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Reevaluating the subjective welfare loss of air pollution

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ABSTRACT

There are data integration and estimation endogeneity problems while estimate the subjective welfare loss of air pollution, which may result in incompatible findings. This paper attempts to integrate the air pollution data and subjective well-being data on individual-level, and use the number of environmental laws and regulations in prefecture-level cities as an instrumental variable for air pollution to evaluate the welfare loss of air pollution. The results show that there is a causal effect between air pollution and individual subjective well-being. 1 $\mu g/m^3$ increase of annual PM2.5 concentration in a city will result in a subjective welfare loss equivalent to 7.7% percent of household disposable income, which implies that previous studies may have underestimated the effect. Further mechanism analysis shows that the effect of PM2.5 on subjective well-being is more through physical health than through mental health.

1. Introduction

Air pollution can cause welfare losses both to society and the individuals. Exposure to air pollution increases more tangible health risks according to social statistics, such as an increase in morbidity (i.e., cardiovascular diseases and respiratory diseases) (Brunekreef and Holgate, 2002; Brook, 2009; Gallagher et al., 2010; Beatty and Shimshack, 2014) and mortality (i.e., infants and the elderly, etc), as well as a decrease in life expectancy (Tanaka., 2015; De Keijzer et al., 2017). Compared with these observable losses, many attention are paid to the effects on the individual subjective welfare such as mental health status (Rotton and Frey, 1984; Power et al., 2015; Sass et al., 2017), depressive symptoms (Wang et al., 2014), life satisfaction (Welsch, 2006, 2007; MacKerron et al, 2009; Ferreira and Moro, 2010; Ambreyet al., 2014) and hedonic happiness (Zhang et al., 2017a,b) and evaluative happiness (Yuan et al., 2018), which can be economically measured as welfare losses for public policy making (Welsch, 2006, 2007; Levinson, 2013).

However, unanimous conclusions can hardly be drawn either on the accurate effect of air pollution on subjective welfare or on the precise monetary cost of air pollution on welfare from existing literature. For instance, two fresh studies on China use the same data and measured variables, but come to quite different conclusions. Specifically, Zhang et al. (2017a) suggest that air pollution reduces hedonic happiness and increases the rate of depressive symptoms, while has little to do with life satisfaction. They evaluate the willingness to pay (WTP) for better air quality and the result is about $42 for Chinese people per year. However, Liang et al. (2018) show that air pollution has significant negative impact on life satisfaction and appraise the WTP is ranging from $239 to $280 for Chinese people per year. The results of the two studies are somehow contrary, and the economic cost of the latter is 6–7 times larger than that of the former. Besides that, many other research also draw some inconsistent conclusions on these issues (Welsch, 2002; Welsch, 2007), which indicates that the accuracy estimation of air pollution and subjective well-being needs to be further improved.

There are two main issues may account for these inconsistencies. The first one is to match and integrate research data. Air pollution data and subjective well-being (SWB) data usually

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come from different levels and channels. Air pollution data are often collected by objective ways, such as from monitoring station records or pollution model estimates in a certain area (Smyth et al., 2008; Ferreira and Moro, 2010; Schmitt, 2013; Ambreyet al., 2014),[1] while SWB data are usually obtained from individual level by subjective reports. A conventional challenge to empirical studies is to seek high quality air pollution data with fine spatial and temporal disaggregation and to connect this information with a specific respondent (Lin et al., 2018).

The spatial data aggregation requires that the air pollution data and subjective welfare data are acquired in the same geographical location. Lin et al. (2015) have summarized three spatial levels to integrate air pollution data and individual SWB data. The first one is the country level, which means using air pollution data at a whole national level to analyze its impact both on overall national SWB (Welsch's, 2002; 2006; 2007) and individual SWB nationwide (Schmitt's, 2013). The main objective of this level is to investigate the differential effect across counties. Obviously, there is significant matching error if the air pollution of whole country was calculated to a sole value. The second is the regional level, which signifies that air pollution data are collected from regional environmental monitoring stations to explore its impact on individual SWB of regional people (Ferreira and Moro, 2010). Compared with the country level, the regional level data seem to be more accurate, but in fact its accuracy is not much better than that of the country level, because the geographical distribution of environmental monitoring stations between regions is not uniform and random, which may also cause obvious errors in data matching. The third is the individual level, which indicates that air pollution data are achieved at the individual locations to analyze the impact on the exact individual SWB. Unfortunately, the data from environmental monitoring stations can not meet the requirements of individual level. Recently some geographic scientists have turned to using pollution estimation models to measure air pollution data (Lin et al., 2018; Lu et al., 2019). The models assume that the air pollution is continuously distributed in geography, and the air pollution data of each specific location is calculated according to the principles of geography and mathematics. The accuracy of the air pollution model applied by the existing scientists can reach a spatial grid of 1 km $\times$ 1 km (Lu et al., 2019). Evidently, the air pollution data from individual level could be better integrated with the individual SWB data than the country level and regional level on spatial dimension. In this paper, we attempt to integrate the air pollution data and SWB data on individual-level based on those air pollution estimation models.

The temporal data aggregation requires that data are collected at the same point or period of time. There are two temporal levels to match air pollution data and individual SWB data. The first one is the long-term level, which usually taking a year or month as temporal unit to measure air pollution (Smyth et al., 2008; Yuan et al., 2018). Since the individual report of happiness is instantaneous, it may inevitably bring about integrating errors between interval air pollution and instant SWB. To minimize such errors, many scholars tend to choose stable SWB indexes such as general life satisfaction or evaluative happiness which are less likely subject to short-term changes in external environment. The second is the immediacy level which means that the air pollution data are achieved in a very short time unit, usually by day (Levinson, 2013; Schmitt, 2013; Liu et al., 2012; Zhang et al., 2017a,b). At immediacy level, the air pollution data and SWB data are integrated on a precise day, which can avoid the errors caused by temporal matching to a greater extent and ensure the analysis more accurate on the moment-to-moment experienced happiness. But it also necessitates acquiring and controlling more instantaneous factors such as the mood of the interviewees and the real-time weather that day, which may definitely increase the difficulty of data acquisition and analysis. Since we are investigating the long term effect of air pollution on individual SWB and evaluating the stable economic welfare loss, we choose to integrate air pollution data with individual well-being data at annual level.

The second issue which may account for those inconsistencies is the endogenous problem. Previous studies pay less attention to dealt with the endogeneity problems when they estimate the impact of air pollution on SWB. It is believed that air pollution affects people's SWB, but individual happiness dose not counteract air pollution, which means that there is little reverse causal effect between them. However, the measurement error of variables and the missing variables in estimation may also cause endogenous problems, which may result in different conclusions. Especially, it is necessary to take into account the endogeneity after the spatial and temporal integration of air pollution data and SWB data. In this paper, we intend to use the instrumental variable approach to deal with the endogenous problems.

It is the existing data integration issues and endogeneity problems that lead to the inconsistent judgment on the relationship between air pollution and SWB and the substantial differences in the assessment of the welfare loss caused by air pollution. Such inconsistent results and assessment errors are very detrimental to the formulation and implementation of public policies.

To address these issues, this paper employs the air pollution model developed by Institute for the Environment of the Hong Kong University of Science and Technology to obtain PM2.5 data in an area with latitude and longitude of $0.03^\circ \times 0.03^\circ$ (approximately 2.5 $\times$ 2.5 km) grid squares, which can contribute to matching air pollution data with happiness data more precisely at individual level. By conducting regression analysis based on the matched data, this paper finds that air pollution has a significantly negative correlation with happiness. 1 $\mu g/m^3$ increase of PM2.5 concentration each year, the individual SWB will be reduced by 0.448 units on average. Using the average marginal substitution rate between air pollution and absolute income to calculate the economic costs, this paper also finds that 1 $\mu g/m^3$ increase of PM2.5 concentration each year is equivalent to ¥3483 ($529[2]) economic loss which accounts for approximately 7.7% of average household disposable income during 2009–2012 in China. The estimated coefficients and calculated economic costs are larger than those of existing studies, indicating that data matching in individual level may have a significant impact on the results. The processing of data matching in this paper probably make the research results more accurate and reliable.

Moreover, this paper attempts to solve the endogenous problems when estimating the effect of air pollution on SWB. First is the missing variables problem. There are many influencing factors of regional air pollution. Although one may try to eliminate these influences by controlling as many variables as possible, including the regional fixed effect, they still cannot exclude the influence of time changes in the district or county. Second is reverse causality problem. Although many people believe that air pollution will affect SWB and SWB will not directly affect air pollution, but some scholars still believe that SWB may affect air pollution through

[1] Of course, a small number of scholars have tried to explore the relationship between subjective air pollution reporting data and subjective well-being, but it is clear that subjective air pollution reports do not accurately represent pollution itself.

[2] The average exchange rate of RMB against the US dollar during the four years from 2009 to 2012 was 6.58:1.

working productivity (Zhang et al., 2017a,b). The last is the measurement error problem. Even though the PM2.5 data can be calculated by the approximate algorithm, the measurement will cause somehow inevitable errors.

This paper uses the number of environmental regulations in prefecture-level cities as instrumental variable (IV) to deal with the endogeneity. The two stage least squares (2SLS) regression results show that the PM2.5 coefficient is significantly negative, which verifies the causal relationship between PM2.5 and SWB. That is, air pollution significantly decreases people's happiness. Compared with the coefficients of ordinary least square (OLS), the coefficients of IV is about 16 times larger than that of OLS in absolute value, which indicates that there are omitting variables in previous studies and it may have seriously underestimated the influence of PM2.5 on SWB.In addition, the thermal inversions also be adopted as another instrumental variable of air pollution for robustness checking. The results also verify the causal effect between air pollution and SWB.

This paper also explores the mechanism of PM2.5 affecting individual subjective well-being. The estimation of intermediary effect model shows that the effect of PM2.5 on individual long-term subjective well-being is mainly through physiological health (the direct effect is about 20.31%), while the effect of psychological health (the direct effect is only about 10.41%) is less than health mechanism.

This study may have three contributions. Firstly, this paper matches the objective air pollution data with the subjective well-being data at the individual level in the spatial dimension, which could make the analysis results more accurate. Secondly, this paper uses instrumental variable method to verify the causal relationship between air pollution and subjective well-being. Finally, this paper verifies that the long-term mechanism of PM2.5 affecting happiness is more through physiological health than through mental health.

The rest of the paper is organized as follows: Section 2 introduces the data and variable measurement; section 3 is the methodology; section 4 is the analysis of regression results; section 5 is the mechanism test and heterogeneity analysis; section 6 is the discussion of the subjective welfare loss; section 7 is the conclusion.

2. Data and measurement

2.1. Subjective well-being

The subjective well-being data come from Chinese General Social Survey (CGSS) data from 2009 to 2012. CGSS is a large-scale nationwide social survey project in China, which systematically collects data of Chinese people and Chinese society. From 2009 to 2012, CGSS randomly selected 130 districts and counties in 87 Chinese cities and conducted survey in the same areas every year. Unfortunately, CGSS is not a follow-up survey for individuals. Each survey re-samples individuals in specific districts and counties. Therefore, the individuals surveyed in the same district and county are not the same each year. In the four years from 2009 to 2012, a total of 33,737 individuals were investigated.

In the CGSS data from 2009 to 2012, the individual SWB is measured by asking respondents to answer an overall question, "In general, do you feel happy with your life?", "1″ means "very unhappy", "2″ means "relatively unhappy", "3″ means "not very happy", "4″ means "relatively happy" and "5″ means "very happy". This method measures the long-term cumulative happiness of individuals, which is usually stable and less affected by immediate emotions (Zhang et al.,2017a,b). In addition, CGSS survey also contains plenty of individual character data, such as gender, age, education, marriage, relative income, absolute income, health and other variables, which may have a significant impact on happiness. By controlling them, we can estimate the effects of air pollution impact on happiness more accurately.

In order to match the air pollution data at the individual level, it is requires a precise knowledge of where the respondent is. The CGSS questionnaire has a very detailed address question for the record of the interview location, which is accurate to the community/village[3]of each respondent. Although the community/village is more accurate in geographical measurement than the district/county, the data matching based on the community/village is likely to bring obvious measurement errors, because a large number of Chinese residences are more than 3 km away from their work places. Matching the data from the district/county level can better reflect the long-term effects of air pollution on individual activities than from the community/village level.

2.2. Air pollution

One goal of this paper is to integrate air pollution data with individual data at the individual level. Many studies on air pollution and individual well-being (including physical health, mental health and well-being) mainly use reported data by environmental monitoring stations (Smyth et al., 2008; Ferreira and Moro, 2010; Schmitt, 2013). They usually choose the monitoring station with the closest geographical distance as the final pollution data (Zhang et al., 2017a). Actually, the number of environmental monitoring stations is more than 1600 in China and the average distance between adjacent environmental monitoring stations is more than 200 km. Although some scholars believe that the distance of environmental monitoring stations has little impact on the significance of the estimated results (Zhang et al., 2017a), there are still measurement errors, which will affect the accuracy of the estimated coefficient, and thus cause the deviation of welfare loss evaluation. Therefore, using air pollution data from environmental monitoring stations cannot accurately match the pollution data to the individual level.

The Institute for the Environment of the Hong Kong University of Science and Technology has developed a PM2.5 pollution calculation model based on spatial remote sensing data from the National Aeronautics and Space Administration (NASA) Earth Observation Satellite, which provides more accurate spatial grid pollution data. The algorithm of the model consists of two steps: the first step is to use the spatial remote sensing data taken by NASA Earth observation satellite to establish aerosol optical thickness (AOD) data with a resolution of 1 km (Li et al., 2005); The second step takes the visibility and relative humidity data observed on the ground as input to deduce the PM2.5 concentration on the ground from AOD (Lin et al., 2018). Using this model, Lu et al. (2019) calculated the annual average PM2.5 concentration data in the latitude and longitude range of China from 2000 to 2018 in the interval of $0.03^\circ \times 0.03^\circ$ (approximately 2.5 km $\times$ 2.5 km).

In this paper, air pollution data is the annual data from the Institute for the Environment of the Hong Kong University of Science and Technology.[4] On this basis, the latitude and longitude range of the district and county was investigated by accurate positioning (for example, the southernmost latitude of a district and county was 29.321°S, the northernmost latitude was 29.345°N, the easternmost longitude was 113.482°E, and the westernmost longitude was 113.441°W, so the latitude and longitude range of the district and county was a rectangular square interval of (N29.345°,

[3] The community is an area of about 1 km $\times$ 1 km in an urban city, while village is about 3 km $\times$ 3 km in a rural area.

[4] Data url: http://envf.ust.hk/dataview/aod2pm/current.

Table 1
Summary statistics.

Variable	Definition	Obs	Mean	Std. Dev	Min	Max
Happiness	Answer to “Overall, how satisfied are you with your life?”, ranging from 1 (completely dissatisfied) to 5 (completely satisfied)	33,737	3.799	0.855	1	5
PM2.5	Particulate matter with a diameter smaller than 2.5 μm (μg/m3)	33,737	64.052	22.516	18.4	129.2
Environmental regulation	Number of environmental regulations in prefecture-level cities	33,737	12.315	20.800	0	109
Thermal inversions_1	Count the days of the first layer is lower than the second layer in the county	33,737	74.5601	34.2068	1	175
Thermal inversions_2	Count the days of the first layer is lower than the third layer in the county	33,737	79.2741	33.6836	2	186
Relative income	self-rated relative income status, ranging from 1 (completely unfair) to 5 (completely fair)	33,737	2.618	0.740	1	5
Absolute income (log)	annual household per capita income (Chinese yuan)	33,737	10.233	1.080	6.685	12.612
Hukou (0−1)	Indicator for people with “urban” registration	33,737	0.593	0.491	0	1
Gender (0−1)	Indicator for males	33,737	0.499	0.500	0	1
Age		33,737	46.873	15.677	14	101
Age square		33,737	2442.842	1538.004	196	10,201
Education	Education years	33,737	8.689	4.561	0	19
Marital (0−1)	Indicator for being married	33,737	0.820	0.384	0	1
Party member (0−1)	Indicator for being a Communist Party member	33,737	0.118	0.322	0	1
Religion (0−1)	Indicator for being religious	33,737	0.117	0.322	0	1
Han nationality (0−1)	Indicator for people with Han nationality	33,737	0.924	0.266	0	1
Health care (0−1)	Indicator for urban basic medical insurance/new rural cooperative medical insurance/public medical treatment	33,737	0.787	0.410	0	1
Healthy (1−5)	Indicator for the physical health status, ranging from 1 (completely unhealthy) to 5 (completely healthy)	33,737	3.506	1.142	1	5
Depression (1−5)	Indicator for the mental health status, ranging from 1 (lest depression) to 5 (most depression)	33,737	2.142	1.00	1	5
Trust (1−5)	Answer to “Do you think most people in this society can be trusted?”, ranging from 1 (completely disagree) to 5 (completely agree)	33,737	3.440	1.049	1	5
Fair (1−5)	Indicator for social fairness, ranging from 1 (completely unfair) to 5 (completely fair)	33,737	3.027	1.075	1	5
Class (1−5)	Indicator for social class, ranging from 1 (the lowest) to 10 (the highest)	33,737	4.163	1.719	1	10

E113.441°; N29.345°, E113.482°). Then, the PM2.5 concentration of each 0.03° × 0.03° grid in this range was calculated on average, which was used as the annual PM2.5 concentration value of this district and county.

2.3. Environmental regulations

Another goal of this paper is to find instrumental variables to deal with those endogenous problems. The number of environmental regulations at the city level is selected as an instrumental variable for air pollution in each district and county. On one hand, environmental regulations at the city level are formulated and implemented specifically for environmental pollution, and their quantity will have a direct impact on air pollution in the whole city (including several districts and counties). On the other hand, the number of environmental regulations is relatively exogenous to each individual in a district or county. Therefore, it can be considered that the environmental regulations in the city will not directly affect the SWB of each individual. Of course, the validity of instrumental variable will be discussed in more detail later.

The annual number of new environmental regulations in China's prefecture-level cities from 2009 to 2012 are obtained from the Wolters Kluwer Database. The Wolters Kluwer Database is one of the most comprehensive and authoritative databases of laws and regulations in China,[5] which systematically collects legal and regulatory documents from various places. Specifically, the number of environmental regulations in prefecture-level cities in this paper mainly includes local environmental laws, regulations and normative documents. These three aspects can cover the behavioral regulations of environmental protection in a region from different levels.

2.4. Thermal inversions

This paper also intends to use as an instrument a measure of atmospheric temperature inversions named thermal inversions for robustness checking. Thermal inversion is a meteorological phenomenon which may exacerbate air pollution near the ground. Under normal circumstances, the temperature of the atmosphere will decrease with the increase of altitude, so that air pollutants near the earth surface can be effectively diffused through the high altitude layer. However, under certain conditions the air temperature at high altitude will be higher than that at low altitude, which contributes the temperature inversion. In this situation, the warmer air at higher altitude prevents pollutants from rising and dispersing, but rather traps them close to the ground, thus causing severe air pollution. As a natural meteorological phenomenon, thermal inversion is less influenced by regional economic or social activities (Feng et al., 2010; Cai et al., 2016). Therefore, many economists regard it as an exogenous source of variation in air pollution level (Hicks et al., 2016; Arceo et al., 2015; Jans et al., 2016; Chen et al., 2017).

In order to better match the PM2.5 data, the thermal inversions data are also obtained from the spatial remote sensing information released by NASA. NASA divides the Earth into a grid of 0.5° × 0.625°longitude and latitude, and has been reporting temperatures at 42 different sea-level layers every 6 h since 1980. This paper obtains the nearest three sea level temperature data close to the ground. First, average the sea level temperature of each grid every day, and count the first layer temperature lower than the second layer as one inversion temperature, and then accumulate the total inversion days of each year of each grid. According to the inverse distance weighting method, figure out the number and weight of grids covered by each prefecture-level city in China, and finally calculate the annual number of inversion days in each prefecture-level city. This paper also calculated the case where the

[5] Data url: http://envf.ust.hk/dataview/aod2pm/current.

Table 2
Baseline regression results for air pollution and subjective well-being.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS			OLOGIT			OPROBIT		
PM2.5	−0.274*	−0.356***	−0.448***	−1.068***	−1.247***	−1.624***	−0.552***	−0.676***	−0.871***
	(0.140)	(0.134)	(0.125)	(0.331)	(0.336)	(0.342)	(0.184)	(0.187)	(0.191)
Relative income		0.293***	0.152***		0.704***	0.389***		0.389***	0.214***
		(0.007)	(0.007)		(0.018)	(0.019)		(0.010)	(0.011)
Absolute income (log)		0.081***	0.058***		0.179***	0.145***		0.103***	0.083***
		(0.005)	(0.006)		(0.013)	(0.015)		(0.007)	(0.008)
Control variables	NO	NO	YES	NO	NO	YES	NO	NO	YES
County dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	33,737	33,737	33,737	33,737	33,737	33,737	33,737	33,737	33,737
R^2	0.038	0.128	0.247						
Pseudo R^2				0.020	0.058	0.120	0.019	0.057	0.119

Notes:*,**,*** indicate significance at the 10%, 5% and 1% level respectively; control variables include hukou, gender, age, age squared, years of schooling, marriage, political identity, religion, ethnicity, social health care, physical health, social trust, social justice, self-evaluation of social class.

temperature of the first layer is lower than that of the third layer.

3. Methods

According to the model setting of Zhang et al. (2017a), the estimating model is construct as follows:

$$H_{ijt} = \beta_0 + \beta_1 P_{jt} + \beta_2 \ln Y_{ijt} + \beta 3 R_{ijt} + \gamma X_{ijt} + \delta_j + \varepsilon_{ijt} \quad (1)$$

In equation (1), the explained variable H_{ijt} is the individual SWB of the respondents in year*t*of district and county*j*. The core explanatory variable$P_{jt}$is the annual mean value of PM2.5 of district and county*j*in year*t*. The absolute income variable $\ln Y_{ijt}$, the logarithm of household annual income, and the relative income variable R_{ijt} are controlled, and the self-reported relative income value from 1 (lowest) to 5 (highest). According to previous literature, a series of individual demographic variables, including gender, age and its square term, years of education, marital status, hukou, party members, health status, social attitudes are also controlled. $\delta_j$is the fixed effect of districts and counties, and $\varepsilon_{ijt}$is the error term. The descriptive statistics of each variable are shown in Table 1.

4. Results and analysis

4.1. Baseline regression

The baseline regressions are conductied through equation (1) using OLS, Ordered Logit model and Ordered Probit model respectively, and the results are shown in Table 2.

Columns (1) to (3) in the table are the results of the OLS estimation, in which column (1) only controls the regional fixed effects of districts and counties, and on the basis of this, column (2) further controls absolute family income and relative income of individuals. Column (3) controls hukou, gender, age, age squared, education, marriage, partisanship, ethnicity, medical security, physical health, and social attitudes.

The results show that PM2.5 has a significant negative effect on SWB. From column (1) to column (3), as more control variables adding into the model, the economic significance and statistical significance of this negative effect are increasing. The coefficients after controlling income and individual characteristics show that a 1ug/m^3 increase of PM2.5 concentration would reduce the SWB by 0.448 units, and the results are statistically significant at the 1% level. Columns (4) to (6) in the table are the estimation results of Ordered Logit model, and columns (7) to (9) are the estimation results of Ordered Probit model. The estimates of Ordered Logit and Ordered Probit all support the same results.

Compared with previous research, the results of baseline regressions consist with the findings of Ferreira and Moro (2010), Ambrey et al. (2014), etc., all of which indicate that air pollution will has a negative impact on long-term subjective welfare (happiness, life satisfaction, etc.) But the difference is that our estimated effect is significantly larger. At the same time, our results are different from those of Welsch (2002) and Zhang et al. (2017a,b), which denote that air pollution does not have a significant impact on

Table 3
2SLS second stage estimation results.

	(1)	(2)	(3)
Dependent variable: SWB (valued 1−5), county level			
PM2.5	−2.950	−7.034***	−7.152***
	(1.881)	(1.928)	(1.671)
Relative income		0.291***	0.149***
		(0.008)	(0.008)
Absolute income (log)		0.087***	0.065***
		(0.006)	(0.006)
Control variables	NO	NO	YES
County dummy	YES	YES	YES
Kleibergen-Paap rk LM statistic	127.206***	124.525***	145.098***
Cragg-Donald Wald F statistic	184.463***	179.427***	209.868***
Kleibergen-Paap rk Wald F statistic	116.537***	114.094***	132.651***
Observations	33,737	33,737	33,737
R^2	0.028	0.064	0.183

Notes:*,**,*** indicate significance at the 10%, 5% and 1% level respectively; control variables include hukou, gender, age, age squared, years of schooling, marriage, political identity, religion, ethnicity, social health care, physical health, social trust, social justice, self-evaluation of social class.

Table 4
Direct effects of IV variable on SWB.

	(1)	(2)	(3)
Environmental regulations (IV)	−0.000	−0.000	−0.001
	(0.001)	(0.001)	(0.001)
PM2.5	−0.007***	−0.008***	−0.009***
	(0.001)	(0.001)	(0.001)
Relative income		0.294***	0.149***
		(0.007)	(0.007)
Absolute income (log)		0.086***	0.060***
		(0.006)	(0.006)
Control variables	NO	NO	YES
Province dummy	YES	YES	YES
Observations	33,737	33,737	33,737
R^2	0.041	0.132	0.254

Notes:*,**,*** indicate significance at the 10%, 5% and 1% level respectively; control variables include hukou, gender, age, age squared, years of schooling, marriage, political identity, religion, ethnicity, social health care, physical health, social trust, social justice, self-evaluation of social class.

Table 5
Robustness test using thermal inversions as IV.

	(1)	(2)	(3)	(4)	(5)	(6)
	Thermal inversions_1			Thermal inversions_2		
Dependent variable: SWB (valued 1−5), county level						
PM2.5	−1.702***	−3.289***	−3.423***	−1.518***	−2.988***	−3.146***
	(0.474)	(0.456)	(0.399)	(0.443)	(0.425)	(0.372)
Relative income		0.292***	0.151***		0.292***	0.151***
		(0.007)	(0.007)		(0.007)	(0.007)
Absolute income (log)		0.084***	0.061***		0.084***	0.061***
		(0.005)	(0.006)		(0.005)	(0.006)
Control variable	NO	NO	YES	NO	NO	YES
County dummy	YES	YES	YES	YES	YES	YES
Kleibergen-Paap rk LM statistic	1260.716***	1265.313***	1390.775***	1543.681***	1550.641***	1695.696***
Cragg-Donald Wald F statistic	3215.912***	3195.521***	3712.674***	3718.021	3697.536***	4302.435***
Kleibergen-Paap rk Wald F statistic	1698.284***	1698.297	1987.434***	2102.111***	2103.992***	2450.479***
Observations	33,737	33,737	33,737	33,737	33,737	33,737
R^2	0.035	0.115	0.234	0.036	0.118	0.236

Notes:*,**,*** indicate significance at the 10%, 5% and 1% level respectively; control variables include hukou, gender, age, age squared, years of schooling, marriage, political identity, religion, ethnicity, social health care, physical health, social trust, social justice, self-evaluation of social class.

Table 6
Influencing mechanism of PM2.5 on SWB.

Dependent variable	(1)	(2)	(3)	(4)
	Health	SWB	Depress	SWB
PM2.5	**−1.057*** **	−0.448***	**0.363** **	−0.503***
	(0.161)	(0.125)	(0.159)	(0.124)
Relative income	0.162***	0.152***	−0.147***	0.146***
	(0.009)	(0.007)	(0.009)	(0.007)
Absolute income (log)	0.081***	0.058***	−0.055***	0.058***
	(0.007)	(0.006)	(0.007)	(0.006)
Health		**0.108*** **		
		(0.005)		
Depress				**−0.161*** **
				(0.005)
Control variables	YES	YES	YES	YES
County dummy	YES	YES	YES	YES
Physiological health effect	(-1.057)*0.108/[-0.448+(-1.057)*0.108] = 20.31%			
Psychological health effect	0.363*(-0.161)/[-0.503 + 0.363*(-0.161)] = 10.41%			
Observations	33,737	33,737	33,737	33,737
R^2	0.259	0.247	0.130	0.262

Notes:*,**,*** indicate significance at the 10%, 5% and 1% level respectively; control variables include hukou, gender, age, age squared, years of schooling, marriage, political identity, religion, ethnicity, social health care, social trust, social justice, self-evaluation of social class.

individual long-term subjective welfare. It is the different matching levels of pollution and subjective welfare data by scholars that results in the inconsistency conclusions.

4.2. IV estimation

Due to the endogenous problems, the baseline regression may have estimation deviation. In this part, the number of environmental regulations at the city level is adopted as an instrumental variable for air pollution for estimation. The results of two-stage least square method (2SLS) estimating is shown in Table 3.

In Table 3, column (1) only controls the regional fixed effect, and the results show that the effect of air pollution on SWB is not statistically significant. Column (2) controls relative income and absolute income on the basis of regional fixed effects, and the results show that the increase of PM2.5 concentration can significantly reduce people's SWB. The absolute value of regression coefficient of PM2.5 increases precipitously, which is nearly 20 times compared with that of the OLS estimation in Table 2. Column (3) further controls the individual characteristic variables, and the absolute value of the coefficient of PM2.5 is also 16 times larger than that of the OLS estimation in Table 2, and the statistically significant level is further improved.

The regression of instrumental variables shows that the increase in PM2.5 concentration significantly bring about a significant decrease in SWB. The causal effect between air pollution and SWB

Table 7
Heterogeneous effects of air pollution.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Male	Female	Age ≤ 39	40 ≤ age ≤ 59	Age ≥ 60	High edu	Low edu	High income	Low income	With young	Without young	High pm2.5	Low pm2.5
Dependent variable: Happiness (valued 1−5), county level:2SLS													
Pm2.5	−12.694***	−3.377*	−6.673**	−8.088***	−2.322	−6.396***	−9.537	−16.653**	−4.478***	−8.537**	−6.758***	−3.354***	−0.414
	−3.241	−1.931	−2.635	−2.458	−4.307	−1.458	−28.473	−7.856	−1.511	−3.683	−1.94	−0.421	−1.054
Relative income	0.155***	0.142***	0.118***	0.150***	0.183***	0.119***	0.193***	0.187***	0.101***	0.118***	0.157***	0.153***	0.148***
	−0.011	−0.011	−0.013	−0.012	−0.015	−0.009	−0.017	−0.012	−0.01	−0.015	−0.009	−0.011	−0.009
Household income (log)	0.076***	0.057***	0.084***	0.082***	0.022**	0.071***	0.056***	0.059***	0.054***	0.081***	0.060***	0.064***	0.062***
	−0.009	−0.008	−0.012	−0.011	−0.01	−0.008	−0.012	−0.011	−0.012	−0.014	−0.007	−0.009	−0.008
Control variable	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
County dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	16,847	16,890	11,636	14,558	7543	21,559	12,178	16,868	16,869	9053	24,684	13,866	19,871
R2	0.054	0.226	0.134	0.196	0.285	0.16	0.215	0.014	0.153	0.126	0.208	0.231	0.248

Notes:*,**,*** indicate significance at the 10%, 5% and 1% level respectively; control variables include hukou, gender, age, age squared, years of schooling, marriage, political identity, religion, ethnicity, social health care, physical health, social trust, social justice, self-evaluation of social class.

has been verified by IV method. At the same time, the coefficient of IV regression is almost 16 times larger than the previous OLS regression. This indicates that the original OLS method may seriously underestimates the impact of air pollution on the long-term subjective well-being of individuals. It is necessary to conduct estimation by IV method, which probably make the conclusion of our research more reliable.

It is necessary to conduct a more accurate statistical test of the validity of the instrumental variables. First test the identification of environmental regulations as instrumental variables. In Table 3, conducting the Kleibergen-Paap unidentifiable test, the results show that the LM statistic is a big number, which may exclude the unrecognizable hypothesis. Second, check the weak IV possibility of environmental regulations. In Table 3, the Cragg-Donald and Kleibergen-Paap Wald tests show that the F statistic is much larger than 10, which can exclude the weak IV hypothesis.

Last but not least, it is also need to test the exogeneity (i.e. exclusive constraints) of the IV, which is extreme difficult. Nunn and Leonard (2011) argues that though IV is not plausible exogenenous or does not fully satisfy the exclusive constraints, as long as it doesn't significantly affect the dependent variable directly, the sign and significance of estimating results are still reliable. In light of Nunn and Leonard (2011), Table 4 is the results testing the direct effect of environmental regulations on SWB.

The results show that the coefficients of environmental regulations are extremely close to 0, and the statistical significance is not significant at all, which denotes that the direct effect of environmental regulations on SWB is almost null. Comparing the coefficients of PM2.5 in Table 4 with those in column (1), (2) and (3) of Table 3, the absolute values of coefficients in Table 4 are 2−2.5 times compared with those in Table 2 respectively, which indicates that there is an obvious indirect effect of environmental regulations on SWB. Therefore, the results in Table 4 show that the direct effect of environmental regulations on SWB is almost null, while the indirect effect through PM2.5 is distinctive. According to the standards of Nunn and Leonard (2011), it can be assumed that environmental regulation is an effective instrumental variable for this study.

In order to verify the conclusions of IV estimation in Table 3, the thermal inversion is adopted as another instrument variable to conduct the robustness check. The 2SLS results are shown in Table 5, and column (1), (2), (3) use the thermal inversions_1 variable while column (4), (5), (6) use the he thermal inversions_2 variable. All the coefficient of PM2.5 are negative and at significant level of 1%. The Kleibergen-Paap unidentifiable test excludes unrecognized hypothesis, and the Cragg-Donald and Kleibergen-Paap tests that thermal inversion is a strong IV. Robustness test of thermal inversion as an instrument variable shows that there is a negative causal effect of air pollution on individual SWB, which verifies the previous conclusions.

5. Mechanism test and heterogeneity analysis

5.1. Mechanism test

Previous studies have discussed the physiological and psychological mechanisms of air pollution's effect on SWB. According to the physiological mechanism, air pollution will worsen individual physical health, such as increasing the prevalence of cardiovascular and respiratory diseases, and then have a negative impact on their SBW (Tella et al., 2003). In light of psychological mechanism, air pollution will have adverse effects on individual SWB by affecting people's mood or mental health, such as making people feel more depressed or increasing the risk of psychological diseases (Sass et al., 2017). Therefore, this paper will test those mechanisms of air pollution on individual long-term SWB from physical and mental health.

Using mediating effect model to test those possible mechanisms, the results are shown in Table 6. Columns (1) and (2) are mediating effects in testing physical health, while columns (3) and (4) are testing mental health. For physical health, PM2.5 will significantly deteriorate health, thus has a significant negative impact on SWB, and the effect is about 20.31%. For mental health, PM2.5 can obviously aggravate the depression, thus also has a negative effect to SWB, and the effect is 10.41%. The physiological and psychological mechanisms of PM2.5 affecting individual long-term SWB have been verified, and the mediating effect of physical health is obviously larger than that of mental health. Therefore air pollution will reduce the long-term SWB by worsening their physical and mental health, and the effect of physical health mechanism is greater than that of mental health mechanism.

The results of mechanism test in physical and mental health can be supported by many previous studies (Rotton and Frey, 1984; Wang et al., 2014; Power et al., 2015; Sass et al., 2017). However, the effect of PM2.5 on long-term SWB is more through physical health than through mental health. Compared with other air pollutants, PM2.5 particles are smaller. On one hand, people cannot perceive them visually, so they are not likely to affect short-term mood or psychology. On the other hand, it will stay in the air for a longer time and enter our lungs, blood (Wu et al., 2013) and even brains (Guo et al., 2008; Calderon-Garciduenas et al., 2008), which are more likely to cause long-term damage to the body.

5.2. Heterogeneity analysis

This paper also wish to know the heterogeneous effects of air pollution on SWB in different people and areas. In order to make the estimation more accurate, IV approach is also used, and the2SLS results are shown in Table 7. Base on previous literature (Mitchell and Dorling, 2003; Zhang et al., 2017a), the heterogeneous analysis mainly including gender, education, age, income, child-caring, heavy polluted zone, etc..,

The male and people under 60s is more sensitive to PM2.5, which is similar to the conclusion of Zhang et al. (2017a). It may be due to the fact that women are more tolerant to air pollution than men and people aged 60 are more tolerant to air pollution than young people (Yang et al., 2018).The results of education and income show that PM2.5 has a greater negative effect on SWB of people with high education and income, which consist with the findings of Yuan et al. (2018), but are contrary to the results of Huang and He (2013), Zhang et al. (2017a). People with higher education and incomes should be more sensitive to air pollution because they have higher requirements for the quality of environment. In addition, people who care young children (under the age of 16) are more sensitive to PM2.5. The results is consistent with that of Zhang et al. (2017a). People living in areas with higher pollution are more sensitive to PM2.5.

5.3. Discussion of the subjective welfare loss

Using the estimation method of average marginal rate of substitution for air pollution and absolute income which is developed by Welsch (2006, 2007) and applied by Levinson (2013), Zhang et al. (2017a,b), Liang et al.(2018) ect., the evaluation of the economic welfare loss of each household can be calculated by the following equation:

$$\frac{\partial Y}{\partial P}_{|dH=0} = -Y\hat{\beta}_1/\hat{\beta}_2 \tag{2}$$

In equation (2), variables have the same meaning as in equation (1). Calculating the subject welfare loss base on the IV estimation results in Table 3, the result is $\frac{\partial Y}{\partial P} = ¥3{,}483$, which means that from 2009 to 2012 Chinese families were willing to pay 3483 Chinese yuan for PM2.5 every year, accounting for 7.7% of the average household disposable income, which was significantly larger than that of Zhang et al. (2017a,b) (about 0.5%) and Liang et al. (2018)(about 3%–4%).

The subjective welfare loss evaluated is obviously larger than previous studies. Two main reasons may account for that. The first one is the data matching of spatial dimension at individual level. Comparing the coefficients of the base line OLS regression with the results of Levinson (2013), Ferreira and Moro (2010), Mabahwi et al. (2014), Zhang et al. (2017a,b), and the coefficients of the base line Ordered Logit and Ordered Probit regression with the results of Ambrey et al. (2014),Ebenstein et al. (2013), Liang et al. (2018), the estimated coefficients in Table 2 are significantly larger than those of others, which means that data matching of spatial dimension at individual level may have obvious influence on the analysis. It is possible that the cross-section data in this paper may also results in the larger coefficients.

To address the cross-section data issues, IV approach is adopted for more accurate estimation, which is the second reason account for the larger coefficients. Theoretically, the IV method can produce more accurate estimation by excluding the influence of possible potential variables, including those variables related time. This paper takes use of environmental regulations as an IV for PM 2.5 to estimate the effects, and conducts detailed analysis on the validity of IV including identifiability, weak IV possibility and exogeneity, and also uses thermal inversion as another IV to test the robustness. The results show that the IV approach is appropriate and effective, which means that evaluation of welfare loss in this paper would be more reliable.

It is extremely difficult to deal with the endogenous problem between SWB and income. Although the estimates do not address the endogenous issue of income and SWB, as other researchers do (Levinson, 2012; Ferreira and Moro, 2013; Zhang et al., 2017a,b; Liang et al., 2018),a series variables related to individual income and SWB have been controlled, such as hukou, gender, age, years of schooling, marriage, political identity, religion, ethnicity, social health care, physical health, social trust, social justice, self-evaluation of social class, etc. By controlling those variables the estimated coefficients of absolute income can be sufficiently accurate.

6. Conclusion

Many studies have evaluated the subjective welfare loss of air pollution by individual reported SWB, but their results often vary. The data integration and the endogeneity problems between air pollution and SWB may account for that.This paper attempts to address these issues to reexamine the subjective welfare loss of air pollution.

This paper first measure the air pollution data by pollution estimation models which developed by the Institute for the Environment of the Hong Kong University of Science and Technology (Lin et al., 2018; Lu et al., 2019), and match the pollution data to the individual level from the spatial dimension. The estimation results show that PM2.5 has a negative impact on individual subjective long-term happiness, and each 1ug/m^3 increase in PM2.5 concentration will reduce individual subjective well-being by 0.448 units, and this elastic coefficient result is significantly larger than the existing results.

This paper then use the number of environmental regulations in prefecture-level cities as an instrumental variable for air pollution to deal with the endogeneity. The results show that the PM2.5 coefficient is significantly negative, which verifies the causal relationship between PM2.5 and SWB. 1 μg/m^3 increase of annual PM2.5 concentration in a city will result in a subjective welfare loss equivalent to 7.7% percent of household disposable income, which implies that previous studies may have underestimated the effect. This paper conducts enough analysis on the validity of IV including identifiability, weak IV possibility and exogeneity, and uses thermal inversions as another instrumental variable of air pollution for robustness checking. The results also verify the causal effect between air pollution and SWB.

The mechanism of PM2.5 affecting SWB also has been explored in this paper. By conducting intermediary effect estimation, the effect of PM2.5 on individual long-term SWB is more through physiological health (the direct effect is about 20.31%), than through psychological health (the direct effect is only about 10.41%).

Finally, this paper analyzes the heterogeneous effects of air pollution on SWB in different people and areas and find that men, those under the age of 60, those with high education, high income, raising minor children and those living in high-pollution areas are more sensitive to PM2.5. Those results are consistent with many existing studies (Huang and He, 2013; Yang et al., 2018; Zhang et al., 2017a,b).

Of course, this paper has some limitations. Firstly, the measurement variables of air pollution and SWB are single. Secondly, subject to the happiness data from CGSS, our data in this paper are limited to 2009 to 2012.Thirdly, the data are cross-sectional not panel. Although this study is about the impact on long-term SWB and the IV method is conducted, the estimation would be more accurate if time changes are fully controlled. These problems need to be further studied and solved in the future.

Declaration of competing interest

The authors declared that they have no conflicts of interest to this work. We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

CRediT authorship contribution statement

Daqian Shi: Methodology, Software, Data curation, Validation. **Hongwei Yu:** Visualization, Conceptualization, Writing - original draft, Writing - review & editing.

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References

Ambrey, Christopher L., Fleming, C.M., Chan, Y.C., 2014. Estimating the cost of air pollution in South East Queensland: an application of the life satisfaction non-market valuation approach. Ecol. Econ. 97, 172–181.
Arceo, E., Hanna, R., Oliva, P., 2015. Does the effect of pollution on infant mortality differ between developing and developed countries?: evidence from Mexico city. Econ. J. 126, 257–280.
Beatty, Timothy K.M., Shimshack, J.P., 2014. Air pollution and children's respiratory health: a cohort analysis. J. Environ. Econ. Manag. 67 (1), 39–57.
Brook, R.D., 2009. Cardiovascular effects of air pollution. Nat. Clin. Pract. Cardiovasc. Med. 115 (6), 36–44.

Brunekreef, B., Holgate, S.T., 2002. Air pollution and health. Lancet 360 (9341), 1233–1242.
Cai, R., Feng, S., Michael, O., Mariola, P., 2016. Climate variability and international migration: the importance of the agricultural linkage. J. Environ. Econ. Manag. 79, 135–151, 2016.
Calderon-Garciduenas, L., Solt, A.C., Henríquez-Roldán, C., Torres-Jardón, R., Nuse, B., Herritt, L., Villarreal-Calderón, R., Osnaya, N., Stone, I., García, R., Brooks, D.M., González-Maciel, A., Reynoso-Robles, R., Delgado-Chávez, R., Reed, W., 2008. Long-term air pollution exposure is associated with neuroinflammation, an altered innate immune response, disruption of the blood-brain barrier, ultrafine particulate deposition, and accumulation of amyloid beta-42 and alpha-synuclein in children and young adults. Toxicol. Pathol. 36 (2), 289–310.
Chen, S., Oliva, P., Zhang, P., 2017. The Effect of Air Pollution on Migration: Evidence from China. NBER working paper.
De Keijzer, C., Agis, D., Ambrós, Albert, et al., 2017. The association of air pollution and greenness with mortality and life expectancy in Spain: a small-area study. Environ. Int. 99, 170–176.
Ebenstein, A., Fan, M., Greenstone, M., et al., 2013. New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River Policy. Pnas 110 (32), 12936–12941.
Feng, S., Alan, B.K., Michael, O., 2010. Linkages among climate change, crop yields and Mexico-US cross-border migration. Proc. Natl. Acad. Sci. Unit. States Am. 107 (32), 14257–14262.
Ferreira, S., Moro, M., 2010. On the use of subjective well-being data for environmental valuation. Environ. Resour. Econ. 46 (3), 249–273.
Gallagher, P., Lazarus, W., Shapouri, H., et al., 2010. Cardiovascular disease—risk benefits of clean fuel technology and policy: a statistical analysis. Energy Pol. 38 (2), 1210–1222.
Guo, Y.M., Liu, L.Q., Chen, J.M., 2008. Association between the concentration of particulate matters and the hospital emergency room visits for circulatory diseases: a case-crossover study. Chin. J. Epidemiol. 11.
Hicks, D., Marsh, P., Oliva, P., 2016. Air Pollution and Procyclical Mortality: Causal Evidence from Thermal Inversions. NBER working paper.
Huang, Y.M., He, L.Y., 2013. Urbanization, environmental pollution and subjective well-being: an empirical study on China. China Soft Sci. 12.
Jans, J., Johansson, P., Nilsson, J., 2016. Economic Status, Air Quality, and Child Health: Evidence from Inversion Episodes. NBER working paper.
Levinson, A., 2013. Happiness, Behavioral Economics, and Public Policy. NBER Working Papers.
Li, C., Lau, K.H., Mao, J., et al., 2005. Retrieval, validation, and application of the 1-km aerosol optical depth from MODIS measurements over Hong Kong. IEEE Trans. Geosci. Rem. Sens. 43 (11), 2650–2658.
Liang, Yuana, Shinb, Kongjoo, Managi, Shunsuke, 2018. Subjective well-being and environmental quality: the impact of air pollution and green coverage in China. Ecol. Econ. 153, 124–138.
Lin, C., Li, Y., Yuan, Z., et al., 2015. Using satellite remote sensing data to estimate the high-resolution distribution of ground-level PM2.5. Rem. Sens. Environ. 156, 117–128.
Lin, C.Q., Liu, G., Lau, A.K.H., et al., 2018. High-resolution satellite remote sensing of provincial PM 2.5 trends in China from 2001 to 2015. Atmos. Environ. 180, 110–116.
Liu, B., Li, L., Mo, J., 2012. Will happiness be contagious. J. World Econ. 6.
Lu, X., Lin, C., Li, W., et al., 2019. Analysis of the adverse health effects of PM2.5 from 2001 to 2017 in China and the role of urbanization in aggravating the health burden. Sci. Total Environ. 652, 683–695.
Mabahwi, N.A.B., Leh, O.L.H., Omar, D., 2014. Human health and wellbeing: human health effect of air pollution. Procedia - Soc. Behav. Sci. 153, 221–229.
MacKerron, George, Mourato, et al., 2009. Life satisfaction and air quality in London. Ecol. Econ. 68 (5), 1441–1453.
Mitchell, G., Dorling, D., 2003. An environmental justice analysis of British air quality. Environ. Plann. 35 (5), 909–929.
Nunn, N., Leonard, W., 2011. The slave trade and the origins of mistrust in Africa. Am. Econ. Rev. 101 (7), 3221–3252.
Power, M.C., Kioumourtzoglou, M.A., Hart, J.E., et al., 2015. The relation between past exposure to fine particulate air pollution and prevalent anxiety: observational cohort study. BMJ Br. Med. J. (Clin. Res. Ed.) 350, 1–9.
Rotton, J., Frey, J., 1984. Psychological costs of air pollution: atmospheric conditions, seasonal trends, and psychiatric emergencies. Popul. Environ. 7 (1), 3–16.
Sass, V., Kravitz-Wirtz, N., Karceski, S.M., et al., 2017. The effects of air pollution on individual psychological distress. Health Place 48, 72–79.
Schmitt, M., 2013. Subjective Well-Being and Air Quality in Germany, vol. 133. Social Science Electronic Publishing, pp. 275–286.
Smyth, R., Mishra, V., Qian, X., 2008. The environment and well-being in urban China. Ecol. Econ. 68 (1–2), 547–555.
Tanaka, Shinsuke, 2015. Environmental regulations on air pollution in China and their impact on infant mortality. J. Health Econ. 42, 90–103.
Tella, R.D., Macculloch, R.J., Oswald, A.J., 2003. The macroeconomics of happiness. Rev. Econ. Stat. 85 (4), 809–827.
Wang, Y., Eliot, M.N., Koutrakis, P., et al., 2014. Ambient air pollution and depressive symptoms in older adults: results from the MOBILIZE boston study. Environ. Health Perspect. 122 (6), 553–558.
Welsch, H., 2007. Environmental welfare analysis: a life satisfaction approach. Ecol. Econ. 62 (3–4), 544–551.
Welsch, H., 2002. Preferences over prosperity and pollution: environmental valuation based on happiness surveys. Kyklos 55 (4), 473–494.
Welsch, H., 2006. Environment and happiness: valuation of air pollution using life satisfaction data. Ecol. Econ. 58 (4), 801–813.
Wu, S., Deng, F., Huang, J., et al., 2013. Blood pressure changes and chemical constituents of particulate air pollution: results from the healthy volunteer natural relocation (HVNR) study. Environ. Health Perspect. 121 (1), 66–72.
Yang, Y., Tang, R., Qiu, H., et al., 2018. Long term exposure to air pollution and mortality in an elderly cohort in Hong Kong. Environ. Int. 117, 99–106.
Yuan, L., Guan, D., Shu, T., et al., 2018. A review of air pollution impact on subjective well-being: survey versus visual psychophysics. J. Clean. Prod. 184, 959–968.
Yuan, L., Guan, D., Shu, T., et al., 2018. A review of air pollution impact on subjective well-being: survey versus visual psychophysics. J. Clean. Prod. 184, 959–968.
Zhang, X., Zhang, X., Chen, X., 2017a. Happiness in the air: how does a dirty sky affect mental health and subjective well-being? J. Environ. Econ. Manag. 85, 81–94.
Zhang, X., Zhang, X., Chen, X., 2017b. Valuing air quality using happiness data: the case of China. Ecol. Econ. 137, 29–36.