**Authors' information**

Kong Joo Shin (First & corresponding author)

kongjooshin@gmail.com

Urban Institute & Department of Urban Environmental Engineering, School of Engineering, Kyushu University, Fukuoka, Japan

Guodong Du (Co-first author)

duguodong42@gmail.com

Graduate School of Engineering, Kyushu University, Fukuoka, Japan

Shunsuke Managi (Last author)

managi.s@gmail.com

Urban Institute & Department of Urban Environmental Engineering, School of Engineering, Kyushu University, Fukuoka, Japan

**Environment and Life Satisfaction: Evaluating the Effects of Air Pollution on Subjective Well-being in Beijing**

**Abstract**

This paper evaluates the impact of air pollution on life satisfaction (LS). We use the geo-statistical spatial interpolation technique to construct disaggregated air pollution data for $SO_2$, $NO_2$, $PM_{10}$ and $PM_{2.5}$ and match them with geo-coded individual respondents from original survey data. The results show that all pollutants have significant negative impacts on LS. $NO_2$ and $SO_2$ have a higher marginal negative impact and a higher average willingness to pay (WTP) for a reduction than the particulate matters pollutants. We calculate LS improvement from reducing pollutants based on the Chinese and the U.S. air quality index (AQI). Despite the relatively higher health risk of $PM_{2.5}$ based on both AQI standards, Beijing citizen have relatively low WTP for $PM_{2.5}$. We find that, achieving the Beijing government's Clean Air Action Plan, which targets a 25% reduction of $PM_{2.5}$ concentration between 2013 and 2017, would provide an LS benefit that exceeds the cost.

**Keywords**: Subjective well-being; Life satisfaction; Air pollution; Air Quality Index (AQI); survey data; geo-statistical spatial interpolation technique; Beijing

## 1. Introduction

In the field of environmental economics, it is important to consider how people perceive environmental problems. Subjective evaluation of the impacts of pollution on human well-being is crucial because it allows us to incorporate people's environmental concerns in addition to the stated-preference (e.g. Wang and Mullahy, 2006) or revealed-preference approaches (e.g. Kim et al., 2003) that have traditionally been used by economists to incorporate subjectivity into such evaluations.[1] Self-reported well-being is regarded as a robust empirical approximation with overall utility; thus, it is meaningful to use subjective

[1] The stated-preference approach aims to directly elicit environmental preference (the typical approach is contingent valuation), whereas the revealed-preference approach utilizes complementarity and substitutive relationships between non-marketed and marketed goods to infer the value attributed to public goods from market transactions in private goods (e.g., travel cost and hedonic pricing approaches). A discussion of the advantages and disadvantages of the different approaches (stated preference, revealed preference and SWB) can be found in Frey et al., 2004.

well-being (SWB) for a direct evaluation of environmental quality (Welsch and Kühling, 2009).

In this paper, we evaluate the impact of one of the most prevalent and prioritized environmental problems: air pollution. According to the World Health Organization (WHO), air pollution is responsible for an estimated seven million deaths annually, or one in eight premature deaths every year (WHO, 2015). Cities are hit hardest by the impact of air pollution as more than 80% of people living in urban areas are exposed to air quality levels that exceed WHO limits (e.g., 25 μg/$m^3$ for $PM_{2.5}$) worldwide.[2]

Our study focuses on the city of Beijing, one of the world's largest cities with a severe air pollution problem. In recent years, Beijing has frequently experienced heavy haze in the winter (Han et al., 2015; Zhang et al., 2016). In January 2013, the daily $PM_{2.5}$ concentration was so high that it sometimes exceeded the recording range of the monitoring instruments. The government enacted a series of regulations and invested a huge sum of funds in air pollution abatement.[3] Additionally, the government started to pay attention to the impact of air pollution on residents' well-being. In 2014, Chinese president Jinping Xi said at an official government press conference, "air quality has directly affected Chinese people's happiness."[4]

We analyze the impact of air pollution on Beijing residents using the SWB approach, which models people's subjective well-being as a function of determinants that affect their subjective evaluation of their welfare. Income and a series of personal and household characteristics are important determinants of people's well-being. Additionally, previous studies have shown that environmental conditions have a statistically significant impact on SWB, e.g., climate change (Sekulova and van den Bergh, 2013), airport noise (Van Praag and Baarsma, 2005), ecosystem diversity (Ambrey and Fleming, 2014), and air pollution (Welsch, 2002; 2007; Ferreira, 2013; Levinson, 2012). According to these studies, the SWB approach provides an effective quantitative evaluation of the environment as a public good and enables us to efficiently estimate an individual's willingness to pay (WTP).

[2] Released by the WHO in 2016 (http://www.who.int/mediacentre/news/releases/2016/air-pollution-rising/en/).
[3] Approximately 760 billion *yuan* (USD $110 billion) funds for air pollution abatement over three years starting from 2014 declared by Beijing government.
[4] The report of this government press conference in Chinese can be accessed online: http://www.gov.cn/xinwen/2014-03/07/content_2632820.htm.

This study makes three primary contributions to the existing literature. First, despite the severe air pollution condition and the government's attention to people's SWB, few studies have analyzed the relationship between air pollution and people's SWB in Beijing. Our analysis provides an empirical environmental evaluation based on the SWB approach for megacities in the developing world using an original Internet survey for Beijing conducted in 2016 to analyze the impact of air pollution on Beijing residents' life satisfaction (LS).[5] Beijing and other typical rapidly expanding megacities in China, as well as cities such as New Delhi (Legg, 2006; Kumar et al., 2015) and Jakarta (Resosudarmo and Napitupulu, 2004) in other developing countries, share issues such as severe air pollution and congested traffic conditions.

Second, this study matches geo-coded survey data with air pollution data from the monitoring network of Beijing. Air pollution is a localized phenomenon, and air pollution levels have great spatial variation, particularly in big cities such as Beijing. Thus, we use geographic information science (GIS) interpolation techniques to disaggregate pollution data and precisely estimate people's exposure to each pollutant.

Third, this study sheds light on the differences between the impacts of specific air pollutants on SWB. Air pollution levels are determined by the concentrations of a complex mixture of air pollutants. However, most of the existing literature uses one pollutant as a proxy for overall air pollution level (e.g. Levinson, 2012; Ferreira et al., 2013), though that approach is insufficient for fully understanding the relationship between air pollution and subjective well-being. In this study, we compare the impacts of four major pollutants: $SO_2$, $NO_2$, $PM_{10}$ and $PM_{2.5}$. Our results show robust negative impacts of these pollutants on SWB but with different magnitudes.

The rest of this paper is organized as follows. Section 2 provides a literature review on the application of the SWB approach to environmental problems. Section 3 describes the survey, and Section 4 describes the objective air pollutant data and GIS interpolation technique.

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[5] Economists frequently use both life satisfaction and happiness as measures of subjective well-being. Although these measures can be used interchangeably in some cases, there is a distinction in meaning in both English and Chinese. The Chinese term "*xingfu*" is usually used as the translation of "happiness," which is closest to an overall evaluation of one's life, especially in terms of interpersonal relationships. The Chinese word "*manyi*," which corresponds to "life satisfaction," invokes concern with a relative standard of living or material comforts (Chen at al., 2015). Given that we focus primarily on the impact of air pollution, it is more appropriate for us to use life satisfaction (*manyi*) than happiness (*xingfu*).

Section 5 explains the empirical regression model. Section 6 presents the regression results and discussion. Section 7 concludes.

## 2. Literature review

In spite of the prevalence of air pollution problems across nations, few empirical SWB studies have focused on air pollution. Most of the related literature uses data from developed countries due to the limited availability of self-reported subjective well-being and air pollution data elsewhere. Welsch (2006) analyzed the impacts of a series of air pollutants, including $NO_2$, total suspended particulate (TSP) and lead (Pb), in 10 European countries and found that $NO_2$ and Pb have a statistically significant negative effect on life satisfaction.[6] Welsch (2007) extended the SWB approach to a welfare analysis by estimating not only the monetary benefit of air pollution abatement but also the associated costs in terms of foregone income using a cross-national dataset that covers 54 countries.[7] Other studies have focused on particular parts of a country. Cuñado et al. (2013) evaluated the roles of both air pollution ($PM_{10}$ and $NO_2$) and climate change to explain the regional difference in life satisfaction among Spanish regions. Ambrey et al. (2014) used the SWB approach to estimate the cost of air pollution ($PM_{10}$) in southeast Queensland, Australia.

Our study is most closely related to empirical studies that use Chinese survey and pollution data. Smyth et al. (2008) used a 2003 survey with 8,890 valid responses collected in 30 major Chinese cities and found that respondents from areas with relatively high levels of $SO_2$ emissions reported significantly lower subjective well-being. Smyth et al. (2011) used an updated 2007 survey with 2,741 samples from six Chinese cities and found that atmospheric pollution, $SO_2$ and suspended particle concentrations have a negative impact on an originally constructed personal well-being index. Using happiness data collected in 2012, Liao et al. (2014) examined the effect of estimated perceived risk from air pollution on happiness in mining areas of China. Their results showed that air pollution significantly lowered people's

[6] The reason that TSP has a non-significant effect is that, as Welsch explains, TSP has a strong negative association with gross national product (GNP), which is included as an income indicator in the regression model. Because this study uses self-reported household income rather than GNP, there is no such concern.
[7] In that study, he computed the net marginal benefit of air pollution abatement, optimal abatement rates and monetary value of optimal abatement based on the results of SWB analysis.

happiness and suggested that air pollution reduction is an important policy measure to improve people's happiness. Xu and Li (2016) also reported negative effects of air pollution on happiness based on happiness measures from the World Values Survey 2007 and subjective air pollution perceptions.

Most related studies use regional- or local-level air pollution data. While these aggregated datasets are sufficient for yielding robust results according to previous studies, Brereton et al. (2008) suggested that the explanatory power of the subjective well-being function would increase if location-specific factors were taken into account. Moreover, some researchers have noted that pollution data constraints at the local and regional levels restricted their analyses to the national level or to focusing on a particular localized area where richer data were available (Rehdanz and Maddison, 2005; Welsch, 2006). These remarks indicate the importance of local analyses with detailed pollution data.

Previous studies have matched survey and pollution data in various ways. A spatial interpolation method is rarely used in SWB studies, but some studies have incorporated advanced techniques such as geographic information system (GIS) or atmospheric modeling techniques to match individual survey data and location-specific air pollution data. Ferreira et al. (2013) used a spatial interpolation method (inverse distance weighting) to generate individual-level $SO_2$ concentrations for respondents in 23 European countries to analyze the pollutant's relationship with people's life satisfaction. Levinson (2012) used a weighted-distance interpolation method to estimate individual-level $PM_{10}$ concentration in the U.S. MaKerron and Mourato (2009) estimated $NO_2$ concentration from an air dispersion model in their SWB study for London. Orru et al. (2016) also used a Eulerian air quality dispersion model to generate $PM_{10}$ data for 30 nations across Europe. Based on air pollution datasets created by various estimation techniques, these studies found that robust significant negative effects of air pollution were reported. In this study, we also incorporate GIS techniques to match location-specific pollution data to individual survey data.

In addition to the impact of pollution levels on SWB, researchers have examined the impacts of subjective environmental indicators such as environmental attitudes and behaviors. Sekulova et al. (2013) examined whether ecological consumption reflects ecological awareness and affects life satisfaction. Binder and Blankenberg (2016) found that people's environmental concern (egoistic) has a negative impact on life satisfaction, while volunteering (altruistic) is positively associated with life satisfaction.[8] Ferrer-i-Carbonell and Gowby (2007) examined the effects of people's concern about specific environmental issues, ozone layer and animal extinction and reported a negative effect of concern about the ozone layer and a positive effect of concern about species extinction. Suárez-Varela et al. (2014) used a series of environmental actions and behaviors, such as water saving, and showed that environmental actions and behaviors do not have a negative influence. Kaida and Kaida (2015) found that pro-environmental behavior[9] might enhance not only the current subjective well-being but also expectations of future subjective well-being.

Building on previous studies, we also analyze the impact of reported environmental attitudes and environment-related behaviors. In addition to the individual impacts of these environment-related variables, we examine the interaction of the effects of objective air pollution level and subjective environmental attitudes and behaviors on people's life satisfaction.

## 3. Subjective well-being survey

### 3.1 Survey

In this study, we use an original Internet survey conducted during January and February 2016 in Beijing.[10] The survey questionnaire was designed to collect self-reported overall life satisfaction levels as well as other personal and household characteristics. Internet surveys have an advantage in avoiding interviewer bias caused by arbitrary factors, such as the appearance or gender of interviewers, in responses to sensitive questions such as household

[8] Specifically, Binder and Blankenberg (2016) found that people who are more concerned about environmental problems have relatively lower life satisfaction, but people who are more likely to volunteer for environmental activities have relatively higher life satisfaction.

[9] Pro-environmental behavior is collectively defined as behavior responsible for protecting the environment in its diverse domain.

[10] In this study, we set the sample target based on general age x gender distribution. The survey was closed for each cell when the sample target was filled. If cells did not meet the target sample number (e.g., the cells for females and males x age above 60 were not filled) during the survey period, then the nearest cells (e.g., respondents in the 50-59 age group) were substituted. The respondents' reward was adjusted by the expected response in each target cell, their income level, and the number of questions that they answered and ranged from USD$.50 to $5. Further details about sampling can be found online: https://www.surveysampling.com/technology/ssi-dynamix.

income, employment status and WTP (Welsch and Kühling, 2009). Out of 2,853 responses, 1,064 had an accurate Beijing area zip code, which was necessary to merge the survey data with pollution data. We further excluded 42 responses without household income data and 64 responses that were collected during the Chinese New Year holiday.[11] We were left with a sample of 958 for the analyses.

Our target area, Beijing, covers 16,807 km$^2$ and is surrounded by the Yanshan Mountains except to the south. Due to this special geographical structure, the downtown area is located in the central area, where the majority of the total population and nearly 75% of the urban population reside.[12] Fig. 1 shows the locations of our respondents, which are geo-coded according to the residential addresses or zip codes reported by respondents. Of 958 respondents, 836 reside in the central downtown area; hence, the results of this study heavily represent the urban population of Beijing.

Table 1 provides a comparison of basic demographic characteristics between our sample and the data from statistical yearbooks and the Chinese General Social Survey (CGSS 2013). We compare ages and gender distributions with official statistics from the 2015 Beijing Statistical Yearbooks. Our sample has relatively fewer respondents who are older than 60 due to the difficulty of reaching this age group through an Internet survey. However, we address this issue by collecting more samples in the age group of 50–60, who would closely share many characteristics with respondents over the age of 60.

Given the lack of official statistical data for gross annual household income, we compare our income distribution with CGSS data that were used by similar previous SWB studies (e.g., Wang et al., 2015; Qian and Qian, 2015). The average annual household income of our sample is approximately 174,000 *yuan* (USD $26,000), which is higher than the average income shown in the CGSS in Beijing by approximately 31,000 *yuan* (USD $5,000). Because most of our respondents live in the urban area, some upward bias in income is inevitable.

[11] A one-week-long national holiday starts the day before Chinese New Year. People living or working in Beijing usually leave the city for a vacation or go to their hometown to visit their parents and other relatives according to the custom of this traditional festival. It is possible that some or even most of our respondents who took the survey during this period might not have been in Beijing; thus, their responses may have been biased by the experience of staying in other regions and hence may not accurately represent the ordinary life they live in Beijing. In 2016, the Chinese New Year holiday was February 7-13.

[12] The *Hukou* system of China allows us to easily distinguish urban and rural residents. Data from *Beijing Statistical Yearbook 2016*.

Additionally, our data do include samples from the lower-income distribution; thus, the skewness is not extreme.

### 3.2 Life satisfaction measures

We use an overall life satisfaction measure as a dependent variable in the analysis. Given that subjective well-being-related questions are particularly vulnerable to the context and timing in which they are asked, they were placed at the beginning of our questionnaire in order to avoid short-term bias from questions that were asked prior to the SWB-related questions. We asked the following question:

"*Please imagine a ladder with steps numbered from 0 to 10 at the top. The top of the ladder represents the best possible life for you, and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time?"*

The respondents chose a number from an 11-point scale from 0 (worst possible life) to 10 (best possible life). Fig. 2 shows the distribution of self-reported life satisfaction rating, with a mean of 6.81 and a median of 7. The ratings are normally distributed and slightly skewed toward the right. We refer to this life satisfaction variable as LS in the analysis.

### 3.3 Household and personal characteristics

Using our survey, we constructed various variables of household and personal characteristics. We control for determinants that have commonly been used in previous SWB studies: annual household income (*household income*), age (*young, middle-aged, old)*, gender (*female*), education degree (*college graduate*), marital status (*single*, *married*, *divorced or widowed*), household members (*household with children* and *household with young children*) and employment status (*unemployed*).[13] Previous studies have shown that current mood and context may cause fluctuations in people's answers to subjective well-being from day to day

[13] Because both of the commonly used continuous age control variables, age and age-squared, have no significant effect on life satisfaction, we use age dummies to control for the age effect.

(Kahneman and Krueger, 2006).[14] Therefore, we control for the self-reported health evaluation (*poor subjective health*) and a series of psychological factors, including the importance of being trusted by others (*trust*), weather (*sunny*), mood (*enjoy* and *sad*) and personality (*stable*, *passive* and *outgoing*). We also control for two commuting-related factors, *commuting modes* and *congestion time*, both of which have been shown to have an impact on people's life satisfaction (Bergstad et al., 2011; Olsson et al., 2013; Sekulova and van den Bergh, 2013).

Since, we examine the impact of air pollution, we also employ some environment-related subjective indicators to represent people's attitude or behavior toward the environment. We control for how much importance the respondents place on the environment (*environ. importance*), their dissatisfaction with the current environmental quality (*environ. dissatisfaction*), and participation in environmental activities through financial contributions or by participating full time, part time or as a volunteer (*contribution to environ. act.* and *work/volunteer for environ. act.*).

## 4. Air pollution exposure

### 4.1 Monitored air pollution data

In this analysis, we use aggregated data of hourly monitored air pollution data that are collected at thirty-five stations in Beijing (Fig. 3). At each station, automatic monitoring systems measure the ambient concentrations of $SO_2$, $NO_2$, CO, $O_3$, $PM_{10}$ and $PM_{2.5}$ based on China's Environmental Protection Standards (HJ 193-2013 and HJ 655-2013). The real-time concentration values from monitoring stations are automatically transferred to the China National Environmental Monitoring Center and then published with validation from the Technical Guidelines on Environmental Monitoring Quality Management (HJ 630-2011). Of the thirty-five monitoring stations, thirty are stationary stations and five are mobile stations located near the main urban expressways.

[14] We asked respondents to report their present mood in the on-line survey. We included five questions, each of which corresponds to different moods, including pleasure, anger, sadness, enjoyment and smiling. We found that positive emotions (pleasure, enjoyment and smiling) had significant correlations with each other (with Pearson's r above 0.5), as did the negative emotions (sadness and anger). However, there was no significant correlation between factors from each group (with Pearson's r below 0.1).

We aggregate the published[15] hourly data of four air pollutants ($SO_2$, $NO_2$, $PM_{10}$ and $PM_{2.5}$) during January and February 2016. The average concentrations of $SO_2$, $NO_2$, $PM_{10}$ and $PM_{2.5}$ in this period are 14.55 μg/m$^3$, 33.37 μg/m$^3$, 53.95 μg/m$^3$ and 48.48 μg/m$^3$, respectively. The average concentrations of the four pollutants in the winter (from mid-November 2015 to mid-February 2016) are 19.98 μg/m$^3$, 67.73 μg/m$^3$, 101.86 μg/m$^3$ and 121.32 μg/m$^3$, respectively, and the average concentrations in the first six months of 2015 are 14.98 μg/m$^3$, 52.07 μg/m$^3$, 112.29 μg/m$^3$ and 85.91 μg/m$^3$.[16]

Overall, the average pollution level of our sample is lower than both the average level in the winter and the average level for the first six months of 2015.[17] The average concentrations of $SO_2$ have little variation over time, but the average $NO_2$, $PM_{10}$ and $PM_{2.5}$ concentrations in our samples are significantly lower than the average levels in 2015 and in almost half of the winter. This comparison indicates that the air pollution level used in this analysis is moderate and does not reflect the extreme worst pollution level that people in Beijing can experience.

### 4.2 Spatial interpolation

We use the ordinary kriging (OK) method, a spatial interpolation technique, to match air pollution data with geo-coded survey data at the individual level. The SWB study by Ferreira et al. (2013) uses inverse distance weighting (IDW) as the interpolation method. One of the key differences between OK method and IDW is that IDW does not take the spatial autocorrelation into account, whereas OK method does. As Ferreria et al. (2013) analyzed cross country data of 23 European countries, there might have been relatively little spatial autocorrelation. However, our study uses an intra-urban data at city level. Therefore, the presence of spatially correlation in our air pollution data is a major concern in the estimation. Hence we use OK method to deal with this possible spatial autocorrelation in our merged data. (See, Li and Heap (2011) for further comparison of various interpolation methods including two methods above).

[15] Real-time data are available for no charge, but historical data that we have used were purchased.
[16] Average concentrations of the winter and of 2015 are also the average individual air pollutant concentrations derived from the GIS interpolation technique.
[17] The average pollutant concentrations for winter, particularly the $PM_{2.5}$ concentration, are extremely high, which may be because there were heavy haze episodes in Beijing 8 times in the period between mid-November and the end of December.

For each respondent, we use the OK method to estimate the average concentration of each pollutant at the given home address. Specifically, we average the hourly concentrations during a week prior to the date on which the respondent took the survey. The OK method is a popular method in the field of epidemiological studies for conducting exposure assessment (e.g., O'Leary et al., 2014; Arifin et al., 2015). This method accounts for spatial trends and spatial autocorrelation of air pollution concentrations measured in the available network of sampling sites. The idea is to predict the value of a function at a given point by computing a weighted average of the known values of the function in the neighborhood of the point. The general function can be written as follows:

$$\hat{z}(s_0) = \sum_{i=1}^{n} w_i z(s_i) + \epsilon(s_0) \qquad (1)$$

Pollutants are represented as the Z variable. $\hat{z}(s_0)$ is the concentration at unobserved location $s_0$ and is estimated with a weighted average of known neighborhood samples $z(s_i)$. $w_i$ is the optimal weight assigned to neighborhood $z(s_i)$. $\varepsilon_i$ is the random field with covariogram function *C(h)* and variogram $\Upsilon(h)$. $w_i$ should satisfy two objectives in the geo-statistical formulation: unbiased, which means $\sum_{i=1}^{n} w_i = 1$, and minimal variance of estimation, which is expressed as $\mathrm{Var}(\varepsilon_i) = 0$. The weights are determined by solving this minimization problem by using variogram $\Upsilon(h)$[18], the definition of which is

$$\gamma(h) = \frac{1}{2n} \sum_{i=1}^{n} \{z(s_i) - z(s_i + h)\}^2 \qquad (2)$$

n is the number of pairs of sample points of observations, and *h* is the spatial lag distance.

This technique is implemented using ArcGIS. A detailed description of the dataset construction can be found in the appendix. Note that while conducting OK interpolation, we observed substantially high $NO_2$ concentrations at mobile monitoring sites compared with concentrations at stationary sites.[19] This spatial heterogeneity, which is common in urban areas, may lead to an upward bias in exposure estimation, especially for residences near the

[18] OK usually use variogram rather than covariogram because it has better statistical properties (unbiased and consistent). More comprehensive description about the theory of OK method can be found in Cressie (1988).
[19] Given that the fuel combustion of vehicle engines is the main source of $NO_2$, it is not surprising to see this difference. However, we did not observe significant differences between stationary and mobile sites for the other pollutants ($SO_2$, $PM_{10}$ and $PM_{2.5}$).

mobile sites. Therefore, we exclude the 5 mobile monitoring sites for the interpolation process of $NO_2$. Table 2 presents the statistics of estimated air pollution exposure. For the concentration of air pollutants, $PM_{10}$ and $PM_{2.5}$ show the highest variation from their standard deviation.

## 5. Empirical model

In previous studies, both ordinary least squares (OLS) and ordered probit have been used as common empirical methods (e.g., Ferrer-i-Carbonell and Gowdy, 2007; Luechiger, 2009). Although using ordered probit theoretically seems to be more appropriate, given that the SWB measures are ordinal, Ferrer-i-Carbonell and Frijters (2004) have found that both approaches can provide robust and similar results. This claim is supported by the results of van den Berg and Ferrer-i-Carbonell (2007), MacKerron and Mourato (2009), Levinson (2012) and others. Moreover, one advantage of the linear probability model over the logit or probit is that it permits estimation of group-specific dummy variables when the dichotomous outcome of interest does not vary within the group (Caudill, 1988). This feature is especially important because it helps to avoid these restrictions as a source for selection bias (Evans and Smith, 2005). In addition, using OLS also allows us to easily interpret the implications of the estimated coefficients and make comparisons between them. Hence, we use OLS as the main regression algorithm for the interpretation. We specify the function of life satisfaction as follows:

$$LS = f\{Income, Environment, Personal\ characteristics\} \qquad (3)$$

Our dependent variable is self-reported life satisfaction rating (*LS)*. ***Income*** is the gross annual household income. ***Environment*** contains both objective indicators (air pollutant concentrations) and subjective indicators (environmental attitudes and behaviors). ***Personal characteristics*** is a set of control variables such as age, gender, subjective health condition, and others. Table 3 presents all the employed variables.

We further add several interaction variables to the regression model. We use interactions of air pollutant concentration and *environ. importance, environ. dissatisfaction,* *Contribution to environ. act.*, and *work/volunteer for environ. act.* We intend to use these interactions to determine whether there are interaction effects between air pollution and environmental attitudes and behaviors. Pollutant concentrations are centered before being included in the regression in order to eliminate possible collinearity.[20]

In addition, using the estimated coefficients, we estimate the implicit willingness to pay (WTP), which indicates the trade-off between household income and $PM_{2.5}$ concentrations when holding people's life satisfaction constant.

First, we calculate the WTP based on the OLS estimation without taking interaction variables into account.

$$\text{WTP} = -Income_i \, {}^{ß_{air}}/_{ß_{income}} \tag{4}$$

$ß_{air}$ is the estimated coefficient of each pollutant. $ß_{income}$ is the coefficient of income.

Then, we add each interaction variable to Eq. (3) if the estimated regression coefficient is statistically significant.

$$\text{WTP} = -Income_i \, {}^{(ß_{air} + ß_{int} I_{int})}/_{ß_{income}} \tag{5}$$

$ß_{int}$ is the coefficient of the interaction variable. $I_{int}$ is the interaction variable (i.e., if the interaction is between *$PM_{2.5}$ concentration* and *environ. importance*, then $I$ is *environ. importance*).

## 6. Empirical results and discussion

### 6.1 The effect of air pollution

Table 4 shows the regression results for four air pollutants. Models without interactions (Model 1) are in columns 1–4, and models that include interaction terms (Model 2) are in columns 5–8.

[20] A variable is centered by using the following calculation: $Centered\ Variable_i = Variable_i - \overline{Variable}$, where $Variable_i$ is the observation of one variable and $\overline{Variable}$ is the mean of one variable. Robinson and Schumacker (2009) provided a detailed explanation of why centering of variables is required when examining interaction effects.

We perform several robustness checks using ordered probit and alternative life satisfaction measures.[21] The results are provided in Table A1 in the appendix.

The results shown in Table 4 indicate that all four pollutants have statistically significant negative impacts on people's life satisfaction. This result supports the negative effect of air pollution reported by previous empirical studies (e.g. Smyth et al., 2008; MacKerron and Mourato, 2009). The coefficients indicate the change in life satisfaction rating with a 1 $\mu g/m^3$ change in a pollutant's concentration, and the magnitudes of impact vary across pollutants. According to the results in Model 1 without interaction variables, the coefficients of $NO_2$ and $SO_2$ are approximately 2.5 times larger than the coefficients of $PM_{10}$ and $PM_{2.5}$, indicating greater marginal impacts of $NO_2$ and $SO_2$. $NO_2$'s strong marginal impact has also been found in previous studies. Welsch (2006) reported in multi-country analyses that $NO_2$ has a significant impact on life satisfaction, whereas TSP does not.

We calculate that the total life satisfaction reductions caused by $SO_2$, $NO_2$, $PM_{10}$ and $PM_{2.5}$ with the current pollution level in our samples and reduction effects are 0.31, 0.66, 0.32 and 0.27, respectively. Although $SO_2$ has a high marginal impact, due to its relatively low concentration, the total negative impact is close to those of $PM_{10}$ and $PM_{2.5}$. However, $NO_2$ still has the greatest total negative impact, which is approximately 3 times larger than those of the other three pollutants.

Furthermore, we calculate the possible LS improvement from reducing air pollutant concentration to a lower health risk level based on the Chinese and the U.S. air quality index (AQI) (see Table 5 for the both countries' AQI standards.).[22] In AQI standards, air pollution concentrations are categorized into different levels that correspond to certain health risk levels. The U.S. and Chinese standards are similar for all pollutants except the thresholds of $PM_{2.5}$. Current average pollution levels in our sample correspond to the following health risk levels in China's AQI standards: $SO_2$ is in the "Good" category, while $NO_2$, $PM_{10}$ and $PM_{2.5}$ are in the

[21] The alternative life satisfaction indicator is based on this question: "*All things considered, how satisfied are you with your life as a whole these days?*" also with an 11-point scale from 0 (completely dissatisfied) to 10 (completely satisfied).

[22] The AQI is a simplified index for informing the public of the air pollution and health risk level. The US EPA first introduced it, and then the Chinese Ministry of Environmental Protection (MEP) developed the Chinese AQI standard in 2012 following the US EPA AQI approach. In addition to China's AQI standards, we consider the US AQI standards as a complement because they are prevalent standards that have been used in many previous studies, including studies for China (e.g., Rohde and Muller [2015]).

“Moderate” category. $SO_2$ pollution is under control, and the other three pollutant concentrations may still achieve the “Good” category via a reduction in their concentration levels. If the average pollution levels of $NO_2$, $PM_{10}$ and $PM_{2.5}$ decrease to the upper-limit concentration of the “Good” category, then LS would improve on average by 0.11, 0.16, and 0.12 points, respectively. However, if we use the U.S. standard, Beijing’s current average $PM_{2.5}$ pollution concentration is in the “Unhealthy” category. Reducing $PM_{2.5}$ concentration to the “Moderate” or “Good” category in the U.S. standard would improve the average LS by 0.11 or 0.22, respectively.

Our results imply that people in Beijing may be underestimating the impact of $PM_{2.5}$ pollution. The $PM_{2.5}$ pollution is much more severe than that of the other three pollutants even according to China’s AQI standards, which are much more lenient than the U.S. standards (see both Table 2 and Table 5). Moreover, $PM_{2.5}$ is more detrimental to people’s health than other pollutants (Dockery et al., 1993; Muller and Mendelsohn, 2007; Beelen et al., 2014). Hence, people in Beijing should be more attentive to the $PM_{2.5}$ level and perhaps should acknowledge the difference between the Chinese AQI standards and stricter global standards.

### 6.2 The impact of environmental attitudes and behaviors

As shown in Table 4, environmental attitude indicators (*environ. importance* and *environ. dissatisfaction*) have significant negative effects on LS, while the indicators of environmental behaviors (*contribution to environ. act.* and *work/volunteer for environ. act.*) have significant positive effects on LS. These results indicate that people who think the environment is important and are unsatisfied with the current environmental quality have relatively lower LS. This perception may reflect anxiety that is accentuated by the value that respondents assign to environmental quality.

In contrast, the results show that participation in environmental activities by either monetary contribution or working/volunteering improve LS. The coefficient of *contribution to environ. act.* is greater than that of *work/volunteer for environ. act.*, but the Wald tests show that there is no significant difference between the magnitudes of the two coefficients. This result is consistent with the findings of previous studies of the positive effect on well-being of volunteering for environmental activities (Suárez-Varela et al., 2014; Kaida and Kaida, 2015).

We further examine the interaction effects between air pollution and environmental attitudes and behaviors. Table 4 shows the results of the interaction variables between pollutant concentrations and *environ. importance* or *environ. dissatisfaction*. Both interaction effects are non-significant. The interaction effect of pollution and *contribution to environ. act.* is non-significant, but for *work/volunteer for environ. act.*, pollution levels have a significant positive impact on LS. This result indicates that the LS gain from working for environmental activities is attenuated at higher levels of air pollution.

Our results suggest that policy makers may want to further encourage people to take part in environmental activities to enhance their subjective well-being. In addition, we find that working or volunteering for environmental activities has a higher impact on SWB than simply making financial contributions. Furthermore, based on our survey data, there seems to be no significant correlation among Beijing residents between whether people think environment is important and their actual participation in environmental activities.[23] This phenomenon has also been reported in other countries, such as Japan (Hiramatsu et al., 2015). Hence, propaganda or education policy to raise environmental awareness may not be sufficient to incentivize Beijing residents to participate in environmental activities. Thus, policy makers may need to construct more direct incentive systems to increase participation in environmental activities, which in turn will raise people's perceived well-being.

### 6.3 Willingness to pay

Table 6 shows the average WTP of all respondents and for respective subgroups. The values are calculated based on the estimated coefficients in Model 1 and Model 2 of Table 5. On average, respondents are willing to pay approximately USD \$2,100 (13,682 *yuan*) and \$2,190 (14,235 *yuan*) for a 1 μg/m$^3$ reduction of average $SO_2$ and $NO_2$ concentrations, respectively. In contrast, the WTP for $PM_{10}$ or $PM_{2.5}$ is USD \$810 (5,271 *yuan*) and \$741 (4,816 *yuan*),

[23] The correlation coefficients of *Environ. importance* and *Contribution to/Work experience in environ. act.* are 0.076 and 0.027, respectively.

respectively. When groups are divided by whether respondents participate in environmental activities, we find significant gaps in the two WTPs; those who work or volunteer for environmental activities are willing to pay 3 times as much for $NO_2$ reduction or 10+ times as much for $SO_2$, $PM_{10}$ and $PM_{2.5}$ reduction as those who do not participate in environmental activities. This difference may reflect a feeling among people who participate in environmental activities that they have already made efforts for air pollution mitigation; thus, they are less willing to make financial contributions.

Using the estimated WTPs, we conduct a rough cost-benefit analysis of the Clean Air Action Plan, a recent pollution mitigation action issued by the State Council of China in 2013.[24] Beijing's target was to reduce the annual average $PM_{2.5}$ concentration to approximately 60 μg/m$^3$ by 2017. Starting in 2014, the Beijing government planned to invest approximately 760 billion *yuan* (USD $110 billion) for $PM_{2.5}$ control to reach the target by 2017. If the target concentration were met, the average exposure would decrease by 30.1 μg/m$^3$. Given that there are approximately 20 million residents in Beijing, the total welfare benefit calculated from the average per-person WTP would be approximately 2,900 billion *yuan* (USD $445 billion). In the context of people's well-being, the minimal achievement of the Clean Air Action Plan would be beneficial. According to recently reported yearly $PM_{2.5}$ data, it seems to be difficult for the Beijing government to meet the target of 60 μg/m$^3$,[25] but based on the 2016 $PM_{2.5}$ concentration of 73 μg/m$^3$, the benefit in terms of increased LS is approximately 1,637 billion *yuan* ($218 billion). Note that the number used as the total benefit of LS could be upwardly biased because the estimated average WTP heavily represents the WTP of residents in the central urban area. If we use the average household income collected in the CGSS (142,000 *yuan*), which is lower than our household income average, to calculate WTP, the total benefit of $PM_{2.5}$ reduction from 2013 to 2016 would be approximately 1,348 billion *yuan* (USD $207 billion). Thus, the reduction effort far exceeds the cost in terms of nonmonetary well-being.

[24] The full plan report in Chinese is available online at http://zhengwu.beijing.gov.cn/gzdt/gggs/t1322955.htm.
[25] The annual average $PM_{2.5}$ concentrations have declined from 2013 to 2016: 90 μg/m$^3$ (2013), 85 μg/m$^3$ (2014), 80 μg/m$^3$ (2015) and 73 μg/m$^3$ (2016).

### 6.4 The impacts of other personal characteristics

Table 4 also shows the effects of individual and household characteristics on LS. The results show that elders tend to have lower life satisfaction than young or middle-aged respondents. This difference may reflect the fact that urban life has taken a greater toll on older generations dealing with the substantial changes in living environment and lifestyle caused by the rapid urbanization of Beijing over the past few decades. This result is different from the U-shaped effect of age reported in previous studies. In addition, we do not find a significant impact of gender, marital status, education level, unemployment or the number of household members. Furthermore, commuting modes do not significantly affect LS. This result is contrary to the results of Du and Shin et al., who found a significant positive effect of commuting by cars in northeastern China. Nevertheless, *Congestion time* has a significant negative impact on life satisfaction; for instance, ten minutes of congestion time reduces LS by one point on a 0-10 scale. Lastly, the *Trust* variable has a significant positive effect, which indicates that people value social relationships, particularly where the other person is perceived as trustworthy. We found no significant effect of weather on life satisfaction but a significant positive effect of positive moods on life satisfaction and vice versa.

## 7. Conclusion

This study uses the SWB approach to evaluate the effect of air pollution on people in Beijing. We use self-reported life satisfaction data from an original Internet survey conducted in 2016, which enables us to provide the latest empirical evidence on subjective well-being in China. We combine the survey data with separately collected air pollution data for four major pollutants ($SO_2$, $NO_2$, $PM_{10}$ and $PM_{2.5}$) from thirty-five monitoring sites in Beijing to identify the role of environmental quality in determining people's subjective well-being.

We constructed an individual-level air pollution dataset using a GIS interpolation technique to match estimated pollution data with geo-coded survey data. This data aggregation can provide more reliable results for air pollution effects, as the matching of pollution data and survey data is relatively more precise than using district-level data.

Our results show that all four pollutants have significant negative impacts on respondents' life satisfaction levels. By comparing the estimated coefficients, we find that the marginal negative effects of $NO_2$ and $SO_2$ are much stronger than those of $PM_{10}$ and $PM_{2.5}$. However, in terms of the total impact when taking the current pollution level into account, $NO_2$ still has the greatest impact, while the other three pollutants are quite close to each other in impact. In either case, $PM_{2.5}$ always shows a relatively minor impact on life satisfaction despite the fact that the current level of $PM_{2.5}$ presents a more serious potential health impact than the current levels of the other pollutants. Therefore, we suppose that people may underestimate the negative impact of $PM_{2.5}$ because of the loose standard for $PM_{2.5}$ in China's Air Quality Index.

Moreover, we examine the effects of environmental behaviors. We find that contributing money and working/volunteering for environmental activities have positive effects on life satisfaction. Furthermore, in terms of interaction effects with air pollution indicators, we also find that people who are working/volunteering for environmental activities are less affected by the negative impact of air pollution, whereas there is no such effect for people who contribute money to environmental activities. Therefore, we suggest that Beijing's government could improve public life satisfaction by encouraging citizens to take part in environmental activities, particularly by working (full/part time) or volunteering.

In terms of demographic indicators, we find that some results of main variables such as gender, marital status and education deviate from the usual results of previous studies.[26] Beijing seemed to differ from typical metropolitan areas in developed countries. Beijing is a still rapidly developing city with frequent migration traffic and rapid outward urban expansion. Additionally, the city has become a melting pot, with diversity in residents' ideology and cultural background, which in turn makes the impact of people's background on their well-being more difficult to predict.

Our analysis highlights the facts that air pollution is an important determinant of people's life satisfaction and that people's perception of pollutants may digress from the actual severity or threat. This study has several limitations that could be addressed in future studies.

[26] In previous studies, it has been commonly reported that females/married people/highly educated individuals have higher life satisfaction and people who have no job have lower life satisfaction (Welsch, 2009; Welsch and Kühling, 2009), which all differ from the results of this study. Only the results of household members' indicators are consistent with previous studies in northeastern China (Du and Shin et al.).

We have provided a simple cost-benefit analysis of the Clean Air Action Plan for Beijing based on the estimated WTP from our results to show a possible application of the SWB approach to environmental policy planning.

The framework of this study could be extended in future studies to perform a comprehensive and more sophisticated cost-benefit policy analysis using improved survey data in terms of representativeness. Additionally, we use congestion as a control variable in this study; there seems to be no significant issue of multicollinearity in the estimation, but theoretically, congestion may affect people’s well-being partially through air pollution. Our study did not fully explore the possible mediation effect, but also the intricate relationship between SWB and pollution. The link can be further elucidated with appropriate datasets and analyses.

Lastly, the pollution environment and people’s perceptions vary across cities and countries. Similar studies in other metropolitan area, especially in developing countries with fast-paced urbanization that are facing pollution problems, would provide further evidence for comparison and generalization.

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