in their sleep schedule (Gulia and Kumar, 2018). Therefore, upon restricting the sample to individuals aged above 55, a negative impact on sleep duration is observed. This finding suggests that elderly individuals may be more susceptible to the effects of light pollution on sleep.[18]

Additionally, we utilize the natural logarithm transformation on sleep duration to assess the impact of nighttime light pollution on sleep duration logarithmically. The findings presented in Column (3) reveal that nighttime light pollution correlates with a 0.24% (p-value = 0.0017) reduction in sleep duration across all samples. Specifically, among individuals aged 55 and above, the effect is more pronounced, with a 0.80% decrease in sleep duration attributed to nighttime light pollution. Nevertheless, given the relatively modest impact on sleep duration, we proceed to examine the effect of light pollution on sleep quality.

Column (5) in Table (6) presents the IV estimation of the impact of light pollution on sleep quality. In this survey, participants rate their self-perceived sleep quality on average each night using a scale ranging from 1 (Very good) to 4 (Very bad)[19]. Therefore, a positive estimation suggests that a decrease in sleep quality is affected by nighttime light pollution. Furthermore, we specifically examine the results pertaining to the elderly population. Column (6) indicates an estimated coeffi-

[17] Instrumental variable: cloud cover

[18] Table (A.8) presents the results using the AQI as a measure of air quality control instead of $PM_{2.5}$. The findings remain consistent, and the IV estimation of the impact of light pollution on sleep duration for individuals aged 55 and above is significant at the 5% level.

[19] Sleep quality is a category variable: 1(Very good), 2(Fairly good), 3(Fairly bad), and 4(Very bad).

cient of 0.0389, which is statistically significant at the 10% level.

In summary, the estimation results presented in Table (6) indicate that nighttime light pollution has a more notable effect on the sleep behavior of the elderly population. Figure (6) illustrates the IV results depicting the impact of light pollution on average sleep duration and sleep quality across different age groups. It is evident that there is a discernible change in the coefficient size and significance level with increasing age, suggesting that the impact of light pollution on sleep behavior intensifies as individuals age.

Based on the results, we anticipated that the detrimental effects of nighttime light pollution on mental health would amplify with age. Consequently, we segmented the samples into distinct age groups (18-39, 40-59, and 60+). Figure (5) presents these findings, indicating a more pronounced impact of nighttime light pollution on mental health among the elderly population.

Furthermore, we investigate the impact across different demographic groups, including gender and race. Table (7) displays the effects of light pollution on sleep duration and quality by gender. The estimation results for the female sample, presented in Column (3), reveal a significant decrease in sleep quality attributed to nighttime light pollution among females. However, no significant impact on males is observed in our analysis. Then, Figure (5) illustrates the impact of nighttime light pollution on PHQ-4 scores by gender, highlighting a stronger impact experienced by females.

Nadybal et al. (2020) uncover evidence of disparities in exposure to light pollution, particularly among racial/ethnic minorities and low-to-mid socioeconomic status groups. Their study revealed that individuals of Asian, Black, or Hispanic race/ethnicity experienced population-weighted mean exposures to light pollution in their neighborhoods that were approximately twice as high as those of White Americans. Table (8) presents the effects of light pollution on sleep quality among different racial groups. We do not observe a significant impact of worsening sleep quality among Black or Hispanic individuals due to light pollution.

Symptom: Dizzy - In everyday life, the common experience of light pollution often manifests as dizziness for pedestrians and drivers due to the reflection of light off mirrored buildings. Studies have shown that exposure to intense artificial light can cause discomfort and symptoms such as dizziness (Falchi et al., 2016). An indirect measure of the frequency of experiencing such symptoms can be gleaned from the HINTS Survey cycle 4 (2014), where respondents were asked to rate their interest in electronically exchanging various types of medical information with healthcare providers, including symptoms such as nausea, pain, and dizziness.[20] While willingness to ex-

[20]Survey questions: How interested are you in exchanging the following types of medical information with a health care provider electronically? Symptoms (e.g., nausea, pain, dizziness, etc.) Answer: Not at all (4 points), A little (3 points), Somewhat (2 points), Very (1 point)

change medical information may be influenced by trust in the system, this data provides insight into the prevalence of these symptoms among the surveyed population.

Table (9) displays the IV results of the impact of light pollution on symptoms. Column (1) presents the estimation for all samples in 2014. While the coefficient does not reach statistical significance at the 10% level, the negative sign of the coefficient suggests that light pollution may indeed influence respondents' interest in reporting symptoms such as dizziness and nausea.

Following this, we divide the data into two groups based on age: above 55 and below 55. This division allows us to examine whether the impact of light pollution on symptoms varies among different age groups. Column (2) in Table (9) reveals that young adults and middle-aged individuals experience a significant impact of light pollution on symptoms such as dizziness or nausea. The coefficient in Column (2) is significant at the 5% level. However, we did not find any evidence suggesting that the impact of light pollution on these symptoms increased among the elderly group. One possible reason that the symptoms are only significant for the young population is that they may feel dizziness, especially when they go out or drive at night, and light reflected from mirror buildings.

Furthermore, we were also interested in examining the impact of light pollution on symptoms among different racial groups. Columns (4), (5), and (6) present the IV results for the White, Black, and Hispanic groups, respectively. The sign of all the coefficients suggests that light pollution indeed affects the symptoms. Particularly noteworthy is Column (5), which shows a statistically significant impact, indicating that light pollution has a significant effect on dizziness and nausea among Black individuals.

7 Conclusion

To the best of our knowledge, this study represents the first attempt to investigate the causal impact of nighttime light pollution on mental health among individuals aged 18 and above in the United States. Specifically, leveraging restricted data, we obtain precise measurements of nighttime light pollution for each individual based on their residential location. Moreover, in contrast to prior research, we identify a robust instrumental variable capable of mitigating the endogeneity concerns associated with light pollution across diverse urban and rural settings.

Specifically, we find that ambient nighttime light pollution exhibits a statistically significant, causal effect on mental health. Our IV estimates indicate that respondents' mental health deteriorates by 0.0095 standard deviations with a one-unit increase in ambient light pollution. This effect translates to approximately 2.7% of respondents who previously reported minimal mental health issues exhibiting mild mental health symptoms.

One plausible biological mechanism underlying our findings, as suggested by existing literature, is the disruption of circadian rhythms induced by light pollution. This disruption can lead to sleep disorders, which in turn may contribute to adverse mental health outcomes. Additionally, 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). Additionally, another potential mechanism is that light pollution may directly induce symptoms of illness, such as dizziness and nausea, which could impact mental health.

The impact of non-chemical triggers on human health has been relatively understudied in terms of their welfare effects. Notably, the United States stands out among developed nations due to its high rates of mental health disorders. Concurrently, the US is distinguished by widespread outdoor nighttime light usage across industrial and recreational sectors. Consequently, the regulation of light pollution has emerged as a significant policy concern in recent years.

Specifically, Arizona holds the distinction of being the first state to enact laws aimed at reducing light pollution, dating back to 1986. So far, a total of 19 states, the District of Columbia and Puerto Rico have laws in place to reduce light pollution. In Figure (7), we find that states with laws aimed at reducing light pollution actually exhibit higher levels of light pollution overall. The HINTS respondents from these states are more likely to experience a larger value of light pollution, as evidenced by the dominance of the red dashed curve over the solid blue curve for larger values of light pollution.

We also find emerging evidence indicating that the adoption of light reduction laws seems to be able to reduce local respondents' light pollution exposure successfully. Maryland and New York both implemented such laws in 2014. As illustrated in Figure (8), HINTS respondents from both states experienced a reduction in average light pollution exposure following the implementation of these laws. Therefore, we argue that federal or state governments should take a more proactive role in establishing appropriate legislation to regulate local light pollution.

While the adverse effects of nighttime light pollution on mental health that we uncover may appear relatively mild, even slight declines in mental well-being can yield substantial 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. According to the Federal Reserve, total wages and salaries in the US amounted to $9,720.96 billion in 2021. Our research indicates that approximately 81 out of 3,017 respondents (for the survey year 2020) may transition from experiencing "little" to "mild" depressive symptoms due to each decibel increase in ambient light pollution.

Applying the estimates from Germinario et al. (2022), this translates to a loss in welfare ranging between \$42-47 billion (in 2021 dollars).[21] Similarly, according to Peng et al. (2016), the presence of mild depressive symptoms (the most severe) relative to no depressive symptoms increases work loss days by 1.9 (4.5) days, contributing to an annual total cost of workplace absenteeism ranging from \$0.9-1.9 billion (in 2009 dollars). Our back-of-the-envelope calculation suggests that the potential labor market penalties resulting from the detrimental effects of ambient nighttime light pollution could surpass those from workplace absenteeism.

Moreover, the ramifications of light pollution reverberate through various other facets of society, necessitating urgent action. Astronomical and scientific pursuits suffer significantly from the widespread artificial illumination, as it obscures celestial visibility and complicates observations, hindering our comprehension of the universe and impeding advancements in scientific research. Simultaneously, the nuisance effects of light pollution are tangible, evident in the form of excessive glare and the omnipresent glow of skyglow, disrupting the serenity of nocturnal settings and diminishing the aesthetic allure of our urban areas and natural landscapes. Economically, light pollution exacts a heavy toll, with wasted energy costs running into billions of dollars annually, alongside detrimental impacts on the burgeoning tourism and outdoor recreation industries, as obscured night skies detract from the allure of stargazing and nocturnal activities.

To mitigate these challenges, policymakers must enact regulations and initiatives aimed at promoting the adoption of energy-efficient lighting technologies, reducing unnecessary outdoor lighting, and increasing awareness about the significance of preserving natural darkness for both human well-being and scientific advancement. By prioritizing responsible lighting practices, we can mitigate the adverse effects of light pollution and establish a more sustainable and enjoyable nighttime environment for present and future generations.

[21] $9720.96 \times 2.7\% \times 16\%(18\%) = 41.99(47.24)$. 2.7% is calculated as 81/3017

Figures

FIGURE 1 –LIGHT POLLUTION IN THE US (2018)

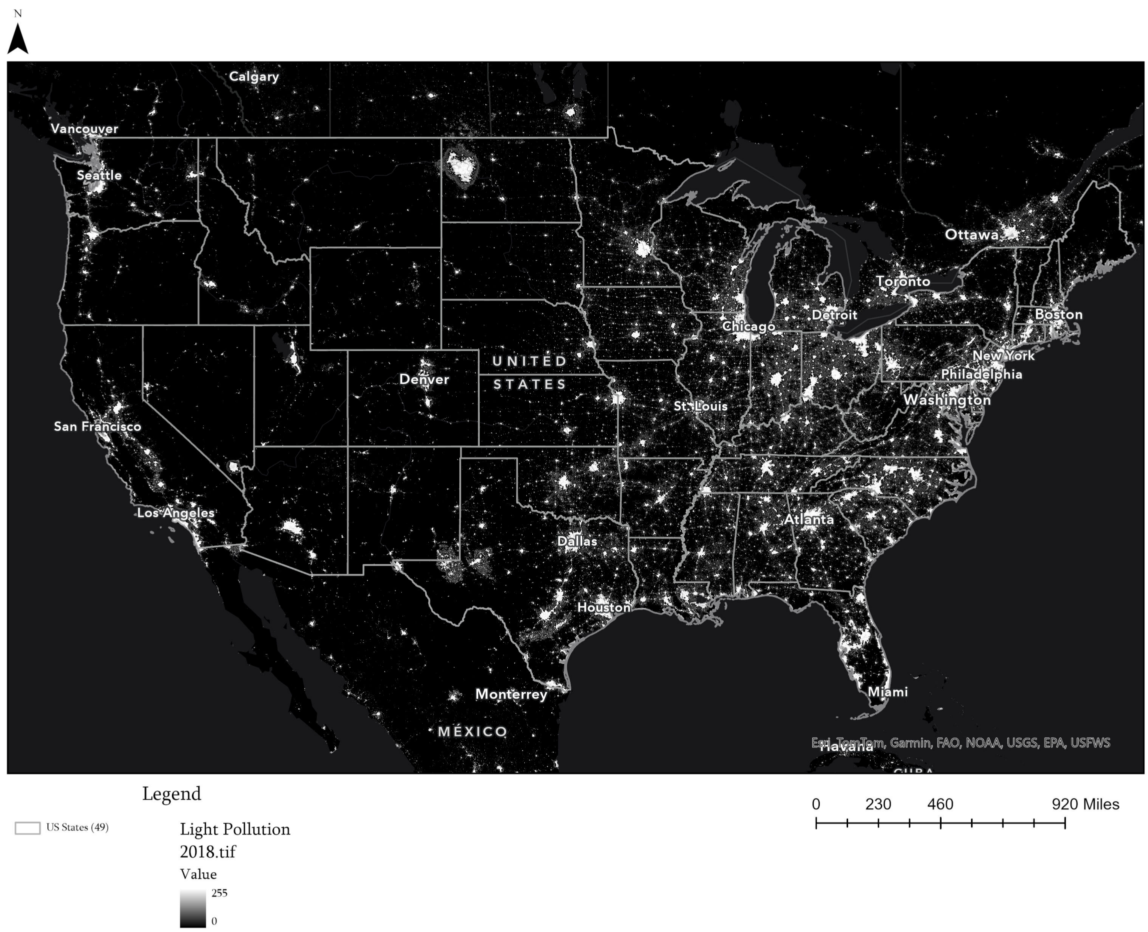
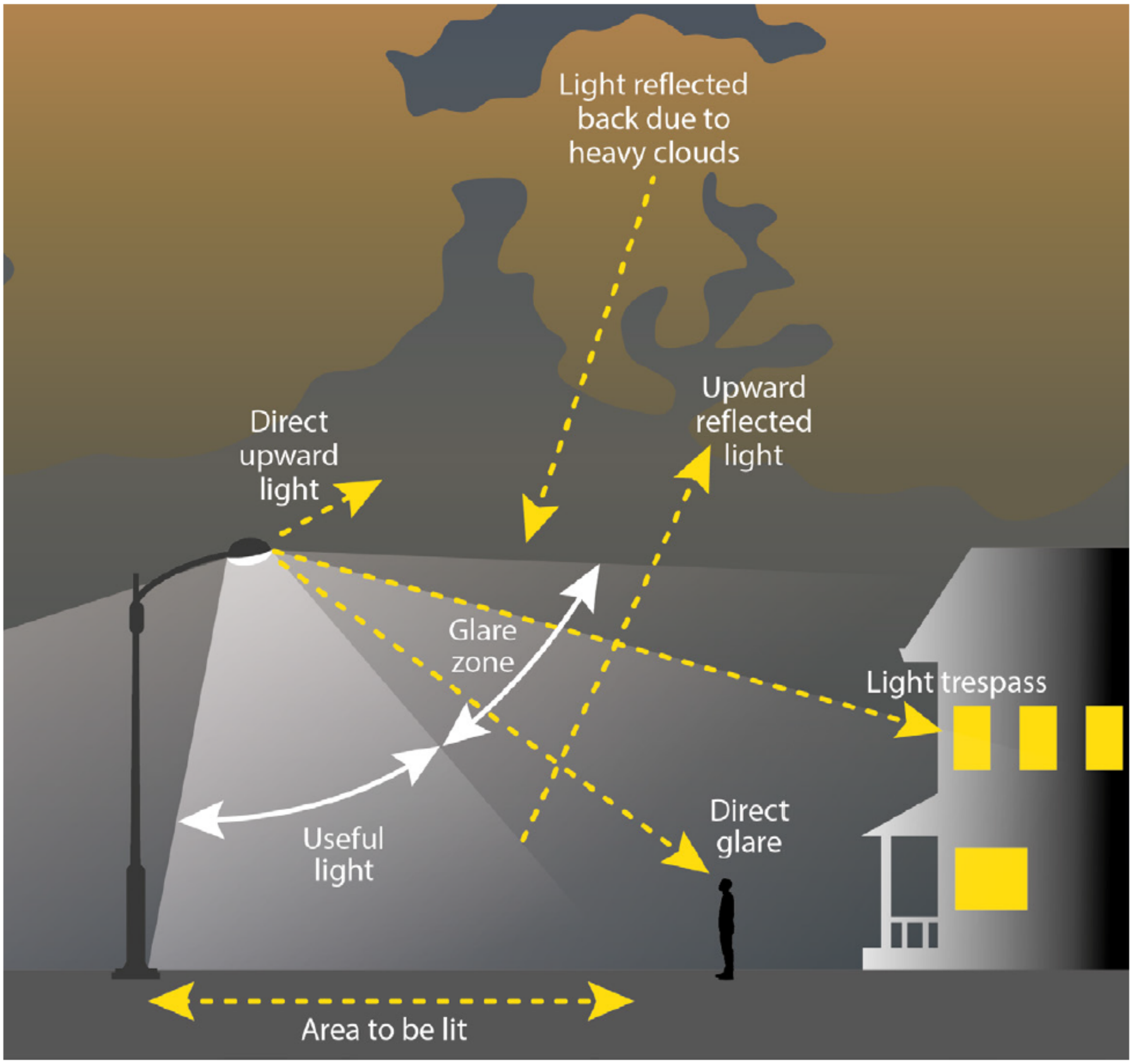
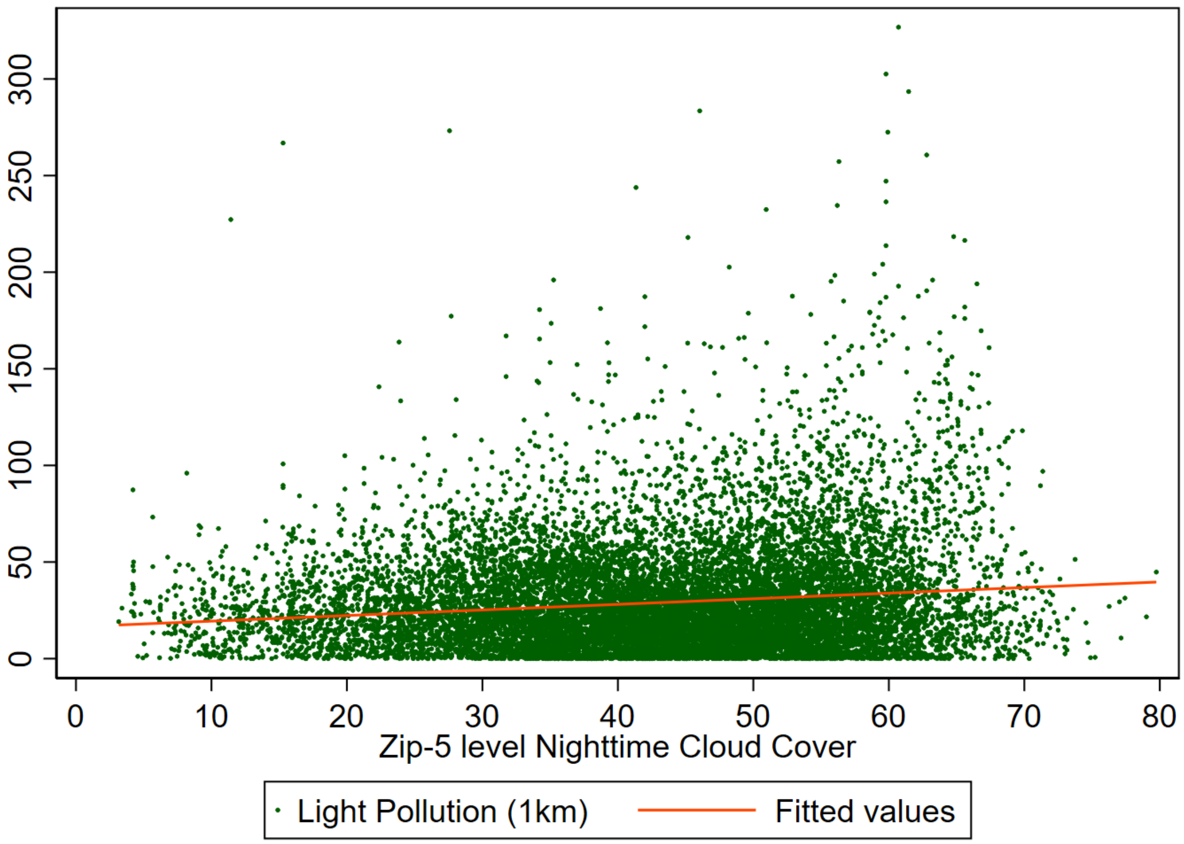


Figure 2 – Light Pollution and Cloud Cover



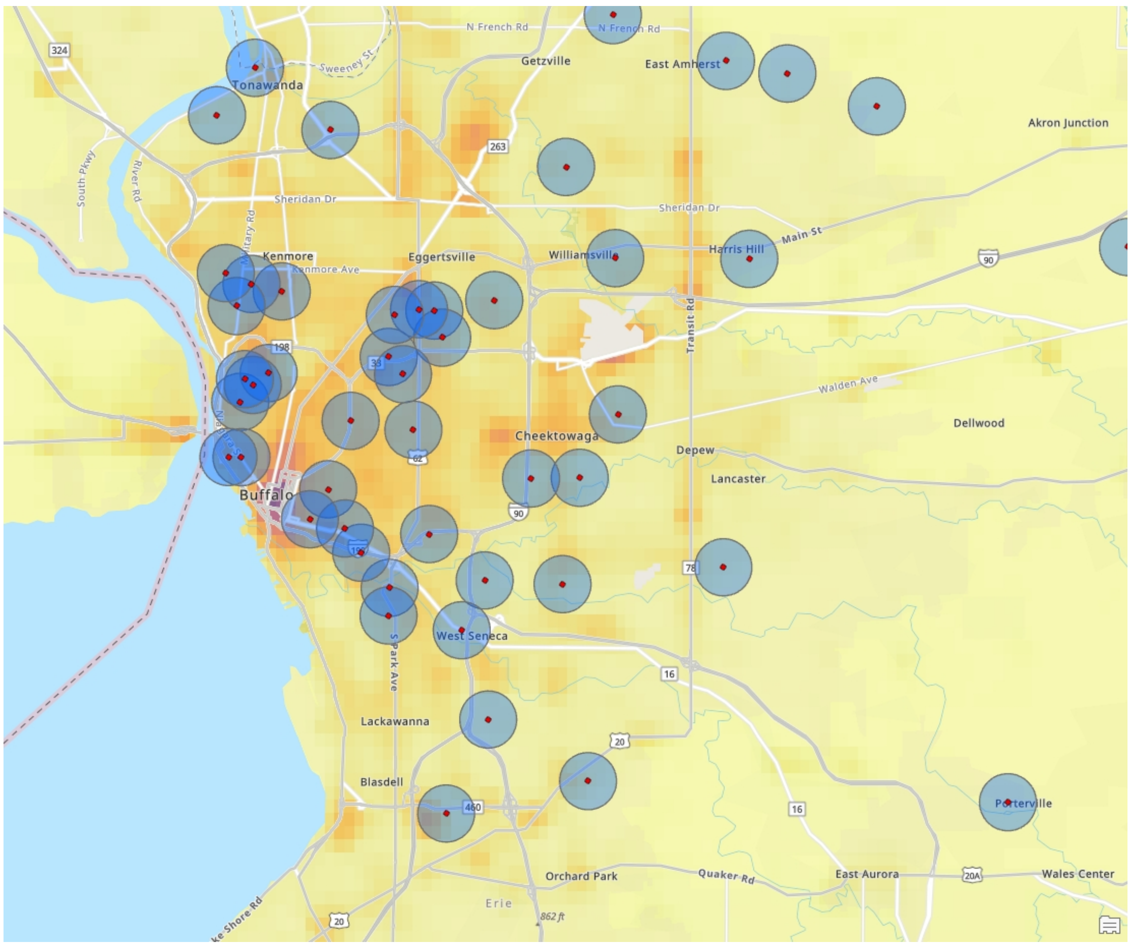
Note: This figure illustrates the different forms of light pollution and showcases the correlation between cloud cover and light pollution. Source: Bureau of Land Management (BLM). (2021). *Night Sky and Dark Environments: Best Management Practices for Artificial Light at Night on BLM-Managed Lands*.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

Figure 3 –Light Pollution and Nighttime Cloud Cover



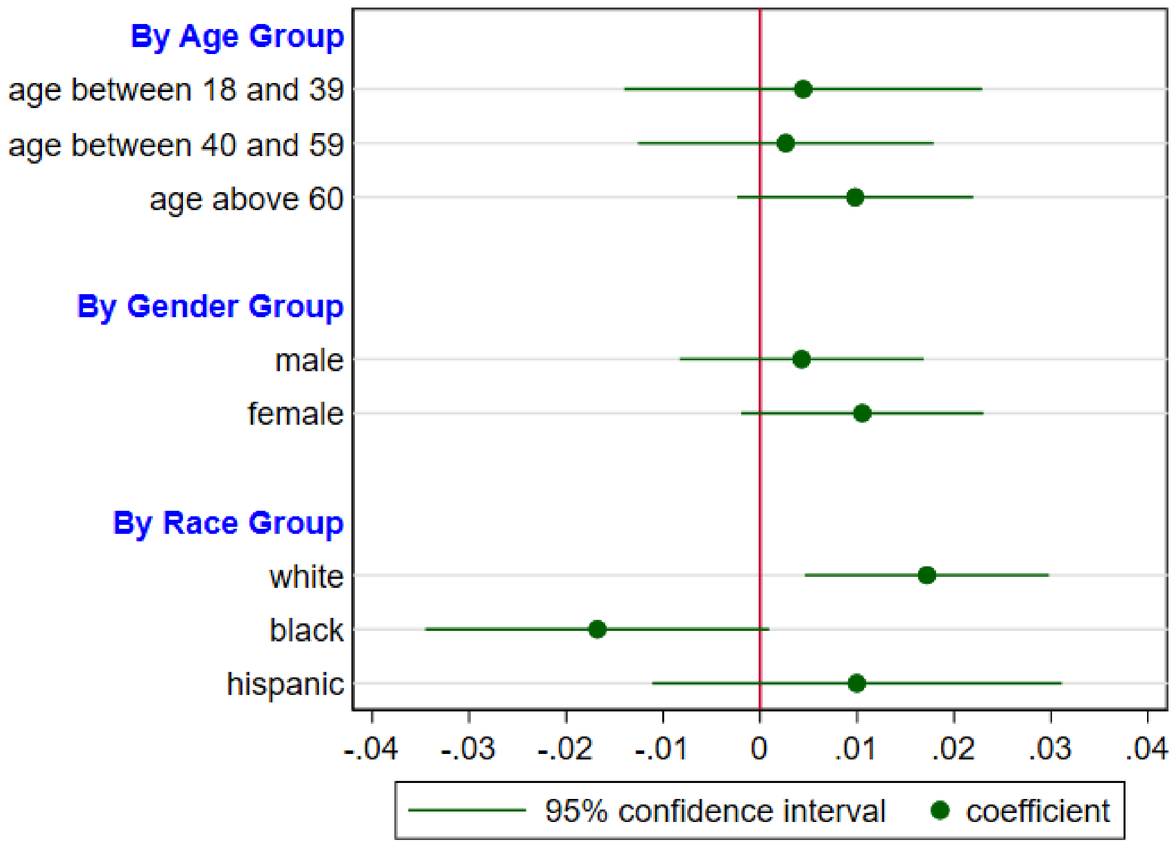
Note: This figure illustrates the correlation between nighttime light pollution(1km buffer) and nighttime cloud cover(5-digit zip code).

Figure 4 –Light Buffers for Hypothetical HINTS Respondents



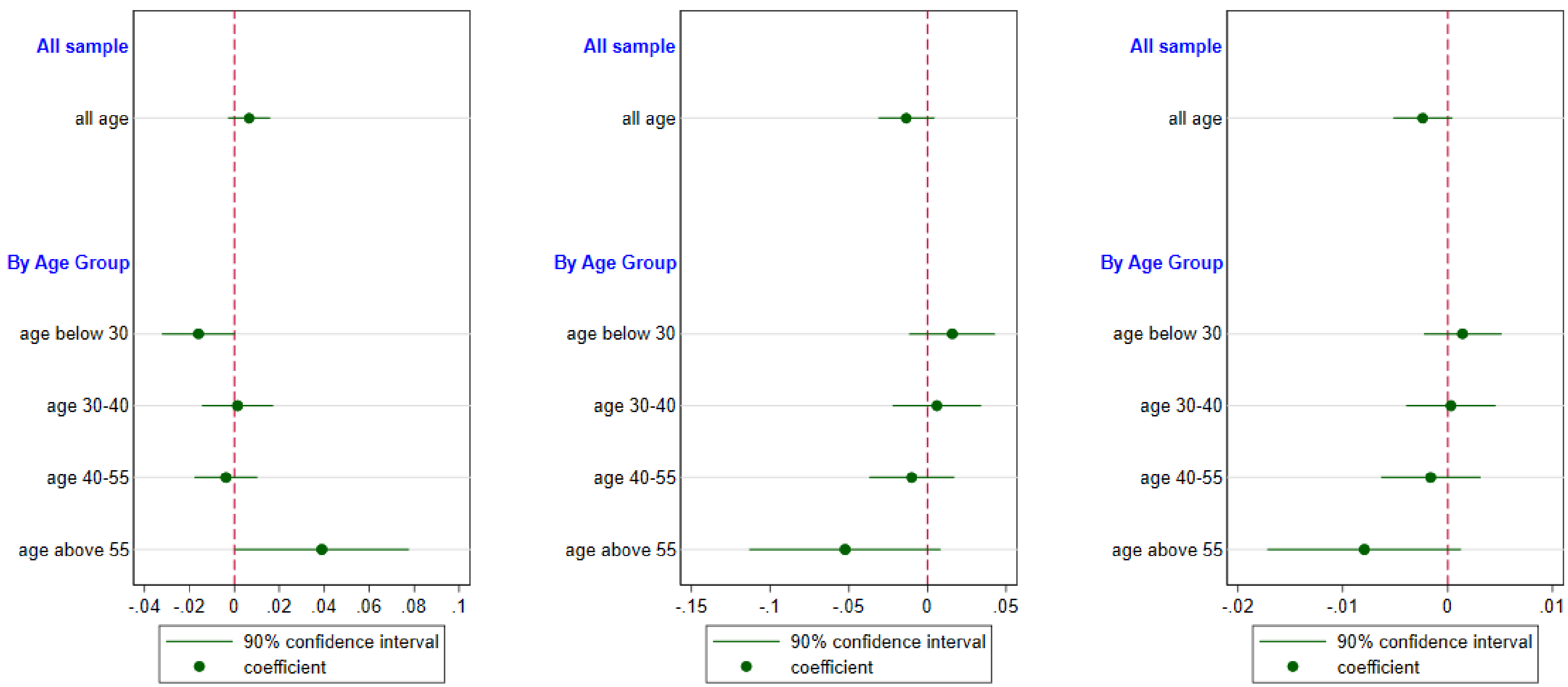
Note: This figure depicts the buffer approach for each respondent (red circle). The exposure to light pollution for each respondent is calculated by averaging the radiance within a 1km radius (marked by the blue circle) of each respondent's 9-digit zip code.

Figure 5 –The Impact of Light Pollution on Mental Health by Group



Note: The figure displays the IV result (cloud cover) of the impact of light pollution (1km radiance) on mental health, stratified by age, gender, and race. The specific results refer to Table (A.6).

Figure 6 –The Impact of Light Pollution on Sleep Duration and Sleep Quality



(a) Sleep Quality (b) Sleep Duration (c) log(Sleep Duration)

Note: The figure (6a) displays the IV result of the impact of light pollution (1km radiance) on average sleep quality per day. The figure (6b) displays the IV result of the impact of light pollution (1km radiance) on average sleep duration per day. The figure (6c) displays the IV result of the impact of light pollution (1km radiance) on the log(average sleep duration per day).

Figure 7 –Policy Implication - Light pollution density by law

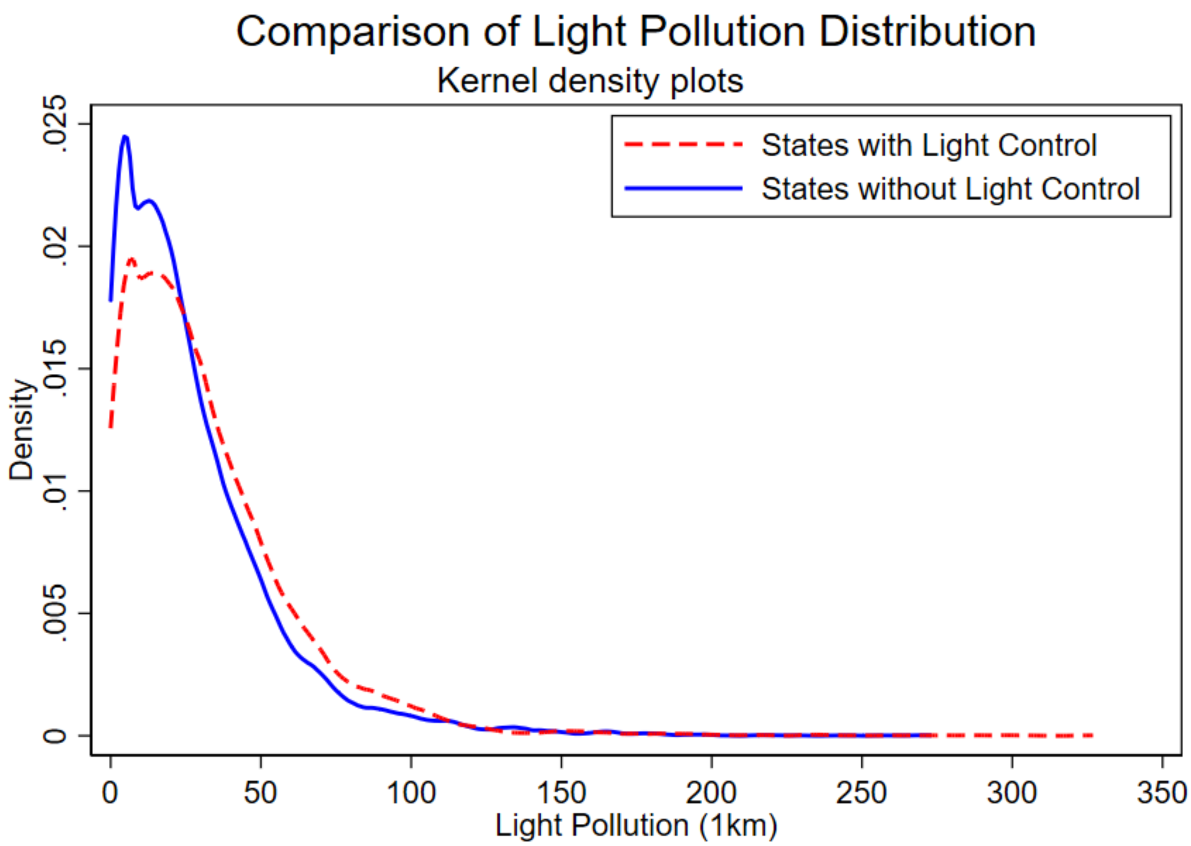
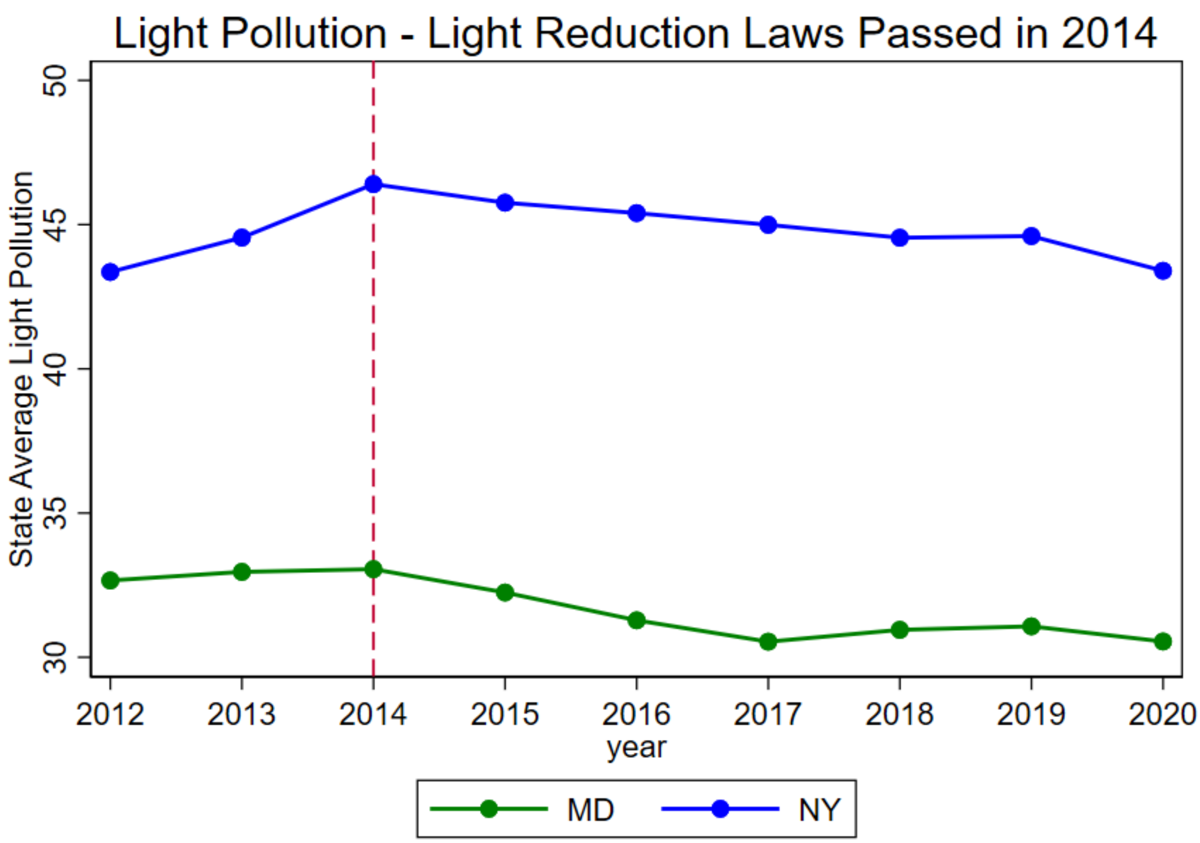


Figure 8 –Policy Implication - Light Pollution Law



Note: This figure illustrates the state average light pollution in New York and Maryland from 2012 to 2020. Both states implemented the light pollution law in 2014, indicated by the red dashed line on the graph.

Tables

TABLE 1 –DATA SUMMARY - PART 1

	Mean	SD	Min	Max
Dependent variable				
PHQ-4 Score (standardized)	-0.00	0.99	-0.69	3.65
PHQ-4 Score (raw index)	1.90	2.79	0.00	12.00
Major explanatory variable				
Light Pollution (1km)	29.29	28.00	0.02	326.83
NELM	3.70	1.06	0.51	7.00
Instrumental variable				
Nighttime Cloud Cover	43.17	12.68	3.16	79.75
Individual-level controls: Demographics				
Education: High School	0.17	0.37	0.00	1.00
Education: College (Not Graduate)	0.23	0.42	0.00	1.00
Education: College (Graduate)	0.28	0.45	0.00	1.00
Education: Postgraduate	0.19	0.40	0.00	1.00
Gender	0.58	0.49	0.00	1.00
Marital Status	0.50	0.50	0.00	1.00
Household Size (number of people)	2.43	1.45	1.00	8.00
Age	55.15	16.52	18.00	104.00
Age Square	3314.38	1807.19	324.00	10816.00
Race: Black	0.14	0.35	0.00	1.00
Race: Hispanic	0.16	0.36	0.00	1.00
Other Race	0.08	0.27	0.00	1.00
Family Income Ranges: 15,000 - 19,999 dollars	0.05	0.22	0.00	1.00
Family Income Ranges: 20,000 - 34,999 dollars	0.13	0.33	0.00	1.00
Family Income Ranges: 35,000 - 49,999 dollars	0.13	0.34	0.00	1.00
Family Income Ranges: 50,000 - 74,999 dollars	0.18	0.38	0.00	1.00
Family Income Ranges: 75,000 - 99,999 dollars	0.13	0.33	0.00	1.00
Family Income Ranges: 100,000 - 19,999 dollars	0.19	0.39	0.00	1.00
Family Income Ranges: 100,000 - dollars	0.07	0.25	0.00	1.00

Table 2 –Data Summary - Part 2

	Mean	SD	Min	Max
Individual-level controls: Health indices				
Doctor, nurse, or other health professional health care (per month)	3.49	2.96	0.00	10.00
Physical Activity or Exercise (per week)	2.74	2.24	0.00	7.00
Body Mass Index	28.45	6.59	10.60	78.30
Diabetes or High Blood Sugar	0.20	0.40	0.00	1.00
High Blood Pressure of Hypertension	0.43	0.50	0.00	1.00
Family History of Cancer	0.56	0.50	0.00	1.00
Environmental controls				
County Average AQI Quality Index	40.07	20.29	0.00	138.34
County Levels PM2.5	7.13	1.32	2.51	21.13
Zip-5 Total onsite emission (lbs/year)	79892.86	829717.35	0.00	34174856.00
Number of Days (year) with daily maximum temperature below freezing	12.46	19.39	0.00	122.00
Number of Days (year) with daily maximum temperature above 85°F	83.85	56.06	0.00	260.00
Zip-5 Solar energy (MJ/m^2)	15.17	4.14	0.14	93.60
Zip-9 level fraction of people own home	0.55	0.26	0.00	1.00
Zip-9 level fraction of people rent home	0.35	0.24	0.00	1.00
Observations	14512			

Table 3 –Baseline Results - The Impact of Light Pollution on Mental Health

	Panel A				*Panel B*			
	(1) OLS	(2) IV	(3) Reduced-form	(4) First-stage	(5) OLS	(6) IV	(7) Reduced-form	(8) First-stage
Light Pollution (1km)	0.0043***	0.0100***			0.0014***	0.0095**		
	(0.0004)	(0.0036)			(0.0004)	(0.0046)		
Nighttime Cloud Cover			0.0042***	0.4149***			0.0031**	0.3251***
			(0.0015)	(0.0312)			(0.0015)	(0.0295)
County and year FE	✓	✓	✓	✓	✓	✓	✓	✓
Individual controls					✓	✓	✓	✓
Environmental controls					✓	✓	✓	✓
Observations	14,030	14,030	14,030	14,030	14,030	14,030	14,030	14,030
First-stage effective F-stat				179.944				131.067
AR weak IV robust test (p-value)				0.005				0.037

Notes: The table reports baseline estimates. The dependent variable is the standardized PHQ-4 score (A higher score indicates more severe mental health issues). Table (A.2) displays the results based on the raw PHQ-4 score. The unit of observation is an individual. Statistically significant estimates for two-tailed tests: * 0.10, ** 0.05, *** 0.01. The statistical significance stars for each result are based on the standard error reported in parentheses. Refer to Table (1) and (2) for variable definitions.

Table 4 –Different Measurement - The Impact of Light Pollution (NEML) on Mental Health

	PHQ-4 (Standardized)			
	(1) OLS	(2) IV	(3) Reduced-form	(4) First-stage
NELM	0.0008	-0.5947**		
	(0.0108)	(0.2919)		
Nighttime Cloud Cover			0.0038**	-0.0063***
			(0.0016)	(0.0015)
County and year FE	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓
Environmental controls	✓	✓	✓	✓
Observations	11,297	11,297	11,297	11,297
First-stage effective F-stat				18.647
AR weak IV robust test (p-value)				0.021

Notes: The dependent variable is the standardized PHQ-4 score (A higher score indicates more severe mental health issues). The unit of observation is an individual. Statistically significant estimates for two-tailed tests: * 0.10, ** 0.05, *** 0.01. The statistical significance stars for each result are based on the standard error reported in parentheses. Refer to Table (1) and (2) for variable definitions.

Table 5 –Different IV Approach (Walker's Law): The Impact of Light Pollution on Mental Health

	Panel A				*Panel B*			
	(1) OLS	(2) IV	(3) Reduced-form	(4) First-stage	(5) OLS	(6) IV	(7) Reduced-form	(8) First-stage
Light Pollution (1km)	0.00122**	0.02509			0.00132***	0.02520		
	(0.00049)	(0.01689)			(0.00045)	(0.01630)		
Walker's Law (20km)			0.00002*	0.00082***				
			(0.00001)	(0.00027)				
Walker's Law (50km)							0.00002*	0.00083***
							(0.00001)	(0.00025)
County and year FE	✓	✓	✓	✓	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓	✓	✓	✓	✓
Environmental controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	8,787	8,787	8,787	8,787	11,629	11,629	11,629	11,629
First-stage effective F-stat				9.178				10.584
AR weak IV robust test (p-value)				0.093				0.083

Notes: The dependent variable is the standardized PHQ-4 score. The unit of observation is an individual. Statistically significant estimates for two-tailed tests: * 0.10, ** 0.05, *** 0.01. The statistical significance stars for each result are based on the standard error reported in parentheses. Refer to Table (1) and (2) for variable definitions.

Table 6 –Channel - The Impact of Light Pollution on Sleep Duration and Sleep Quality

	Sleep Duration		*log(Sleep Duration)*		*Sleep Quality*	
	(1)	(2)	(3)	(4)	(5)	(6)
	All	55+	All	55+	All	55+
Light Pollution (1km)	-0.0135	-0.0524	-0.0024	-0.0080	0.0066	0.0389*
	(0.0109)	(0.0370)	(0.0017)	(0.0056)	(0.0057)	(0.0236)
Individual controls	✓	✓	✓	✓	✓	✓
Environmental controls	✓	✓	✓	✓	✓	✓
Observations	4,107	2,330	4,104	2,330	4,175	2,361
First-stage effective F-stat	27.996	4.825	27.843	4.825	27.891	4.579
AR weak IV robust test (p-value)	0.2024	0.0707	0.1497	0.0699	0.2402	0.0114

Notes: The unit of observation is an individual. Statistically significant estimates for two-tailed tests: * 0.10, ** 0.05, *** 0.01. The statistical significance stars for each result are based on the standard error reported in parentheses. Refer to Table (1) and (2) for variable definitions. Table (A.8) shows the results using AQI as a control instead of PM2.5.

Table 7 –Channel - The Impact of Light Pollution on Sleep Duration and Sleep Quality by Gender

	log(Sleep Duration)		*Sleep Quality*	
	(1) female	(2) male	(3) female	(4) male
Light Pollution (1km)	-0.0036	-0.0011	0.0152*	-0.0024
	(0.0025)	(0.0026)	(0.0090)	(0.0084)
Individual controls	✓	✓	✓	✓
Environmental controls	✓	✓	✓	✓
Observations	2,332	1,772	2,373	1,802
First-stage effective F-stat	14.671	11.077	13.334	12.455
AR weak IV robust test (p-value)	0.1229	0.6696	0.0555	0.7820

Notes: The unit of observation is an individual. Statistically significant estimates for two-tailed tests: * 0.10, ** 0.05, *** 0.01. The statistical significance stars for each result are based on the standard error reported in parentheses. Refer to Table (1) and (2) for variable definitions.

Table 8 –Channel - The Impact of Light Pollution on Sleep Quality by Race

	Sleep Quality		
	(1) white	(2) black	(3) hispanic
Light Pollution (1km)	0.0073	0.0055	-0.0645
	(0.0083)	(0.0076)	(0.0848)
Individual controls	✓	✓	✓
Environmental controls	✓	✓	✓
Observations	2,630	539	621
First-stage effective F-stat	15.090	25.761	0.682
AR weak IV robust test (p-value)	0.3649	0.4766	0.0902

Notes: The unit of observation is an individual. Statistically significant estimates for two-tailed tests: * 0.10, ** 0.05, *** 0.01. The statistical significance stars for each result are based on the standard error reported in parentheses. Refer to Table (1) and (2) for variable definitions.

Table 9 –Channel - The Impact of Light Pollution on Symptoms(Dizzy) by Age and Race

	Symptoms: Dizzy					
	(1)	(2)	(3)	(4)	(5)	(6)
	All	age 18-55	age 55+	white	black	hispanic
Light Pollution (1km)	-0.0086*	-0.0138**	-0.0012	-0.0053	-0.0307**	-0.0150
	(0.0051)	(0.0056)	(0.0098)	(0.0064)	(0.0140)	(0.0164)
Individual controls	✓	✓	✓	✓	✓	✓
Environmental controls	✓	✓	✓	✓	✓	✓
Observations	2,552	1,269	1,283	1,562	419	390
First-stage effective F-stat	87.184	60.926	29.412	56.428	12.570	8.431
AR weak IV robust test (p-value)	0.0880	0.0107	0.9065	0.4154	0.0102	0.3505

Notes: The unit of observation is an individual. Statistically significant estimates for two-tailed tests: * 0.10, ** 0.05, *** 0.01. The statistical significance stars for each result are based on the standard error reported in parentheses. Refer to Table (1) and (2) for variable definitions.

References

Adhvaryu, Achyuta, James Fenske, and Anant Nyshadham. 2019. "Early life circumstance and adult mental health." *Journal of Political Economy*, 127(4): 1516–1549.

Andrews, Isaiah, James H. Stock, and Liyang Sun. 2019. "Weak Instruments in Instrumental Variables Regression: Theory and Practice." *Annual Review of Economics*, 11(Volume 11, 2019): 727–753.

Ao, Chon-Kit, Yilin Dong, and Pei-Fen Kuo. 2021. "Industrialization, indoor and ambient air quality, and elderly mental health." *China Economic Review*, 69: 101676.

Argys, Laura M, Susan L Averett, and Muzhe Yang. 2021. "Light pollution, sleep deprivation, and infant health at birth." *Southern Economic Journal*, 87(3): 849–888.

Baird, Sarah, Jacobus De Hoop, and Berk Özler. 2013. "Income shocks and adolescent mental health." *Journal of Human Resources*, 48(2): 370–403.

Banzhaf, Spencer, Lala Ma, and Christopher Timmins. 2019. "Environmental justice: The economics of race, place, and pollution." *Journal of Economic Perspectives*, 33(1): 185–208.

Bogard, Paul. 2013. *The end of night: searching for natural darkness in an age of artificial light.* Hachette UK.

Boslett, Andrew, Elaine Hill, Lala Ma, and Lujia Zhang. 2021. "Rural light pollution from shale gas development and associated sleep and subjective well-being." *Resource and energy economics*, 64: 101220.

Brei, Michael, Agustín Pérez-Barahona, and Eric Strobl. 2016. "Environmental pollution and biodiversity: Light pollution and sea turtles in the Caribbean." *Journal of Environmental Economics and Management*, 77: 95–116.

Burton, Anne M, and Travis Roach. 2022. "Particulate Matter Pollution and Fatal Car Crashes." Working Paper, 2022.

Cajochen, Christian, Sylvia Frey, Doreen Anders, Jakub Späti, Matthias Bues, Achim Pross, Ralph Mager, Anna Wirz-Justice, and Oliver Stefani. 2011. "Evening exposure to a light-emitting diodes (LED)-backlit computer screen affects circadian physiology and cognitive performance." *Journal of applied physiology*.

Cao, Miao, Ting Xu, and Daqiang Yin. 2023. "Understanding light pollution: Recent advances on its health threats and regulations." *Journal of Environmental Sciences*, 127: 589–602.

Cinzano, P., and F. Falchi. 2012. "The propagation of light pollution in the atmosphere." *Monthly Notices of the Royal Astronomical Society*, 427(4): 3337–3357.

Davies, Thomas W, Jonathan Bennie, Richard Inger, and Kevin J Gaston. 2013. "Artificial light alters natural regimes of night-time sky brightness." *Scientific Reports*, 3(1): 1722.

De Graaf, Ron, Margreet Ten Have, and Saskia Van Dorsselaer. 2008. "The economic burden of mental disorders: Do our societies react appropriately to the enormous challenge?" *BMC Public Health*, 8(1): 1–11.

Doleac, Jennifer L, and Nicholas J Sanders. 2015. "Under the cover of darkness: How ambient light influences criminal activity." *Review of Economics and Statistics*, 97(5): 1093–1103.

Dzhambov, Angel M, Iana Markevych, Boris Tilov, Zlatoslav Arabadzhiev, Drozdstoj Stoyanov, Penka Gatseva, and Donka D Dimitrova. 2018. "Pathways linking residential noise and air pollution to mental ill-health in young adults." *Environmental Research*, 166: 458–465.

Falchi, Fabio, P Cinzano, D Duriscoe, CCM Kyba, CD Elvidge, K Baugh, BA Portnov, NA Rybnikova, and R Furgoni. 2016. "The new world atlas of artificial night sky brightness. Sci Adv 2: e1600377."

Freeman, Daniel, Bryony Sheaves, Guy M Goodwin, Ly-Mee Yu, Alecia Nickless, Paul J Harrison, Richard Emsley, Annemarie I Luik, Russell G Foster, Vanashree Wadekar, Christopher Hinds, Andrew Gumley, Ray Jones, Stafford Lightman, Steve Jones, Richard Bentall, Peter Kinderman, Georgina Rowse, Traolach Brugha, Mark Blagrove, Alice M Gregory, Leanne Fleming, Elaine Walklet, Cris Glazebrook, E Bethan Davies, Chris Hollis, Gillian Haddock, Bev John, Mark Coulson, David Fowler, Katherine Pugh, John Cape, Peter Moseley, Gary Brown, Claire Hughes, Marc Obonsawin, Sian Coker, Edward Watkins, Matthias Schwannauer, Kenneth MacMahon, A Niroshan Siriwardena, and Colin A Espie. 2017. "The effects of improving sleep on mental health (OASIS): a randomised controlled trial with mediation analysis." *The Lancet. Psychiatry*, 4(10): 749–758.

Gallaway, Terrel, Reed N Olsen, and David M Mitchell. 2010. "The economics of global light pollution." *Ecological economics*, 69(3): 658–665.

Gaston, Kevin J, Sian Gaston, Jonathan Bennie, and John Hopkins. 2015. "Benefits and costs of artificial nighttime lighting of the environment." *Environmental Reviews*, 23(1): 14–23.

Germinario, Giuseppe, Vikesh Amin, Carlos A Flores, and Alfonso Flores-Lagunes. 2022. "What can we learn about the effect of mental health on labor market outcomes under weak assumptions? Evidence from the NLSY79." *Labour Economics*, 79: 102258.

Goodman, Alissa, Robert Joyce, and James P Smith. 2011. "The long shadow cast by childhood physical and mental problems on adult life." *Proceedings of the National Academy of Sciences*, 108(15): 6032–6037.

Gulia, Kamalesh K., and Velayudhan Mohan Kumar. 2018. "Sleep disorders in the elderly: a growing challenge." *Psychogeriatrics*, 18(3): 155–165.

Hakuba, Maria Z, Doris Folini, Martin Wild, Charles N Long, Gabriela Schaepman-Strub, and Graeme L Stephens. 2017. "Cloud effects on atmospheric solar absorption in light of most recent surface and satellite measurements." Vol. 1810, AIP Publishing.

Jariwala, Hiral J, Huma S Syed, Minarva J Pandya, and Yogesh M Gajera. 2017. "Noise pollution & human health: a review." *Indoor Built Environ*, 1(1): 1–4.

Joshi, Nayan Krishna. 2016. "Local house prices and mental health." *International Journal of Health Economics and Management*, 16(1): 89–102.

Juda, Myriam, Céline Vetter, and Till Roenneberg. 2013. "Chronotype modulates sleep duration, sleep quality, and social jet lag in shift-workers." *Journal of biological rhythms*, 28(2): 141–151.

Kesavayuth, Dusanee, Prompong Shangkhum, and Vasileios Zikos. 2022. "Building physical health: What is the role of mental health?" *Bulletin of Economic Research*, 74(2): 457–483.

Kristiansen, Ida Lykke. 2021. "Consequences of serious parental health events on child mental health and educational outcomes." *Health Economics*, 30(8): 1772–1817.

Kumar, Pravin, Mahendra S Ashawat, Vinay Pandit, and Dinesh K Sharma. 2019. "Artificial Light Pollution at Night: A risk for normal circadian rhythm and physiological functions in humans." *Current Environmental Engineering*, 6(2): 111–125.

Kyba, Christopher CM, Theres Kuester, Alejandro Sánchez de Miguel, Kimberly Baugh, Andreas Jechow, Franz Hölker, Jonathan Bennie, Christopher D Elvidge, Kevin J Gaston, and Luis Guanter. 2017. "Artificially lit surface of Earth at night increasing in radiance and extent." *Science advances*, 3(11): e1701528.

Kyba, Christopher CM, Thomas Ruhtz, Jürgen Fischer, and Franz Hölker. 2011. "Cloud coverage acts as an amplifier for ecological light pollution in urban ecosystems." *PloS one*, 6(3): e17307.

Lin, Haizhen, Jonathan D Ketcham, James N Rosenquist, and Kosali I Simon. 2013. "Financial distress and use of mental health care: Evidence from antidepressant prescription claims." *Economics Letters*, 121(3): 449–453.

Longcore, Travis, and Catherine Rich. 2004. "Ecological light pollution." *Frontiers in Ecology and the Environment*, 2(4): 191–198.

Löwe, Bernd, Inka Wahl, Matthias Rose, Carsten Spitzer, Heide Glaesmer, Katja Wingenfeld, Antonius Schneider, and Elmar Brähler. 2010. "A 4-item measure of depression and anxiety: validation and standardization of the Patient Health Questionnaire-4 (PHQ-4) in the general population." *Journal of affective disorders*, 122(1-2): 86–95.

Mikkelsen, Kathleen, Lily Stojanovska, Momir Polenakovic, Marijan Bosevski, and Vasso Apostolopoulos. 2017. "Exercise and mental health." *Maturitas*, 106: 48–56.

Molin, Jeanne, Erling Mellerup, Tom Bolwig, Thomas Scheike, and Henrik Dam. 1996. "The influence of climate on development of winter depression." *Journal of affective disorders*, 37(2-3): 151–155.

Mullins, Jamie T, and Corey White. 2019. "Temperature and mental health: Evidence from the spectrum of mental health outcomes." *Journal of health economics*, 68: 102240.

Münzel, Thomas, Mette Sørensen, and Andreas Daiber. 2021. "Transportation noise pollution and cardiovascular disease." *Nature Reviews Cardiology*, 18(9): 619–636.

Nadybal, Shawna M., Timothy W. Collins, and Sara E. Grineski. 2020. "Light pollution inequities in the continental United States: A distributive environmental justice analysis." *Environmental research*, 189: 109959–.

National Institute of Mental Health. 2021. "Mental Illness." *National Institute of Mental Health*.

Oeconomics, Team, David McDaid, A-La Park, Eva Bonin, Jennifer Beecham, Sally Johnson, and Martin Knapp. 2020. "The cost of mental illness: A population-wide, record-linked analysis of the effects of mental health on productivity in the workplace." *Journal of Mental Health Policy and Economics*, 23(3): 110–119.

Ohayon, Maurice M, and Cristina Milesi. 2016. "Artificial outdoor nighttime lights associate with altered sleep behavior in the American general population." *Sleep*, 39(6): 1311–1320.

Organization, World Health. 2017. "Depression and Other Common Mental Disorders: Global Health Estimates." *World Health Organization*.

Peng, Lizhong, Chad D Meyerhoefer, and Samuel H Zuvekas. 2016. "The Short-Term Effect of Depressive Symptoms on Labor Market Outcomes." *Health Economics*, 25(10): 1223–1238.

Van Donkelaar, Aaron, Randall V Martin, Michael Brauer, N Christina Hsu, Ralph A Kahn, Robert C Levy, Alexei Lyapustin, Andrew M Sayer, and David M Winker. 2016. "Global estimates of fine particulate matter using a combined geophysical-statistical method with information from satellites, models, and monitors." *Environmental science & technology*, 50(7): 3762–3772.

Walker, Merle F. 1977. "The effects of urban lighting on the brightness of the night sky." *Publications of the Astronomical Society of the Pacific*, 89(529): 405.

Watson, Barry, and Lars Osberg. 2018. "Job insecurity and mental health in Canada." *Applied Economics*, 50(38): 4137–4152.

Wen, Kaiyi, and Neha Khanna. 2024. "Beyond the Haze of Air Pollution: Traffic Noise and Mental Health." *Available at SSRN 4771912*.

Whiteford, Harvey A, Louisa Degenhardt, Jürgen Rehm, Amanda J Baxter, Alize J Ferrari, Holly E Erskine, Fiona J Charlson, Rosana E Norman, Abraham D Flaxman, Nicole Johns, et al. 2013. "Global burden of disease attributable to mental and substance use disorders: findings from the Global Burden of Disease Study 2010." *The lancet*, 382(9904): 1575–1586.

Zhang, Xin, Xiaobo Zhang, and Xi Chen. 2017. "Happiness in the air: How does a dirty sky affect mental health and subjective well-being?" *Journal of environmental economics and management*, 85: 81–94.

Zou, Eric Yongchen. 2021. "Unwatched pollution: The effect of intermittent monitoring on air quality." *American Economic Review*, 111(7): 2101–2126.

Appendix Tables

Table A.1 –Mental Score - Data Summary

	Mean	SD	Min	Max
PHQ-4				
PHQ-4 Score (standardized)	-0.00	0.99	-0.69	3.65
PHQ-4 Score (raw index)	1.90	2.79	0.00	12.00
Over the past 2 weeks, how often have you been bothered by:				
a. Little interest or pleasure in doing things	3.50	0.84	1.00	4.00
b. Feeling down, depressed, or hopeless	3.59	0.76	1.00	4.00
c. Feeling nervous, anxious, or on edge.	3.47	0.82	1.00	4.00
d. Not being able to stop or control worrying	3.54	0.82	1.00	4.00

Notes: The PHQ-4 Score (raw index) is calculated by summing the scores of all four items (a, b, c, d), with each of these questions being reverse coded. Additionally, scales for each of the four questions were adjusted so that the anchors were 0 to 3 rather than 1 to 4. Scores are rated as normal (0-2), mild (3-5), moderate (6-8), and severe (9-12). For each question, the survey provides 4 different choices. = 1: Nearly every day; = 2: More than half the days; = 3: Several days; = 4: Not at all. PHQ-4 Score (standardized) is the standardized raw PHQ-4 index.

Table A.2 –Baseline Results - The Impact of Light Pollution on Mental Health (PHQ-4)

	Panel A				*Panel B*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	Reduced-form	First-stage	OLS	IV	Reduced-form	First-stage
Light Pollution (1km)	0.0120***	0.0283***			0.0039***	0.0271**		
	(0.0012)	(0.0102)			(0.0012)	(0.0130)		
Nighttime Cloud Cover			0.0117***	0.4149***			0.0088**	0.3251***
			(0.0042)	(0.0312)			(0.0042)	(0.0295)
County and year FE	✓	✓	✓	✓	✓	✓	✓	✓
Individual controls					✓	✓	✓	✓
Environmental controls					✓	✓	✓	✓
Observations	14,030	14,030	14,030	14,030	14,030	14,030	14,030	14,030
First-stage effective F-stat				179.944				121.778
AR weak IV robust test (p-value)				0.005				0.036

Notes: The table reports baseline estimates. The dependent variable is the raw PHQ-4 score. The unit of observation is an individual. Statistically significant estimates for two-tailed tests: * 0.10, ** 0.05, *** 0.01. The statistical significance stars for each result are based on the standard error reported in parentheses. Refer to Table (1) and (2) for variable definitions.

Table A.3 –Different IV Approach (Walker's Law): The Impact of Light Pollution on Mental Health (PHQ-4)

	Panel A				*Panel B*			
	(1) OLS	(2) IV	(3) Reduced-form	(4) First-stage	(5) OLS	(6) IV	(7) Reduced-form	(8) First-stage
Light Pollution (1km)	0.00346**	0.07052			0.00373***	0.07084		
	(0.00139)	(0.04762)			(0.00127)	(0.04594)		
Walker's Law (20km)			0.00006*	0.00082***				
			(0.00003)	(0.00027)				
Walker's Law (50km)							0.00006*	0.00083***
							(0.00003)	(0.00025)
County and year FE	✓	✓	✓	✓	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓	✓	✓	✓	✓
Environmental controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	8,787	8,787	8,787	8,787	11,629	11,629	11,629	11,629
First-stage effective F-stat				9.178				10.584
AR weak IV robust test (p-value)				0.094				0.084

Notes: The dependent variable is the raw PHQ-4 score. The unit of observation is an individual. Statistically significant estimates for two-tailed tests: * 0.10, ** 0.05, *** 0.01. The statistical significance stars for each result are based on the standard error reported in parentheses. Refer to Table (1) and (2) for variable definitions.

Table A.4 –Different Measurement - The Impact of Light Pollution (NEML) on Mental Health

	raw PHQ-4			
	(1) OLS	(2) IV	(3) Reduced-form	(4) First-stage
NELM	0.0013	-1.6860**		
	(0.0305)	(0.8249)		
Nighttime Cloud Cover			0.0107**	-0.0063***
			(0.0046)	(0.0015)
County and year FE	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓
Environmental controls	✓	✓	✓	✓
Observations	11,297	11,297	11,297	11,297
First-stage effective F-stat				18.647
AR weak IV robust test (p-value)				0.020

Notes: The dependent variable is the raw PHQ-4 score. The unit of observation is an individual. Statistically significant estimates for two-tailed tests: * 0.10, ** 0.05, *** 0.01. The statistical significance stars for each result are based on the standard error reported in parentheses. Refer to Table (1) and (2) for variable definitions.

Table A.5 – Data Summary - Sleep and Dizziness

	Mean	SD	Min	Max
Channel variable				
Q1: During the past 7 days, how many hours of sleep did you get on average per day?	6.57	2.44	-9.00	20.00
Q2: In the past 7 days, how would you rate your sleep quality overall?	2.03	0.92	-9.00	4.00
Q3: How interested are you in exchanging information about symptoms Symptoms (e.g., nausea, pain, dizziness, etc.)?	1.98	2.46	-9.00	4.00

Note: Q2-Answer: 1(Very good), 2(Fairly good), 3(Fairly bad), and 4(Very bad); Q3-Answer: Not at all (4 points), A little (3 points), Somewhat (2 points), Very (1 point).

Table A.6 –The Impact of Light Pollution on Mental Health by Group

	By Age Group			*By Gender Group*		*By Race Group*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	age 18-40	age 40-60	age 60+	male	female	white	black	hispanic
Light Pollution (1km)	0.00444	0.00265	0.00981	0.00429	0.01054*	0.01721***	-0.01679*	0.00999
	(0.00941)	(0.00778)	(0.00620)	(0.00641)	(0.00638)	(0.00643)	(0.00904)	(0.01077)
County and year FE	✓	✓	✓	✓	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓	✓	✓	✓	✓
Environmental controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2,640	4,680	5,824	5,577	7,945	8,600	1,843	2,073
First-stage effective F-stat	22.656	44.212	67.774	51.448	67.974	70.790	30.126	25.587
AR weak IV robust test (p-value)	0.6358	0.7335	0.1077	0.5028	0.0936	0.0051	0.0453	0.2594

Notes: The dependent variable is the standardized PHQ-4 score. The unit of observation is an individual. Statistically significant estimates for two-tailed tests: * 0.10, ** 0.05, *** 0.01. The statistical significance stars for each result are based on the standard error reported in parentheses. Refer to Table (1) and (2) for variable definitions.

Table A.7 –The Impact of Light Pollution on Mental Health (AQI)

	Panel A				*Panel B*			
	(1) OLS	(2) IV	(3) Reduced-form	(4) First-stage	(5) OLS	(6) IV	(7) Reduced-form	(8) First-stage
Light Pollution (1km)	0.0043***	0.0100***			0.0014***	0.0096**		
	(0.0004)	(0.0036)			(0.0004)	(0.0047)		
Nighttime Cloud Cover			0.0042***	0.4149***			0.0031**	0.3173***
			(0.0015)	(0.0312)			(0.0015)	(0.0294)
County and year FE	✓	✓	✓	✓	✓	✓	✓	✓
Individual controls					✓	✓	✓	✓
Environmental controls					✓	✓	✓	✓
Observations	14,030	14,030	14,030	14,030	14,030	14,030	14,030	14,030
First-stage effective F-stat				177.117				116.159
AR weak IV robust test (p-value)				0.005				0.039

Notes: The dependent variable is the standardized PHQ-4 score. The unit of observation is an individual. Statistically significant estimates for two-tailed tests: * 0.10, ** 0.05, *** 0.01. The statistical significance stars for each result are based on the standard error reported in parentheses. Refer to Table (1) and (2) for variable definitions.

Table A.8 –The Impact of Light Pollution on Sleep Duration and Quality (AQI)

	Sleep Duration		*log(Sleep Duration)*		*Sleep Quality*	
	(1)	(2)	(3)	(4)	(5)	(6)
	All	55+	All	55+	All	55+
light1km	-0.0075	-0.0242**	-0.0013	-0.0035**	0.0022	0.0108**
	(0.0052)	(0.0106)	(0.0008)	(0.0016)	(0.0027)	(0.0054)
Individual controls	✓	✓	✓	✓	✓	✓
Environmental controls	✓	✓	✓	✓	✓	✓
Observations	4,107	2,330	4,104	2,330	4,175	2,361
First-stage effective F-stat	120.002	41.179	119.378	41.179	120.486	41.866
AR weak IV robust test (p-value)	0.2024	0.0162	0.1184	0.0215	0.4095	0.0372

Notes: The unit of observation is an individual. Statistically significant estimates for two-tailed tests: * 0.10, ** 0.05, *** 0.01. The statistical significance stars for each result are based on the standard error reported in parentheses. Refer to Table (1) and (2) for variable definitions.

Table A.9 –PHQ-4 Distribution in 2020

	Frequency	*Percent*
PHQ-4 Score (raw index)		
0	1,429	47.36
1	397	13.16
2	332	11.00
3	213	7.06
4	199	6.60
5	109	3.61
6	78	2.59
7	59	1.96
8	66	2.19
9	34	1.13
10	26	0.86
11	17	0.56
12	58	1.92
Total	3,017	100.00

Table A.10 –Standardized PHQ-4 Distribution in 2020

	Frequency	*Percent*
PHQ-4 Score (standardized)		
-.6870699	1,429	47.36
-.3345567	397	13.16
.0179564	332	11.00
.3704696	213	7.06
.7229828	199	6.60
1.075496	109	3.61
1.428009	78	2.59
1.780522	59	1.96
2.133035	66	2.19
2.485548	34	1.13
2.838062	26	0.86
3.190575	17	0.56
3.543088	58	1.92
Total	3,017	100.00

TABLE **A.11** –EDUCATION DISTRIBUTION

	Frequency	*Percent*
Education		
Less than 8 years	257	1.76
8 through 11 years	656	4.48
12 years or completed high school	2,460	16.80
Post high school training other than college (vocational or technical)	1,033	7.05
Some college	3,345	22.84
College graduate	4,061	27.73
Postgraduate	2,831	19.33
Total	14,643	100.00

TABLE **A.12** –INCOME DISTRIBUTION

	Frequency	*Percent*
Income		
$0 to $9,999	169	5.60
$10,000 to $14,999	151	5.00
$15,000 to $19,999	149	4.94
$20,000 to $34,999	381	12.63
$35,000 to $49,999	402	13.32
$50,000 to $74,999	543	18.00
$75,000 to $99,999	372	12.33
$100,000 to $199,999	629	20.85
$200,000 or more	221	7.33
Total	3,017	100.00