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# Air quality, human behavior and urban park visit: A case study in Beijing

Yaqiong Jiang [a], Ganlin Huang [a, b, *], Brendan Fisher [c]

[a] Center for Human-Environment System Sustainability (CHESS), State Key Laboratory of Earth Surface Processes and Resource Ecology (ESPRE), Beijing Normal University, Beijing, 100875, China
[b] School of Natural Resources, Faculty of Geographical Science, Beijing Normal University, Beijing, 100875, China
[c] Gund Institute/Rubenstein School of Environment and Natural Resources, University of Vermont, Burlington, VT, 05405, USA

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ABSTRACT

Parks provide critical ecosystem services to urban residents. Many of these services can only be realized when people visit parks. Particulate matter exposure poses negative health impacts and may turn the health benefits brought by park visits into health risks. This tradeoff relationship is heavily moderated by how individuals behave under varying ambient air quality conditions. While there is a growing evidence base regarding the benefits brought by urban parks, little is known about how people adjust their park visitation to air pollution. Here we use two approaches to understand if air quality affects urban park visits in Beijing: a stated preference survey on social media and a year-long faceto-face survey in a neighborhood park. Quantile regression and ANOVA analysis were used. We found particulate pollution has a negative impact on the maximum number of visits a park may receive. A significant drop occurred when the pollution level changed from moderate to heavy pollution. Therefore, the ecosystem services provided by parks are not fully realized due to the reduced number of visits caused by air pollution. Second, regardless of how poor air quality is, a proportion of people (41-64%) put themselves at exposure risk to enjoy the benefits brought by parks. Third, the inconsistency between behavior and intention signals people are less protected from the potential adverse health impacts of poor air quality than they think. Future study should look into what factors may cause the divergence between people's intentions and behaviors. Understandings on this issue will contribute to design better guidance and incentives to reduce the adverse health cost of air pollution exposure from park visitation.



## 1. Introduction

Urban parks and greenspace provide critical ecological and social benefits to urban residents across the globe. These spaces have been shown to provide habitat (Ngiam et al., 2017), mitigate air pollution (Yang et al., 2005; Nowak et al., 2006), reduce noise (Pathak et al., 2011) and alleviate urban heat island effects (Li et al., 2012; Zhou et al., 2017). Moreover, urban parks and greenspace benefit urban residents by promoting physical exercise (Sang et al., 2016), enhancing social connections among people (Campbell et al., 2016), and reducing stress (Ulrich et al., 1991). For example, living nearby a park has been linked to greater physical exercise in the park and reduced risk of child obesity and the total number of deaths (Roemmich et al., 2006; Coutts et al., 2010). A postal survey in Gothenburg, Sweden showed that higher perceived naturalness of an area generated higher self-reported well-being for residents living nearby (Sang et al., 2016). In a cohort study of 976 elderly people in Hong Kong, researchers found geographical variation in telomere length, a marker of biological ageing. People living in areas with more parks had longer telomeres after adjusting for other factors including age, smoking, socioeconomic status and physical activity level, which indicated that a restorative environment provides real health benefits (Woo et al., 2009).

In China, urban parks and green spaces have been shown to encourage physical activities (Liu H, Li et al., 2017), deliver health benefits (Chen et al., 2017; Wong et al., 2017), and improve psychological wellbeing (Wang et al., 2016; Dong et al., 2017). Among the 300 urban parks in Beijing, the 11 parks managed by the municipal administration center of parks alone received 94 million

* Corresponding author. Center for Human-Environment System Sustainability (CHESS), State Key Laboratory of Earth Surface Processes and Resource Ecology (ESPRE), Beijing Normal University, Beijing, 100875, China.
*E-mail address:* ghuang@bnu.edu.cn (G. Huang).

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visits in 2017. As such, the ecosystem services delivered by these 11 parks benefit an average of 258,164 people daily. Given the importance of urban parks and green spaces in Beijing, it is critical to understand what drives visitation rates.

One suggested driver that might impact the welfare delivered by urban parks in China is outdoor air quality (Huang, 2014; Liu H, Feng et al. 2017; Liu Y et al., 2017). Despite recent improvements in Beijing's air quality the city still experienced 299 days in 2017 where $PM_{2.5}$ (particulate matter < 2.5 μm in diameter) concentrations were above the air quality standard recommended by the World Health Organization (WHO) (WHO, 2006; Zhang et al., 2016; Beijing, 2018). In a city where hundreds of millions of people visit parks yearly, ambient air quality exposure of park visitors could constitute a public health risk. Particulate matter exposure poses a suite of negative health impacts including increased lung cancer incidence, and cardiovascular morbidity and mortality (Dockery et al., 1993; Langrish et al., 2012; Raaschou-Nielsen et al., 2013). Ambient particulate matter pollution ranked ninth globally (Lim et al., 2012) and fourth in China (Yang et al., 2013) among the 67 risk factors for disease burden.

In order to reduce the adverse health impacts of particulate matter, the United States Environmental Protection Agency (US EPA) advises people to stay indoors preferably in an area with filtered fresh air, and reduce activity level to minimize the amount of particle pollution breathed into the lungs at times of poor air quality (2017). Therefore, park activities, which usually bring health benefits, may pose health risks when air quality is poor. However, little is known about how people adjust their park visitation and activities to ambient air pollution levels. While there is a growing evidence base regarding the benefits brought about by urban green spaces and parks, the reception of those benefits (e.g., stress reduction) may come at a cost (e.g., particulate matter exposure). This trade-off relationship is heavily moderated by how individuals behave under varying ambient air quality conditions.

This study aims to employed two approaches to understand if and how air quality affects urban park visits in Beijing. First, we asked people whether and how would they adjust their park visit plan according to air quality through a stated preference survey on social media across the City. Then, we investigated how air quality impacts the numbers of visitors in a residential urban park through a year-long face-to-face survey. We summarized and compared the results from people's intention as well as their behaviors, which will provide a better understanding of if (and/or how) their decisions about visiting parks are affected by pollution levels. Our findings could deliver critical policy-relevant information on how to reduce the unnecessary exposure. While we focused Beijing as a case study, air pollution is a major health risk factor worldwide and our findings may be applicable to other cities as well.

## 2. Methods

### 2.1. Study area

Beijing has a population of 21.5 million (Beijing Municipal Bureau of Statistics, 2016) with over 300 urban parks. As in any other highly urbanized and densely populated city, residents in Beijing receive many benefits from parks and green space, where they exercise, recreate, socialize, and interact with nature.

Beijing experiences severe particulate pollution. In 2016, the average annual $PM_{2.5}$ level was 73μg/m$^3$, much higher than 10μg/m$^3$, the level recommended in the WHO guidelines (2006). There were 298 days in 2016 during which the $PM_{2.5}$ concentrations were above the WHO recommended level (WHO, 2006; Beijing, 2017). As such, Beijing provides a useful case to explore our research questions. In addition, understanding how people may adjust their park use according to air pollution levels could inform policy decisions that aim to reduce the adverse health impacts brought by particulate pollution.

### 2.2. Online survey

We carried out a survey in February 25–28, 2016 through WeChat™, the most popular social media mobile app in China. The purpose of the questionnaire was to find out if the respondents would cancel their park visit plan when faced with different levels of air pollution. The Ministry of Environmental Protection in China (2012) developed a six-level air quality standard to describe the $PM_{2.5}$ level from “clean” to “severe pollution” (Table 1), which was adopted to describe air quality (i.e., slight/moderate/heavy/severe pollution levels) in the survey. This standard has been widely used in air quality report and forecast that people are familiar with. We asked “If you plan to visit a park but find out the air quality is ‘slight pollution’, would you cancel your park visit?” If the answer was yes, then the questionnaire stopped and we assumed the respondent would cancel park visit when facing moderate/heavy/severe pollution levels. If the answer was no, we continued to ask if they will cancel park visit in moderate, heavy and severe heavy pollution.

We used the chain referral sampling, also referred as the snowball sampling (Biernacki and Waldorf, 1981). During the sampling process, researchers identified the initial subjects and then asked them to nominate more subjects. In our survey, each respondent was provided with an option to post the survey to all their contacts or send it out to specific people/groups through WeChat™. We offered a small cash incentive (USD 0.1–0.2) for participating in the survey. We asked the respondents for their locations and used the responses from Beijing for this study. The

**Table 1**
Air quality standard of particulate pollution, number of polluted days and park visit estimations.

| Particulate pollution level[a] | $PM_{2.5}$ (μg/m$^3$) | Number of days in 2016 | Park visits[b] (%) | |
|---|---|---|---|---|
| | | | Questionnaire | Shuangxiu Park |
| Clean | <35 | 68 | – | >90 |
| Fair | 35–75 | 130 | – | 80–90 |
| Slight | 75–115 | 78 | 92 | 71–80 |
| Moderate | 115–150 | 51 | 71 | 64–80 |
| Heavy | 150–250 | 39 | 41 | 47–64 |
| Severe | >250 | | | |

Note.
[a] Source: Particulate pollution level is from Ministry of Environmental Protection, China, 2012. The number of days in each category in 2016 is calculated based on the air pollution report from Beijing MEP (2016).
[b] Park visits indicate the percentage of the potential visits under different air pollution levels. “Questionnaire” indicates the percentage of respondents who will visit a park under corresponding pollution level. Estimates were made for Shuangxiu Park based on the natural exponential function model (Fig. 3), indicating the ratio of number of visits under current pollution level and the maximum number of visits when the air quality is good.

answers to our questions could be influenced by the air pollution levels when people filled out the survey. We limited the survey time period to three days during which Beijing had relatively good air quality to reduce such impact. We considered a response as valid if it is finished between 1.5 and 15 min and passed the two logical tests embedded in the questions. We asked "how many times have you visited a park in the past month?" and "When was the last time you visited a park?" We consider the questionnaire valid if the answers to these questions were consistent. We also asked "Who accompanied you during your last park visit?" as a multi-option question, for which respondent could select more than one option. However, the option "I was by myself" is mutually exclusive with others. We consider the response invalid if other options were chosen along with this one.

We summarized the results from the survey into four categories according to air quality (Fig. 2): clean and fair, slight pollution, moderate pollution, and heavy/severe pollution. We combined "clean" and "fair" into one category as they both represent a "low pollution" situation. The question asked was "If you plan to visit a park and find out the air quality is slight/moderate/heavy/severe pollution, would you still go to the park?", which assumes all the respondents will visit a park under the condition of "clean and fair" air quality and asks if they would change their plan when the air quality deteriorates.

### 2.3. Park visits survey

We carried out a park visits survey at Shuangxiu Park in Beijing in January 1st – December 31st, 2016. Shuangxiu Park is a small neighborhood park with an area of 6.4 ha (Shuangxiu Park Office) (Fig. 1). It serves about 12,000 households in six neighborhoods within a 20-min walking distance. It received 1.58 million visits in 2016 and about 60% of visitors used annual/monthly pass to enter the park (Shuangxiu Park Office, 2016). The entry fee is 3 cents, and is unlikely to pose an economic barrier for park users. Residents living nearby, especially the elderly people and young children, visit Shuangxiu Park on a regular basis. Major park activities include walking, jogging, physical exercises, and children's activities. It also provides space for people to meet, chat, dance, sing and play chess/poker together.

We randomly sampled 164 days of the year 2016 to conduct the survey. During each survey, we arrived at 9 a.m. in the summer and 10 a.m. in the winter. We decided to survey at 9/10 a.m. since we found it had the most visitors in the morning during our trial survey conducted Nov 1–20, 2015. Each survey took about 20 min. We counted and recorded the number of visitors in the two most popular places in the park, the square and the playground. We retrieved and recorded real-time $PM_{2.5}$ level in the Shuangxiu Park survey.

### 2.4. Quantile regression analysis

We used a quantile regression model to examine the relationship between air quality and park visits. Quantile regression is a type of regression analysis that has been widely used in macro ecology (Cade et al., 1999) and behavioral physiology (Horning,

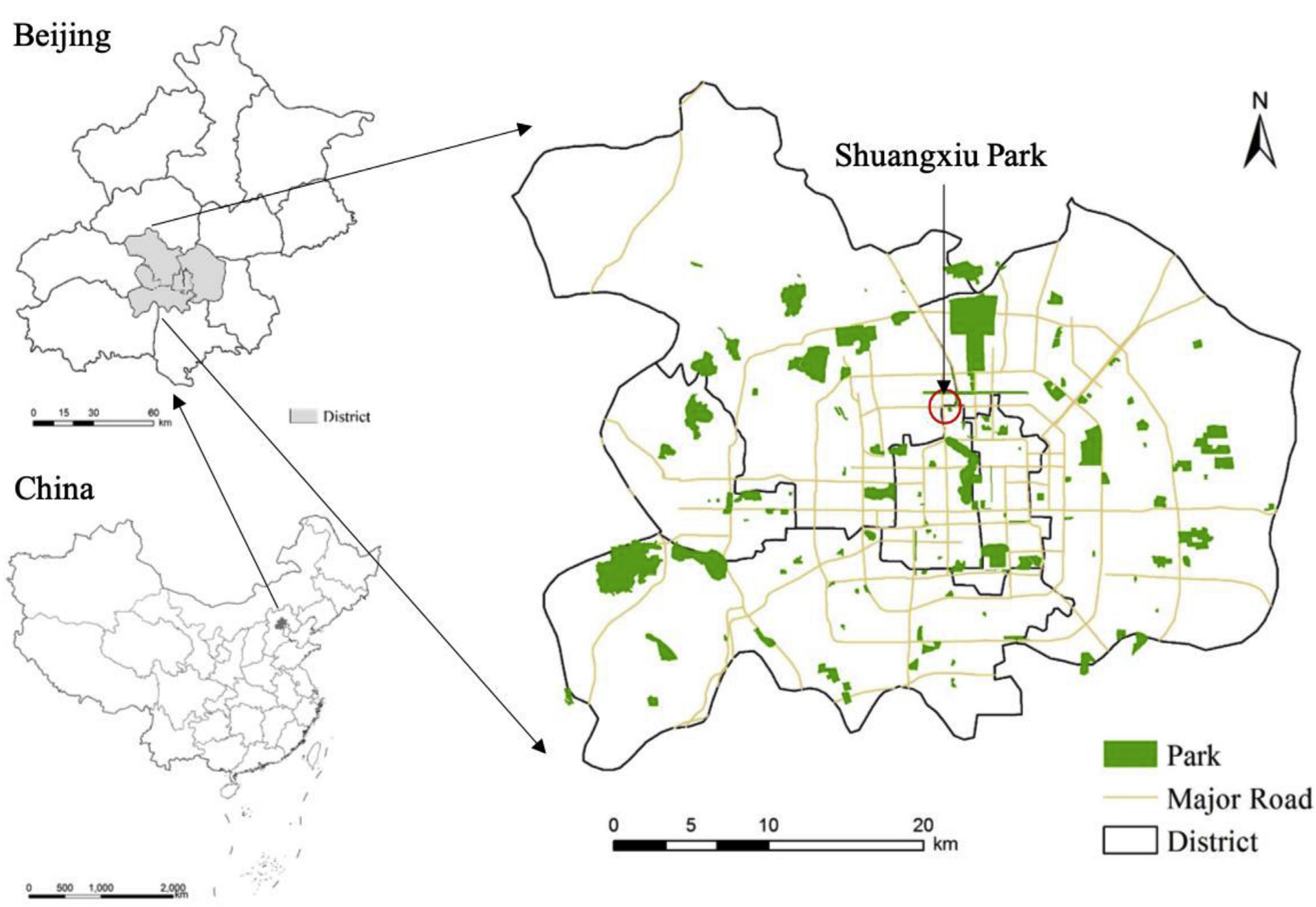


**Fig. 1.** Study area: the Shuangxiu Park.

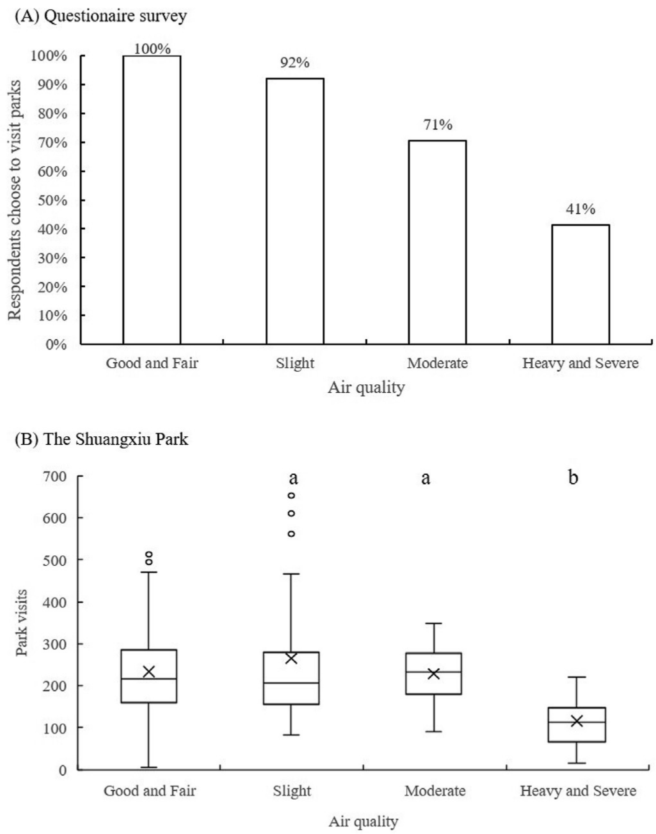


**Fig. 2.** Air quality categories, percentage of respondents who are willing to visit a park from (A) the survey, and (B) visits to Shuangxiu Park. The box-and-whisker plot in (B) indicate the maximum, upper quantile, median, lower quantile and the minimum (outliers excluded) for each category. Notations "a" and "b" indicate significant differences using ANOVA ($p < 0.01$).

2012) to articulate the limiting relationships between the measured factor and the response variable.

Quantile regression estimates a portion (certain quantiles) of the response variable, instead of the mean of response variable as in ordinary least squares regressions (Koenker and Bassett, 1978; Cade et al., 2003). Quantile regression addresses the constraining effects by estimating changes in certain areas of data distributions such as 95th or 99th quantiles. Because it is widely used to draw a boundary line and address the constraining effects, it is also referred as "boundary line analysis" or "constraint line analysis" (e.g., Mediniski et al., 2010; Horning, 2012). In addition to air quality, there are other unmeasured factors could affect park visits such as weather, season, and whether it is a workday or weekend/holiday. These unmeasured factors might have an impact on air quality, which violates the homogeneity of variance assumption required by linear relationships (Hao et al., 2016). Consequently, quantile regression, which avoids the homogeneity assumption, is better suited for analyzing the limiting effects of air quality on park visits.

In the quantile regression model, we used a segmented quantile approach to divide the data into segments/classes according to the independent variable (i.e., the number of daily visits), following the method proposed in Medinski et al. (2010). Specifically, we divided the data into a certain number of segments, each having 15 days (note that the last class could have less than 15 days) to balance the number of data points in each class and the total number of classes. As a result, the Shuangxiu Park dataset has 11 classes with the last class having 14 days ($N = 164$). Then we selected 90th −95th quantiles to define the upper boundary (i.e., the draw the constraint line). Using the 90th −95th quantiles can effectively exclude the outliers (Medinski et al., 2010). Finally, we fitted the constraint line by three different models, linear, natural exponential function and power function, and chose the one with the best fitness according to the adjusted $R^2$ value (Mills et al., 2009; Hao et al., 2016). We used the resulting model to estimate numbers of park visits in response to different pollution levels.

### 2.5. ANOVA analysis

We categorized the particulate pollution levels by the six-level air quality standard: clean, fair, slight pollution, moderate pollution, heavy pollution and severe pollution (MEP China 2012). We summarized the numbers of park visits, and applied ANOVA analysis to examine if the park visits vary significantly across the six air quality levels. The samples were normally distributed but failed the homogeneity of variance assumption of ANOVA. We combined the heavy and severe pollution categories so that each group had a similar number of samples (i.e., 21 for slight, 19 for moderate, and 21 for heavy/severe pollution). Descriptive statistics were performed to examine the relationships between observed visits and air quality levels. We compared results from the Shuangxiu park to responses from the survey.

## 3. Results

### 3.1. Impacts of air quality on potential park visit plan based on survey

We collected 2,792 valid questionnaires from respondents in Beijing. The valid response rate was 46.7%. Table 2 compared our sample with the population in Beijing in terms of age, gender ratio, education level and annual household income (Beijing Municipal Bureau of Statistics, 2016). Our sample is younger, has more female respondents, and higher education level than the overall population in Beijing. Beijing releases the annual household income levels by quantiles (e.g., 20%). The income level of our sample is roughly consistent with the distribution of Beijing (Table 2). The results showed when it is slightly polluted ($75–115 \mu g/m^3$), 92% respondents indicated they would visit the park as planned. The percentage was reduced to 71% when it is moderately polluted ($115–150 \mu g/m^3$), and 41% when it is heavily/severely polluted ($>150 \mu g/m^3$) (Fig. 2).

### 3.2. Impacts of air quality on visits in Shuangxiu Park

Our results showed that the natural exponential function model fits the constraint lines the best (Fig. 3). The adjusted $R^2$ is 0.51. The maximum number of visits declined when the pollution level increased. The coefficients indicated that the maximum number of visits was reduced to 74% for every $100 \mu g/m^3$ $PM_{2.5}$ increase. The intercept was 453, which indicates the greatest number of visits the Shuangxiu park can possibly receive when the air quality is extremely good.

When we examined park visits according to air quality categories, we found that the number of visits decrease dramatically from clean to severe pollution. Based on the model, we estimated the number of visits for Shuangxiu park under different pollution levels, which were roughly similar to the range of the results from the park survey (Table 1).

Results from the ANOVA analysis showed there was a significant effect of air pollution on the number of visits across the groups ($F(2, 58) = 10.505$, $p < 0.001$). Post hoc test comparison indicated that the mean score of the slight pollution group (mean = 265,

**Table 2**
Sample description: Gender, age and education.

| | | Sample (%) | Beijing (%) | |
|---|---|---|---|---|
| Gender | Female | 56.1 | 48.5 | |
| | Male | 43.9 | 51.5 | |
| Age | <18 | 5 | 2.5 | |
| | 18–30 | 55.7 | 33.8 | |
| | 30–40 | 27.7 | 19.5 | |
| | 40–50 | 7.8 | 17.8 | |
| | 50–60 | 2.4 | 13.7 | |
| | >60 | 1.5 | 12.7 | |
| Education | Primary school | 1.5 | 9.5 | |
| | Junior school | 7.4 | 32.9 | |
| | High school | 18 | 23.2 | |
| | College | 55.3 | 30.6 | |
| | Graduate | 17.8 | 3.9 | |
| Annual household income | <USD5,500 | 15.7 | <USD8,600 | 20 |
| | USD5,500–10,900 | 29 | USD8,600–15,000 | 20 |
| | USD10,900–18,200 | 27.5 | USD15,000–18,500 | 20 |
| | USD18,200–27,200 | 15 | USD18,500–23,900 | 20 |
| | >USD27,200 | 12.8 | USD23,900–36,200 | 20 |

*Source: Beijing Municipal Bureau of Statistics, Beijing Statistical Yearbook 2016.

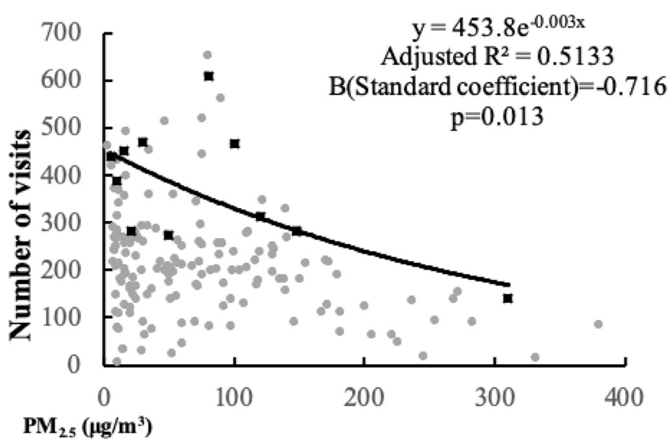


**Fig. 3.** p.m.$_{2.5}$ levels and numbers of visits for Shuangxiu park (n = 164). Constraint lines derived from segmented quantile regression depicting the relationships between $PM_{2.5}$ levels and park visits. Dark dots represent the 90th to 95th quantiles for 11 classes.

SD = 166) was not significantly different from the moderate pollution group (mean = 229, SD = 65), while the mean scores of heavy/severe pollution group (mean = 116, SD = 61) was significantly lower than those of both slight and moderate groups.

## 4. Discussion

### 4.1. Air quality as a limiting factor for park use

Our study found that particulate pollution has a negative impact on park visits. The higher the pollution level is, the more reluctant people are to visit parks. This result is consistent in the investigations of a neighborhood park as well as the survey. The quantile regression analysis showed that air quality is a limiting factor on park visits. The maximum number of visits declined when pollution level increased in Shuangxiu Park. In addition, the natural exponential function model indicated that the limiting effect was stronger when the particulate pollution level was low. As shown in Fig. 3, the decrease in the maximum number of visits tends to be greater when the pollution level is worse, suggesting a stronger limiting effect.

Researchers interested in ecosystem service (ES) differentiate ES supply and the service actually used by people (Fisher et al., 2009; Villamagna et al., 2013). In terms of the cultural service provided by urban parks, many studies examined the ES supply in a spatial explicit way (e.g., Peña et al., 2015), and considered accessibility (Schipperijn et al., 2010), park characteristics (Grahn and Stigsdotter, 2010) and safety (McCormack et al., 2010) as the major factors influencing how the cultural service supply from parks were actually used by visitors. Our study revealed that air pollution was an important factor, which reduced the number of park visits and further reduced the recreational service provided by parks. To put it in a positive way, we will not only achieve the benefits from clean air but also enhanced park services from more visits when we mitigate particulate pollution in the future. Researchers define the “win-win” situation of mutual enhancement of both ES as “synergy” (Bennett et al., 2009; Haase et al., 2012), which describes the relationship between air quality and park service —— the improvement of air quality will enhance the ES people receive from parks.

### 4.2. Comparing behavior and intention

When we grouped park visits data by air pollution categories, they showed a significant drop when particulate pollution increased from moderate to heavy, which indicated people do not adjust their park visit behavior until air quality deteriorates beyond 150$\mu g/m^3$. This observed behavior is markedly different from the intention expressed in our questionnaire, in which more than 20% of people indicated they would alter their park visit when air quality goes from slight to moderate pollution. The percent of respondents choosing to visit parks as planned further reduced from 71% to 41% when it changes to heavy/severe pollution (Fig. 2), which is more aligned with the park visitation data.

Putting the results from both surveys together, they indicate that more people think they might not consider a park visit during moderate pollution than those who cancelled their visits. If we consider park visits as an example of people adjusting their decisions according to air pollution levels, the results suggest that the intended behavior of the people who were surveyed online was inconsistent with the behavior of the people who were sampled in the park. This may indicate an inconsistency between behavior and intention that signals people are less protected from the potential adverse health impacts of poor air quality than they think they are.

The inconsistency between findings from park visit and survey is interesting and worth further exploration. People may think slight pollution is bad and they will not risk their health to visit a park when they were asked during a survey. But in real life they decide to visit a park despite the slight pollution. The difference between intention and behavior may have serious health impacts related to $PM_{2.5}$ exposure. Differences in behavior and intentions have been well studied (Kah et al., 2016; Miller, 2017). For example, a study of camping intention and behavior found that several intervening factors could influence recreational behavior, such as exposure to new information, the complexity of the behavior, and the dependency upon others to completing the behavior (Young and Kent, 1985). These factors could be applicable in the context of air pollution's impact on park visit.

It is worth noting that sample bias may also contribute to the inconsistency between results from the questionnaire survey and park visitation. Compared with the demographics of Beijing residents as summarized in Census (2010), our questionnaire respondents tend to be younger, have more females, earn higher income and receive higher level of education. Given that these factors are likely to associate with more informed decision making (Hammitt and Robinson, 2011), our results might be an overestimation for people's response to air quality. While we did not survey demographics in the park, we noticed that a considerable proportion of the visitors were elderly people. Future studies may focus on one sample group to investigate whether people's behaviors are aligned with their intention in terms of adjusting park visitation according to air quality.

Other factors may also cause the inconsistency. People appraise air quality in different ways including getting forecast or real-time report (from smart phone apps, websites and TV), monitoring by portable equipment, or simply observing. This study did not investigate the potential relationship between people's decision and the way they appraise air quality.

Second, when people were asked the question during the survey “when it is slightly/moderately/heavily/severe heavily polluted, would you cancel your park visit plan?“, the underlying assumption is that all factors that influence their park visit decisions remain the same except for air quality. However, we cannot isolate the impact of air quality on park visits from other factors in the real world. The model generated by the quantile regression analysis had an adjusted $R^2$ of 0.51, which indicated a strong relationship between air quality and the maximum visits. However, it also showed that air quality only explained half of the variation of the maximum visit. For example, a clean day with excellent air quality can be windy and chilly, which keeps people from going outside. The decision of whether or not to visit a park is influenced by a suite of factors such as weather, season, whether it was a holiday or weekend, etc. All these potential factors may cause the divergence between responses from the survey and the real park visits.

Finally, air quality of the previous days may have an impact on how people respond to the pollution level in park visits. For example, if it has been heavily polluted in the previous week, people might consider a slight pollution day as a break and would like to have some outdoor activities. Instead, if it has been clean in the past several days, people might consider a slight pollution day as polluted and choose to stay inside. Future study should explore the elasticity of the park visit demand, which will contribute to our understanding on how the length and severity of a pollution event affect our decisions and well-being.

## 5. Conclusions

This study examined how particulate pollution affects urban park use through empirical surveys as well as a survey. Our results showed that particulate pollution has a negative impact on the maximum number of visits a park may receive. The maximum number of visits decreased faster when the pollution level is worse. The results indicated that recreational ecosystem service potentially generated by parks were not realized due to the reduced number of visits because of air pollution. When the air quality improves, not only direct health benefits but also enhanced park services from increased visits will be achieved in Beijing.

It is worth noting that a considerable proportion of people did not respond to air pollution and visited parks even on heavy and severe pollution days. These findings have direct policy-relevant implications on how continued poor air quality will affect exposure to air pollution across Beijing (and potentially other urban areas). Many urban residents might not be aware of how their decisions might heighten their exposure to pollutants that are linked to lung cancer and cardiovascular disease. It is therefore important to raise awareness by policies, warning systems and innovative health risks communications.

Furthermore, we found more than 29% of the respondents in the survey indicated they would cancel their park visit plan at the moderate pollution level. In contrast, the significant park visit drop as we observed in park survey happened when the air quality deteriorated from moderate to heavy pollution. Future study should look into what factors may cause the divergence between how people think they will respond to air pollution and what they actually do. Understandings on this issue will contribute to design better guidance and incentives to avoid the adverse health cost caused by air pollution.

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