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Air Pollution as a Cause of Sleeplessness: Social Media Evidence from a Panel of Chinese Cities*

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Abstract

We provide first evidence of a link from daily air pollution exposure to sleep loss in a panel of Chinese cities. We develop a social media-based, city-level metric for sleeplessness, and bolster causal claims by instrumenting for pollution with plausibly exogenous variations in wind patterns. Estimates of effect sizes are substantial and robust. In our preferred specification a one standard deviation increase in AQI causes an 11.6% increase in sleeplessness, and for $PM_{2.5}$ is 12.8%. The results sustain qualitatively under OLS estimation but are attenuated. The analysis provides a previously unaccounted for benefit of more stringent air quality regulation. It also offers a candidate mechanism in support of recent research that links daily air quality to diminished workplace productivity, cognitive performance, school absence, traffic accidents, and other detrimental outcomes. **Keywords:** Air pollution - social costs - IV methods

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1 Introduction

Our objective in this paper is to investigate a possible causal effect of urban air pollution on the sleep of city inhabitants. Air quality - particularly in cities - is one of the great policy challenges of our time. Understanding the full range of negative impacts of pollution is an essential prerequisite for welfare evaluation of policy interventions.

Sleep is an essential input to human well-being. Loss of sleep reduces mental function along various dimensions, such as learning (Huber et al., 2004), memory (Diekelmann and Born, 2010), judgement (Killgore et al., 2006), speed of reflex (Maquet, 2001) and emotional balance (Ireland and Culpin, 2006). It is correlated with lower self-reported well-being (Hamilton et al., 2007; Steptoe et al., 2008). Tiredness - the inevitable consequence of sleeplessness - has been causally linked to various negative outcomes, including road traffic accidents (Valent et al., 2010), reduced workplace productivity (Zammit et al., 2010; Rosekind et al., 2010), industrial injuries (Barnes and Wagner, 2009), absenteeism (Daley et al., 2009), deteriorated relationship quality (Gordon and Chen, 2014), domestic violence (Meijer et al., 2010), and compromised school performance (Chung and Cheung, 2008). In terms of health outcomes, shortage of sleep over various time scales has been linked to reduced functioning of immune systems and subsequent increased susceptibility to disease, increased risk of hypertension, cardiac and breathing problems, increased adiposity, and negative mental health outcomes.[1]

It is not a surprise that both individuals and governments invest in protecting sleep, and that individuals when asked express a substantial willingness-to-pay to avoid sleep loss (Pollinger, 2014; Delfino et al., 2008).[2] In summary, given that the typical adult in most societies spends between 7 and 8 hours of each day engaged in the activity of sleep (and

[1]There is a large literature on the health implications of both short-term and chronic sleep loss (Altevogt and Colten, 2006; Cappuccio et al., 2010).

[2]For example, individuals spend on good mattresses and other aids to healthful sleep, worry about the noise environment when they buy a home, etc.. Governments spend on sleep research, impose regulation on night-time noise around airports, etc.. Employers are also aware of the benefits of sleep. See for example the lead article *Why Companies are Willing to Pay to Make Sure You Get a Good Night's Sleep* in Executive Style Magazine (21 April 2016) on the productivity benefits of well-rested employees.

children longer): "If sleep does *not* serve an absolutely vital function, then it is the biggest mistake the evolutionary process has ever made." (Rechtschaffen, 1971).

Despite the centrality of sleep to humans, and the diverse contributions that it makes to individual and societal well-being, economic analysis of it has been cursory. Biddle and Hamermesh (1990) treat sleep choice as a time allocation problem. Similarly, Asgeirsdottir and Zoega (2011) provide a model of sleep behavior as an investment that an individual makes in the level of alertness he then enjoys during the day, in the spirit of the approach taken to health as human capital.

While the channels that might link pollution exposure to lower quantity or quality of sleep are obvious (shortness of breath, elevated heart-rate, irritation of upper airways, eyes etc.), research linking pollution exposure to sleep outcomes is limited. (1) Strøm-Tejsen et al. (2016) manipulate indoor air quality in the campus bedrooms of 16 students and find that indoor air quality impacts both sleep quality (as measured by subject-worn actigraphs) and next-day performance on math and language tests. (2) Using measures of outdoor air quality in a small number of US cities, Zanobetti et al. (2010) show that the same-night AQI in the city in which the subject resides correlates with likelihood of episodes of sleep apnea (pauses in breathing during sleep) and other physiological correlates of sleep health. This is an important paper to which ours is complementary. The advantage of their methods is that they deliver very precise individual-level metrics of sleep. The downsides relate to its focus on sleep-illness, and the observation of subjects via a polysomnograph (sensors at nose, fingers, face and scalp) - not more natural sleeping circumstances - and at much lower levels of ambient pollution than we see in the Chinese cities that we study. (3) Focusing on long-term exposure, and without using tools that would allow for causal inference, Billings et al. (2017) find a negative association between sleep efficiency amongst a sample of older people and 5-year and 1-year measures of $PM_{2.5}$ in the neighborhoods of the six US cities in which they live.

Sleep loss is a significant problem in China (Luo et al., 2013) and elsewhere. For the 19 largest Chinese cities, we construct a nightly, population-level measure of sleeplessness using frequency of use of the Chinese characters meaning 'can't sleep', 'sleepless' etc. on the very widely-used social media site Weibo.[3] We estimate an equation using OLS to characterize a positive association between that measure and same-day local air quality. To reinforce our causal interpretation of this relationship, we apply IV methods, using plausible exogenous variations in short-term wind patterns to instrument for air quality. In our preferred specifications, we find that a one standard deviation in AQI causes an 11.6% increase in sleeplessness relative to mean, and for $PM_{2.5}$ the number is 12.8%. The statistical significance and estimated effect size prove to be remarkably robust to a battery of alternative specifications and tests.

We are cautious not to over-interpret the results. Monetizing the sleep loss caused by diminished air quality is beyond the scope of this paper, though it is worth noting that previous research does provide WTP estimates that could be exploited in a back-of-the envelope exercise. The results are instructive in two ways. First, the loss of sleep plausibly impacts the well-being of the affected individual him or herself through a variety of channels. Second, as noted, the results provide a mechanism consistent with recent research linking short-term variations in air quality to reduced workplace productivity (Zivin and Neidell, 2012; Chang et al., 2016), school absence (Currie et al., 2009), exam performance Mendell and Heath (2005), motor vehicle accidents (Sager, 2016) etc..

Section 2 details data sources. Section 3 describes methods. Section 4 and Section

[3] We will be careful to qualify our use of the term "population level" in the data section. Population-level behavior on various internet platforms is increasingly being exploited by social scientists. Choi and Varian (2012) show that Google search data can be used to predict demand for automobiles, home sales and travel behavior. Several papers demonstrate the efficacy of using internet search metrics to predict health outcomes - especially flu - and Google itself established the Google Flu Trends tool in 2008. Goel et al. (2010) show that searches can predict the success of movies, songs and video games. In an environmental application, Herrnstadt and Muehlegger (2014) show that searches for "climate change" and "global warming" in a particular US city are sensitive to short-term deviations of weather from normal. Much recent work has been devoted to Twitter-driven predictive analytics. For three examples among many: Bollen et al. (2011) show that Twitter mood can be used to add explanatory power to stock market forecasts, Gerber (2014) uses Twitter key words to predict crime patterns, and Gayo-Avello et al. (2011) are among several papers using Twitter to predict elections. A central way in which our methods depart from this literature is that we will use measures from social media as our dependent variable. In that regard the paper relates to Baylis (2015), who shows the effect on unusual temperature on Twitter-sentiment.

5 present main and robustness results. Section 6 conducts the placebo test. Section 7 summarizes the results from joint estimation. Section 8 concludes.

2 Data

We investigate the effect of air pollution on sleep in the "first-tier" Chinese cities (19 cities). To do this we develop a nightly, city-level measure of sleep quality derived from posts on social media and connect it to high frequency data on air quality. We also include detailed meteorological data both to control for the likely confounding influences of weather on sleep and for the construction of our instrument.

2.1 Sleep

A challenge in this research is to develop a defensible measure of sleeplessness that is a nightly index for how badly (or well) the inhabitants of a particular city are sleeping.

A number of surveys have asked questions about sleep.[4] However none of these provide the temporal granularity that we require (the exact date of interview and some question about short-term, ideally daily, sleep experience). Even if such questions were asked, the resulting responses would be threatened by imperfect recall of respondents, and other shortcomings typical of retrospective survey-derived data.

We exploit what people are saying on the Chinese micro-blogging Weibo. Weibo was launched in August 2009, and growth in its use was explosive, not least because most of the key social media platforms familiar to those living elsewhere (including Twitter, Facebook, Instagram and Youtube) are blocked in China. It is the biggest social media site in China, and by 2016 it had more than 503 million registered and 313 million regular users amongst the 720 million internet users in that country (DeLuca et al., 2016). As with Twitter, messages were - at least during the period that we analyse - subject to a tight word limit.

[4] For example Chen et al. (2004), Yu et al. (2007), and Sun et al. (2015).

In comparison to Twitter, it has a greater personal than professional orientation in the way it is used (Sullivan, 2012), with substantially more posts outside standard office hours (Gao et al., 2012). Users typically post what they see, hear and think (Cain K, 2015, September 21) and, while it needs to be mined with caution, the content of posts provides the researcher with a potential 'window' into the mind of users and a rich data source.

Keywords Written Chinese is not alphabetic but rather comprises self-standing characters or glyphs. It is logo-syllabic, which means that a character represents a whole word (physical object, concept, *etc.*). Literacy requires the memorization of a large number of such characters, and a well-educated Chinese person knows more than 4000, while between 2000 and 3000 are needed to read a newspaper (Norman, 1988). This characteristic is helpful to us. By its nature there are many fewer duplicative ways to express concepts than is common in alphabetic languages such as English. "Shimian" and "Shuibuzhao" are the two characters that have meaning equivalent to that covered by English words and expressions such as "sleepless", "can't fall asleep", "losing sleep", "insomnia", *etc.*. A further advantage of Chinese is that these are used in the affirmative, so we avoid complications arising from conventions for negation that would arise in most other languages.

We search for the hourly use of these keywords in Weibo posts from users located within each of the "first-tier" cities in China (these are Shanghai, Beijing, Shenzhen, Guangzhou, Chengdu, Hangzhou, Chongqing, Wuhan, Suzhou, Xi'an, Tianjin, Nanjing, Zhengzhou, Changsha, Shenyang, Qingdao, Ningbo, Dongguan, and Wuxi). Weibo offers advanced search tools that enable users to obtain the public posts filtered by keyword, date, time period (minimum duration 1 hour), and location (city). We use these to construct a panel of the number of posts featuring the keywords of interest for each hour of each night (11pm through 7am) for each city for the two year period 2014 and 2015.

It is worth reflecting on this as a dependent variable. The question is not whether keyword use on Weibo is a perfect measure of the thing that we want to measure (the extent to which inhabitants of a particular city are sleeping on a particular night) - of course it is not. Rather, is it a good enough measure, and is it better than others available?

There are two main challenges to our claim that intensity of use of the words "shimian" and "shuibuzhao" provides a valid proxy for city-level sleeplessness. First, perhaps other terms exist that might be used to express the difficulty sleeping that we fail to consider. Inspection of Chinese thesauri and discussion with Chinese speakers make us doubt that this is the case. However, even if it were, it is unlikely to disturb our conclusions. (1) The correlation between use of "shimian" and "shuibuzhao" in our sample is very high (0.96), and the ratio between use of one and the other proves to be insensitive to air quality conditions. We use the word counts as an index, rather than focus on absolute levels. If an additional synonym exists that we have ignored, then provided that focussing its use is closely correlated with these two, then its exclusion is not a concern.[5] (2) Measurement error in the dependent variable that such an oversight would imply should not bias OLS or 2SLS estimates, only reduce their efficiency. We also investigate and refute the possibility that what we are picking up is a simple proxy for overall Weibo use by showing that the sleep metric is uncorrelated with the use of a series of sleep-neutral words (table, cat, etc.), with appearances of the latter not systematically sensitive to air pollution conditions.

Second, Weibo users are not representative of the Chinese population in general. In particular users are younger, more educated, and earn higher income than the broader population (Chan et al., 2012; Chiu al., 2012). While results should most properly be seen as reflecting a treatment effect in the Weibo-using part of the community, we do not see this as problematic. These are likely the high-value workers in Chinese urban society, and disturbance of their sleep can be expected to have correspondingly important economic impacts. Further, there is no reason to think that effects observed in this group would not be observed in the non-Weibo-using part of the population. Indeed, it is plausible to think that those effects could be larger for at least two reasons: (1) In terms of self-protection from pollutants,

[5]A problem would arise for us if there was an excluded means of expression whose comparative intensity of use varied systematically with air quality conditions. This seems implausible.

those with internet access are disproportionately likely to own both air conditioners and air purifiers. (2) Weibo-users are younger than the general population, and most physical effects of pollution are more pronounced among the old.

An additional point to note is that when interpreting coefficients, we assume that the propensity to report sleeplessness is not itself sensitive to pollution conditions. In other words, if we observe a 5% rise in messages about sleeplessness, we take that to imply a 5% increase in sleeplessness in the Weibo-using population. This is similar to the approach in which many researchers have interpreted changes in people reporting health symptoms of pollution, or attending a physician with health symptoms, for example, to reflect changes in the prevalence of those symptoms in the population. If there were some change in the propensity to report - for example via pollution-induced changes in emotional state (as suggested by Zeidner and Shechter (1988) - then the observed change in the proxy would have to be calculated by the actual prevalence multiplied by the propensity. If it happened that the propensity was *increased* by high pollution, then our estimates would over-state the true effect size. However, recent evidence linking short-run exposure to a depressive mood and risk aversion might lead us to speculate that the propensity to message would be reduced. While we are unable to address definitively either possibility, we have no reason to expect any such effect would be significant. However, in the interest of caution, it is worth keeping this in mind when interpreting results.

2.2 Pollution

Data on pollution at our locations of interest were collected from www.aqistudy.cn. This website compiles real-time data on pollutants from the Chinese Ministry of Environmental Protection (MEP) and converts it into daily average measures. The pollutants for which we have data are $PM_{2.5}$, CO, NO_2, SO_2, and O_3 (in addition to AQI).[6] Summary statistics for daily ambient measures in our whole sample are included in Table 1 (and by city in the

[6] PM_{10} is not reported or studied due to its high correlation with $PM_{2.5}$.

Appendix Table A1).[7]

Table 2 lists the categories of air quality days as defined by the Chinese government and - in the right hand column - the percentage of days in our sample that fall within each category on the AQI measure. Table 3 summarizes the correlations between daily city-level measures of the individual pollutants in our sample. In a number of cases, the correlations are quite high, often exceeding 0.6. Most of our analysis will be conducted pollutant by pollutant; only later do we include all pollutants in the same regressions. This follows Schlenker and Walker (2016).

Our analysis is conducted at the city-level, and we calculate air quality measures by taking a simple arithmetic mean of data from all monitors within a city (the number of monitors within our 19 cities varies between 9 and 17). While we know that a user is based in a particular city, we do not know precisely where, nor his or her movements during the day. To allay concerns about intra-city variations in pollution conditions, we calculate the correlations between readings at each pair of monitors in each city. The results are reported in Appendix Table A2 (and for illustration in detail for Beijing in Appendix Table A3 through A8). With the exception of CO - a more localized pollutant - pairwise correlations are very high, especially for AQI, $PM_{2.5}$ and O_3 which are close to or above 0.9. In other words pollution measured at any particular monitor is a good indicator of levels across the city.[8]

2.3 Weather

Disentangling the potentially confounding effects of weather is important. Weather conditions (in particular temperature, humidity, precipitation) can influence sleep activity directly (Okamoto-Mizuno and Mizuno, 2012; Van, 2006). For example, in recent interesting analysis, Obradovich et al. (2017) identify an effect of external ambient temperature on sleep.

[7] Historically the quality of official data on air quality in China has been questioned. In particular there has been evidence of manipulation around key thresholds (Chen et al., 2012). Stoerk (2016) tests the consistency of official data with Benford's Law, and with US Embassy data, and concludes that it is reliable from 2013.

[8] Insofar as measurement error exists in this regressor, we expect it to attenuate OLS estimates, implying that the effect sizes identified under OLS should be interpreted as *under*-stating true effects. The coefficients from the IV exercise will not be subject to such bias.

Meteorological data are obtained from the weather stations registered by the World Meteorological Organization (WMO) that are collated by the National Oceanic and Atmospheric Administration (NOAA). The weather variables involved in the study comprise average temperature ($^{\circ}C$), average humidity (%), sea-level pressure (hPa), wind speed (Km/h), wind direction (°) and precipitation (mm). We combine the hourly weather data into daily mean levels corresponding to the daily average air pollution levels of each city. Summary statistics for the dataset appear in Table 1 (and for each city separately in the Appendix Table A1).

3 Methods

We investigate a link from air pollution in city i on day t to our city-level metric for sleeplessness in that city on that night. In simple terms: if the air in Nanjing is highly polluted today, does that damage the quality of sleep in Nanjing tonight?

3.1 Ordinary least squares

We first use OLS to estimate the association between air quality and sleeplessness in a straight-forward panel fixed effects setting. We estimate the following specification

$$lnS_{it} = \alpha_0 + P_{it}\beta + W_{it}\gamma + \theta_i + \lambda_t + \epsilon_{it}. \tag{1}$$

S_{it} is the sleeplessness index in city i on the night following calendar date t. lnS_{it} denotes that the outcome variable is logged. P_{it} is the daily average pollutant concentration in city i on date t. The primary pollutants that we consider in turn are $PM_{2.5}$ and the composite AQI measure.

We control for a wide set of potential confounders. W_{it} is a vector of weather controls containing average temperature, average humidity, precipitation, wind speed, and sea-level pressure. The temperature and humidity measures enter as indicators or 'bins' (5 $^{\circ}C$ indicators for average temperature, 20 % indicators for average humidity) to accommodate possible non-linear effects.[9] θ_i is a city fixed effect that controls for time-invariant city characteristics. λ_t is a vector of time fixed effects, comprising year by month fixed effects, city by year fixed effects, city by quarter fixed effects, day of week and a dummy for holiday dates. ϵ_{it} is the error term.

Our coefficient of interest is β, which relates air pollution to sleeplessness. It can be interpreted as 100*β% increase in sleeplessness due to additional unit of pollutant. Most of the estimated effect sizes that we will report are based on the percentage change due to one standard deviation change in pollutant, which could be computed by multiplying 100*β by one standard deviation (44.993 for $PM_{2.5}$ and 52.202 for AQI).

3.2 Single pollutant versus joint estimation

Our initial results are derived from single pollutant models in which regressions are run that incorporate $PM_{2.5}$ without co-emission. There is also an AQI variant, where AQI is a composite measure that captures the 'binding' pollutant on any particular date. We report the joint estimation exercise in Section 7. Note that research in this area is plagued by the difficulties of disentangling the effects of *particular* pollutants from the overall cocktail of pollutants that an individual will typically be inhaling on a 'bad air' day.

Some settings do allow for a clean route around this problem. A nice recent example is Lavaine and Neidell (2017). Helpfully for them, the oil refinery strikes that they exploit as exogenous events that temporarily improved air quality in a set of French towns acted on sulphur dioxide in particular, leaving ambient levels of other key pollutants undisturbed. But often the inclusion or exclusion of pollutants is driven by data availability in particular settings. Papers typically report results of regressions that include a single (or limited subset) of pollutants. For example, among well-known investigations of the effect of short term air quality variations on various outcomes; (1) Zivin and Neidell (2012), who look at productivity of agricultural works, select ozone as their pollutant of interest and control only

[9] Results prove to be similar under quadratic estimation, a popular alternative approach to non-linearity.

for $PM_{2.5}$. (2) Ransom and Pope (1992), looking at school absences, exploit data only on PM_{10}, finding negative effects.[10] (3) Ebenstein, Lavy and Roth (2016), studying the effect of daily pollution levels on the exam performance of Israeli children, consider only $PM_{2.5}$.[11] (4) Schlenker and Walker (2016), looking at the health impacts of pollution, exploit data on only CO, NO_2 and ozone, and their main results are derived from specifications in which each pollutant is used as explanatory variable sequentially, without controls for the other two (indeed all but one of the eight tables in Schlenker and Walker (2016) report results of single pollutant exercises). They later insert the three pollutants in the same regression, which generated a qualitative loss of results.[12]

We are to some extent insulated from these problems because our main estimates derive from IV methods. However, given the (sometimes strong) covariance between pollutants, we will follow Schlenker and Walker's caution in tying effects to particular individual pollutants. As it turns out, our results all work in the same direction - more pollution causing greater sleeplessness. But we are more confident interpreting this as a story about 'dirty air', and circumspect as far as pollutant by pollutant inferences are concerned.

3.3 Instrumental variable estimation

There are several challenges to the validity of OLS estimation here. First, there is likely measurement error in pollution. Our theoretical foundation is predicated on the possibility, founded on plausible physiological foundations, that exposure of an individual to elevated levels of pollution increases the chance of disturbed sleep. However, we observe ambient

[10] In the pursuant literature various authors have considered varying permutations of the major pollutants. For example, Gilliland et al. (2001) add ozone and NO_2 and find *beneficial* effects of PM_{10} on absences. Currie et al. (2009) study three of the main pollutants, CO, PM_{10} and ozone.

[11] While in an earlier version (Ebenstein et al., 2016) they also investigate CO, they did not do so simultaneously, and were unable to account for other major pollutants.

[12] They are explicit in "...acknowledging that we may be picking up the health effects of other pollutants" (page 787). The omission of $PM_{2.5}$ and PM_{10} - with clear links to a variety of cardiovascular and other health outcomes - is a challenge for the interpretation of their results. In an Appendix exercise, they note that this is due to the absence of data. As such they conclude that: "We believe that some amount of caution is warranted in interpreting CO as the unique pollution-related causal channel leading to adverse health outcomes; there may be in fact other unobserved sources of ambient air pollution that covary with CO that may also effect health" (page 800).

air quality (which we have shown to be comparatively uniform across monitor sites within a particular city on a particular date) rather than individual exposure. For example, we do not observe self-defensive behavior, such as closing of windows and use of air purifiers, which can reduce effective exposure.[13] The measurement error that would be present in the independent variable would lead to attenuated OLS estimates of our coefficient of interest.[14] Second, while we included a rich set of controls for potential confounders - taking particular care with weather - we cannot rule out the presence of omitted variables. For example, air pollution may be positively correlated with unobserved variations in city-level economic activity, which may in turn influence sleeplessness through other channels. For these reasons we supplement our OLS analysis using two-stage least squares (2SLS), with an instrument based on wind direction.

Instrumental variable Air pollution in Chinese cities is known to be highly sensitive to wind direction and speed, as pollutants are carried from neighboring cities (Fu et al., 2017). Ambient pollutants, especially fine particles, can travel over long distances by wind, ranging from hundreds to thousands of kilometers (EPA, 1996). The fact that airborne particles can be transported by wind and affect the places on the downwind side has been used in linking air pollution to health outcomes, for example by Schlenker and Walker (2016) in their study of adverse health effects downwind of airports. Bayer et al. (2009) use pollution levels in nearby (but further than 80km) cities to instrument for local pollutant levels. There are also studies that focus on estimating movement of air pollutants between cities (for example Chen and Ye (2015)). We develop an instrument based on plausibly exogenous day-to-day variations in wind patterns which, consistent with the existing literature, proves to have strong relevance (satisfies the first stage). The method is similar to that applied by Schlenker and Walker (2016), but whereas they exploited a single source of emission of

[13] In some sense this doesn't matter. What we end up with is not an individual level sleep 'production function' but a population-level effect from ambient conditions to sleep. In terms of defensive behaviors, our results should be interpreted as incorporating such margins of adjustment.

[14] In their investigation of the effects of short-term exposure to health, Moretti and Neidell (2011) provide evidence and insightful discussion of the problems associated with measurement error in this context.

pollution (an airport) to any particular neighborhood, our study's cities typically import wind-borne emissions from multiple neighboring cities, requiring that we apply an intuitive weighting scheme.

For each study or target city i - recall that we consider the 19 most populous in China - we identify other smaller cities located (centre to centre) within between 100km and 200 km. These are likely sources of pollution imported to city i if the wind happens to blow in the 'right' direction. We refer to these as 'source' cities for city i. Neighboring cities within 100km are excluded to minimize risk of endogeneity (Bayer et al., 2009; Zheng et al., 2014).[15] Source cities and their coordinates are listed in Appendix Table A9.

We deliberately take a 'standard' approach to constructing our first stage equation, which is

$$P_{it} = \eta_0 + \psi P_{source_{it}} + W_{it}\gamma + \theta_i + \lambda_t + \epsilon_{it} \tag{2}$$

where

$$P_{source_{it}} = \sum_{j}^{J} \omega_{ijt} \overline{P_{jtmonth}}$$

P_{it} is actual pollution in target city i on date t. The coefficient of interest is ψ and captures the effect of pollution from upwind source cities on the target city. $P_{source_{it}}$ is an index that proxies the amount of pollution expected imported into target city i from source cities on a particular day. It is important that the construction of this index is fully understood, so that we will describe its components in some detail. Validity of the instrument will require that the only way in which wind directions influence sleep patterns in the target city is through induced changes in target city air quality.

$\overline{P_{jtmonth}}$ is the mean level of pollution in source city j in the associated month. In other

[15] Bayer et al. (2009) exclude the distant sources within 80km, Zheng et al. (2014) within 120km. In their study of medium-term health effects of $PM_{2.5}$ and SO_2, Barreca, Neidell and Sanders (2017) allow for the transport of pollution from a single power station up to 100 miles (161 km). We also tried the different cut-off distances with 100 to 300km, but the instrument is not strong enough because of the uncertainty embedded in long-distance travel.

words a measure of how 'potent' a particular source is as a supplier of pollution. As is well known, transport of pollution from source to target city on a particular day depends upon wind direction and speed. In particular, other things being equal, imports of pollution from city j by air to city i are greater when: (a) the city is close, (b) windspeed is high on a particular day, and (c) the angle between wind direction and an imaginary line joining the two cities is narrow (Zahran et al., 2017; Anderson, 2015; Schlenker and Walker, 2016). The vector of weights ω_{ijt} capture this. In particular we weight the source cities by inverse-distance (Equation 3), where geographical distance is adjusted to allow for windspeed and angle (Equation 4).

$$\omega_{ijt} = \frac{\frac{1}{trans_{jt}}}{\sum_j^J \frac{1}{trans_{jt}}} = \sum_j^J \frac{\frac{1}{trans_{jt}}}{\frac{1}{trans_{1t}} + \frac{1}{trans_{2t}} + \frac{1}{trans_{3t}} + ... + \frac{1}{trans_{Jt}}}, \tag{3}$$

where

$$trans_j = \frac{dj}{windspeed_i * \cos|\phi_i - \phi_j|_{>0}} \tag{4}$$

Wind direction can vary during the course of a day. We use daily average direction constructed from hourly data, consistent with first principles and most existing studies (including Schlenker and Walker (2016) and Herrnstadt et al. (2016)). Only positive values of $\cos|\phi_i - \phi_j|$ are included when the index is calculated, *i.e.* attention is limited to source cities that are (not necessarily directly) downwind on any particular day.[16] This occurs where the difference between wind direction and the direction of the vector between cities j and i is

[16]The angle between wind direction and the line joining the central points of cities i and j is $|\phi_i - \phi_j|$. All angles are measured in degrees clockwise from due North (0° and 360° equal North). The cosine transformation implies a particular weighting to sources at different angles. Recall that the cosine of zero degrees is 1, cosine of 20 degrees is 0.93, cosine of 60 degrees is 0.5 and so on. So other things being equal, a source 60 degrees off the wind line carries half the weight as a source that is directly upwind. The weighting is consistent with first principles (Anderson, 2015). In our unreported analysis, the results are also qualitatively robust to dropping the weighting scheme altogether. As would be expected the precision of estimates is compromised, though significance of results is maintained.

less than 90 degrees. In a robustness check we find that results are largely undisturbed if we instead limit to those where the difference is no greater than 60 degrees. The complexities of pollution transport by wind do not allow us to specify fully the process whereby pollution from one city influences air quality in another, but the functional form here is a simplified version standard in modelling of this sort. For a recent application, the analysis here coincides with Schlenker and Walker (2016), who account for the cosine of variation of wind direction from point source (airport) to the centre point of zipcode. Importantly, it is unlikely that the precise functional form adopted here would influence the defensibility of the exclusion restriction. Moreover, we will try some alternatives for the purposes of robustness later. The relevance of the instrument is assessed statistically at the first stage.

Lagged instrumental variable As noted, in our base specifications, we limit attention to source cities located 100 to 200 km from the target city ($100km < d_{ij} < 200km$). Airborne pollutants leaving one city take more time to transport over a greater distance, which points to a delayed impact on the target. Our primary measure of pollution is average ambient concentrations from midnight to midnight, and the outcome of interest is sleeplessness in pursuant night (11 pm to 7 am). With average wind speed in the sample at around 8 km/h transport of air from a city at distance of 100 km would take over 12 hours, from 200km over 24 hours. To capture this lagged effect in some specifications, we include a one-day lag,

$$P_{it} = \eta_0 + \psi_{it-1} \sum_{j}^{J} \omega_{ij(t-1)} \overline{P_{j(t-1)month}} + \psi_{it} \sum_{j}^{J} \omega_{ijt} \overline{P_{jtmonth}} + W_{it}\gamma + \theta_i + \lambda_t + \epsilon_{it} \tag{5}$$

We expect each of the coefficients ψ_{it-1} and ψ_{it} to be positive and similar in order of magnitude. In unreported analysis we have tried alternative specifications with additional lags without disturbing results discernibly.

4 Results

4.1 Ordinary least squares

Table 4 reports the coefficients from estimating equation (1) using OLS regression model for AQI (Panel A) and $PM_{2.5}$ (Panel B), where the dependent variable is log form of sleeplessness, and the independent variable of interest is daily pollution. Each of the 14 coefficients reported in Table 4 is derived from a separate regression. We will talk for now about coefficient magnitudes, and return to interpret the effect size that they imply later.

Standard errors are clustered at city level. As there are only 19 clusters (cities), we use wild cluster bootstrap method (Cameron et al., 2008), one of the most versatile remedies for small numbers of clusters.[17] The likely alternative approaches would have been cluster-adjustment of the t-statistics (Bakirov and Székely, 2006) and pairs cluster bootstrap (Cameron et al., 2008; Harden, 2011).[18]

Column (1) is the sparsest specification and includes only city fixed effects, netting out any unobserved, time-invariant city characteristics (size, Weibo-penetration, building characteristics, etc.). Reading down this column, we see positive coefficients for each pollutant, in most cases significantly stronger than 5%.

From Column (2) to Column (6), we add time controls (year by month fixed effects, city by year fixed effects, city by quarter fixed effects, day of week and holiday fixed effects one by one). As expected, monthly effects have an important impact on sleep. Cities have different characteristics that vary by year and season. Besides, sleep behavior may be expected to be different on weekdays versus weekends, and on holidays versus non-holidays. The inclusion of these has little impact on the estimated coefficients on the pollution regressors in Column (6).

In Column (7) we control for weather effects. The weather controls include bins for

[17] We report P-values based on wild cluster-bootstrap (1000 replications) in brackets. Robust standard errors clustered at city level are reported in parentheses.

[18] Unfortunately, our data are insufficient to generate the estimates under pairs wild bootstrap due to the inclusion of multiple fixed effects.

average temperature and humidity, and linear measures for precipitation, sea-level pressure, and wind speed. Weather effects are known to have a meaningful impact both on sleep (estimates not presented in this table) but, more importantly for us, may affect the strength of the relationship between air quality and sleeplessness. However, after inclusion of time fixed effects and city by time fixed effects, the inclusion of weather controls does not disturb substantially our coefficient estimate of interest. For the part of the empirical analysis based on OLS estimation, Column (7) summarizes the preferred specification.

While the sign and significance obtained for coefficients on all pollutants in this section provide valuable insight, earlier we identified concerns - in particular measurement error related to effective pollution exposure levels - that led us to expect attenuation in estimated coefficient values. Insofar as these concerns are valid we would expect the effects summarized in the last paragraph to *under*-state true effect sizes. To address this concern we will report IV estimates below.

Non-linear effects In order to check for the possible non-linear effects of air pollution on sleeplessness, we incorporate the categorical variables for different levels of pollution in the regression model. AQI and $PM_{2.5}$ are classified into five bins: less than 50, 50 - 100, 100 - 150, 150 - 200 and larger than 200, with the first group serving as the reference group. In Table 5, the coefficients display evidence of an increasing effect at higher pollution levels. Compared to the reference group, a realization $PM_{2.5}$ between 100 and 150 $\mu g/m^3$ causes an increase in sleeplessness of 3.5%, 150 to 200 an increase of 6.2% and 200 plus an increase of 8.4%. Notice that the effects are close to their linear counterpart, which motivates our use of the linear specifications elsehwere in the paper. They are also comparable with the effects obtained by linear OLS, namely 4.3%, 6.5% and 8.6% respectively.[19]

We also plot the points estimates and the corresponding 95% confidence intervals in Figure 1. Graphs (a) and (b) depict the estimates reported in Table 5 with 50 unit as the width of each bin. Graphs (c) and (d) repeat the exercise but with bins 25 units in width.

[19] 4.3% is calculated by multiplying the coefficient under the preferred estimation in Column (7) by 100.

4.2 Instrumental variable

The main IV results are reported in Table 6. From Columns (1) to (4), all the regressions include the full suite of controls which are shown under the preferred specification in Column (7) of Table 4. Each column reports the outcome of a separate regression, and for $PM_{2.5}$ and AQI, we run alternatives without and with the lagged instrument included in the first stage (odd and even numbered columns respectively).

The dependent variable in the first stage is daily-mean pollutant in target city i, and the IV is the weighted average pollution of surrounding source cities. Recall that cities are included if they are between 100km and 200km in the upwind direction, where upwind is defined as within 90 degrees of the average within-day wind direction.

The first stage estimation works well. We find a strong effect of variations in pollution in source (upwind) cities on the target city. In each case significance is achieved at better than the 1% level. The lagged pollutant measure is also significant in both cases, as anticipated. The Kleibergen-Paap-Wald-F statistic in each of the four first-stages are high enough compared to the Stock-Yogo weak ID test critical values (10% maximal IV size) listed below. So we have no concerns about weak instruments.

The second stage replicates the preferred OLS specification, regressing the daily sleeplessness measure on the predicted level of pollution obtained from the first stage. Comparing the coefficients in the odd and even columns, the lagged pollution measure 'matters' in the first stage; its inclusion has a little decease impact on coefficient of interest in the second.

The estimates under stronger instruments with larger F-statistics are chosen to be our preferred specifications, which are listed in odd column of Table 6.[20] In each case the estimated coefficients are four times larger in absolute size than those derived from OLS, consistent with our expectation that the estimates from the latter were attenuated.

A one standard deviation increase in $PM_{2.5}$ causes an increase in sleeplessness equal to

[20] In addition, and following Schlenker and Walker (2016) Table 1, we explore the possibility that pollution may be dispersed by high winds by adding an interaction term $P_{source_{it}} * windspeed_{it}$ to our preferred first-stage specification. This has little impact on results - summarized in the Appendix Table A10.

12.8% of the daily mean. For AQI a one standard deviation increase causes a similar increase in sleeplessness, amounting to 11.6% of mean level.

5 Robustness and falsification

5.1 Wind direction

In developing the instrument, to be considered 'upwind', the angle between the wind line and a straight line drawn between source and target city had to be less than 90 degrees (*i.e.* $|\phi_i - \phi_j| < 90°$). Since source cities are described by their monthly average pollutant characteristics, and locations do not move, the only variation in source city across dates comes from plausibly exogenous day-to-day variations in wind direction. As such it is important to check that alternative definitions of 'upwind' would not deliver a substantially different result.

In Table 7 we report the results of re-estimating the preferred IV specification but with cities selected as sources if they lie within a narrower, 60 degree angle of the wind line (*i.e.*, $|\phi_i - \phi_j| < 60°$). The results from the first stage maintain significance at the 1% level, but decrease a bit in magnitude for both odd and even columns due to the loss of that part of the information at $60° < |\phi_i - \phi_j| < 90°$. The second stage regression looks very similar to those reported in Table 6. Significance and coefficient values are little disturbed.[21]

5.2 Reduced form

Table 8 reports the results of the reduced form estimation corresponding to our preferred IV specification. Columns (1) and (2) reproduce the OLS and IV results respectively. The coefficients in Column (1) coincide with Column (7) from the OLS regressions in Table 4. Column (2) repeats the second stage results under the odd columns in Table 6. Column (3)

[21]The F-statistics from the first stages are somewhat smaller, though still good. This reflects the fact that building the instrument on a basis that excludes source cities at $60° < |\phi_i - \phi_j| < 90°$ means that we lose part of correlation of the instrument with target city pollution.

reports the reduced form exercise in which $P_{source_{it}}$ is the regressor of interest in an OLS regression with lnS_{it} as the dependent variable. In other words from:

$$lnS_{it} = \alpha_0^{'} + P_{source_{it}}\beta_{up} + W_{it}\gamma^{'} + \theta_i + \lambda_t + \epsilon_{it}^{'} \tag{6}$$

Again, each coefficient presented in this table comes from a different regression. As expected, the estimates from the upwind variant remain significant - the usual reduced form ‘works’.

5.3 Alternative fixed effects

Our preferred estimation accounts for a suite of fixed effects, including year by month, city by year, city by quarter, day of week and holiday. Table 9 re-conducts the OLS regression using alternative fixed effects. Each of the eight coefficients comes from a separate regression. Column (1) reprints the outcomes reported in Column (7) of Table 4. Column (2) adds date-of-observation fixed effects, which helps to account for likely daily heterogeneity in economic activity. Column (3) further controls the variations from the differential trends by week of year, replacing year by month fixed effects in Column (1) with year by week fixed effects. Column (4) replaces city by quarter fixed effects with city by month fixed effects. Results are consistent across specifications. Similarly, we re-estimate the IV regressions in table 10.[22] Again, second stage results vary only a little between columns.

5.4 Precipitation

The confounding role of rain is a potentially important challenge to our inference. Introspection suggests that rainfall - either contemporaneously, or lagged through effect on mood etc. - might plausibly inhibit sleep. While we include controls for daily-average pre-

[22] City by month fixed effects are not considered under IV because they render our instrument weak.

cipitation amongst our weather controls, we further probe this possibility by conducting two sub-sample exercises.

First, we re-estimate our preferred specifications on that sub-sample of days on which recorded night-time precipitation (from 11 pm to 7 am) in the target city is zero. This causes us to lose around 21% of the sample. The results of this exercise are reported in Column (2) of Table 11 and in Column (2) of Table 12 for OLS and IV respectively. Results are little disturbed. This implies that the effects observed are not driven by contemporaneous rainfall.

Second, we re-estimate our preferred specifications on that sub-sample of days on which recorded precipitation during the night in question *and* the whole of the preceding calendar day in the target city is zero. This causes us to lose around 34% of the sample. The results of this exercise are reported in Column (3) of Table 11, and Column (3) of Table 12 for OLS and IV respectively. The signs and magnitudes of the coefficients are in all cases quite similar (the IV estimates in each case in fact become somewhat larger than those derived from the whole sample). The level of statistical significance obtained is sustained in almost all cases - better than might have been anticipated given the considerable erosion of sample size.

5.5 Beijing and environs, Shanghai and environs, Guangzhou and environs

While we derive results from a panel of the 19 most populous cities in China, a further concern might be that the results are driven by a small subset of the cities. In an unreported exercise we re-estimate our preferred specifications on restricted samples of cities, dropping each individually in turn, and in no case do we observe more that slight disturbances in our results. However, in this section, we report the impact of dropping clusters of cities that may exhibit particular features that might be driving the results. In particular, first, we exclude the cities of Beijing and Tianjin (the Beijing-Tianjin corridor is the country's most heavily industrialized 'rust-belt' area (Shao et al., 2006); second, separately we exclude the cluster of the south-eastern coastal cities of Shanghai, Hangzhou and Suzhou, as well as southern coastal cities of Guangzhou, Shenzhen and Dongguan (these are less polluted, less industrialized, and more influenced by coastal effects).

The results of these exercises are summarized from Columns (2) to (4) of Appendix Tables A14 and A15 for OLS and IV respectively. Again, the results are little-disturbed. The first stage regressions continue to work well, and the second stage estimates are largely robust.

It is also concerned that whether air pollution remains its health effect across the 19 cities in the sample. Both OLS and IV estimators of individual city are reported in Appendix Tables A16 and A17 for AQI, and A18 and A19 for $PM_{2.5}$ respectively. Although the magnitude of the effects varies across the cities, most of them still have a significant impact on city sleeplessness.

5.6 Alternative standard errors

In the calculation of standard errors in the main tables, we chose to cluster at the city level, judging this to account for the potential correlations among regressors and errors within clusters. However, this approach delivers only nineteen clusters (each with around 730 observations), which Angrist and Pischke (2008) suggest may be too few. Cameron et al. (2008) show that small cluster numbers can bias downwards cluster-robust standard errors, leading researchers to overstate the statistical significance of results. To address this we use the wild cluster bootstrap technique for the results in our main tables (Cameron et al., 2008; Esarey and Menger, 2015).

We also supplement the analysis with more clusters by using cluster-robust standard errors at city by year by season (152 clusters), city by year by month (456 clusters) and city by year by week (1976 clusters) to explore whether our conclusions would have been changed substantially by such alternative approaches. The results are displayed in Appendix Tables A11, A12 and A13 for OLS and IV respectively. All the estimators retain significance at conventional levels (in almost all cases at better than 1%).

A separate concern related to standard errors is that spatial correlation can in some circumstances bias standard errors and so invalidate inference (Hoechle, 2007). To investigate this possibility in our setting, we apply the methods of Driscoll and Kraay (1998). They introduce a non-parametric covariance matrix estimator for which standard errors are assumed to be heteroscedastic, auto-correlated with $MA(q)$ within panel (each city), and potentially correlated among panels. The method is appropriate for panels with small numbers of panels (in our case 19) but many observations per panel (730). The results of this exercise (for $q = 7$, though very similar results emerge with different values) are reported in Column (2) of Tables A11 to A13. Again statistical significance is maintained at conventional levels.

6 Placebos

The air pollution of our target city is instrumented by the daily weighted average pollutants of source cities upwind. The exogeneity of our instrument would be threatened if there were unobserved (and therefore uncontrolled for), daily-varying factors that are correlated between source and target cities and cause pollution in both places. For example, daily variations in traffic density could be correlated across cities source and target cities.

A number of elements of our design, however, point to this not being a big problem. First, we exclude potential source cities within 100 km of the target, and these sorts of correlations are likely to be less pronounced over longer distances (think of the traffic spike caused by a major sporting event, for example). Second, the potency or 'dirtiness' of a particular city as a source of exported pollution is based on a long-run, *monthly* average measure of air pollution in that city. As such daily variations in the instrument are - by construction - *not* driven by daily or short-term variations in pollution levels in the source city. As such the variation in daily contribution of distant sources to air quality in a particular target city should be driven only by variations in wind direction.

However, to further test the instrument we conduct two placebo tests, replacing wind directions in the vicinity of each target city with placebo series of irrelevant wind directions. The tests differ in how we generate the irrelevant or placebo wind data. First, we scramble the wind directions within our sample of Chinese cities by using a reverse-alphabetical assignment. For example Beijing, the first city in our sample when listed alphabetically, is falsely-assigned the wind direction series from Zhengzhou, which appears last, and so on.[23] Second, we conduct an out-of-sample placebo. To do this we draw wind directions from US cities (19 largest cities by population), which we matched based on alphabetical assignment. For example, the first city in our sample (Beijing) is falsely-assigned the wind direction in the first-alphabetical US city (Austin). The fifth city, Dongguan, has the wind direction from Dallas in US sample, and so on.

The results of these exercises are reported in Table 13. We can see that in each case, the first-stage regression breaks down comprehensively. This provides compelling evidence that the variation in target-city pollution in our IV specifications is driven by (plausibly exogenous) variations in wind direction, not by correlated day-to-day variations in local air quality conditions in source and target cities.

7 Joint estimation

Disentangling the independent effects of particular pollutants is a challenge for research on both health and non-health outcomes. Various authors have addressed the problem in different ways; typically this involves excluding a subset of the potentially confounding substances altogether (often due to data limitations). If pollutants tend to positively covary then this leads to effects being loaded onto that pollutant or subset of pollutants that are included.[24]

[23] For the middle one, we replace that using wind direction in Beijing.

[24] A different approach taken in some recent work (for example Gendron-Carrier et al. (2017)) exploits data from NASA satellites that measures Aerosol Optical Depth (AOD). AOD in effect measures how optically 'thick' the air is over a particular GIS point, but does not allow for pollutant-by-pollutant inference.

Ambient levels of the various pollutants (with the exception of ozone) covary positively.[25] Some of the pollutants are precursors in the production of ozone. Furthermore the overall impact of a particular cocktail of pollutants may depend upon their mixture in complex ways. This leads us to be cautious in interpreting the results reported thus far. Taken collectively we believe that the results presented in Tables 4 though 13 provide a compelling case that polluted air has a causal impact on city-level sleep quality. While we have focussed on $PM_{2.5}$ and the multi-pollutant AQI measure, for completeness we summarize in Table 14 the results of additional joint estimation exercises.

Columns (1) and (3) report the OLS and IV results from estimation of our preferred specifications on each single pollutant ($PM_{2.5}$, CO, NO_2 and O_3) in turn. Column (2) reports the results of including the four pollutants in an OLS regression simultaneously - the so-called 'horse-race' regression. As in Schlenker and Walker (2016), signs become mixed. $PM_{2.5}$ remain its positive sign and retains significance at the 3.7% level.

Column (4) follows the method proposed by Schlenker and Walker (2016), Knittel et al. (2016) and Sager (2016).[26] In our case, different pollutants are instrumented by their corresponding levels in source cities, and the instrumented pollution levels are then included simultaneously in the same regression.[27] The coefficient on $PM_{2.5}$ remains positive and is comparable in magnitude to those from the single pollutant exercises; significance is maintained at better than 1%.

An alternative approach - adopted by Moretti and Neidell (2011) - is to instrument for one pollutant at a time, in each case including the other pollutants, uninstrumented, as linear controls in both the first and second-stage regressions.[28] In that case the coefficient on the instrumented pollutant is unbiassed, though those on the control pollutants are not. Column

[25] In our dataset, the correlation between $PM_{2.5}$ and CO is 0.709, between $PM_{2.5}$ and NO_2 is 0.669, and between CO and NO_2 is 0.584.

[26] Only pollutants with strong instrument are included in the joint estimation, otherwise it is presented by "-". See the first stage results in Appendix Table A22 from Column (1) to Column (4).

[27] To be clear, while each coefficient in Columns (1), (3) and (5) is derived from a separate regression, Column (2) and (4) each report a single regression.

[28] More concretely, Moretti and Neidell (2011) instrument for ozone, and include controls (uninstrumented) for CO, O_3 and NO_2. They do not include measures for particulate matter.

(5) reports the results of conducting that exercise repeatedly, with each pollutant in turn being the one that is subject to instrumentation.[29] Under this alternative approach, $PM_{2.5}$ remains significant at the 5% level with an associated coefficient estimate that is somewhat larger than in our preferred specification.

8 Conclusions

Sleep is a central contributor to human well-being, and its disturbance has been linked to a wide set of negative outcomes. If pollution in a city has a significant detrimental impact on how the inhabitants of that city sleep, this would imply a hitherto unaccounted for social cost of air pollution. Understanding the full range of channels through which pollution effects welfare - and by implication the benefits of clean air - is a prerequisite for the design of welfare-maximising policy interventions in this area.

We provide what we believe to be the first evidence that air pollution on a particular day has a causal impact on sleep quality in a city on the following night. The estimated effect is substantial. For the composite air quality index (AQI), notionally moving from a median clean decile day to a median dirty day (in other words from the 5th to the 95th percentile when days are ranked from clean to dirty) increases city-level sleeplessness by 36.3% of its mean value. For $PM_{2.5}$ that number is 37.3%. The estimates prove to be robust to a wide set of checks.

The analysis provides further evidence of the susceptibility of individual and social outcomes to anthropogenic pollution. We have argued that sleep loss is an important outcome in its own right, but also that it can provide a mechanism to underpin a suite of less proximate outcomes identified in recent research. Further validation of the results, using alternative metrics and instruments, is planned in future research.

[29] Only pollutants with strong instrument are included in the joint estimation, otherwise it is presented by "-". See the first stage results in Appendix Table A22, Columns (5) through (8).

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Table 1: Summary Statistics

	Obs	Mean	Std. Dev.	Min	Max
Sleeplessness Index	13870	798.306	5226.540	12	301569
AQI	13620	92.598	52.202	12	486.5
PM2.5 ($\mu g/m^3$)	13620	61.810	44.993	0	884
CO (mg/m^3)	13620	1.117	0.555	0	12.6
NO2 ($\mu g/m^3$)	13620	44.706	18.717	0	171
SO2 ($\mu g/m^3$)	13620	25.050	25.332	0	335
O3 ($\mu g/m^3$)	13620	91.101	49.431	0	294
Temperature ($^{\circ}C$)	13870	16.869	9.814	-21.9	34.8
Humidity (%)	13870	69.481	16.450	7.875	99.5
Sea-level Pressure (hPa)	13870	1016.262	9.378	983.2	1054.5
Wind Speed (Km/h)	13870	7.944	3.598	1	33
Precipitation (mm)	13870	3.35	11.253	0	204.8

Notes: The dataset contains daily data from 19 target cities from 2014 to 2015.

Table 2: Air Quality Index (AQI) and Pollutant Concentrations

	Level	Description	AQI	PM2.5 (24hr) ($\mu g/m^3$)	Number of Days (AQI)	Percent
Low	I	Excellent	0-50	0-35	2145	15.75%
	II	Good	51-100	36-75	7090	52.06%
Medium	III	Light Polluted	101-150	76-115	2801	20.57%
		Moderately Polluted	151-200	115-150	912	6.70%
High	IV	Heavily Polluted	201-300	151-250	578	4.24%
	V	Severely Polluted	301-500	251-500	94	0.69%

Notes: The table maps $PM_{2.5}$ to AQI categories. Classification principles are taken from the *Technical Regulation on Ambient Air Quality Index HJ 633-2012*. Levels I and II do not have health implications, and are thus suitable for outdoor activities. Higher levels of pollutants leads to higher risk of breathing or heart problems. Outdoor exercise should be reduced. Level V may induce respiratory diseases, and outdoor exposure is to be avoided for elderly and sick people. The last two columns report the number of days and corresponding percentage of days falling into each category in the sample.

Table 3: Correlations between Pollutants

	AQI	PM2.5	PM10	CO	NO2	SO2	O3
AQI	1.000						
PM2.5	0.957	1.000					
PM10	0.896	0.875	1.000				
CO	0.672	0.709	0.672	1.000			
NO2	0.640	0.669	0.658	0.584	1.000		
SO2	0.490	0.498	0.522	0.496	0.508	1.000	
O3	0.008	-0.125	-0.064	-0.313	-0.155	-0.223	1.000

Notes: The table displays correlation matrix of pollutants in the dataset.

Table 4: Air Quality and Sleeplessness — OLS

Independent Variable Daily Pollutant	Dependent Variable Ln(Sleepless)						
	City FEs	Temporal Controls					Weather Covariates
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: AQI	0.050***	0.056**	0.055***	0.041**	0.040**	0.038**	0.037***
	(0.017)	(0.022)	(0.018)	(0.014)	(0.014)	(0.014)	(0.012)
	[0.010]	[0.029]	[0.008]	[0.021]	[0.025]	[0.034]	[0.001]
Panel B: PM2.5	0.043*	0.056**	0.057***	0.049***	0.046**	0.044**	0.043***
	(0.021)	(0.018)	(0.015)	(0.016)	(0.016)	(0.016)	(0.017)
	[0.072]	[0.019]	[0.007]	[0.011]	[0.021]	[0.030]	[0.012]
Observations	13617	13617	13617	13617	13617	13617	13617
Additional Controls							
City FEs	Y	Y	Y	Y	Y	Y	Y
Year by month FEs	N	Y	Y	Y	Y	Y	Y
City by year FEs	N	N	Y	Y	Y	Y	Y
City by quarter FEs	N	N	N	Y	Y	Y	Y
Day of Week FEs	N	N	N	N	Y	Y	Y
Holiday FEs	N	N	N	N	N	Y	Y
Weather Covariates	N	N	N	N	N	N	Y

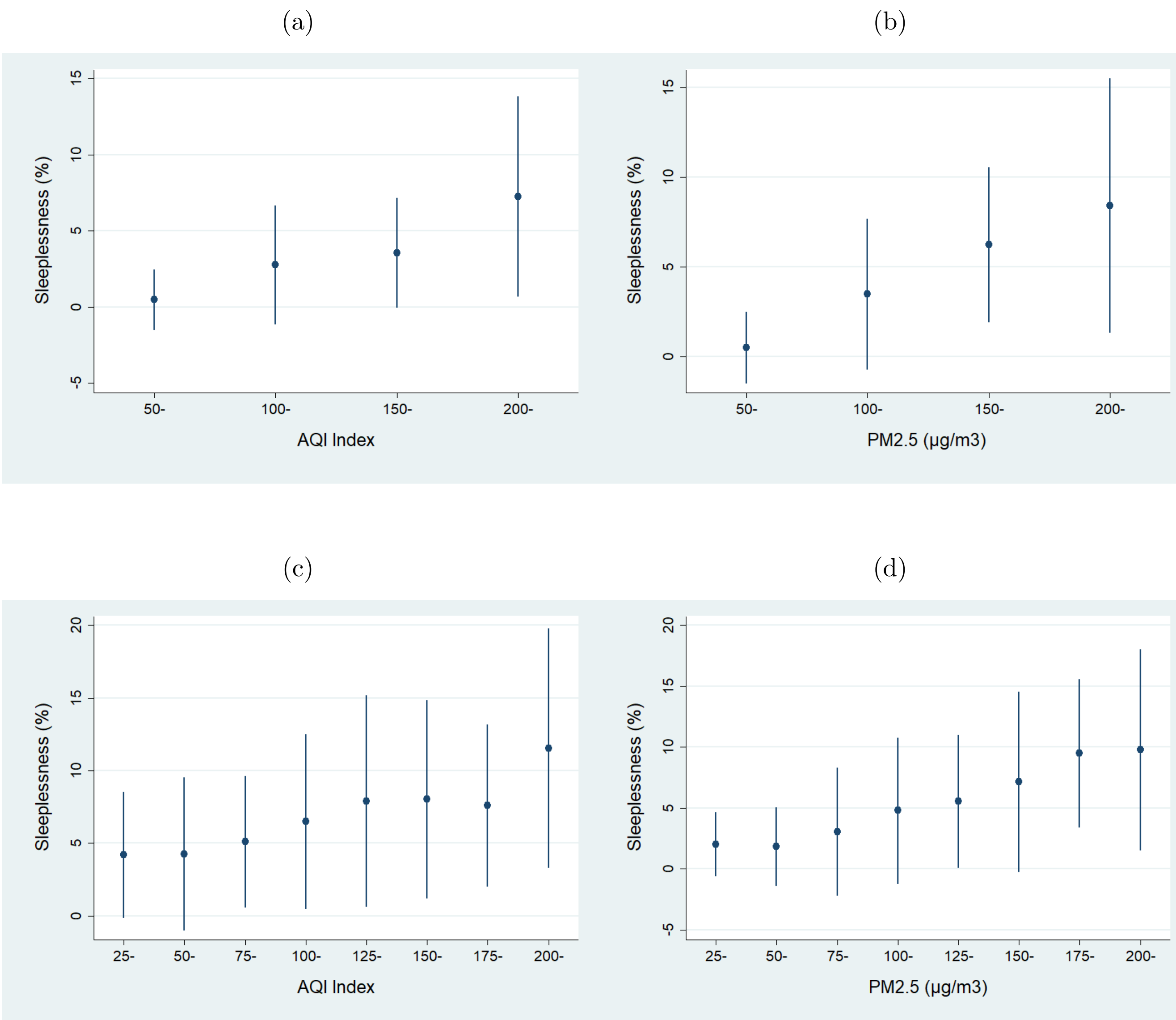
Notes: Dependent variable is log form of Sleeplessness Index. Data collection period runs from 11pm to 7am. Independent variable of interest is daily average measure of specific pollutant. All estimators have been adjusted into percentage by multiplying 100. Temporal controls include year by month fixed effects, city by year fixed effects, city by quarter fixed effects, as well as day of week and holiday fixed effects. Weather controls contain temperature, humidity, precipitation, wind speed and sea-level pressure. Temperature and humidity are measured by the way of bins (5 degree C indicators for average temperature, 20 percent indicators for average humidity). Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table 5: Non-linear Effects

	AQI	PM2.5
	(1)	(2)
AQI/PM2.5 <50 Omitted		
[50, 100)	0.483	0.504
	(0.932)	(0.942)
	[0.749]	[0.622]
[100, 150)	2.766*	3.493*
	(1.839)	(1.992)
	[0.094]	[0.060]
[150, 200)	3.561**	6.231***
	(1.702)	(2.043)
	[0.044]	[0.002]
>200	7.264**	8.411**
	(3.112)	(3.368)
	[0.021]	[0.051]
Observations	13617	13617
Additional Controls		
City FEs	Y	Y
Year by month FEs	Y	Y
City by year FEs	Y	Y
City by quarter FEs	Y	Y
Day of week FEs	Y	Y
Holiday FEs	Y	Y
Weather Covariates	Y	Y

Notes: This table reports the non-linear effects of pollutants on sleeplessness, with AQI and $PM_{2.5}$ incorporated in the form of bins (50 units in each bin). All the regressions include city fixed effects, temporal controls, and weather covariates. Temperature and humidity are measured in the form of bins. Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Figure 1: Non-linear Effects



Notes: This diagram displays the estimates of non-linear effects of AQI and $PM_{2.5}$. Graphs (a) and (b) plots the point estimates reported in Table 5, as well as the corresponding 95% confidence intervals. (c) and (d) break the pollutant into more bins with 25 units per bin, and re-estimate the effects in the same way as Table 5 did.

Table 6: Air Quality and Sleeplessness — IV

2SLS	AQI (1)	AQI (2)	PM2.5 (3)	PM2.5 (4)
First Stage[(a)]				
Instrumental Pollution t	0.455***	0.181***	0.463***	0.201***
	(0.062)	(0.034)	(0.061)	(0.032)
	[<0.01]	[<0.01]	[<0.01]	[<0.01]
Instrumental Pollution lagged t-1		0.514***		0.50***
		(0.059)		(0.065)
		[<0.01]		[<0.01]
Kleibergen-Paap rk Wald F statistic	54.791	52.868	56.846	46.156
Stock-Yogo weak ID test critical values: 10% maximal IV size	16.38	19.93	16.38	19.93
Second Stage[(b)]				
Instrumented Pollution	0.223**	0.149**	0.285**	0.213**
	(0.096)	(0.075)	(0.118)	(0.098)
	[0.039]	[0.045]	[0.033]	[0.045]
Observations	12904	12579	12989	12662
Additional Controls				
City FEs	Y	Y	Y	Y
Year by month FEs	Y	Y	Y	Y
City by year FEs	Y	Y	Y	Y
City by quarter FEs	Y	Y	Y	Y
Day of week FEs	Y	Y	Y	Y
Holiday FEs	Y	Y	Y	Y
Weather Covariates	Y	Y	Y	Y

Notes: (a) Dependent variable in the first stage is daily-mean pollutant of target city, and independent variable is daily weighted average pollution of surrounding cities ($100km < d_{ij} < 200km$) from upwind direction (within 90 degree to the wind). (b) Second stage reports the results regressing the log form of Sleeplessness Index on the instrumented daily pollution with estimators being adjusted into percentages by multiplying by 100. Columns (2) and (4) incorporate the day before variable as an additional instrument. Temporal controls include year by month fixed effects, city by year fixed effects, city by quarter fixed effects, as well as day of week and holiday fixed effects. Weather controls contain temperature, humidity, precipitation, wind speed and sea-level pressure. Temperature and humidity are measured by the way of bins. Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table 7: Robustness — IV with 60 Degree Wind Angle Inclusion

2SLS	AQI		PM2.5	
	(1)	(2)	(3)	(4)
First Stage[a]				
Instrumental Pollution t	0.378***	0.175***	0.392***	0.200***
	(0.077)	(0.033)	(0.078)	(0.032)
	[<0.01]	[<0.01]	[<0.01]	[<0.01]
Instrumental Pollution lagged t-1		0.437***		0.433***
		(0.077)		(0.078)
		[<0.01]		[<0.01]
Kleibergen-Paap rk Wald F statistic	23.883	23.415	25.092	23.919
Stock-Yogo weak ID test critical values: 10% maximal IV size	16.38	19.93	16.38	19.93
Second Stage[b]				
Instrumented Pollution	0.250**	0.173*	0.306**	0.234**
	(0.098)	(0.079)	(0.114)	(0.097)
	[0.038]	[0.057]	[0.030]	[0.034]
Observations	11944	11049	12021	11116
Additional Controls				
City FEs	Y	Y	Y	Y
Year by month FEs	Y	Y	Y	Y
City by year FEs	Y	Y	Y	Y
City by quarter FEs	Y	Y	Y	Y
Day of week FEs	Y	Y	Y	Y
Holiday FEs	Y	Y	Y	Y
Weather Covariates	Y	Y	Y	Y

Notes: (a) Dependent variable in the first stage is daily-mean pollutant of target city, and independent variable is the daily weighted average pollution of surrounding cities ($100km < d_{ij} < 200km$) from upwind direction (within 60 degree to the wind). (b) Second stage reports the results regressing the log form of Sleeplessness Index on the instrumented daily pollution. Columns (2) and (4) incorporate the day before measure as an additional instrument. Temporal controls include year by month fixed effects, city by year fixed effects, city by quarter fixed effects, as well as day of week and holiday fixed effects. Weather controls contain temperature, humidity, precipitation, wind speed, and sea-level pressure. Temperature and humidity are measured by the way of bins. Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table 8: Reduced Form

	OLS	IV	Reduced Form
	(1)	(2)	(3)
Panel A: AQI	0.037***	0.223**	0.102**
	(0.012)	(0.096)	(0.044)
	[0.001]	[0.039]	[0.039]
Observations	13617	12904	13093
Panel B: PM2.5	0.043***	0.285**	0.132**
	(0.017)	(0.118)	(0.055)
	[0.012]	[0.033]	[0.033]
Observations	13617	12989	13179
Additional Controls			
City FEs	Y	Y	Y
Year by month FEs	Y	Y	Y
City by year FEs	Y	Y	Y
City by quarter FEs	Y	Y	Y
Day of week FEs	Y	Y	Y
Holiday FEs	Y	Y	Y
Weather Covariates	Y	Y	Y

Notes: Column (1) repeats the OLS results of Column (7) in Table 4. Column (2) repeats the second stage results under Column (1) and Column (3) in Table 6. Column (3) presents the results of reduced form regressing the log form of daily Sleeplessness Index on daily weighted average pollutant of peripheral cities ($100km < d_{ij} < 200km$) from the upwind direction (within 90 degree to the wind). All the regressions include city fixed effects, temporal controls (year by month fixed effects, city by year fixed effects, city by quarter fixed effects, as well as day of week and holiday fixed effects) and weather controls (average temperature bins, average humidity bins, precipitation, sea-level pressure, and wind speed). Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table 9: Alternative Fixed Effects — OLS

	(1)	(2)	(3)	(4)
Panel A: AQI	0.037***	0.041***	0.032***	0.025***
	(0.012)	(0.013)	(0.011)	(0.008)
	[0.001]	[<0.01]	[0.001]	[0.010]
Panel B: PM2.5	0.043***	0.046***	0.036***	0.027*
	(0.017)	(0.018)	(0.016)	(0.012)
	[0.012]	[0.008]	[0.013]	[0.060]
Observations	13617	13617	13617	13617
Additional Controls				
City FEs	Y	Y	Y	Y
Year by month FEs	Y	Y	N	Y
City by year FEs	Y	Y	Y	Y
City by quarter FEs	Y	Y	N	N
City by month FEs	N	N	N	Y
Year by week FEs	N	N	Y	N
Date FEs	N	Y	N	N
Day of week FEs	Y	Y	Y	Y
Holiday FEs	Y	Y	Y	Y
Weather Covariates	Y	Y	Y	Y

Notes: This table re-runs the OLS estimation for AQI and $PM_{2.5}$ under various sets of fixed effects. Column (1) replicates the preferred OLS results of Column (7) in Table 4. Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table 10: Alternative Fixed Effects — IV

	AQI			PM2.5		
	(1)	(2)	(3)	(4)	(5)	(6)
First Stage						
Instrumental Pollution t	0.455***	0.518***	0.455***	0.463***	0.522***	0.462***
	(0.062)	(0.046)	(0.059)	(0.061)	(0.048)	(0.058)
	[<0.01]	[<0.01]	[<0.01]	[<0.01]	[<0.01]	[<0.01]
Kleibergen-Paap rk Wald F statistic	54.791	130.600	60.317	56.846	117.546	62.509
Stock-Yogo weak ID test critical values: 10% maximal IV size	16.38	16.38	16.38	16.38	16.38	16.38
Second Stage						
Instrumented Pollutant	0.223**	0.200*	0.204**	0.285**	0.264*	0.264**
	(0.096)	(0.097)	(0.092)	(0.118)	(0.121)	(0.113)
	[0.039]	[0.063]	[0.044]	[0.033]	[0.056]	[0.045]
Observations	12904	12904	12904	12989	12989	12989
Additional Controls						
City FEs	Y	Y	Y	Y	Y	Y
Year by month FEs	Y	Y	N	Y	Y	N
City by year FEs	Y	Y	Y	Y	Y	Y
City by quarter FEs	Y	Y	N	Y	Y	N
City by month FEs	N	N	N	N	N	N
Year by week FEs	N	N	Y	N	N	Y
Date FEs	N	Y	N	N	Y	N
Day of week FEs	Y	Y	Y	Y	Y	Y
Holiday FEs	Y	Y	Y	Y	Y	Y
Weather Covariates	Y	Y	Y	Y	Y	Y

Notes: This table re-conducts the IV estimation under various sets of fixed effects. Column (1) and Column (4) reprint the preferred second stage results under Column (1) and Column (3) in Table 6. Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table 11: Precipitation Exclusion — OLS

	Full (1)	Clear Nights (2)	Zero Rain Days (3)
Panel A: AQI	0.037***	0.039***	0.049***
	(0.012)	(0.013)	(0.016)
	[0.001]	[0.003]	[<0.01]
Panel B: PM2.5	0.043***	0.044**	0.057***
	(0.017)	(0.017)	(0.021)
	[0.012]	[0.016]	[0.001]
Observations	13617	10774	9051
Additional Controls			
City FEs	Y	Y	Y
Year by month FEs	Y	Y	Y
City by year FEs	Y	Y	Y
City by quarter FEs	Y	Y	Y
Day of week FEs	Y	Y	Y
Holiday FEs	Y	Y	Y
Weather Covariates	Y	Y	Y

Notes: Dependent variable is log form of Sleeplessness Index. Independent variable is city daily-mean value of specific pollutant. Column (1) displays the results for all observations replicating the results under Column (7) in Table 4. Column (2) excludes days with precipitation from 11pm to 7am. Column (3) excludes days with precipitation from 12pm to 7am on the following day. All the regressions include city fixed effects, temporal controls and weather covariates. Temperature and humidity are measured in the form of bins. Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table 12: Precipitation Exclusion — IV

	Full (1)	Clear Nights (2)	Zero Rain Days (3)
	Panel A: AQI		
First Stage			
Instrumental AQI t	0.455***	0.440***	0.454***
	(0.062)	(0.080)	(0.082)
	[<0.01]	[<0.01]	[<0.01]
Kleibergen-Paap rk Wald F statistic	54.791	30.529	30.417
Stock-Yogo weak ID test critical values: 10% maximal IV size	16.38	16.38	16.38
Second Stage			
Instrumented AQI	0.223**	0.225**	0.215**
	(0.096)	(0.094)	(0.084)
	[0.039]	[0.037]	[0.038]
Observations	12904	10207	8560
	Panel B: PM2.5		
First Stage			
Instrumental PM2.5 t	0.463***	0.436***	0.446***
	(0.061)	(0.082)	(0.082)
	[<0.01]	[<0.01]	[<0.01]
Kleibergen-Paap rk Wald F statistic	56.846	28.070	29.399
Stock-Yogo weak ID test critical values: 10% maximal IV size	16.38	16.38	16.38
Second Stage			
Instrumented PM2.5	0.285**	0.284**	0.288**
	(0.118)	(0.116)	(0.104)
	[0.033]	[0.041]	[0.032]
Observations	12989	10280	8633
Additional Controls			
City FEs	Y	Y	Y
Temporal Controls	Y	Y	Y
Weather Covariates	Y	Y	Y

Notes: Column (1) displays IV results for all observations, replicating the results under Column (1) and Column (3) in Table 6. Column (2) excludes the days with snowy or rainy nights. The results in Column (3) limit the sample to clear days without rain or snow in the daytime or nighttime. All the regressions include the same city fixed effects, temporal controls and weather controls as those in Table 6. Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table 13: Placebo Test

	Preferred	Chinese Cities Reverse-alphabetic (wind direction)	US largest Cities (wind direction)
	(1)	(2)	(3)
		Panel A: AQI	
First Stage			
Instrumental AQI t	0.455***	0.063	0.045
	(0.062)	0.093	0.048
	[<0.01]	[0.658]	[0.352]
Kleibergen-Paap rk Wald F statistic	54.791	-	-
Second Stage			
Instrumented AQI	0.223**	-	-
	(0.096)	-	-
	[0.039]	-	-
Observations	12904	12810	13502
		Panel B: PM2.5	
First Stage			
Instrumental PM2.5 t	0.463***	0.081	0.023
	(0.061)	0.088	0.018
	[<0.01]	[0.537]	[0.18]
Kleibergen-Paap rk Wald F statistic	56.846	-	-
Second Stage			
Instrumented PM2.5	0.285**	-	-
	(0.118)	-	-
	[0.033]	-	-
Observations	12989	12896	13502
Additional Controls			
City FEs	Y	Y	Y
Temporal Controls	Y	Y	Y
Weather Covariates	Y	Y	Y

Notes: Column (1) reports the IV estimations from the preferred specification in Table 6. Column (2) and Column (3) re-construct the weights based on the scrambled wind directions in other Chinese cities (reverse-alphabetic order in the sample) and US largest cities, respectively. All the regressions include city fixed effects, temporal controls (year by month fixed effects, city by year fixed effects, city by quarter fixed effects, as well as day of week and holiday fixed effects) and weather controls (average temperature bins, average humidity bins, precipitation, sea-level pressure, and wind speed). Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table 14: Joint Estimation

	OLS		2SLS		
	Single Estimation	Joint Estimation	Single Estimation	Joint Estimation (Schlenker and Walker 2016)	Joint Estimation (Moretti and Neidell 2011)
	(1)	(2)	(3)	(4)	(5)
PM2.5	0.043***	0.041**	0.285**	0.371***	0.519**
	(0.017)	(0.016)	(0.118)	(0.143)	(0.229)
	[0.012]	[0.037]	[0.033]	[0.006]	[0.049]
CO	2.688**	1.030	-	-	-
	(1.135)	(1.570)	-	-	-
	[0.023]	[0.547]	-	-	-
NO2	0.064	-0.024	0.018	-0.551**	-
	(0.041)	(0.047)	(0.220)	(0.250)	-
	[0.171]	[0.674]	[0.944]	[0.032]	-
O3	0.022	0.012	0.072	0.052	0.071
	(0.017)	(0.015)	(0.172)	(0.168)	(0.179)
	[0.261]	[0.521]	[0.835]	[0.854]	[0.834]
Observations	13617	13617	12989	12989	12989
Additional Controls					
City FEs	Y	Y	Y	Y	Y
Temporal Controls	Y	Y	Y	Y	Y
Year by month FEs	Y	Y	Y	Y	Y
City by year FEs	Y	Y	Y	Y	Y
City by quarter FEs	Y	Y	Y	Y	Y
Day of week FEs	Y	Y	Y	Y	Y
Holiday FEs	Y	Y	Y	Y	Y
Weather Covariates	Y	Y	Y	Y	Y

Notes: Column (1) and Column (3) repeat the OLS and IV estimations from the preferred specification in Table 4 and 6. Joint estimations that include co-emission are reported in Column (2), Column (4) and Column (5). Column (4) regresses Sleeplessness Index on different instrumented pollutants together. Column (5) instruments for one pollutant at a time, in each case including the other pollutants, uninstrumented, as linear controls in both the first and second-stage regressions. All the regressions include city fixed effects, temporal controls and weather covariates. Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Online Appendix — Not for Publication

Table A1: Summary Statistics by City

	Beijing (1)	Changsha (2)	Chengdu (3)	Chongqing (4)	Dongguan (5)	Guangzhou (6)	Hangzhou (7)
Sleeplessness Index	5676.008	258.247	458.869	347.193	127.575	3331.537	649.112
	(18024.220)	(58.018)	(92.582)	(78.808)	(26.877)	(12400.320)	(562.917)
AQI Index	119.335	92.860	97.616	85.764	71.122	68.645	93.996
	(76.912)	(52.043)	(54.903)	(45.355)	(36.409)	(31.623)	(43.868)
$PM_{2.5}$ ($\mu g/m^3$)	81.882	67.443	67.006	58.570	40.202	42.988	62.780
	(70.034)	(43.542)	(47.492)	(37.251)	(22.462)	(23.035)	(36.668)
CO (mg/m^3)	1.278	1.026	1.079	1.127	0.878	0.976	1.087
	(0.997)	(0.344)	(0.363)	(0.269)	(0.238)	(0.259)	(0.345)
NO_2 ($\mu g/m^3$)	51.290	37.999	50.815	39.849	37.702	45.168	44.422
	(24.239)	(16.290)	(15.475)	(11.703)	(16.570)	(17.459)	(16.274)
SO_2 ($\mu g/m^3$)	16.605	20.756	16.742	19.638	17.372	14.529	32.338
	(19.585)	(10.794)	(8.407)	(11.792)	(9.014)	(6.364)	(14.689)
$O_3(\mu g/m^3)$	100.085	76.858	90.064	66.825	110.322	89.897	98.223
	(65.199)	(39.527)	(51.312)	(46.810)	(53.341)	(49.914)	(48.935)
Temperature ($°C$)	14.093	18.531	17.125	17.849	22.835	22.317	17.075
	(10.693)	(8.294)	(7.152)	(7.567)	(6.196)	(6.622)	(8.535)
Humidity (%)	52.560	58.076	80.219	78.975	76.225	75.011	74.596
	(19.837)	(16.823)	(8.506)	(10.441)	(10.140)	(12.878)	(12.992)
Sea-level Pressure (hPa)	1016.923	1015.726	1014.542	1014.212	1013.424	1013.655	1016.579
	(10.044)	(9.083)	(8.963)	(9.060)	(6.995)	(7.328)	(9.221)
Wind Speed (Km/h)	7.826	8.185	4.914	6.023	8.327	7.341	6.589
	(2.930)	(4.024)	(1.581)	(1.738)	(3.276)	(3.197)	(2.814)
Precipitation (mm)	1.260	4.007	2.542	3.813	6.447	6.680	3.974
	(5.700)	(10.063)	(8.533)	(10.857)	(16.846)	(18.671)	(10.722)

continued

	Nanjing (8)	Ningbo (9)	Qingdao (10)	Shanghai (11)	Shenyang (12)	Shenzhen (13)	Suzhou (14)
Sleeplessness Index	471.386	141.430	133.243	845.545	206.784	468.010	307.849
	(109.433)	(42.431)	(26.092)	(2498.374)	(45.883)	(151.464)	(226.141)
AQI Index	96.843	71.608	88.059	81.320	104.742	51.551	90.072
	(46.782)	(33.376)	(40.671)	(39.625)	(57.086)	(20.945)	(41.381)
$PM_{2.5}$ $(\mu g/m^3)$	65.151	45.067	52.833	53.053	70.576	31.140	61.765
	(39.841)	(28.382)	(36.993)	(33.542)	(58.055)	(17.731)	(34.119)
CO (mg/m^3)	0.936	0.924	0.926	0.836	1.044	0.978	0.927
	(0.346)	(0.267)	(0.698)	(0.286)	(0.499)	(0.213)	(0.291)
NO_2 $(\mu g/m^3)$	50.200	41.779	36.529	44.465	47.634	32.823	51.744
	(19.145)	(17.972)	(17.297)	(19.910)	(17.768)	(11.581)	(18.590)
SO_2 $(\mu g/m^3)$	20.958	18.707	30.090	17.220	67.358	8.130	20.886
	(12.057)	(10.378)	(18.949)	(9.977)	(67.123)	(3.132)	(10.223)
$O_3(\mu g/m^3)$	100.517	96.606	102.146	102.752	92.272	78.678	97.158
	(53.182)	(39.177)	(40.703)	(42.989)	(48.966)	(32.456)	(48.678)
Temperature $(^\circ C)$	16.828	17.551	14.214	17.261	9.290	24.130	17.261
	(8.495)	(7.556)	(8.996)	(8.220)	(12.749)	(5.605)	(8.220)
Humidity (%)	72.626	79.627	69.600	72.682	59.307	71.594	72.682
	(14.393)	(11.447)	(16.290)	(12.602)	(15.627)	(11.839)	(12.602)
Sea-level Pressure (hPa)	1017.057	1016.565	1017.550	1017.085	1016.625	1013.252	1017.085
	(9.250)	(8.695)	(9.170)	(8.974)	(9.859)	(6.657)	(8.974)
Wind Speed (Km/h)	9.412	7.616	11.823	9.308	8.018	7.579	9.308
	(3.789)	(3.170)	(4.735)	(3.308)	(3.250)	(2.472)	(3.308)
Precipitation (mm)	3.915	4.789	1.490	4.035	1.277	4.424	4.035
	(13.777)	(13.851)	(6.889)	(11.550)	(4.298)	(15.748)	(11.550)

continued

	Tianjin (15)	Wuhan (16)	Wuxi (17)	Xian (18)	Zhengzhou (19)
Sleeplessness Index	443.933	459.155	105.373	357.637	375.643
	(369.787)	(106.965)	(34.321)	(59.897)	(78.325)
AQI Index	112.737	106.519	95.279	104.029	128.748
	(62.388)	(54.983)	(42.070)	(54.515)	(62.903)
PM2.5 ($\mu g/m^3$)	78.577	74.769	64.210	66.339	91.210
	(54.586)	(47.490)	(33.967)	(48.639)	(55.645)
CO (mg/m^3)	1.526	1.149	1.078	1.783	1.664
	(0.796)	(0.393)	(0.335)	(0.730)	(0.665)
NO2 ($\mu g/m^3$)	48.008	50.227	42.725	43.593	52.807
	(23.867)	(20.332)	(16.349)	(14.638)	(18.164)
SO2 ($\mu g/m^3$)	38.401	25.905	26.976	27.380	37.405
	(35.471)	(15.127)	(11.661)	(22.797)	(27.967)
O3($\mu g/m^3$)	80.822	96.440	100.660	71.073	79.994
	(49.732)	(49.278)	(52.992)	(44.906)	(45.317)
Temperature ($^\circ C$)	14.333	17.376	17.075	9.084	16.287
	(10.786)	(8.676)	(8.535)	(15.190)	(9.400)
Humidity (%)	56.554	78.278	74.596	57.982	58.949
	(17.466)	(10.546)	(12.992)	(12.442)	(18.056)
Sea-level Pressure (hPa)	1017.158	1016.150	1016.579	1021.632	1017.183
	(9.992)	(9.260)	(9.221)	(12.655)	(9.726)
Wind Speed (Km/h)	9.970	5.890	6.589	9.167	7.055
	(3.665)	(3.161)	(2.814)	(3.787)	(2.661)
Precipitation (mm)	1.391	3.606	3.974	0.300	1.700
	(6.226)	(11.005)	(10.722)	(1.436)	(6.516)

Notes: The table lists the sample means at daily level. Standard deviations are shown in parentheses.

Table A2: Average Correlation among Monitoring Stations within Each City

City	Average Correlation AQI	Average Correlation PM2.5	Average Correlation CO	Average Correlation NO2	Average Correlation SO2	Average Correlation O3
Beijing	0.885	0.952	0.933	0.881	0.917	0.944
Changsha	0.925	0.966	0.544	0.692	0.635	0.812
Chengdu	0.830	0.932	0.804	0.716	0.593	0.797
Chongqing	0.831	0.895	0.553	0.672	0.723	0.840
Dongguan	0.907	0.965	0.735	0.885	0.802	0.939
Guangzhou	0.845	0.932	0.454	0.795	0.716	0.860
Hangzhou	0.803	0.866	0.665	0.719	0.522	0.852
Nanjing	0.942	0.972	0.720	0.772	0.802	0.880
Ningbo	0.895	0.967	0.742	0.836	0.815	0.860
Qingdao	0.859	0.953	0.714	0.546	0.786	0.791
Shanghai	0.932	0.966	0.773	0.908	0.899	0.873
Shenyang	0.867	0.944	0.872	0.796	0.810	0.847
Shenzhen	0.762	0.901	0.350	0.568	0.424	0.775
Suzhou	0.942	0.977	0.794	0.819	0.819	0.914
Tianjin	0.881	0.940	0.789	0.908	0.837	0.812
Wuhan	0.897	0.947	0.708	0.802	0.649	0.724
Wuxi	0.926	0.972	0.611	0.749	0.767	0.911
Xian	0.765	0.866	0.678	0.454	0.806	0.859
Zhengzhou	0.905	0.955	0.746	0.834	0.880	0.856
Overall Average	0.874	0.940	0.694	0.755	0.747	0.850

Notes: The table reports the average pairwise correlations for daily average pollutant levels from all the monitoring stations in each city. The mean values under Beijing are the same as those average values from Table A3 to A8.

Table A3: Pairwise Correlations among Monitoring Stations in Beijing — AQI

Correlation	Station 1	Station 2	Station 3	Station 4	Station 5	Station 6	Station 7	Station 8	Station 9	Station 10	Station 11	Station 12
Station 1	-											
Station 2	0.792	-										
Station 3	0.957	0.816	-									
Station 4	0.976	0.799	0.962	-								
Station 5	0.947	0.811	0.968	0.960	-							
Station 6	0.962	0.826	0.963	0.961	0.953	-						
Station 7	0.928	0.854	0.936	0.927	0.931	0.961	-					
Station 8	0.883	0.818	0.888	0.888	0.897	0.889	0.879	-				
Station 9	0.840	0.857	0.841	0.841	0.844	0.858	0.864	0.915	-			
Station 10	0.776	0.907	0.795	0.784	0.794	0.804	0.840	0.790	0.821	-		
Station 11	0.931	0.841	0.956	0.938	0.959	0.959	0.950	0.899	0.863	0.812	-	
Station 12	0.912	0.839	0.904	0.900	0.892	0.932	0.940	0.865	0.862	0.817	0.910	-
Average	0.885											
Longitude	116.366	116.170	116.434	116.434	116.473	116.361	116.315	116.720	116.644	116.230	116.407	116.225
Latitude	39.867	40.287	39.952	39.875	39.972	39.943	39.993	40.144	40.394	40.195	40.003	39.928

Notes: The table reports the correlations among daily average AQI generated from each monitoring station in Beijing.

Table A4: Pairwise Correlations among Monitoring Stations in Beijing — $PM_{2.5}$

Correlation	Station 1	Station 2	Station 3	Station 4	Station 5	Station 6	Station 7	Station 8	Station 9	Station 10	Station 11	Station 12
Station 1	-											
Station 2	0.868	-										
Station 3	0.968	0.908	-									
Station 4	0.984	0.894	0.992	-								
Station 5	0.963	0.906	0.992	0.989	-							
Station 6	0.971	0.913	0.992	0.990	0.986	-						
Station 7	0.953	0.937	0.978	0.974	0.975	0.988	-					
Station 8	0.948	0.912	0.957	0.960	0.964	0.962	0.960	-				
Station 9	0.918	0.937	0.926	0.926	0.930	0.940	0.949	0.973	-			
Station 10	0.887	0.978	0.921	0.912	0.924	0.923	0.952	0.921	0.934	-		
Station 11	0.957	0.914	0.989	0.985	0.988	0.994	0.986	0.965	0.939	0.925	-	
Station 12	0.958	0.925	0.967	0.970	0.965	0.979	0.983	0.961	0.951	0.933	0.975	-
Average	0.952											
Longitude	116.366	116.170	116.434	116.434	116.473	116.361	116.315	116.720	116.644	116.230	116.407	116.225
Latitude	39.867	40.287	39.952	39.875	39.972	39.943	39.993	40.144	40.394	40.195	40.003	39.928

Notes: The table reports the correlations among daily average $PM_{2.5}$ generated from each monitoring station in Beijing.

Table A5: Pairwise Correlations among Monitoring Stations in Beijing — *CO*

Correlation	Station 1	Station 2	Station 3	Station 4	Station 5	Station 6	Station 7	Station 8	Station 9	Station 10	Station 11	Station 12
Station 1	-											
Station 2	0.858	-										
Station 3	0.953	0.881	-									
Station 4	0.966	0.872	0.987	-								
Station 5	0.950	0.876	0.980	0.978	-							
Station 6	0.958	0.884	0.989	0.988	0.980	-						
Station 7	0.914	0.885	0.962	0.949	0.946	0.966	-					
Station 8	0.928	0.888	0.932	0.933	0.933	0.927	0.902	-				
Station 9	0.909	0.916	0.913	0.914	0.911	0.914	0.893	0.952	-			
Station 10	0.903	0.944	0.922	0.915	0.916	0.923	0.937	0.911	0.927	-		
Station 11	0.954	0.902	0.977	0.974	0.979	0.981	0.943	0.941	0.922	0.929	-	
Station 12	0.937	0.895	0.942	0.943	0.944	0.951	0.952	0.907	0.911	0.936	0.948	-
Average	0.933											
Longitude	116.366	116.170	116.434	116.434	116.473	116.361	116.315	116.720	116.644	116.230	116.407	116.225
Latitude	39.867	40.287	39.952	39.875	39.972	39.943	39.993	40.144	40.394	40.195	40.003	39.928

Notes: The table reports the correlations among daily average *CO* generated from each monitoring station in Beijing.

Table A6: Pairwise Correlations among Monitoring Stations in Beijing — NO_2

Correlation	Station 1	Station 2	Station 3	Station 4	Station 5	Station 6	Station 7	Station 8	Station 9	Station 10	Station 11	Station 12
Station 1	-											
Station 2	0.799	-										
Station 3	0.962	0.780	-									
Station 4	0.962	0.794	0.965	-								
Station 5	0.946	0.808	0.967	0.948	-							
Station 6	0.968	0.802	0.961	0.955	0.949	-						
Station 7	0.919	0.750	0.882	0.858	0.886	0.904	-					
Station 8	0.897	0.796	0.894	0.872	0.914	0.881	0.868	-				
Station 9	0.827	0.885	0.780	0.792	0.831	0.817	0.818	0.877	-			
Station 10	0.866	0.941	0.856	0.864	0.884	0.872	0.831	0.876	0.892	-		
Station 11	0.932	0.789	0.970	0.948	0.948	0.932	0.847	0.883	0.773	0.844	-	
Station 12	0.943	0.843	0.933	0.929	0.919	0.935	0.887	0.875	0.826	0.881	0.927	-
Average	0.881											
Longitude	116.366	116.170	116.434	116.434	116.473	116.361	116.315	116.720	116.644	116.230	116.407	116.225
Latitude	39.867	40.287	39.952	39.875	39.972	39.943	39.993	40.144	40.394	40.195	40.003	39.928

Notes: The table reports the correlations among daily average NO_2 generated from each monitoring station in Beijing.

Table A7: Pairwise Correlations among Monitoring Stations in Beijing — SO_2

Correlation	Station 1	Station 2	Station 3	Station 4	Station 5	Station 6	Station 7	Station 8	Station 9	Station 10	Station 11	Station 12
Station 1	-											
Station 2	0.869	-										
Station 3	0.973	0.882	-									
Station 4	0.952	0.849	0.937	-								
Station 5	0.974	0.906	0.982	0.944	-							
Station 6	0.976	0.890	0.972	0.936	0.979	-						
Station 7	0.971	0.903	0.969	0.922	0.971	0.975	-					
Station 8	0.903	0.858	0.898	0.896	0.918	0.900	0.901	-				
Station 9	0.875	0.849	0.875	0.879	0.893	0.877	0.875	0.926	-			
Station 10	0.887	0.936	0.879	0.881	0.917	0.909	0.921	0.893	0.877	-		
Station 11	0.936	0.884	0.944	0.900	0.956	0.964	0.953	0.878	0.848	0.914	-	
Station 12	0.961	0.878	0.937	0.912	0.948	0.955	0.967	0.903	0.878	0.914	0.922	-
Average	0.917											
Longitude	116.366	116.170	116.434	116.434	116.473	116.361	116.315	116.720	116.644	116.230	116.407	116.225
Latitude	39.867	40.287	39.952	39.875	39.972	39.943	39.993	40.144	40.394	40.195	40.003	39.928

Notes: The table reports the correlations among daily average SO_2 generated from each monitoring station in Beijing.

Table A8: Pairwise Correlations among Monitoring Stations in Beijing — O_3

Correlation	Station 1	Station 2	Station 3	Station 4	Station 5	Station 6	Station 7	Station 8	Station 9	Station 10	Station 11	Station 12
Station 1	-											
Station 2	0.900	-										
Station 3	0.974	0.907	-									
Station 4	0.974	0.900	0.983	-								
Station 5	0.968	0.905	0.990	0.976	-							
Station 6	0.969	0.901	0.984	0.972	0.978	-						
Station 7	0.946	0.899	0.972	0.951	0.970	0.969	-					
Station 8	0.937	0.912	0.960	0.950	0.961	0.942	0.936	-				
Station 9	0.884	0.915	0.906	0.900	0.905	0.886	0.885	0.957	-			
Station 10	0.933	0.943	0.948	0.941	0.947	0.942	0.947	0.957	0.942	-		
Station 11	0.953	0.902	0.975	0.963	0.974	0.968	0.970	0.948	0.902	0.949	-	
Station 12	0.969	0.896	0.974	0.965	0.969	0.972	0.970	0.936	0.883	0.947	0.971	-
Average	0.944											
Longitude	116.366	116.170	116.434	116.434	116.473	116.361	116.315	116.720	116.644	116.230	116.407	116.225
Latitude	39.867	40.287	39.952	39.875	39.972	39.943	39.993	40.144	40.394	40.195	40.003	39.928

Notes: The table reports the correlations among daily average O_3 generated from each monitoring station in Beijing.

Table A9: Target City and Source Instrumental Cities

Target Cities	Instrumental Cities	Coordinate (°)	Distance (km)	Location (°)
Beijing	Chengde	40.97N 117.94E	175.93	56
39.96N 116.43E	Tangshan	39.62N 118.18E	154.4	101
	Tianjin	39.09N 117.20E	113.34	140
	Langfang	39.54N 116.68E	48.48	150
	Baoding	38.89N 115.47E	140.06	222
	Zhangjiakou	40.76N 114.88E	161.34	297
Changsha	Yueyang	29.36N 113.31E	126.24	10
28.23N 112.94E	Xinyu	27.81N 114.92E	200	102
	Yichun	27.81N 114.42E	152.5	105
	Pingxiang	27.62N 113.85E	112.43	123
	Zhuzhou	27.83N 113.13E	48.86	159
	Xiangtan	27.83N 112.94E	44.99	180
	Hengyang	26.89N 112.57E	153.68	195
	Shaoyang	27.25N 111.47E	181.64	236
	Loudi	27.69N 111.99E	110.36	240
	Yiyang	28.55N 112.36E	66.7	300
	Changde	29.03N 111.7E	149.44	303
Chengdu	Aba	31.91N 102.22E	229.74	305
30.58N 104.07E	Fanzi	30.05N 101.96E	209.96	256
	Yaan	30.00N 103.02E	119.56	241
	Leshan	29.57N 103.76E	115.40	196
	Yibin	28.73N 104.65E	208.80	162
	Zigong	29.33N 104.78E	153.36	150
	Meishan	30.08N 103.85E	58.52	203
	Ziyang	30.13N 104.63E	72.59	128
	Neijiang	29.59N 105.05E	144.97	134
	Luzhou	28.89N 105.43E	229.73	140
	Chongqing	29.56N 106.54E	301.39	112
	Suining	30.54N 105.59E	147.17	91
	Guangan	30.47N 106.63E	246.20	92
	Nanchong	30.85N 106.13E	197.34	82
	Bazhong	31.87N 106.75E	292.92	64
	Guangyuan	32.44N 105.84E	267.09	43
	Deyang	31.13N 104.40E	69.52	30
	Mianyang	31.47N 104.68E	115.30	34

continued

Target Cities	Instrumental Cities	Coordinate (°)	Distance (km)	Location (°)
Chongqing				
29.56N 106.54E	Guangan	30.45N 106.64E	99.19	6
	Dazhou	31.21N 107.47E	203.96	29
	Zunyi	27.73N 106.92E	207.33	168
	Luzhou	28.86N 105.44E	133.13	238
	Yibin	28.73N 104.65E	206.64	246
	Zigong	29.33N 104.78E	173.39	263
	Neijiang	29.58N 105.05E	145.03	271
	Ziyang	30.13N 104.63E	195.25	286
	Suining	30.54N 105.59E	142.07	316
	Nanchong	30.85N 106.13E	148.98	342
Dongguan	Huizhou	23.11N 114.41E	68.26	82
23.02N 113.75E	Heyuan	23.76N 114.7E	127.16	52
	Meizhou	24.3N 116.12E	280.21	61
	Jieyang	23.58N 116.37E	274.72	77
	Chaozhou	23.67N 116.62E	301.64	77
	Shantou	23.37N 116.68E	302.32	83
	Shanwei	22.81N 115.37E	167.44	97
	Zhuhai	22.28N 113.58E	84.11	192
	Yangjiang	21.86N 111.98E	223.00	236
	Jiangmen	22.58N 113.08E	84.49	236
	Foshan	23.03N 113.13E	63.46	270
	Yunfu	22.91N 112.04E	175.50	266
	Zhaoqing	23.02N 112.48E	129.97	0
	Guangzhou	23.12N 113.27E	50.35	281
	Wuzhou	23.46N 111.27E	258.06	280
	Hezhou	24.41N 111.57E	270.65	302
	Qingyuan	23.68N 113.06E	101.72	313
	Shaoguan	24.8N 113.6E	198.51	355
Guangzhou	Shaoguan	24.8N 113.6E	118.05	11
23.12N 113.27E	Heyuan	23.76N 114.7E	162.57	66
	Huizhou	23.11N 114.41E	117.49	91
	Dongguan	23.02N 113.75E	52.29	101
	Shenzhen	22.55N 114.06E	104.1	126
	Zhuhai	22.28N 113.58E	99.92	160
	Jiangmen	22.58N 113.08E	64.29	119
	Yangjiang	21.86N 111.98E	192.95	226
	Foshan	23.03N 113.13E	18.27	236
	Yunfu	22.91N 112.04E	127.79	260
	Zhaoqing	23.02N 112.48E	80.5	263
	Qingyuan	23.68N 113.06E	64.85	340

continued

Target Cities	Instrumental Cities	Coordinate (°)	Distance (km)	Location (°)
Hangzhou				
30.28N 120.15E	Suzhou	31.32N 120.59E	118.59	23
	Jiaxing	30.75N 120.76E	78.84	52
	Shanghai	31.23N 121.47E	164.45	54
	Zhoushan	30.02N 122.21E	200.09	97
	Ningbo	29.88N 121.54E	142.69	105
	Shaoxing	30.01N 120.61E	52.9	124
	Lishui	28.48N 119.95E	203.64	187
	Jinhua	29.06N 119.65E	140.28	203
	Quzhou	29N 118.9E	188.8	225
	Huangshan	29.72N 118.38E	183.42	253
	Xuancheng	30.94N 118.76E	152.66	295
	Wuhu	31.37N 118.42E	203.74	302
	Huzhou	30.89N 120.08E	68.97	355
	Changzhou	31.81N 119.97E	172.53	353
Nanjing	Huaian	33.6N 119.02E	172.28	8
32.06N 118.79E	Yangzhou	32.38N 119.41E	68.42	63
	Taizhou	32.45N 119.91E	114.29	71
	Zhenjiang	32.2N 119.43E	61.71	78
	Nantong	31.96N 120.89E	199.18	93
	Changzhou	31.81N 119.97E	115.35	102
	Wuxi	31.48N 120.3E	156.81	111
	Suzhou	31.32N 120.59E	189.96	113
	Huzhou	30.89N 120.08E	178.78	132
	Xuancheng	30.94N 118.76E	126.48	181
	Wuhu	31.37N 118.42E	86.46	206
	Maanshan	31.66N 118.51E	51.54	215
	Tongling	30.94N 117.82E	153.9	221
	Chizhou	30.66N 117.5E	198.53	223
	Hefei	31.83N 117.23E	149.82	262
	Huainan	32.64N 117.01E	179.49	288
	Chuzhou	32.25N 118.33E	48.49	293
	Bengbu	32.91N 117.39E	162.03	301
	Suqian	33.96N 118.28E	216.55	345

continued

Target Cities	Instrumental Cities	Coordinate (°)	Distance (km)	Location (°)
Ningbo	Shanghai	31.23N 121.47E	150.26	357
29.88N 121.54E	Nantong	31.96N 120.89E	239.45	342
	Changzhou	31.81N 119.97E	262.01	320
	Wuxi	31.48N 120.30E	213.80	322
	Suzhou	31.32N 120.59E	183.61	326
	Xuancheng	30.94N 118.76E	291.47	290
	Hangzhou	30.28N 120.15E	141.16	286
	Shaoxing	30.01N 120.61E	90.76	277
	Huangshan	29.72N 118.38E	305.45	267
	Quzhou	29.00N 118.90E	273.73	251
	Jinhua	29.06N 119.65E	204.42	246
	Lishui	28.48N 119.95E	219.34	228
	Wenzhou	28.00N 120.69E	224.78	204
	Taizhou	28.66N 121.42E	136.17	185
	Zhoushan	30.02N 122.21E	66.40	78
Qingdao	Yantai	37.46N 121.46E	181.46	37
36.08N 120.39E	Weifang	36.72N 119.16E	131.51	297
	Jinan	36.66N 117.11E	300.80	280
	Linyi	35.11N 118.35E	213.50	244
	Lianyungang	34.61N 119.21E	194.33	218
	Weihai	37.52N 122.11E	222.18	50
	Dongying	37.45N 118.67E	216.40	308
	Binzhou	37.39N 117.97E	260.94	298
	Zibo	36.82N 118.06E	224.27	287
	Taian	36.21N 117.08E	297.57	272
	Laiwu	36.22N 117.68E	243.63	273
	Rizhao	35.43N 119.52E	106.50	233
	Suqian	33.96N 118.28E	303.02	224
	Huaian	33.56N 119.11E	303.57	206
	Zaozhuang	34.82N 117.33E	310.41	247
Shanghai	Zhoushan	30.02N 122.21E	155.64	149
31.23N 121.47E	Ningbo	29.88N 121.54E	150.87	177
	Shaoxing	30.01N 120.61E	157.34	215
	Hangzhou	30.28N 120.15E	164.45	233
	Suzhou	31.32N 120.59E	82.2	276
	Changzhou	31.81N 119.97E	154.08	292
	Taizhou	32.45N 119.91E	198.03	309
	Nantong	31.96N 120.89E	100.1	323

continued

Target Cities	Instrumental Cities	Coordinate (°)	Distance (km)	Location (°)
Shenyang	Fushun	41.87N 123.96E	44.18	83
41.81N 123.43E	Tonghua	41.73N 125.94E	208.14	91
	Baishan	41.95N 126.41E	247.10	87
	Benxi	41.50N 123.69E	40.49	140
	Anshan	41.14N 122.99E	83.61	212
	Yingkou	40.69N 122.23E	160.51	226
	Panjin	41.14N 122.06E	136.40	243
	Chaoyang	41.60N 120.43E	249.88	265
	Fuxin	42.03N 121.68E	146.73	277
	Tongliao	43.66N 122.24E	226.89	327
	Changchun	43.84N 125.32E	272.86	43
	Siping	43.18N 124.35E	170.16	33
	Tieling	42.23N 123.72E	52.06	34
Shenzhen	Heyuan	23.76N 114.70E	148.86	27
22.55N 114.06E	Meizhou	24.30N 116.12E	286.70	49
	Jieyang	23.58N 116.37E	262.38	65
	Shanwei	22.81N 115.37E	137.27	78
	Shantou	23.37N 116.68E	283.63	72
	Yangjiang	21.86N 111.98E	226.50	251
	Wuzhou	23.46N 111.27E	302.84	288
	Zhaoqing	23.02N 112.48E	174.50	288
	Guangzhou	23.12N 113.27E	106.03	306
	Dongguan	23.02N 113.75E	61.85	326
	Shaoguan	24.80N 113.60E	257.64	348
Suzhou	Taizhou	28.66N 121.42E	305.37	162
31.32N 120.59E	Jinhua	29.06N 119.65E	261.33	203
	Hangzhou	30.28N 120.15E	120.78	202
	Nanjing	32.06N 118.79E	190.64	293
	Nantong	31.96N 120.89E	80.13	25
	Shanghai	31.23N 121.47E	83.71	95

continued

Target Cities	Instrumental Cities	Coordinate (°)	Distance (km)	Location (°)
Tianjin	Tangshan	39.62N 118.18E	103.88	60.84
39.09N 117.19E	Binzhou	37.39N 117.97E	200.5	155.381
	Cangzhou	38.31N 116.84E	92.16	304.27
	Dezhou	37.44N 116.36E	198.12	206.83
	Hengshui	37.73N 115.66E	200.69	228.52
	Baoding	38.89N 115.47E	151.83	263.06
	Langfang	39.54N 116.68E	65.5	310.95
	Beijing	39.96N 116.43E	113.34	319.13
Wuhan	Huanggang	30.45N 14.88E	56.93	104.84
30.61N 114.33E	Hangshi	30.19N 115.05E	84.53	119.04
	Jiujiang	29.71N 116.00E	191.59	117.81
	Xianning	29.83N 114.33E	84.72	178.51
	Yueyang	29.36N 113.31E	178.8	222.77
	Jinzhou	30.34N 112.24E	198.96	262.81
	Xiaogan	30.91N 113.94E	49.14	310.22
	Suizhou	31.69N 113.4E	149.01	319.99
	Xinyang	32.15N 114.09E	173.69	351.97
Wuxi	Suzhou	31.32N 120.59E	32.77	118
31.48N 120.30E	Shanghai	31.23N 121.47E	114.52	102
	Jiaxing	30.75N 120.76E	92.23	147
	Ningbo	29.88N 121.54E	213.80	142
	Zhoushan	30.02N 122.21E	244.27	127
	Shaoxing	30.01N 120.61E	166.12	168
	Hangzhou	30.28N 120.15E	134.10	187
	Jinhua	29.06N 119.65E	276.24	195
	Huzhou	30.89N 120.08E	68.86	200
	Huangshan	29.72N 118.38E	268.74	227
	Chizhou	30.66N 117.50E	281.83	253
	Tongling	30.94N 117.82E	243.37	90
	Xuancheng	30.94N 118.76E	158.29	250
	Wuhu	31.37N 118.42E	178.80	266
	Heifei	31.83N 117.23E	293.17	276
	Maanshan	31.66N 118.51E	170.76	275
	Chuzhou	32.25N 118.33E	204.79	291
	Nanjing	32.06N 118.79E	156.64	291
	Zhenjiang	32.2N 119.43E	114.73	309
	Yangzhou	32.38N 119.41E	130.65	315
	Huaian	33.60N 119.02E	264.51	328
	Taizhou	32.45N 119.91E	113.96	338
	Changzhou	31.81N 119.97E	48.19	315

continued

Target Cities	Instrumental Cities	Coordinate (°)	Distance (km)	Location (°)
Wuxi	Suzhou	31.32N 120.59E	32.77	118
31.48N 120.30E	Shanghai	31.23N 121.47E	114.52	102
	Jiaxing	30.75N 120.76E	92.23	147
	Ningbo	29.88N 121.54E	213.80	142
	Zhoushan	30.02N 122.21E	244.27	127
	Shaoxing	30.01N 120.61E	166.12	168
	Hangzhou	30.28N 120.15E	134.10	187
	Jinhua	29.06N 119.65E	276.24	195
	Huzhou	30.89N 120.08E	68.86	200
	Huangshan	29.72N 118.38E	268.74	227
	Chizhou	30.66N 117.50E	281.83	253
	Tongling	30.94N 117.82E	243.37	90
	Xuancheng	30.94N 118.76E	158.29	250
	Wuhu	31.37N 118.42E	178.80	266
	Heifei	31.83N 117.23E	293.17	276
	Maanshan	31.66N 118.51E	170.76	275
	Chuzhou	32.25N 118.33E	204.79	291
	Nanjing	32.06N 118.79E	156.64	291
	Zhenjiang	32.20N 119.43E	114.73	309
	Yangzhou	32.38N 119.41E	130.65	315
	Huaian	33.60N 119.02E	264.51	328
	Taizhou	32.45N 119.91E	113.96	338
	Changzhou	31.81N 119.97E	48.19	315
Xi'an	Shiyan	32.65N 110.77E	253.39	132
34.34N 108.94E	Shangluo	33.87N 109.93E	104.93	115
	Ankang	32.69N 109.02E	183.80	177
	Hanzhong	33.06N 107.02E	227.65	236
	Tianshui	34.59N 105.70E	298.41	274
	Baoji	34.37N 107.24E	156.23	271
	Pingliang	35.54N 106.63E	249.23	297
	Guyuan	36.01N 106.24E	307.84	301
	Qingyang	35.71N 107.64E	193.39	316
	Tongchuan	34.90N 108.93E	62.41	358
	Yanan	36.59N 109.49E	255.56	13
	Weinan	34.50N 109.49E	53.67	73
	Yuncheng	35.04N 111.00E	203.28	71
	Linfen	36.10N 111.53E	305.97	55
	Sanmenxia	34.80N 111.20E	212.86	78
	Xianyang	34.34N 108.71E	21.57	270

Table A10: Robustness — Accounting for Daily Wind Speed in IV

	AQI		PM2.5	
	(1)	(2)	(3)	(4)
First Stage(a)				
$P_{source_{it}}$	0.529***	0.268***	0.536***	0.270***
	(0.083)	(0.078)	(0.076)	(0.058)
	[<0.01]	[<0.01]	[<0.01]	[<0.01]
$P_{source_{it}} * windspeed_{it}$	-0.010	-0.003	-0.009	-0.001
	(0.007)	(0.008)	(0.005)	(0.005)
	[0.249]	[0.721]	[0.123]	[0.873]
$P_{source_{it-1}}$		0.726***		0.778***
		(0.063)		(0.067)
		[<0.01]		[<0.01]
$P_{source_{it-1}} * windspeed_{it-1}$		-0.035***		-0.045***
		(0.005)		(0.007)
		[<0.01]		[<0.01]
Kleibergen-Paap rk Wald F statistic	40.422	95.029	49.312	103.185
Stock-Yogo weak ID test critical values: 10% maximal IV size	16.38	19.93	16.38	19.93
Second Stage(b)				
Instrumented pollutant	0.219**	0.121**	0.297**	0.170**
	(0.089)	(0.049)	(0.116)	(0.061)
	[0.026]	[0.02]	[0.034]	[0.012]
Observations	12904	12579	12989	12662
Additional Control				
City FEs	Y	Y	Y	Y
Temporal Controls	Y	Y	Y	Y
Weather Covariates	Y	Y	Y	Y

Notes: (a) Dependent variable in the first stage is daily-mean pollutant of target city, and independent variable is source pollutant ($100km < d_{ij} < 300km$) from upwind direction (within 90 degrees to the wind), and its interaction term with wind speed in the target city. (b) Second stage reports the results regressing log form of Sleeplessness Index on the instrumented daily pollution. Column (2) and (4) incorporate day before as an additional instrument. Temporal controls include year by month fixed effects, city by year fixed effects, city by quarter fixed effects, as well as day of week and holiday fixed effects. Weather controls contain temperature, humidity, precipitation, wind speed and sea-level pressure. Temperature and humidity are measured by the way of bins. Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table A11: Alternative Standard Errors — OLS

	Wild Cluster Bootstrap	Driscoll-Kraay Spatial Correlation	Alternative Clusters			
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: AQI	0.037***	0.037***	0.037***	0.037***	0.037***	0.037***
	[0.001]	(0.010)	(0.013)	(0.012)	(0.010)	(0.012)
Observations	12365	12365	12365	12365	12365	12365
Panel B: PM2.5	0.043***	0.043***	0.043***	0.043***	0.043***	0.043***
	[0.012]	(0.012)	(0.013)	(0.013)	(0.011)	(0.017)
Observations	13617	13617	13617	13617	13617	13617
Additional Controls						
City FEs	Y	Y	Y	Y	Y	Y
Year by month FEs	Y	Y	Y	Y	Y	Y
City by year FEs	Y	Y	Y	Y	Y	Y
City by quarter FEs	Y	Y	Y	Y	Y	Y
Day of week FEs	Y	Y	Y	Y	Y	Y
Holiday FEs	Y	Y	Y	Y	Y	Y
Weather Covariates	Y	Y	Y	Y	Y	Y
Clusters	City (19)	-	City by year by season (152)	City by year by month (456)	City by year by week (1976)	City Year by month

Notes: Dependent variable is log form of Sleeplessness Index. Independent variable is city daily-mean value of specific pollutant. Column (1) implements the wild bootstrap procedure as described in Cameron et al. (2008), which replicates the results under Column (7) in Table 4. Column (3) follows Driscoll and Kraay (1998) to consider spatial correlation. Column (3) through Column (5) are clustered at city by year by season, city by year by month and city by year by week, respectively. Column (6) adopts the multi-way clusters at both city and year by month. Temporal controls include year by month fixed effects, city by year fixed effects, city by quarter fixed effects, as well as day of week and holiday fixed effects. Weather controls contain temperature, humidity, precipitation, wind speed and sea-level pressure. Temperature and humidity are measured by the way of bins. Robust standard errors clustered at different levels are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets in Column (1). Robust standard errors clustered at alternative levels are reported in parentheses (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table A12: Alternative Standard Errors — IV

AQI	Wild Cluster Bootstrap (1)	Driscoll-Kraay Spatial Correlation (2)	Alternative Clusters (3)	(4)	(5)	(6)
First Stage						
Instrumental AQI t	0.455***	0.455***	0.455***	0.455***	0.455***	0.455***
	[<0.01]	(0.056)	(0.058)	(0.051)	(0.047)	(0.080)
F-statistic	54.791	65.3	61.362	77.607	92.526	32.120
Second Stage						
Instrumented AQI	0.223**	0.223***	0.223**	0.223***	0.223***	0.223**
	[0.039]	(0.062)	(0.098)	(0.089)	(0.062)	(0.091)
Observations	12904	12904	12904	12904	12904	12904
Additional Controls						
City FEs	Y	Y	Y	Y	Y	Y
Year by month FEs	Y	Y	Y	Y	Y	Y
City by year FEs	Y	Y	Y	Y	Y	Y
City by quarter FEs	Y	Y	Y	Y	Y	Y
Day of week FEs	Y	Y	Y	Y	Y	Y
Holiday FEs	Y	Y	Y	Y	Y	Y
Weather Covariates	Y	Y	Y	Y	Y	Y
Clusters	City (19)	-	City by year by season (152)	City by year by month (456)	City by year by week (1976)	City Year by month

Notes: Dependent variable in the first stage is daily-mean AQI of local city, and independent variable is daily weighted average pollution of source cities. Second stage reports the results regressing log Sleeplessness Index on the instrumented daily pollution. Column (1) repeats the IV results under Column (1) and Column (3) in Table 6, in which wild bootstrap clustered at city is used to indicate the significance level. Column (3) follows Driscoll and Kraay (1998) to consider spatial correlation. Column (3) through Column (5) are clustered at city by year by season, city by year by month and city by year by week, respectively. Column (6) adopts the multi-way clusters at both city and year by month. Temporal controls include year by month fixed effects, city by year fixed effects, city by quarter fixed effects, as well as day of week and holiday fixed effects. Weather controls contain temperature, humidity, precipitation, wind speed and sea-level pressure. Temperature and humidity are measured by the way of bins. Robust standard errors clustered at different levels are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets in Column (1). Robust standard errors clustered at alternative levels are reported in parentheses (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table A13: Alternative Standard Errors — IV

PM2.5	Wild Cluster Bootstrap	Driscoll-Kraay Spatial Correlation	Alternative Clusters			
	(1)	(2)	(3)	(4)	(5)	(6)
First Stage						
Instrumental PM2.5 t	0.463***	0.463***	0.463***	0.463***	0.463***	0.463***
	[<0.01]	(0.058)	(0.063)	(0.057)	(0.052)	(0.075)
F-statistic	56.846	62.820	53.071	65.903	78.358	38.450
Second Stage						
Instrumented PM2.5	0.285**	0.285***	0.285***	0.285***	0.285***	0.285**
	[0.033]	(0.068)	(0.113)	(0.100)	(0.068)	(0.117)
Observations	12989	12989	12989	12989	12989	12989
City FEs	Y	Y	Y	Y	Y	Y
Year by month FEs	Y	Y	Y	Y	Y	Y
City by year FEs	Y	Y	Y	Y	Y	Y
City by quarter FEs	Y	Y	Y	Y	Y	Y
Day of week FEs	Y	Y	Y	Y	Y	Y
Holiday FEs	Y	Y	Y	Y	Y	Y
Weather Covariates	Y	Y	Y	Y	Y	Y
Clusters	City (19)	-	City by year by season (152)	City by year by month (456)	City by year by week (1976)	City Year by month

Notes: Dependent variable in the first stage is daily-mean $PM_{2.5}$ of local city, and independent variable is daily weighted average pollution of source cities. Second stage reports the results regressing log Sleeplessness Index on the instrumented daily pollution. Column (1) repeats the IV results under Column (1) and Column (3) in Table 6, in which wild bootstrap clustered at city is used to indicate the significance level. Column (3) follows Driscoll and Kraay (1998) to consider spatial correlation. Column (3) through Column (5) are clustered at city by year by season, city by year by month and city by year by week, respectively. Column (6) adopts the multi-way clusters at both city and year by month. Temporal controls include year by month fixed effects, city by year fixed effects, city by quarter fixed effects, as well as day of week and holiday fixed effects. Weather controls contain temperature, humidity, precipitation, wind speed and sea-level pressure. Temperature and humidity are measured by the way of bins. Robust standard errors clustered at different levels are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets in Column (1). Robust standard errors clustered at alternative levels are reported in parentheses (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table A14: City Sub-samples — OLS

	Full	Exclude Beijing and Environ	Exclude Shanghai and Environs	Exclude Guangzhou and Environs
	(1)	(2)	(3)	(4)
Panel A: AQI	0.037***	0.026**	0.041***	0.038***
	(0.012)	(0.010)	(0.013)	(0.013)
	[0.001]	[0.019]	[0.002]	[<0.01]
Panel B: PM2.5	0.043***	0.026**	0.047***	0.043***
	(0.017)	(0.011)	(0.018)	(0.017)
	[0.012]	[0.032]	[0.005]	[0.009]
Observations	13617	12173	11479	11433
Additional Controls				
City FEs	Y	Y	Y	Y
Year by month FEs	Y	Y	Y	Y
City by year FEs	Y	Y	Y	Y
City by quarter FEs	Y	Y	Y	Y
Day of week FEs	Y	Y	Y	Y
Holiday FEs	Y	Y	Y	Y
Weather Covariates	Y	Y	Y	Y

Notes: Column (1) replicates the OLS results in Column (7) of Table 4. Column (2) excludes Beijing and its nearby city, Tianjin, both of which are situated in northern heavy industrial region. Column (3) excludes Shanghai and its nearby cities, Suzhou and Hangzhou, which are coastally located and dominated by light industry. Column (4) exludes the cleanest part in Southern China, Guangzhou and its nearby cities, Shenzhen and Dongguan. All the regressions include city fixed effects, temporal controls (year by month fixed effects, city by year fixed effects, city by quarter fixed effects, as well as day of week and holiday fixed effects) and weather controls (temperature, humidity, precipitation, wind speed and sea-level pressure). Temperature and humidity are measured in the form of bins. Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table A15: City Sub-samples — IV

	Full	Exclude Beijing and Environ	Exclude Shanghai and Environs	Exclude Guangzhou and Environs
	(1)	(2)	(3)	(4)
		Panel A: AQI		
First Stage				
Instrumental AQI t	0.455***	0.509***	0.469***	0.436***
	(0.062)	(0.060)	(0.067)	(0.061)
	[<0.01]	[<0.01]	[<0.01]	[<0.01]
Kleibergen-Paap rk Wald F statistic	54.791	72.472	48.488	51.714
Stock-Yogo weak ID test critical values: 10% maximal IV size	16.38	16.38	16.38	16.38
Second Stage				
Instrumented Pollutant	0.223**	0.134*	0.213*	0.239**
	(0.096)	(0.073)	(0.098)	(0.105)
	[0.039]	[0.079]	[0.076]	[0.047]
Observations	12904	11461	11037	10720
		Panel B: PM2.5		
First Stage				
Instrumental PM2.5 t	0.463***	0.524***	0.473***	0.444***
	(0.061)	(0.051)	(0.067)	(0.060)
	[<0.01]	[<0.01]	[<0.01]	[<0.01]
Kleibergen-Paap rk Wald F statistic	56.846	72.472	48.488	51.714
Stock-Yogo weak ID test critical values: 10% maximal IV size	16.38	16.38	16.38	16.38
Second Stage				
	0.285**	0.177*	0.276*	0.302**
	(0.118)	(0.094)	(0.119)	(0.128)
	[0.033]	[0.078]	[0.056]	[0.052]
Observations	12989	11546	11122	10805
Additional Controls				
City FEs	Y	Y	Y	Y
Temporal Controls	Y	Y	Y	Y
Weather Covariates	Y	Y	Y	Y

Notes: Column (1) repeats the IV results under Column (1) and Column (3) in Table 6 with full sample. Column (2) excludes Beijing and its nearby city, Tianjin, both of which are situated in northern heavy industrial region. Column (3) excludes Shanghai and its nearby cities, Suzhou and Hangzhou, which are coastally located and dominated by light industry. Column (4) exludes the cleanest part in Southern China, Guangzhou and its nearby cities, Shenzhen and Dongguan. All the regressions include city fixed effects, temporal controls (year by month fixed effects, city by year fixed effects, city by quarter fixed effects, as well as day of week and holiday fixed effects) and weather controls (temperature, humidity, precipitation, wind speed and sea-level pressure). Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table A16: Individual City Effect — AQI

Independent Variable	Dependent Variable (Ln(Sleepless))										
(Daily Pollutant)	Full	Beijing	Changsha	Chengdu	Chongqing	Dongguan	Guangzhou	Hangzhou	Nanjing	Ningbo	Qingdao
Individual City	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A11: AQI-OLS											
AQI (OLS)	0.037***	0.050	0.046***	0.049***	0.019	0.057**	0.095	0.089**	0.058***	-0.022	0.038**
	[0.001]	(0.046)	(0.015)	(0.017)	(0.017)	(0.024)	(0.089)	(0.037)	(0.018)	(0.037)	(0.018)
Observations	13617	730	713	714	730	724	730	714	714	713	714
Panel A21: AQI-IV											
First Stage											
Instrumental AQI t	0.455**	0.300***	0.781***	0.968***	0.835***	0.690***	0.737***	0.460***	0.937***	0.688***	0.394***
	[<0.01]	(0.112)	(0.122)	(0.165)	(0.092)	(0.098)	(0.101)	(0.182)	(0.161)	(0.126)	(0.108)
F-statistics	54.791	7.13	41.191	34.274	82.471	49.529	53.054	6.407	33.945	29.686	13.454
Second Stage											
Instrumented AQI	0.223**	-0.510	0.190***	0.302***	0.244***	0.288***	-1.573***	1.642***	0.153***	0.017	0.104
	[0.039]	(0.398)	(0.057)	(0.075)	(0.054)	(0.098)	(0.411)	(0.626)	(0.050)	(0.124)	(0.128)
Observations	12904	729	575	651	730	724	730	599	714	692	714
											continued

Table A17: Individual City Effect — AQI

Independent Variable (Daily Pollutant) Individual City	Dependent Variable (Ln(Sleepless)) Full (1)	Shanghai (2)	Shenyang (3)	Shenzhen (4)	Suzhou (5)	Tianjin (6)	Wuhan (7)	Wuxi (8)	Xian (9)	Zhengzhou (10)
					Panel A12: AQI-OLS					
AQI (OLS)	0.037***	-0.010	0.061***	0.121**	-0.005	0.039	0.080***	0.023	-0.030	0.019*
	[0.001]	(0.022)	(0.019)	(0.051)	(0.041)	(0.025)	(0.016)	(0.028)	(0.020)	(0.011)
Observations	13617	714	707	730	710	712	713	708	713	714
					Panel A22: AQI-IV					
First Stage										
Instrumental AQI t	0.455**	0.497***	0.504***	0.526***	0.582***	0.699***	0.613***	0.373***	0.619***	0.504***
	[<0.01]	(0.110)	(0.170)	(0.059)	(0.154)	(0.139)	(0.097)	(0.132)	(0.150)	(0.111)
F-statistics	54.791	20.438	8.745	79.673	14.268	24.05	40.046	7.937	17.029	20.572
Second Stage										
Instrumented AQI	0.223**	-0.076	0.337***	0.745***	0.471**	0.037	0.281***	0.795***	-0.261***	0.452***
	[0.039]	(0.152)	(0.121)	(0.166)	(0.205)	(0.097)	(0.061)	(0.305)	(0.101)	(0.120)
Observations	12904	699	590	730	569	712	708	708	616	714

Notes: Column (1) repeats the preferred results for *AQI* in Table 4 and Table 6. Column (2) through Column (11) present individual health effect of *AQI* for each city via both OLS and IV. The instruments are as used in the Column (6) of Table 5. All the regressions include temporal controls (year by season fixed effect) and weather controls (average temperature bins, average humidity bins, precipitation, sea-level pressure, and wind speed). Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table A18: Individual City Effect — PM2.5

Independent Variable (Daily Pollutant) Individual City	Full (1)	Beijing (2)	Changsha (3)	Chengdu (4)	Chongqing (5)	Dongguan (6)	Guangzhou (7)	Hangzhou (8)	Nanjing (9)	Ningbo (10)	Qingdao (11)
	Dependent Variable (Ln(Sleepless))										
Panel B11: PM2.5-OLS											
PM2.5 (OLS)	0.043***	0.064	0.056***	0.058***	0.039*	0.100***	-0.071	0.100**	0.067***	-0.022	0.039*
	[0.017]	(0.050)	(0.018)	(0.021)	(0.022)	(0.040)	(0.120)	(0.044)	(0.020	(0.045)	(0.020)
Observations	13617	730	713	714	730	724	730	714	714	713	714
Panel B21: PM2.5-IV											
First Stage											
Instrumental PM2.5 t	0.463***	0.306***	0.725***	1.040***	0.787***	0.776***	0.787***	0.360**	0.952***	0.724***	0.524***
	[<0.01]	(0.112)	(0.121)	(0.172)	(0.088)	(0.084)	(0.092)	(0.172)	(0.174)	(0.120)	(0.101)
F-statistics	56.846	7.467	36.137	36.506	79.96	84.809	73.105	4.377	29.83	36.298	26.665
Second Stage											
Instrumented PM2.5	0.285**	-0.192	0.244***	0.347***	0.332***	0.301***	-1.668***	2.374**	0.193***	0.174	0.069
	[0.033]	(0.372)	(0.073)	(0.084)	(0.071)	(0.104)	(0.430)	(1.092)	(0.061)	(0.136)	(0.104)
Observations	12989	729	579	651	730	724	730	599	714	692	714

continued

Table A19: Individual City Effect — PM2.5

Independent Variable										
	Dependent Variable (Ln(Sleepless))									
(Daily Pollutant)	Full	Shanghai	Shenyang	Shenzhen	Suzhou	Tianjin	Wuhan	Wuxi	Xian	Zhengzhou
Individual City	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel B12: PM2.5-OLS									
PM2.5 (OLS)	0.043***	-0.011	0.068***	0.148**	-0.012	0.036	0.095***	0.031	0.007	0.031***
	[0.017]	(0.027)	(0.011)	(0.064)	(0.052)	(0.029)	(0.019)	(0.036)	(0.023)	(0.012)
Observations	13617	714	707	730	710	712	713	708	713	714
	Panel B22: PM2.5-IV									
First Stage										
Instrumental PM2.5 t	0.463***	0.569***	0.628***	0.564***	0.617***	0.595***	0.641***	0.419***	0.790***	0.492***
	[<0.01]	(0.100)	90.2240	(0.061)	(0.147)	(0.129)	(0.101)	(0.133)	(0.154)	(0.107)
F-statistics	56.846	32.357	7.865	86.125	17.612	20.074	40.174	9.983	26.466	21.007
Second Stage										
Instrumented PM2.5	0.285**	-0.032	0.239***	0.907***	0.636***	0.072	0.360***	1.042***	-0.059	0.526***
	[0.033]	(0.155)	(0.096)	(0.194)	(0.239)	(0.125)	(0.074)	(0.352)	(0.093)	(0.136)
Observations	12989	699	290	730	569	712	708	708	701	714

Notes: Column (1) repeats the preferred results for $PM_{2.5}$ in Table 4 and Table 6. Column (2) through Column (11) present individual health effect of $PM_{2.5}$ for each city via both OLS and IV. The instruments are as used in the Column (6) of Table 5. All the regressions include temporal controls (year by season fixed effect) and weather controls (average temperature bins, average humidity bins, precipitation, sea-level pressure, and wind speed). Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table A20: Air Quality and Sleeplessness — All Coefficients

	AQI		**PM2.5**	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Pollutant	0.037***	0.223**	0.043***	0.285**
	(0.012)	(0.096)	(0.017)	(0.118)
	[0.001]	[0.039]	[0.012]	[0.033]
Average Temperature ($T \in [10,15)$ Omitted)				
$T < 0$	8.294	12.653**	7.996	11.573*
	(5.579)	(5.537)	(5.494)	(5.457)
	[0.203]	[0.025]	[0.218]	[0.067]
$T \in [0,5)$	9.926***	11.706***	9.803***	11.205***
	(3.790)	(3.727)	(3.776)	(3.703)
	[0.005]	[<0.01]	[0.007]	[<0.01]
$T \in [5,10)$	6.291***	5.344**	6.305***	5.191**
	(2.377)	(2.257)	(2.393)	(2.188)
	[0.011]	[0.026]	[0.007]	[0.029]
$T \in [15,20)$	7.214***	6.111***	7.227***	6.437***
	(2.148)	(1.817)	(2.131)	(1.888)
	[0.001]	[0.002]	[0.001]	[0.002]
$T \in [20,25)$	13.915***	11.635***	13.808***	12.126***
	(3.681)	(3.156)	(3.678)	(3.166)
	[<0.01]	[<0.01]	[<0.01]	[<0.01]
$T \in [25,30)$	15.546***	10.916***	15.587***	12.020***
	(4.961)	(4.279)	(4.988)	(4.144)
	[<0.01]	[0.008]	[<0.01]	[0.001]
$T \geq 30$	10.943**	5.425	11.311***	8.656*
	(5.872)	(5.613)	(5.940)	(5.327)
	[0.015]	[0.381]	[0.014]	[0.097]
Precipitation	-0.021	0.015	-0.023	0.008
	(0.021)	(0.012)	(0.021)	(0.013)
	[0.316]	[0.128]	[0.277]	[0.472]
Sea-level Pressure	-0.214	-0.047	-0.202	-0.009
	(0.122)	(0.177)	(0.127)	(0.185)
	[0.112]	[0.801]	[0.128]	[0.959]
Wind Speed	0.124	0.503**	0.128	0.546**
	(0.094)	(0.204)	(0.092)	(0.214)
	[0.197]	[0.022]	[0.164]	[0.016]
				Continued

	AQI		PM2.5	
	(1)	(2)	(3)	(4)
Average Humidity (H∈[40,60) Omitted)				
H <20	13.753	22.587	14.134	26.456
	(4.889)	(7.612)	(5.090)	(8.998)
	[0.264]	[0.125]	[0.277]	[0.108]
H ∈[20,40)	0.462	5.480	0.654	7.181
	(2.608)	(3.953)	(2.696)	(4.475)
	[0.849]	[0.312]	[0.808]	[0.229]
H ∈[60,80)	3.285***	2.459**	3.223***	1.311
	(1.128)	(1.078)	(1.186)	(1.226)
	[<0.01]	[0.027]	[0.002]	[0.309]
H ≥ 80	5.613***	7.091***	5.329***	4.802***
	(1.060)	(0.914)	(1.153)	(1.228)
	[<0.01]	[<0.01]	[<0.01]	[0.001]
Day of Week (Monday Omitted)				
Tuesday	-13.195***	-13.065***	-13.186***	-12.968***
	(0.991)	(1.024)	(0.987)	(1.044)
	[<0.01]	[<0.01]	[<0.01]	[<0.01]
Wednesday	-12.798***	-12.507***	-12.782***	-12.333***
	(1.104)	(1.122)	(1.103)	(1.114)
	[<0.01]	[<0.01]	[<0.01]	[<0.01]
Thursday	-13.023***	-12.310***	-13.000***	-12.223***
	(1.128)	(1.209)	(1.131)	(1.198)
	[<0.01]	[<0.01]	[<0.01]	[<0.01]
Friday	-13.465***	-13.165***	-13.445***	-12.984***
	(1.075)	(1.139)	(1.076)	(1.156)
	[<0.01]	[<0.01]	[<0.01]	[<0.01]
Saturday	-14.542***	-14.235***	-14.501***	-14.042***
	(1.060)	(1.125)	(1.067)	(1.138)
	[<0.01]	[<0.01]	[<0.01]	[<0.01]
Sunday	-9.022***	-8.666***	-9.019***	-8.639***
	(0.750)	(0.794)	(0.750)	(0.789)
	[<0.01]	[<0.01]	[<0.01]	[<0.01]
Holiday	-9.664***	-8.576***	-9.521***	-7.924***
	(1.150)	(1.333)	(1.162)	(1.451)
	[<0.01]	[<0.01]	[0.012]	[<0.01]

Notes: The table reports detailed OLS and IV results. Each column represents a separate regression. Dependent variable is log form of Sleeplessness Index. Independent variables include daily mean level of specific pollutant, weather controls (average temperature bins, average humidity bins, precipitation, sea-level pressure, and wind speed), temporal controls (year by month fixed effects, city by year fixed effects, city by quarter fixed effects, as well as day of week and holiday fixed effects) and city fixed effects. Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table A21: Pollution Regressed on Imported Source Pollutants All Coefficients (First Stage)

First Stage	**AQI**	**PM2.5**
	(1)	(2)
Instrumental	0.455***	0.463***
Pollutant t	(0.062)	(0.061)
	[<0.01]	[<0.01]
Average Temperature (T∈ [10,15) Omitted)		
T <0	-26.803**	-18.887*
	(7.187)	(7.094)
	[0.024]	[0.066]
T ∈[0,5)	-15.260***	-10.746***
	(3.759)	(3.196)
	[<0.01]	[0.002]
T∈ [5,10)	1.386	1.702
	(2.145)	(1.782)
	[0.500]	[0.345]
T ∈[15,20)	6.948***	4.064**
	(2.184)	(1.674)
	[0.002]	[0.017]
T∈ [20,25)	12.147***	6.735**
	(3.540)	(2.756)
	[0.002]	[0.023]
T [25,30)	24.962***	14.608***
	(5.463)	(4.169)
	[0.001]	[0.004]
T ≥ 30	30.398***	11.283***
	(5.161)	(3.957)
	[<0.01]	[0.005]
Precipitation	-0.178***	-0.114***
	(0.036)	(0.027)
	[<0.01]	[<0.01]
Sea-level Pressure	-0.937***	-0.835***
	(0.254)	(0.213)
	[0.006]	[0.002]
Wind Speed	-1.914***	-1.602***
	(0.271)	(0.202)
	[<0.01]	[<0.01]
		continued

First Stage	AQI	PM2.5
	(1)	(2)
Average Humidity (H ∈[40,60) Omitted)		
H <20	-42.911	-45.284*
	(14.122)	(11.782)
	[0.108]	[0.086]
H∈ [20,40)	-25.111***	-24.904***
	(9.139)	(7.447)
	[0.014]	[0.001]
H∈ [60,80)	5.814	8.884**
	(4.152)	(3.974)
	[0.197]	[0.026]
$H \geq 80$	-6.629	2.927
	(4.927)	(4.473)
	[0.199]	[0.578]
Day of Week (Monday Omitted)		
Tuesday	-0.368	-0.617
	(0.802)	(0.777)
	[0.631]	[0.426]
Wednesday	-2.114*	-2.215**
	(1.126)	(0.967)
	[0.092]	[0.049]
Thursday	-3.549**	-2.863**
	(1.206)	(1.138)
	[0.019]	[0.048]
Friday	-2.103	-2.228
	(1.259)	(1.274)
	[0.129]	[0.110]
Saturday	-1.631	-1.830*
	(1.159)	(0.945)
	[0.170]	[0.078]
Sunday	-0.834	-0.679
	(0.865)	(0.727)
	[0.383]	[0.384]
Holiday	-7.642***	-7.935***
	(1.346)	(1.029)
	[<0.01]	[<0.01]

Notes: The table reports detailed results of the first stage under IV estimations. Each column represents a separate regression. Dependent variable is daily mean level of specific pollutant for each city. Independent variables include instrumented pollutant, weather controls (average temperature bins, average humidity bins, precipitation, sea-level pressure, and wind speed), temporal controls (year by month fixed effects, city by year fixed effects, city by quarter fixed effects, as well as day of week and holiday fixed effects) and city fixed effects. Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table A22: Joint Estimation (First Stage and Second Stage)

Individual Pollutant	Whether to Control Co-emissions in the first stage							
	NO				Yes			
	PM2.5	CO	NO2	O3	PM2.5	CO	NO2	O3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
First Stage								
Instrumental Pollutant t	0.463***	0.184***	0.326***	0.442***	0.236***	0.105***	0.168**	0.433***
	(0.061)	(0.077)	(0.071)	(0.044)	(0.054)	(0.050)	(0.066)	(0.045)
	[<0.01]	[0.011]	[0.001]	[<0.01]	[<0.01]	[0.006]	[0.023]	[<0.01]
Kleibergen-Paap rk Wald F statistic)	56.846	5.742	20.621	101.465	18.987	4.451	6.508	93.942
Stock-Yogo weak ID test critical values: 10% maximal IV size	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38
Second Stage								
Instrumented Pollutant	0.285**	-	0.018	0.072	0.519**	-	-	0.071
	(0.118)	-	(0.220)	(0.172)	(0.229)	-	-	(0.179)
	[0.033]	-	[0.944]	[0.835]	[0.049]	-	-	[0.834]
Observations	12989	-	12989	12989	12989	-	-	12989
Additional Controls								
City FEs	Y	Y	Y	Y	Y	Y	Y	Y
Temporal Controls	Y	Y	Y	Y	Y	Y	Y	Y
Weather Covariates	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table reports the results from both the first stage and second stage of joint estimation in Table 14. Column (1) through Column (4) does not include co-emissions at the first stage. The second stage regresses Sleeplessness Index on different instrumented pollutants together, which corresponds to Column (4) of Table 14. Column (5) through Column (8) controls co-pollution when making instrument and reports each second stage estimate one by one, which corresponds to Column (5) of Table 14. All the regressions include city fixed effects, temporal controls and weather covariates. Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).

Table A23: Air Pollution and Neutral Keywords

	Sleeplessness (1)	Cat (2)	Table (3)
Panel A: AQI	0.037***	-0.004	-0.017
	(0.012)	(0.015)	(0.027)
	[0.001]	[0.798]	[0.499]
Panel B: PM2.5	0.043***	-0.009	-0.022
	(0.017)	(0.019)	(0.029)
	[0.012]	[0.600]	[0.395]
Observations	13617	13617	13617
Additional Controls			
City FEs	Y	Y	Y
Year by month FEs	Y	Y	Y
City by year FEs	Y	Y	Y
City by quarter FEs	Y	Y	Y
Day of week FEs	Y	Y	Y
Holiday FEs	Y	Y	Y
Weather Covariates	Y	Y	Y

Notes: This table compares the effects of air pollution on the neutral keywords "cat" and "table", by regressing air pollution on the log form of the keywords. Entries have been adjusted to percentage form. All the regressions include city fixed effects, temporal controls and weather covariates. Robust standard errors clustered at the city level are reported in parentheses. P-values based on wild cluster-bootstrap (1000 replications) are reported in brackets. Asterisk indicates the statistical significance according to the wild bootstrap p-values (* significant at 10%, ** significant at 5%, *** significant at 1%).