Urban Noise, Sleep Disruption and Health

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Abstract

Numerous studies have linked sleep disruption to a variety of poor health outcomes, but social scientists still have a very limited understanding of the overall importance of sleep for health in the general population. Limitations on both the scope and duration of laboratory studies make it difficult to establish longer-term causal links, and potential reverse causality may significantly weaken causal inference with observational data. As a result there is little empirical evidence on the potential causal impact of commonly encountered urban noise-induced sleep disruption on health in otherwise healthy adults. Using a survey of Dutch adults, we contribute to the effort to investigate the causal relationship between self-reported sleep disruption and health by using individual-specific exposure to neighbor noise as an instrument for sleep disruption. We argue that neighbor noise is a relatively ex-ante unobservable exogenous shock, and we provide quantitative evidence that it fulfills the relevance, exogeneity, and exclusion restrictions for validity as an instrument. Consistent with theory, we find statistically and economically significant causal effects of sleep disruption on cardiovascular problems, auto-immune diseases such as arthritis and lung disease, and headache. The results survive a battery of robustness checks and highlight the importance of noise-related public policies.

Key words: sleep disruption, health, noise exposure, instrumental variable estimation

JEL classifications: I10, R23, D00

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1 Introduction

As many an urban dweller can attest, residential noise is a particularly vexing aspect of city life, but beyond the annoyance factor few have considered the possibility that the associated sleep disruption could also pose a threat to public health (WHO, 2009). Nevertheless there are sound physiological grounds to suspect that sleep disturbance could have detrimental health effects. Numerous animal and laboratory studies have found theoretical and experimental evidence that sleep duration can interact powerfully with both inflammatory processes and the immune system, providing potential biological channels through which sleep quality could causally be linked to a variety of undesirable health outcomes in people, including problems of the cardiovascular, respiratory, and metabolic systems, auto-immune illnesses, and even Alzheimer's disease (Spiegel et al., 1999, 2005; Lange et al., 2006; Morgan and Tsai, 2015; Shukla and Basheer, 2016).

However, while medical studies strongly point to the potential importance of sleep on health, robust empirical evidence on the magnitude of the long-term impact of common occurrences of sleep disruption in everyday urban settings is more elusive. Many observational studies do find strong correlations between sleep disruption and a variety of health problems, including cardiovascular disease, obesity, diabetes, depression, and respiratory illness (Covassin and Singh, 2016; Palmer and Alfano, 2016; Knutson et al., 2006; Zee and Turek, 2006), but as many of these health conditions themselves both create and exacerbate sleep difficulties, there is a reverse causality problem in interpreting these observational correlations as causal effects (Zee and Turek, 2006). As noted by Hume et al. (2012): "*studies demonstrating a causal pathway that directly link noise (at ecological levels) and disturbed sleep with cardiovascular disease and/or other long term health outcomes are still missing*".

A much more limited set of studies address the problem of causal inference by exploiting 'natural experiments' (Nissenbaum et al., 2012; Gibson and Shrader, 2015) to study the cognitive, productivity, and self-reported health effects of exogenous shifts in sleep patterns. A popular approach has been to examine the effects of daylight savings time on cognitive ability, with the ensuing one hour of sleep deprivation (in April) or extension (in October) being linked to financial market fluctuations (Kamstra et al., 2000), traffic accidents (Ferguson et al., 1995; Sood and Ghosh, 2007), workplace injuries (Barnes and Wagner, 2009), and overall life satisfaction (Kountouris and Remoundou, 2014). For example, Gibson and Shrader (2015) provides causal estimates of the effects of sleep duration on wages using sunset time as an instrument. However, studies that link exogenous variation in sleep quality to non-cognitive-related health outcomes are much scarcer. To date, the only such study to our knowledge is that of Nissenbaum et al. (2012), who exploit variation in household distances to industrial wind turbines as an instrument to document the negative effects on self-reported overall health of noise-related sleep disruption.

This paper adds to the limited literature on the causal effects of sleep disruption on non-cognitive-related health outcomes by analyzing the effects of induced sleep disruption from common and (arguably) exogenous urban neighbor noise. We exploit a high quality longitudinal survey in the Netherlands that provides individual health information and allows us to control for a broad array of physical, socio-economic, psychometric, and residential characteristics, including the presence of noisy neighbors. We argue that, unlike other sources of environmental noise (such as street or airplane noise), neighbor noise is generally not an *ex-ante* observable characteristic of housing. Noisy neighbors may unpredictably move in, or out, and in many cases the monetary and social costs of relocation are sufficiently high that moving house is not an immediately available option, with exposure to noisy neighbors potentially enduring over a significant time frame.

Exploiting this arguably exogenous nature of neighbor noise, we isolate the causal impact of sleep using an instrumental variables estimator. The necessary identifying assumptions of this approach are that disturbance from neighbor noise is exogenous to health outcomes, and that, after controlling for physical, socio-economic, psychometric, demographic, dwelling and neighborhood characteristics, neighbor noise affects health only through its effect on sleep disruption. We explore and interrogate these assumptions via over-identification tests and a variety of robustness exercises, including controlling for individual psychometric attributes such as self-reported sensitivity and well-being.

While the statistical analysis is supportive of our identifying assumptions and causal interpretation of the results, we cannot definitively rule out the potential that neighbor noise is correlated with health via other direct mechanisms independent of sleep, violating the exclusion restriction. We thus further augment our strategy by exploring the heterogeneous effects of sleep disruption on a range of health outcomes, some of which are linked to sleep in the medical literature and some of which are not, reassuringly finding causal relationships only with those health conditions that have been previously linked to sleep.

More specifically, we find OLS associations between urban noise induced sleep disruption and *all* of our measured health outcomes, a result consistent with both sleep-moderated health effects as well as simultaneity and reverse causality. However the instrumental variables estimates are statistically and qualitatively significant for only on a subset of these disorders, specifically cardiovascular, lung, bone & joint diseases (such as arthritis), and headache, all of which have been linked to sleep in previous studies. Conversely, the IV estimator does not find any significant causal effect of sleep disruption on health outcomes not physiologically linked to sleep, namely cancer and high cholesterol. Interestingly, nor does our instrumental variables estimator find significant causal effects of sleep on diabetes, high blood pressure (hypertension), asthma, depression or Alzheimer's disease, health conditions that have been linked with sleep duration in the literature and thus are of particular interest. We consider several possible explanations for these null findings.

The rest of the paper is organised as follows. Section 2 describes the data used in the analysis and outlines the instrumental variables estimation strategy, section 3 presents our main results and discusses their interpretation, and section 4 concludes. An online appendix available at https://bit.ly/3HAf7ZX presents additional robustness tests.

2 Data and Method

2.1 Data and Sample

Data for the analysis come from the Longitudinal Internet Survey for the Social Sciences (LISS) panel administered by CentERdata (Tilburg University, The Netherlands). The LISS is a high quality, population-representative, Internet-based annual longitudinal survey from 2008-2013 of over 8000 individuals, identified using a true probability sample drawn from the Dutch population. It safeguards representativeness by providing an Internet subscription and a computer for households that could not otherwise participate (Crossley et al., 2017), with an enrollment rate of 48% of the total initial sample. Scherpenzeel (2009) evaluates the sampling method and finds that the LISS sample compares favorably to high-standard traditional surveys.[1]

We focus on respondents over 17 years of age in 2007 when the initial survey started, ending up with a total sample size of 5440. The LISS is an ongoing annual survey with multiple waves of question ‘modules’ sent to participants throughout the year. The primary modules used for this analysis was the Health module, collected in November and December in each wave, and the Housing module, collected in June and July for each wave. Although the LISS survey is longitudinal, not all respondents answered all modules in all years, and for some modules respondents answered only once or twice during the entire survey period. We collect binary data on whether respondents have been diagnosed and/or received medication for a health condition, we do not have information on the severity of disease.

As we are primarily interested in the effects of chronic sleep disruption on long-term health problems for continuous variables we calculate the average for each individual across the seven survey waves, and for dichotomous variables we code them as taking the value ‘1’ if any of the surveys records a non-zero outcome. This approach is similar to Braga et al. (2020), who estimates the long-term effect of tax credits on health outcomes.

This time-averaged, cross-sectional approach is better suited to the data and the research question for several reasons. First, we are interested in the effects of sleep disruption on primarily ***long-term*** and progressive health problems, not the changes from year to year in diagnoses (which would be the focus if we focused on the *within* variation using individual fixed effects). For

[1] For details, check Scherpenzeel and Das (2010) or visit www.lissdata.nl.

example, if a respondent suffers from sleep disruption one year and not the next, we would not expect a diagnosis of cardiovascular problems to come and go in tandem. For the same reason we would not expect year-on-year variation in noise exposure to yield much information; as we discuss further below, due to high moving costs and relatively low residential mobility in the Netherlands, this cross-sectional measure is likely to be quite correlated with long-term noise exposure. Moreover, to the extent that we fail to record health problems that have not yet progressed to the level of diagnosis, or fail to record exposure to noise that just happened to stop during the survey, these measurement errors bias the coefficient against finding a relationship.

Finally, more formally, Madsen (2005) shows that theoretically the relationship from cross-sectional data can capture a long-term cointegrating relationship, unless variables of interest are sensitive to time-varying aggregate shocks. While we do not have enough time-series variation to test these conditions, based on first principles we feel it is unlikely that the processes of health and noise under study would be so generated.

2.2 Sleep Disturbance and Health Variables

In the Health module of the LISS respondents were asked both general and specific questions about their health, including whether they suffered from sleep disturbance (from any cause). Respondents were also asked factual health questions by having them select from a list of possible health problems in response to "Do you regularly suffer from the following diseases/problems;" "Are you currently taking medicine at least once a week?" and "Has a physician told you this last year that you suffer from the following diseases/problems?" Respondents were coded with a specific health problem if they indicated in the affirmative with respect to that health problem to any of these questions. Specifically, health problems were coded as relating to the cardiovascular system; joints & bones (including arthritis and skeletal problems), cancer, lung disease (including bronchitis), asthma, diabetes, blood pressure (hypertension), cholesterol, fatigue, headache (including migraine), depression, and Alzheimer disease.

2.3 Instrumental Variables

Our instrumental variable, collected from the Housing module, is the binary responses to the question "Are you ever confronted with the problems listed below in your home environment?" *Neighbor Noise* takes the value 1 if respondents indicated 'noise annoyance caused by neighbors', and 0 otherwise. We also collect information on noise from the street; *Street Noise* takes the value 1 if respondents indicated 'noise annoyance caused by factories, traffic or other street sounds,' at any time during the survey period, and 0 otherwise. Our subjective noise data is arguably a better measure of the true disruptiveness of the sound than the objective decibel level, as what we want to measure is the actual disruptiveness of the sound to the individual, which will vary with both the social information contained in that noise (largely unrelated to decibel level) as well as the individual's sensitivity. Thus we view the subjective nature of our indicator as an advantage of our approach. Nevertheless a concern that does arise is that sensitivity to noise could be related to both health status and the likelihood of reporting neighbor noise, a potential issue we address below in section 3.3.

2.4 Control Variables

Further control variables are drawn from across the survey. The Personality module of the LISS survey asks respondents to rank from 1 (very inaccurate) to 5 (very accurate) whether statements about personality characteristics describes them. We use their response to 'Am easily disturbed' to explore to what extent variation in individual sensitivity might explain observed correlations throughout the analysis.

In addition to the key variables of interest, the LISS also provides a large amount of data on physical, socio-economic, demographic, housing and neighborhood characteristics that we follow the literature (Spiegel et al., 1999; Hume et al., 2012; Hamermesh and Pfann, 2022) to use as control variables in the analysis. These include information on monthly household income, education level (from primary to university level), marital status, labor market status, number of hours worked gender, age, whether the respondent has ever smoked, whether they consume more than one alcoholic drink per day, body mass index (BMI), number of children in the household, and whether the respondent is religious. We also data on the respondents' neighborhood and dwelling, including whether the neighborhood is very urban, moderately urban (as the reference category), or rural, whether the respondent has experienced vandalism or crime at home, and whether the respondent finds their dwelling to be too small, too dark, too damp, too cold, has a leaking roof, or has rotten window frames or floors. To control for poor air quality associated with being near a busy road or factory, *Air Quality* takes the value 1 if respondents indicate their dwelling suffers from 'stench, dust or dirt, caused by traffic or industry,' and 0 otherwise. Finally, additional information provided by CENTeR Data allows us to construct an annual indicator of whether a respondent has moved residence during the sample period.

2.5 Estimation strategy

We start with the OLS association between sleep disruption and health outcomes as specified below:

$$health_i = \beta_1 sleep_i + X_i^t \beta_X + \varepsilon_i, \tag{1}$$

where $health_i$ is a dummy variable indicating having a specific health problem, $sleep_i$ is a dummy variable equal to 1 if an individual i reports sleep disruption and otherwise equals 0. X_i^t is a vector of control variables of individual, dwelling and neighborhood characteristics.

We cannot interpret $\hat{\beta}_1$ as the *causal* effect of sleep on health due to potential endogeneity, including reverse causality (that ill health leads to sleep disruption) and simultaneity (some underlying unobservable condition that leads to both ill health and sleep disruption). We adopt instead an instrumental variable estimation to examine the causal impact of sleep disruption on health outcomes. Specifically, we exploit reported exposure to neighborhood noise as an instrument for sleep disruption; in other words, we model sleep disruption as a function of exposure to neighbor noise, and then examine whether this measure of noise-induced sleep disruption is associated with health outcomes. By exploiting variation in sleep disruption only related to neighbor noise, we effectively remove the potential reverse causality and simultaneity between health and sleep, and are thus able to recover causal estimates.

The internal validity of this instrumental variables approach requires three conditions: (i) relevance - that neighbor noise significantly and adversely affects the sleep quality; (ii) exogeneity - that those with ill health do not report more noisy neighbors or self-select into noisy dwellings; and (iii) the exclusion restriction - that the mechanism through which noisy neighbors affect health outcomes is only through their effect on sleep disruption. We investigate all three of these assumptions, showing that, first, there is ample evidence of noise-moderated sleep disruption in the Dutch sample.

Second, we argue that the presence of noisy neighbors is largely an *ex-ante* unobservable characteristic of housing and thus exogenous to health outcomes. Due to high moving costs and the resulting relatively low residential mobility in the Netherlands (Helderman et al., 2004; Van Ommeren and Van Leuvensteijn, 2005), it is not easy for residents to move away from unexpected noise, and within our sample, moving home is uncorrelated with health outcomes. Furthermore, for both the OLS and IV estimation we provide two sets of estimates, a baseline specification and an augmented specification controlling for moving home during the sample period (*Ever Moved*). As we discuss further below, the estimated coefficients of interest on *sleep* remain stable across the two specifications, providing reassurance that it is unlikely that selection via moving house is driving the results.

Third, we show that variation in observed personal sensitivity does not explain the observed correlation between noise, sleep and health. Again, in both the OLS and IV estimation we provide both a baseline set of results as well as an augmented specification that controls for our psychometric measure of sensitivity. The coefficients of interest on *sleep* remain qualitatively and quantitatively robust and stable, suggesting that as long as unobservable sensitivity is broadly correlated with observed sensitivity, this is not a first-order mechanism driving the primary baseline causal relationship between sleep and health.

Fourth, to address any concerns that other control variables could also be endogenous to health outcomes, we provide robustness check in the Online Appendix Table A.3, sequentially adding control variables in stages. The results show stable consistent patterns, mitigating the concerns about endogeneity of the controls to health outcomes.

Fifth, we formally test the exclusion restriction by conducting Anderson-Rubin over-identification tests using *two* noise-related instruments: neighbour *and* street noise. In addition, in the Online Appendix we further interrogate the exclusion restriction by running a number of robustness tests: specifically, following the literature (Jensen et al., 2019; Hanibuchi et al., 2021) we augment our baseline set of controls with two further psychometric variables (self-reported anxiety and 'happiness'), and three measures of lifestyle (drug taking, exercise, job risk) as controls. Our primary results remain robust, suggesting that variation in psychometric and lifestyle attributes are unlikely to be first-order mechanisms.

Finally, a more technical issue arises from the fact that the dependent variable, *health*, the explanatory variable of interest, *sleep*, and the instrumental variable, *noise* are all binary dummy variables. A common approach to modelling binary health outcomes is to use nonlinear probit/logit models that constrain the predicted values to lie between 0 and 1, yielding coefficient estimates with convenient odds-ratio interpretations. However, introducing an instrumental variable derived from a similarly nonlinear first stage regression in two-stage least squares (or alternatively using two-stage residual inclusion, or 2SRI) can generate biased estimates under a wide range of distributional scenarios (Basu et al., 2017) and is generally econometrically controversial, as is illustrated by a contentious debate in the literature (Smith and Blundell, 1986; Blundell and Smith, 1989; Blundell and Powell, 2003, 2004; Terza et al., 2008; Bhattacharya et al., 2006).

Thus, we follow Angrist and Pischke (2008) and Basu et al. (2017) who suggest using linear probability models (LPM) within a two-stage least squares (2SLS) approach that produces consistent estimates, easy-to-compute marginal effects, and unbiased standard errors. Specifically, we adopt a LPM 2SLS estimation framework to generate our instrumental variables estimates. The first stage regression is estimated as:

$$sleep_i = \alpha_1 noise_i + X_i^t \alpha_X + \mu_i, \tag{2}$$

where $noise_i$ is a dummy variable which indicates individual i reports noise annoyance caused by neighbors and other variables are as described above. In the second stage estimation, we use instrumented sleep disruption from the first stage to recover the causal relationship between sleep and health outcomes:

$$health_i = \gamma_1 + \widehat{sleep_\iota} + X_i^t \gamma_X + \epsilon_i, \quad (3)$$

Conditional on satisfying the identifying assumptions, the LPM 2SLS instrumental variables estimator addresses one major problem of inference related to *incidence* in observational studies of sleep and health—reverse causality—effectively. Nevertheless, the nature of the estimator (instrumental variables) combined with the nature of the survey data (cross sectional and primarily binary in nature) combine to preclude the approach from accurately estimating the *magnitude* of an effect in a clinically meaningful way. This point can perhaps be seen most clearly by thinking of the IV estimate as the ratio of two marginal effects - the estimated effect of noise on health (*dh/dn,* the reduced form) divided by the estimated effect of noise on sleep (*ds/dn*, the first-stage estimator). Within the linear probability framework the estimate for *dh/dn* gives us an estimate of the increase in the probability of reporting a health problem if neighbor noise is reported. Dividing *dh/dn* by *ds/dn* gives us the causal estimate of the likelihood that health problems (of unknown differing severity) will be reported if sleep disturbance (of unknown differing magnitudes) is reported, among the subset of the population who report neighbor noise (of unknown frequency or loudness). This *incidence* estimate is purged of reverse causality and, if it is valid and statistically significant, tells us that sleep disturbance can have a *causal* effect on health, but it does not tell us the magnitude of that effect.

In sum, as discussed below in the Results section 3 below, all of the robustness tests support the validity of our IV identification strategy. Nevertheless it is impossible to definitively rule out potential violations of the exclusion restriction. In addition, taken at face value our approach addresses reverse causality concerns to generate causal *incidence* estimates of sleep disturbance on health, but assessing the *extent* of the effects of differing degrees of sleep disruption on health outcomes is left to future research. We further discuss the implications of these limitations below.

3 Results

3.1 Descriptive Statistics

Table 1 presents summary statistics for all variables. The upper panel displays summary statistics for continuous variables. On average, surveyed individuals report a health level of 3.1 out of 5, which indicates ‘good’ health level. The average age is 49.5 years old, with an average BMI of 25.7. Individuals work about 32.3 hours per week, with a monthly household income of 2968.8 Euros. The lower panel presents frequencies for dichotomous variables. Around 30% experience sleep disruption, and as many as 33.5% report experience of neighbor noise. Notably, exposure to street noise (which is *ex ante* more observable than neighbor noise) is relatively low, at 19.5%. The most frequent health problem is fatigue (75.9%), followed by bone & joint problems (63.9%).

3.2 Correlations between sleep, health, psychometric sensitivity and moving house: OLS estimates

In Tables 2a-2c we present the baseline OLS correlations between sleep disruption and all health outcomes considered, controlling for full set of socioeconomic, physical, and dwelling/neighborhood variables. As described above, for each health outcome, we consider two alternative specifications: in specification (a) we present the baseline regression, and in specification (b) we explore the extent to which including additional (but possibly endogenous) controls for individual sensitivity to disturbance (*Easily Disturbed*) and moving house during the sample period (*Ever Moved*) in the reduced form equation moderates the coefficient estimate on *sleep*.

In both specifications (a) and (b) of the OLS estimates in Tables 2a-c we find large and statistically significant correlations between sleep disruption and *all* of the health outcomes, whether they have been linked in the literature to sleep disruption (such as autoimmune and cardiovascular disorders), or not (such as cancer). As discussed above we cannot interpret these estimates as *causal* effects of sleep on health, as it is just as possible that poor health leads to disrupted sleep (direct reverse causality). Other control variables show associations with health outcomes as expected, such as a significantly positive correlation of BMI and significantly negative correlation of income with almost all diseases. Dwelling and neighborhood characteristics, such as dwelling small or dark and living in urban or rural, however, do not have statistically significant association with most of the health outcomes.

In Tables 2a-c specification (b) we explore the extent to which individual sensitivity and self-selection could influence the relationship estimated in the baseline specification (a). We find evidence that individuals who are more easily disturbed are indeed more likely to experience ill health across most of health conditions (with the exception of asthma and diabetes), though again the direction of causality is not known. Having moved house is weakly correlated with less cardiovascular disease or fatigue (with statistical significance at the 10% or 5%, respectively) but not with other health outcomes. More importantly, across all augmented (b) specifications, the inclusion of the additional controls for sensitivity and moving have only small effects on the magnitude and statistical significance of the coefficient estimates on *sleep disturbance*. We interpret the relative stability of the coefficient on *sleep disturbance* between specifications (a) and (b) as strongly suggestive evidence that sensitivity and selection are unlikely to be first-order drivers of the observed correlations between sleep disturbance and health outcomes.

3.3 The Causal Effects of Sleep on Health: Instrumental Variables Estimates

3.3.1 The proposed instrument: neighbor noise

A first-order threat to identification in the OLS estimates presented in section 3.2 is the possibility of reverse causality—that poor health status could cause sleep disruption. To address this possibility, we exploit a plausibly exogenous source of variation in sleep disruption: exposure to noisy neighbors. The intuition is that noisy neighbors are an *ex-ante* unobservable characteristic of housing, and/or may arise (unexpectedly) with the arrival of new inhabitants. As long as moving is sufficiently costly and individuals' sensitivity to noisy neighbors does not depend on health, variation across individuals in their reported exposure to noisy neighbors is thus plausibly exogenous with respect to health outcomes. Although these two key identifying assumptions—that moving is sufficiently costly and that health does not drive sensitivity to noise—cannot be definitively proven within the constraints of our analysis, we present strong suggestive evidence that these potential sources of selection are not first-order drivers of the observed relationships.

First, as anyone who has moved house can confirm, relocation does indeed carry significant costs in time, money, and social relationships. Furthermore, evidence suggests that moving home is especially costly in the Netherlands; a UNHSP report rated property transfer taxes the Netherlands to be 'High' (Un-Habitat, 2013), and a report from the government indicates that almost three quarters of Dutch rental properties are highly rationed social housing that can have waiting lists that approach 7 years (Government of the Netherlands, 2016). Properties (including rental homes) in the Netherlands are mostly offered unfitted and unfurnished—they lack not only furniture, but also basics like carpets, light fittings, and major appliances. Indeed, Praag and Baarsma (2005) investigated the impact of airplane noise on housing prices in Amsterdam and found that moving home was so difficult that the dis-amenity of airplane noise was absorbed not in housing prices but exclusively as a 'residual' in the life satisfaction of homeowners. If moving home is not an available option in the Netherlands for such a clear, identifiable noise source as flight paths, then it is very unlikely to be an easily available remedy for neighbor noise either.

Second, more formally, we saw above in section 3.2 that the inclusion of *Ever Moved* in Tables 2a-b did not impact the estimated correlation between sleep disturbance and health. In Table 5 we repeat this exercise for the 2SLS estimates, presenting the results both with and without *Ever Moved* for each health outcome, focusing on whether the coefficients of interest remain stable between the two specifications. As can be observed, there is very little impact on the estimated coefficients of interest, strongly suggesting that moving house is not a first-order driver of the IV results between sleep and health.

The second potential concern with the exogeneity of the proposed instrument is that being more easily disturbed could be associated both with poor health outcomes as well as the likelihood of reporting noisy neighbors. Again, the OLS correlations in Tables 2a-b suggested that these variables do not much interact, but nevertheless we repeat the basic exercise for the 2SLS results by exploring to what extent controlling for self-reported sensitivity to disturbance (*Easily Disturbed*) in Table 5 changes the primary results of the analysis. Again, the relative stability of the estimated coefficients of interest suggests that individual sensitivity is unlikely to be a first-order driver of the IV results between sleep and health.

Having argued that our proposed instrument, neighbor noise, is plausibly exogenous to health outcomes, we now turn to the next condition for a valid instrumental variable estimation, relevance.

3.3.2 First-Stage Regressions

Table 4 presents the results of the first-stage regressions that models sleep disturbance as a function of noisy neighbors. However as shown in the balance table of Table 3, neighbor noise may not be unconditionally exogenous as it is related to individual demographic, socio-economic, and household characteristics.[2] Therefore, following Oster (2013), in Table 4 we present first-stage results of the effect of reported neighbor noise on sleep disruption gradually adding controls for individual, household and neighborhood observables.[3] In Table 4 column (1) we explore the unconditional bivariate relationship and find that, compared to those with no reports of neighbor noise, individuals in the environment with noise from neighborhood are about 11 percentage points more likely to experience sleep disruption. In column (2) we additionally control for socioeconomic, physical, and dwelling/neighborhood characteristics and the coefficient estimate and statistical significance remain robust. In column (3) we also include *Easily Disturbed* and *Ever Moved* and show that even when controlling for these variables, the effect of neighbor noise on sleep disruption remains stable, robust and highly statistically significant with a p-value less than 0.01. The F-statistics of all three specifications are above the threshold of 10 suggested by Staiger and Stock (1997) as a test for weak instruments.

3.3.3 IVE Results

With strong first-stage results, we proceed to the second stage using neighbor noise as the instrument for sleep disruption. Results are presented in Table 5 and include physical, dwelling, neighborhood, demographic, and socio-economic controls (not presented to save space but available upon request). Baseline specification (a) includes the full set of baseline controls, whereas in specification (b) we additionally control for (potentially endogenous) *Easily Disturbed* and *Ever*

[2] The full balance table with all control variables reported is presented in Table A.1.
[3] The full first-stage table with all control variables reported is presented in Table A.2.

Moved, primarily in order to compare how robust the estimates and statistical significance of *sleep disruption* are between the two specifications.

The results presented in Table 5 find statistically significant causal effects of sleep disruption on cardiovascular disease, bone & joint problems, headache and lung disease. These results are broadly consistent with the existing medical literature. For the case of cardiovascular disease, the empirical relationship with sleep has been long studied and also found to be qualitatively large (Hume et al., 2012). For example Chien et al. (2010) compares Americans with insomnia complaints to those without and finds a relative risk ratio of 1.78 of having cardiovascular disease. Ayas et al. (2003) assesses the relationship between self-reported sleep duration and incident coronary heart disease in the Nurse's Health Study, finding conditional relative risk ratios of up to 1.45.

However, as discussed above, it is difficult to directly interpret the *magnitude* of the LPM coefficient estimates from Table 5 in clinically meaningful terms comparable to the odds-ratios reported in existing medical studies; a concrete example may be instructive here. In the case of cardiovascular disease, the (unreported but available upon request) marginal increase in the likelihood of reporting a health problem if a noise problem is reported is 0.032 (roughly we can think of this as 3.2%, although since this is a LPM we need to keep in mind the range that the computation is allowed is greater than the 0-1 bounds we would naturally be considering). At the same time, from Table 4 regression (17), the increase in the likelihood of reporting sleep disruption if noise is reported is 0.074. The ratio of these, 0.032/0.074, gives us our IVE estimate from Table 5 column (19b), 0.44. Now consider how the estimate would adjust if the denominator (the likelihood of reporting sleep problems given a noise report) decreased—in other words, if hearing a noise was less likely to cause sleep problems—but the numerator (the likelihood of cardiovascular problem given a noise report) stayed constant. In that case the IVE would find a bigger impact per sleep incident caused by noise, and the IVE estimate would increase. Clearly then, directly comparing the IVE coefficients with the odds-ratios in other studies is not appropriate.

Beyond cardiovascular disease we also find evidence of a causal link from sleep disruption to bone & joint problems, lung disease, and headache. While the existing literature provides plausible theoretical biological channels for these latter three health outcomes (Spiegel et al., 1999; Morgan and Tsai, 2015), there are no comparable clinical/empirical studies. Clearly, more research would be fruitful.

The pattern of statistically insignificant results presented in Table 5 are just as interesting as the significant results. While the (biased) OLS estimates presented in Tables 2a-2c found associations between sleep disruption and *all* of our measured health outcomes, the instrumental variables estimates reassuringly fail to find any causal impact of sleep disruption on several health conditions *not* causally associated with sleep in the medical literature – high cholesterol, cancer, and depression.

However the IV estimator also finds null results for diabetes, high blood pressure (hypertension), asthma, and Alzheimer's disease, which are all conditions that have been either theoretically or empirically linked to sleep deprivation in the medical literature and thus are of particular interest. There are several possible explanations for our differing results. First, some health studies link sleep disruption to intermediate outcomes, such as obesity, that are themselves then associated with health outcomes (i.e. Patel and Hu, 2008 for asthma)., but since we control for BMI directly, we would not expect to find any relationship in these cases. Second, epidemiological evidence based on observational data is limited and possibly susceptible to reverse causality (Spiegel et al., 2005; Meisinger et al., 2005; Knutson et al., 2006), so our results may in fact be more accurately finding no causal link. Finally, the LISS survey only asks very general questions about health outcomes, depending on yes-no self-reports, and thus our method and data may not be sensitive enough to measure the extent of disease, or pick up some kinds of relationships in the existing sample size. Further research is necessary.

3.3.4 The Exclusion Restriction

As discussed above, a first-order concern is that noisy neighbors could affect health via a mechanism other than sleep disruption (the exclusion restriction). The IV estimator attributes all the (conditional) relationship between neighbor noise incidence and cardiovascular incidence to sleep disturbance. However, if the reporting of neighbor noise incidence is causally related to cardiovascular incidence by some other channel (not controlled for) other than sleep disturbance, this will result in a bias in estimate of the magnitude of the coefficient on sleep disturbance.

To explore the exclusion restriction more formally, in Table 6 we present the analysis using *two* noise-related instruments: neighbor *and* street noise. Using two instruments allows us to formally statistically test the exclusion restriction by conducting Anderson-Rubin over-identification tests (although we note these are weak tests). On the other hand, street noise is arguably less convincing as a valid instrumental variable for sleep disruption; busy streets are both clearly observable, potentially inducing a greater degree of health-related selection, and may generate higher levels of localized air pollution, potentially further violating the exclusion restriction.

In the event, the two-instrument IVE results presented in Table 6 reveal a very similar pattern to those found in Table 5. More importantly, in all cases we fail to reject the hypothesis that the instruments are excludable, confirming the statistical validity of the exclusion restriction. Although technically above the critical 5% threshold, we note that the over-identification test for cardiovascular problems, with p-values under 0.10, is somewhat weaker; this could be consistent with either street or neighbor noise having a weak but direct effect on cardiovascular health independent of its effect on sleep. For the case of street noise this is an especially plausible concern given that street noise could be correlated with air pollution, which itself has been linked to cardiovascular and other diseases (Dominski et al. 2021). However we cannot definitively pinpoint the mechanism here so leave open the possibility that IVE estimates could be somewhat overstated, especially those for cardiovascular disease, and leave this question for further research.

In addition to the over-identification exercise, to further test the validity of the exclusion restriction, following the literature (Jensen et al., 2019; Hanibuchi et al., 2021) we add additional controls to our baseline specification, including two psychometric variables, self-reported anxiety and happiness, and three measures of lifestyle (drug taking, exercise, job risk) as controls. The results, presented in the Online Appendix Table A.4, show that the coefficients of interest remain stable and broadly consistent with the primary results, supporting our interpretation that the primary mechanism that noise affects health is via sleep disruption.

Thus overall we find that our data is not consistent with alternative mechanisms linking noise and health via moving house, psychometric attributes, or lifestyle differences that would violate the exclusion restriction. Of course these tests are not definitive, but we note that to the extent that in addition to sleep disruption there may also be a (small) direct effect of neighbor noise (as discussed, most likely on cardiovascular disease) via stress, that is potentially an interesting result by itself which is beyond the scope of this research.[4]

4. Conclusion and Discussion

In this paper we investigate the causal impact of sleep disruption on health using data on a wide variety of health outcomes from a representative survey of over 5,000 Dutch adults using an instrumental variables estimation strategy. In particular, controlling for a broad array of physical, socioeconomic, psychometric, demographic, dwelling, and neighborhood characteristics, we instrument for sleep disruption using self-reported exposure to noise from neighbors. We document a highly significant correlation between noisy neighbors and sleep disruption, and provide evidence that our instrumental variables estimates are unlikely to be driven by either selection due to moving homes or individual-level variation in sensitivity to disturbance.

Our study contributes to a better understanding of both the impact of conventional urban noise and sleep quality on health outcomes in everyday, modern settings. Specifically, our results suggest that conventional neighbor noise can contribute to a wide variety of poor health outcomes via the mechanism of sleep disruption. Our analysis also implies that common patterns of sleep disruption identified in the broader population (from any source) may be causally contributing to disease.

[4] We also conducted additional robustness checks in sub-samples excluding individuals under 30 years old or restricting to daytime workers, with results presented in Tables A.5-A.6. The magnitudes and levels of statistical significance of estimates remain robust with reasonable variations.

While the statistical analysis is supportive of our interpretation of the patterns reported here, there are several caveats and limitations that should be kept in mind. First, due to the binary nature of our data our analysis is limited to conclusions about the causal relationship between the incidence of noise, sleep disruption and poor health—we do not make statements about thresholds, severity, or dose-response relationships and leave this to further research. Second, as discussed throughout the paper, we cannot definitively rule out that neighbor noise could affect health (especially cardiovascular disease) via a mechanism other than sleep disruption, a violation of the exclusion restriction. If that is the case, the magnitude of the causal effects of sleep reported here could be overstated. Nevertheless, taking into account the numerous robustness tests and consistent pattern of results, this study is among the first to strongly suggests that the combination of neighbor noise and sleep disruption could be a causal contributor to variation in health outcomes, and we hope that further research will continue to improve our knowledge of this important topic.

Finally, the paper also highlights some hidden costs of noise pollution. Traditionally neighbor noise has been viewed more of a local nuisance than as a public health issue (Hammer et al., 2017), but as evidence of the health costs of everyday noise mounts, the question of noise control should become more of a priority for policy makers and urban planners.

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Tables

Table 1: Summary Statistics

Continuous Variables					
Variable	Obs	Mean	St. Dev.	Min	Max
Health Level	5104	3.12	0.64	1	5
Easily Disturbed	5104	2.7	0.85	1	5
BMI	5104	25.7	4.3	11	50
Age	5104	49.5	13.1	19.5	88.5
HH number of kids	5104	0.88	1.02	0	6
HH Income	5104	2,968.8	2,863	250	126,111
Hours	5104	32.3	12.9	0	106
Rec Drugs (freq.)	570	1.14	2.20	0.03	31

Dichotomous Variables (take the value 1 if the variable ever took the value 1 during sample period)					
Variable	Obs	Frequency	Variable	Obs	Frequency
Sleep Disruption	5104	0.302	Unemployed	5104	0.091
Neighbor Noise	5104	0.335	Housewife	5104	0.397
Street Noise	5104	0.195	Student	5104	0.073
Bad Air	5104	0.103	Retired	5104	0.327
Cardiovascular	5104	0.147	Primary Education	5104	0.015
Cholesterol	5102	0.150	Secondary Education	5104	0.163
Blood Pressure	5102	0.238	Post-Secondary Education	5104	0.683
Asthma	5099	0.057	Tertiary Education	5104	0.175
Lung Disease	5104	0.137	Religious	5104	0.453
Bones&Joints	5104	0.639	Crime in Area	5104	0.164
Diabetes	5102	0.074	Urban Area	5104	0.593
Fatigue	5104	0.759	Rural Area	5104	0.247
Headache	5104	0.272	Ever Moved	5195	0.229
Alzheimer	5049	0.004	Dwelling dark	5104	0.040
Depression	5104	0.083	Dwelling cold	5104	0.060
Cancer	5049	0.042	Dwelling leaky	5104	0.039
Ever Smoked	5104	0.661	Dwelling damp	5104	0.081
Daily Drinker	5104	0.251	Dwelling rotten	5104	0.033
Male	5104	0.506	Dwelling small	5104	0.136
Married	5440	0.776	Rec Drugs	4589	0.124

Table 2a: Correlation between sleep disruption and health outcomes: OLS regression

	(1) cardiovascular		(2) cholesterol		(3) blood pressure		(4) Asthma	
VARIABLES	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Sleep Disruption	0.090***	0.080***	0.076***	0.067***	0.099***	0.090***	0.023***	0.022***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.008)	(0.008)
Easily Disturbed		0.029***		0.026***		0.027***		0.002
		(0.006)		(0.006)		(0.007)		(0.004)
Ever moved		-0.022*		-0.015		-0.018		0.009
		(0.011)		(0.012)		(0.013)		(0.009)
Smoker	0.014	0.014	0.032***	0.032***	0.022*	0.022*	-0.002	-0.002
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.007)	(0.007)
BMI	0.005***	0.005***	0.009***	0.009***	0.019***	0.019***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.012***	-0.013***	0.001	0.000	0.002	0.002	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Age^2	0.018***	0.018***	0.007**	0.007**	0.007**	0.008**	0.002	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Male	0.038***	0.049***	0.070***	0.080***	0.015	0.025*	-0.023***	-0.023***
	(0.012)	(0.013)	(0.012)	(0.013)	(0.014)	(0.014)	(0.008)	(0.009)
Married	0.031**	0.029**	0.027**	0.025**	0.014	0.013	0.005	0.005
	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.009)	(0.009)
University	-0.010	-0.006	-0.017	-0.014	-0.016	-0.013	0.018*	0.018*
	(0.013)	(0.013)	(0.014)	(0.014)	(0.015)	(0.015)	(0.010)	(0.010)
HH Income	-0.038***	-0.037***	-0.027**	-0.025**	0.004	0.005	-0.006	-0.006
	(0.012)	(0.011)	(0.012)	(0.012)	(0.014)	(0.014)	(0.008)	(0.008)
Bad Air	0.006	0.003	0.029	0.026	0.022	0.019	-0.013	-0.013
	(0.017)	(0.017)	(0.018)	(0.018)	(0.019)	(0.019)	(0.011)	(0.011)
Dwelling small	0.011	0.013	-0.016	-0.015	-0.009	-0.007	0.015	0.014
	(0.014)	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)	(0.011)	(0.011)
Dwelling dark	-0.010	-0.013	0.027	0.025	0.018	0.015	0.005	0.005
	(0.024)	(0.024)	(0.027)	(0.027)	(0.028)	(0.028)	(0.019)	(0.018)
Dwelling cold	0.018	0.019	0.003	0.003	-0.005	-0.005	0.042**	0.041**
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.018)	(0.018)
Dwelling leaky	0.005	0.004	-0.025	-0.026	-0.025	-0.026	-0.027*	-0.027*
	(0.025)	(0.025)	(0.024)	(0.024)	(0.026)	(0.026)	(0.015)	(0.015)
Dwelling damp	0.009	0.007	-0.008	-0.010	-0.018	-0.019	-0.000	-0.000
	(0.018)	(0.018)	(0.018)	(0.018)	(0.020)	(0.020)	(0.013)	(0.013)
Dwelling rotten	-0.008	-0.006	-0.010	-0.008	0.011	0.013	-0.011	-0.011
	(0.021)	(0.021)	(0.021)	(0.021)	(0.022)	(0.022)	(0.015)	(0.015)
Secondary education	0.001	0.004	0.010	0.012	0.021	0.023	0.015	0.015
	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.010)	(0.010)
Post-secondary education	-0.010	-0.006	-0.020	-0.017	0.008	0.011	-0.002	-0.002
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.008)	(0.008)
Primary education	-0.041	-0.038	0.043	0.045	0.070	0.073	0.000	0.000
	(0.035)	(0.035)	(0.045)	(0.045)	(0.048)	(0.048)	(0.026)	(0.026)
Daily Drinker	0.028**	0.028**	0.019	0.019	0.004	0.003	-0.004	-0.004
	(0.013)	(0.013)	(0.014)	(0.014)	(0.015)	(0.014)	(0.008)	(0.008)
Unemployed	-0.003	-0.004	-0.007	-0.008	-0.002	-0.003	0.003	0.002
	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.012)	(0.012)
Housewife	0.007	0.005	0.013	0.011	0.007	0.005	-0.001	-0.001
	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.007)	(0.007)
Student	0.031	0.031	0.036*	0.036*	0.031	0.031	-0.004	-0.004
	(0.021)	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)	(0.014)	(0.014)
Retired	0.015	0.017	0.020	0.021	0.023	0.024	-0.007	-0.008
	(0.014)	(0.014)	(0.015)	(0.015)	(0.016)	(0.016)	(0.009)	(0.009)
Number of kids	-0.002	-0.003	-0.017***	-0.017***	-0.021***	-0.022***	-0.002	-0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.004)	(0.004)
hours	0.000	0.000	-0.001	-0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Religion	0.030***	0.029***	0.027***	0.026**	0.035***	0.034***	0.011	0.011
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.007)	(0.007)
Crime in Area	0.029**	0.029**	-0.013	-0.014	-0.019	-0.020	0.014	0.013
	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.010)	(0.010)
Urban Area	0.016	0.018*	0.003	0.004	-0.009	-0.008	-0.008	-0.008
	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.007)	(0.007)

Rural Area	0.008	0.009	0.006	0.008	-0.016	-0.015	0.000	0.000
	(0.011)	(0.011)	(0.012)	(0.012)	(0.013)	(0.013)	(0.008)	(0.008)
Observations	5,104	5,104	5,102	5,102	5,102	5,102	5,099	5,099
R-squared	0.115	0.120	0.163	0.166	0.209	0.212	0.015	0.015

robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2b: Correlation between sleep disruption and health outcomes: OLS regressions (cont.)

	(5) lung disease		(6) bone & joint		(7) diabetes		(8) fatigue	
VARIABLES	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Sleep Disruption	0.116***	0.107***	0.170***	0.147***	0.020**	0.017**	0.121***	0.103***
	(0.012)	(0.012)	(0.014)	(0.014)	(0.008)	(0.009)	(0.012)	(0.012)
Easily Disturbed		0.027***		0.063***		0.009*		0.053***
		(0.006)		(0.008)		(0.005)		(0.007)
Ever moved		-0.007		0.025		-0.011		-0.036**
		(0.012)		(0.017)		(0.009)		(0.015)
Smoker	0.030***	0.031***	0.054***	0.054***	0.018**	0.018**	0.037***	0.038***
	(0.010)	(0.010)	(0.015)	(0.015)	(0.007)	(0.007)	(0.013)	(0.013)
BMI	0.008***	0.009***	0.010***	0.010***	0.011***	0.011***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.011***	-0.011***	0.008**	0.010***	-0.003	-0.004*	-0.018***	-0.019***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)
Age^2	0.013***	0.013***	-0.002	-0.004	0.006***	0.007***	0.013***	0.013***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)
Male	-0.015	-0.005	-0.073***	-0.052***	0.022**	0.026***	-0.057***	-0.038**
	(0.012)	(0.012)	(0.017)	(0.017)	(0.009)	(0.009)	(0.015)	(0.015)
Married	0.026**	0.024*	0.037**	0.032*	0.012	0.011	0.013	0.010
	(0.012)	(0.012)	(0.017)	(0.017)	(0.009)	(0.009)	(0.015)	(0.015)
University	0.009	0.012	-0.007	-0.002	-0.006	-0.005	0.004	0.010
	(0.013)	(0.013)	(0.019)	(0.019)	(0.009)	(0.009)	(0.017)	(0.017)
HH Income	-0.046***	-0.044***	-0.028*	-0.025	-0.016*	-0.015*	-0.040***	-0.037***
	(0.012)	(0.012)	(0.016)	(0.016)	(0.009)	(0.009)	(0.014)	(0.014)
Bad Air	0.031*	0.029	0.052***	0.047**	0.030**	0.028**	0.013	0.007
	(0.018)	(0.018)	(0.020)	(0.020)	(0.013)	(0.013)	(0.019)	(0.019)
Dwelling small	0.021	0.020	0.081***	0.074***	0.014	0.015	-0.003	-0.001
	(0.015)	(0.015)	(0.020)	(0.020)	(0.010)	(0.010)	(0.017)	(0.017)
Dwelling dark	0.041	0.039	-0.004	-0.008	0.002	0.001	0.056**	0.051*
	(0.028)	(0.027)	(0.032)	(0.032)	(0.017)	(0.017)	(0.027)	(0.027)
Dwelling cold	0.012	0.011	-0.016	-0.023	-0.014	-0.013	-0.012	-0.011
	(0.023)	(0.023)	(0.029)	(0.029)	(0.014)	(0.014)	(0.025)	(0.025)
Dwelling leaky	0.001	-0.000	0.051	0.049	-0.029*	-0.030**	-0.030	-0.032
	(0.026)	(0.026)	(0.033)	(0.033)	(0.015)	(0.015)	(0.031)	(0.031)
Dwelling damp	0.020	0.019	0.050**	0.049**	-0.011	-0.012	-0.000	-0.003
	(0.020)	(0.020)	(0.024)	(0.024)	(0.013)	(0.013)	(0.022)	(0.022)
Dwelling rotten	0.009	0.011	0.024	0.028	0.015	0.015	0.015	0.019
	(0.022)	(0.022)	(0.027)	(0.027)	(0.016)	(0.016)	(0.025)	(0.025)
Secondary education	0.026*	0.027**	-0.009	-0.006	0.017	0.018	-0.006	-0.002
	(0.014)	(0.014)	(0.019)	(0.019)	(0.011)	(0.011)	(0.017)	(0.017)
Post-secondary education	-0.016	-0.013	0.018	0.024	-0.006	-0.005	-0.003	0.003
	(0.011)	(0.011)	(0.015)	(0.015)	(0.009)	(0.009)	(0.014)	(0.014)
Primary education	0.027	0.029	0.048	0.051	0.014	0.015	0.023	0.028
	(0.042)	(0.042)	(0.052)	(0.051)	(0.031)	(0.031)	(0.043)	(0.043)
Daily Drinker	-0.009	-0.009	0.018	0.017	-0.006	-0.006	-0.022	-0.023
	(0.012)	(0.012)	(0.016)	(0.016)	(0.009)	(0.009)	(0.015)	(0.015)
Unemployed	0.023	0.022	0.026	0.021	0.005	0.005	-0.028	-0.030
	(0.017)	(0.017)	(0.023)	(0.022)	(0.012)	(0.012)	(0.020)	(0.020)
Housewife	-0.001	-0.003	0.022	0.017	0.005	0.005	0.006	0.003
	(0.011)	(0.011)	(0.014)	(0.014)	(0.008)	(0.008)	(0.013)	(0.013)
Student	-0.009	-0.008	0.071**	0.070**	0.010	0.010	-0.044*	-0.043*
	(0.022)	(0.022)	(0.029)	(0.029)	(0.014)	(0.014)	(0.024)	(0.024)
Retired	0.008	0.010	-0.012	-0.011	0.016	0.017*	-0.037**	-0.033**
	(0.014)	(0.013)	(0.018)	(0.018)	(0.010)	(0.010)	(0.017)	(0.016)
Number of kids	0.001	0.001	-0.006	-0.005	-0.007**	-0.007**	0.017***	0.016**
	(0.005)	(0.005)	(0.007)	(0.008)	(0.003)	(0.003)	(0.006)	(0.006)
hours	0.000	0.000	-0.000	-0.000	-0.000	-0.000	0.001	0.001*
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Religion	0.009	0.008	0.020	0.018	0.004	0.004	-0.029**	-0.031***
	(0.010)	(0.010)	(0.013)	(0.013)	(0.007)	(0.007)	(0.012)	(0.012)
Crime in Area	0.042***	0.041***	0.031*	0.029*	-0.007	-0.007	-0.010	-0.011
	(0.014)	(0.014)	(0.017)	(0.017)	(0.010)	(0.010)	(0.016)	(0.016)
Urban Area	0.005	0.006	-0.040***	-0.038***	0.005	0.006	0.018	0.021*
	(0.010)	(0.010)	(0.014)	(0.014)	(0.008)	(0.008)	(0.013)	(0.013)

Rural Area	-0.012	-0.011	-0.028*	-0.027*	0.002	0.003	-0.013	-0.010
	(0.011)	(0.011)	(0.015)	(0.015)	(0.009)	(0.009)	(0.014)	(0.014)
Observations	5,104	5,104	5,104	5,104	5,102	5,102	5,104	5,104
R-squared	0.083	0.086	0.104	0.115	0.092	0.093	0.066	0.076

robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2c: Correlation between sleep disruption and health outcomes: OLS regressions (cont.)

VARIABLES	(9) headache (a)	(b)	(10) Alzheimers (a)	(b)	(11) depression (a)	(b)	(12) cancer (a)	(b)
Sleep Disruption	0.202***	0.179***	0.009***	0.009***	0.106***	0.090***	0.034***	0.031***
	(0.014)	(0.015)	(0.003)	(0.003)	(0.010)	(0.010)	(0.007)	(0.007)
Easily Disturbed		0.062***		0.002*		0.043***		0.006*
		(0.007)		(0.001)		(0.005)		(0.003)
Ever moved		0.023		-0.001		0.009		0.009
		(0.016)		(0.002)		(0.010)		(0.007)
Smoker	0.009	0.009	-0.001	-0.001	0.009	0.010	0.002	0.003
	(0.013)	(0.013)	(0.002)	(0.002)	(0.008)	(0.008)	(0.006)	(0.006)
BMI	0.004***	0.004***	0.000	0.000	0.003***	0.003***	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.003	-0.002	-0.000	-0.000	0.005**	0.006***	-0.004**	-0.004*
	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Age^2	0.000	-0.002	0.001	0.001	-0.005**	-0.006***	0.007***	0.006***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Male	-0.158***	-0.137***	0.001	0.002	-0.026***	-0.011	0.001	0.003
	(0.015)	(0.015)	(0.002)	(0.002)	(0.010)	(0.010)	(0.007)	(0.007)
Married	0.039**	0.034**	0.007***	0.007***	0.009	0.006	0.009	0.008
	(0.016)	(0.016)	(0.002)	(0.002)	(0.010)	(0.010)	(0.007)	(0.007)
University	-0.008	-0.003	-0.000	0.000	-0.000	0.003	-0.001	-0.001
	(0.016)	(0.016)	(0.002)	(0.002)	(0.011)	(0.011)	(0.008)	(0.008)
HH Income	-0.044***	-0.040***	-0.006**	-0.006**	-0.050***	-0.048***	-0.010	-0.009
	(0.016)	(0.015)	(0.003)	(0.003)	(0.011)	(0.011)	(0.008)	(0.008)
Bad Air	0.021	0.015	0.003	0.003	0.003	-0.001	-0.011	-0.011
	(0.021)	(0.021)	(0.004)	(0.004)	(0.014)	(0.014)	(0.010)	(0.010)
Dwelling small	0.002	-0.005	0.002	0.002	0.011	0.007	0.001	-0.000
	(0.019)	(0.019)	(0.004)	(0.004)	(0.013)	(0.013)	(0.007)	(0.007)
Dwelling dark	-0.007	-0.011	0.010	0.010	0.013	0.010	-0.015	-0.015
	(0.032)	(0.032)	(0.009)	(0.009)	(0.023)	(0.022)	(0.013)	(0.013)
Dwelling cold	0.005	-0.002	-0.002	-0.003	0.030	0.026	-0.000	-0.002
	(0.028)	(0.028)	(0.005)	(0.005)	(0.021)	(0.021)	(0.012)	(0.012)
Dwelling leaky	-0.026	-0.029	0.013	0.013	-0.044**	-0.046**	0.026	0.026
	(0.034)	(0.034)	(0.009)	(0.009)	(0.020)	(0.020)	(0.016)	(0.016)
Dwelling damp	0.092***	0.091***	-0.004	-0.004	0.048***	0.047***	-0.006	-0.006
	(0.025)	(0.024)	(0.004)	(0.004)	(0.018)	(0.018)	(0.009)	(0.009)
Dwelling rotten	0.005	0.010	-0.003	-0.003	0.025	0.028	-0.030***	-0.030***
	(0.027)	(0.027)	(0.003)	(0.003)	(0.020)	(0.020)	(0.007)	(0.007)
Secondary education	0.014	0.017	-0.001	-0.001	0.006	0.008	-0.000	0.000
	(0.017)	(0.017)	(0.002)	(0.002)	(0.012)	(0.011)	(0.008)	(0.008)
Post-secondary education	-0.001	0.005	0.001	0.001	-0.015*	-0.011	-0.003	-0.003
	(0.014)	(0.014)	(0.002)	(0.002)	(0.009)	(0.009)	(0.007)	(0.007)
Primary education	0.079	0.082	0.010	0.010	0.006	0.009	-0.012	-0.012
	(0.054)	(0.053)	(0.013)	(0.013)	(0.035)	(0.035)	(0.019)	(0.019)
Daily Drinker	-0.048***	-0.050***	-0.001	-0.001	0.007	0.005	0.003	0.002
	(0.014)	(0.014)	(0.002)	(0.002)	(0.010)	(0.010)	(0.008)	(0.008)
Unemployed	0.021	0.017	-0.004***	-0.005***	0.015	0.012	-0.021***	-0.022***
	(0.021)	(0.021)	(0.001)	(0.001)	(0.015)	(0.015)	(0.007)	(0.007)
Housewife	0.028**	0.023*	-0.001	-0.001	0.001	-0.003	-0.006	-0.007
	(0.013)	(0.013)	(0.002)	(0.002)	(0.009)	(0.009)	(0.006)	(0.006)
Student	-0.055**	-0.055**	0.001	0.001	0.005	0.005	0.011	0.011
	(0.027)	(0.026)	(0.004)	(0.004)	(0.018)	(0.018)	(0.013)	(0.013)
Retired	-0.033**	-0.031*	-0.005**	-0.005**	-0.008	-0.007	0.002	0.002
	(0.016)	(0.016)	(0.002)	(0.002)	(0.011)	(0.011)	(0.008)	(0.008)
Number of kids	0.007	0.008	0.000	0.000	0.000	0.000	-0.001	-0.001
	(0.007)	(0.007)	(0.001)	(0.001)	(0.004)	(0.004)	(0.003)	(0.003)
hours	-0.000	-0.000	0.000	0.000	-0.000	-0.000	-0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Religion	0.016	0.014	0.002	0.002	0.011	0.009	0.006	0.005
	(0.012)	(0.012)	(0.002)	(0.002)	(0.008)	(0.008)	(0.006)	(0.006)
Crime in Area	0.059***	0.057***	-0.004	-0.004*	0.019	0.018	0.021**	0.021**
	(0.017)	(0.017)	(0.002)	(0.002)	(0.012)	(0.012)	(0.009)	(0.009)
Urban Area	-0.004	-0.003	0.001	0.001	0.007	0.008	0.007	0.007
	(0.013)	(0.013)	(0.002)	(0.002)	(0.008)	(0.008)	(0.006)	(0.006)
Rural Area	-0.009	-0.008	-0.000	-0.000	0.011	0.012	0.000	0.000

	(0.014)	(0.014)	(0.002)	(0.002)	(0.009)	(0.009)	(0.007)	(0.007)
Observations	5,104	5,104	5,049	5,049	5,104	5,104	5,049	5,049
R-squared	0.129	0.142	0.015	0.016	0.067	0.082	0.049	0.050

robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Balancing Table between Individuals Exposed with and without Neighbor Noise

	(13) With Neighbor Noise mean (s.d.)	(14) Without Neighbor Noise mean (s.d.)	(15) Difference mean (s.e.)
BMI	25.612	25.735	0.124
	(4.610)	(4.170)	(0.128)
Age	46.872	50.827	3.955***
	(12.780)	(13.105)	(0.385)
HH income	2688.644	3109.789	421.144***
	(1554.376)	(3323.712)	(84.712)
Hours	31.826	32.513	0.688*
	(12.492)	(13.157)	(0.384)
Smoker	0.655	0.664	0.009
	(0.475)	(0.472)	(0.014)
Male	0.474	0.522	0.048***
	(0.449)	(0.448)	(0.013)
Married	0.705	0.812	0.107***
	(0.456)	(0.390)	(0.012)
University	0.194	0.166	-0.028**
	(0.395)	(0.372)	(0.011)
Ever moved	0.295	0.195	-0.100***
	(0.456)	(0.396)	(0.012)
Easily Disturbed	2.810	2.627	-0.182***
	(0.864)	(0.839)	(0.025)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Instrumental variables estimation: first stage regressions

	(16) Sleep Disruption	(17) Sleep Disruption	(18) Sleep Disruption
Neighbor Noise	0.111***	0.074***	0.058***
	(0.014)	(0.014)	(0.014)
Smoker		0.033**	0.033**
		(0.014)	(0.013)
BMI		0.007***	0.007***
		(0.002)	(0.001)
Age		0.007**	0.011***
		(0.004)	(0.004)
Age^2		-0.003	-0.006*
		(0.004)	(0.004)
Male		-0.117***	-0.078***
		(0.016)	(0.016)
Married		-0.009	-0.017
		(0.017)	(0.016)
University		-0.020	-0.011
		(0.018)	(0.017)
HH Income		-0.068***	-0.061***
		(0.017)	(0.017)
Easily Disturbed			0.102***
			(0.008)
Ever moved			0.052***
			(0.016)
N	5102	5102	5102
R^2	0.013	0.079	0.113
$F - statistic$	67.44***	14.48***	20.24***

robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Included in regression but not shown: Dwelling characteristics, neighborhood characteristics, alcohol consumption, educational level, labor market status, number of children, religious status.

Table 5: Instrumental Variables Estimation

	(19) cardiovascular		(20) cholesterol		(21) blood pressure		(22) asthma	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Sleep Disruption	0.444***	0.484**	0.085	0.036	0.108	0.059	0.166	0.197
	(0.160)	(0.206)	(0.150)	(0.190)	(0.162)	(0.205)	(0.107)	(0.138)
Easily Disturbed		-0.013		0.030		0.030		-0.016
		(0.023)		(0.021)		(0.022)		(0.015)
Ever moved		-0.044**		-0.014		-0.016		-0.000
		(0.017)		(0.016)		(0.017)		(0.012)
N	5104	5104	5102	5102	5102	5102	5099	5099
	(23) lung disease		(24) bone & joint		(25) diabetes		(26) fatigue	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Sleep Disruption	0.410***	0.433**	1.262***	1.402***	-0.040	-0.071	0.035	-0.089
	(0.156)	(0.198)	(0.289)	(0.391)	(0.103)	(0.132)	(0.177)	(0.228)
Easily Disturbed		-0.007		-0.068		0.018		0.073***
		(0.021)		(0.043)		(0.015)		(0.025)
Ever moved		-0.025		-0.043		-0.006		-0.026
		(0.017)		(0.034)		(0.011)		(0.020)
N	5104	5104	5104	5104	5102	5102	5104	5104
	(27) headache		(28) Alzheimer		(29) depression		(30) cancer	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Sleep Disruption	0.764***	0.766***	0.023	0.022	0.228*	0.162	-0.055	-0.096
	(0.216)	(0.273)	(0.023)	(0.029)	(0.120)	(0.148)	(0.083)	(0.108)
Easily Disturbed		0.001		0.001		0.035**		0.019
		(0.030)		(0.003)		(0.016)		(0.012)
Ever moved		-0.009		-0.002		0.005		0.016*
		(0.024)		(0.002)		(0.013)		(0.009)
N	5104	5104	5049	5049	5104	5104	5049	5049

robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Included in regression but not shown: Dwelling characteristics, neighborhood characteristics, BMI, Age, Age^2, Male, Married, HH income, educational level, labor market status alcohol consumption, number of children, religious status.

Table 6: Use Neighbor Noise and Street Noise as Instruments

	cardio-vascular		cholesterol		blood pressure		asthma	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Sleep Disruption	0.290**	0.279*	0.084	0.050	0.180	0.170	0.134	0.146
	(0.128)	(0.155)	(0.127)	(0.154)	(0.139)	(0.169)	(0.090)	(0.110)
Easily Disturbed		0.009		0.028		0.019		-0.011
		(0.017)		(0.017)		(0.019)		(0.012)
Ever moved		-0.033**		-0.014		-0.023		0.002
		(0.015)		(0.015)		(0.016)		(0.011)
N	5104	5104	5102	5102	5102	5102	5099	5099
over-id test	3.622	3.388	0.000	0.016	0.684	0.865	0.348	0.435
p-value	0.057	0.066	0.992	0.901	0.408	0.352	0.555	0.509
	lung disease		bone & joint		diabetes		fatigue	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Sleep Disruption	0.363***	0.371**	1.155***	1.235***	-0.069	-0.101	0.112	0.051
	(0.131)	(0.159)	(0.234)	(0.297)	(0.088)	(0.108)	(0.150)	(0.182)
Easily Disturbed		-0.001		-0.051		0.021*		0.058***
		(0.018)		(0.033)		(0.012)		(0.020)
Ever moved		-0.021		-0.034		-0.004		-0.034*
		(0.015)		(0.029)		(0.011)		(0.018)
N	5104	5104	5104	5104	5102	5102	5104	5104
over-id test	0.341	0.316	0.557	0.657	0.289	0.157	0.712	1.208
p-value	0.559	0.574	0.456	0.418	0.591	0.692	0.399	0.272
	headache		Alzheimer		depression		cancer	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Sleep Disruption	0.722***	0.712***	0.041	0.047	0.180*	0.112	-0.005	-0.023
	(0.179)	(0.216)	(0.026)	(0.033)	(0.100)	(0.118)	(0.073)	(0.090)
Easily Disturbed		0.006		-0.002		0.041**		0.011
		(0.024)		(0.004)		(0.013)		(0.010)
Ever moved		-0.006		-0.003		0.008		0.012
		(0.021)		(0.003)		(0.012)		(0.008)
N	5104	5104	5049	5049	5104	5104	5049	5049
over-id test	0.139	0.123	1.742	1.747	0.607	0.339	1.234	1.357
p-value	0.710	0.726	0.187	0.186	0.436	0.561	0.267	0.244

robust standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01
Included in regression but not shown: Dwelling characteristics, neighborhood characteristics, BMI, Age, Age2, Male, Married, HH Income, educational level, labor market status alcohol consumption, number of children, religious status.