Effects of air pollution on Beijing residents' willingness to pay for green amenities

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ABSTRACT

In this paper, we investigate the effects of urban air pollution on the value of green amenities. On the one hand, residents of severely polluted areas may derive additional benefits from green amenities, as trees are commonly believed able to enhance air quality. On the other hand, air pollution may as well devalue green amenities, by forcing people to reduce outdoor activities on high pollution days. Thirdly, where people choose to locate in a city, as reflected by their exposure to air pollution, may imply their preferences or demand for greenspace which would otherwise be hard to measure. We undertook choice experiment surveys in Beijing at different locations and times to elicit the value of green amenities in the form of the public's willingness to pay (WTP). We purposefully valued three types of green amenities, including a neighbourhood park near a respondent's home, a city park in central Beijing and a nature reserve type of national park in an outlying location. We use real-time pollution data to help explain the spatial and temporal variation in WTP, whilst controlling for other possible influencing factors. Our results suggest that respondents exposed to higher levels of pollution are willing to pay more for neighbourhood parks, which is likely attributable to trees' air purification effect. In contrast, short-term exposure to higher levels of pollution seems associated with lower WTP for the city park. This finding is possibly due to people's inclination to reduce outdoor activities on heavily polluted days. However, we find no such effect for long-term pollution exposure. Moreover, we find no connection between pollution and WTP for the national park.

Keywords: Green amenities; Urban air pollution; Spatial heterogeneity of preferences; Choice experiment; Willingness to pay; Mixed logit model

JEL codes: Q51; Q53; Q57; Q58

1 INTRODUCTION

There exists a substantial body of literature that seeks to measure the economic value of green amenities such as parks and forests.[1] This strand of literature is by and large intended to inform land-use decision making as to whether the net benefits of green amenities outweigh other competing land-use options. The findings of previous studies exhibit considerable heterogeneity in terms of the relative value of greenspace and the determinants of this value (Bateman & Jones, 2003; Brander & Koetse, 2011; D'Amato et al., 2016; Ferraro et al., 2012; Ninan & Inoue, 2013). Such heterogeneity has likely sprung from methodological dissimilarities, the features of green amenities being valued and the characteristics of those who benefit. Possible determinants of value which have been explored include local socioeconomic and demographic features such as income levels (Perino et al., 2014; Schindler, Le Texier, & Caruso, 2018) and age (Arnberger & Eder, 2011), the presence of substitute outdoor recreation sites (Schaafsma, Brouwer, Gilbert, van den Bergh, & Wagtendonk, 2013; Thiene, Swait, & Scarpa, 2017), the proximity to and conditions of existing green amenities (Czajkowski, Budziński, Campbell, Giergiczny, & Hanley, 2017), perceptions of nuisances associated with improperly managed greenspaces such as crime (Troy & Grove, 2008) and other antisocial behaviour (Andrews, Ferrini, & Bateman, 2017), and the timing of visits to green amenities such as seasons (Bartczak, Englin, & Pang, 2012) or weekdays versus weekends (Bertram, Meyerhoff, Rehdanz, & Wüstemann, 2017).

In this paper, we investigate the effects of urban air pollution on the value of green amenities. On the one hand, residents of severely polluted areas may derive additional benefits from green amenities, as trees are commonly believed able to enhance air quality by absorbing and diffusing ambient pollutants such as particulate matters (Lin et al., 2017), ozone and nitrogen dioxide (Kroeger et al., 2014), and may be an offsetting source of utility for those living in highly-polluted urban environments. On the other hand, air pollution may devalue green amenities, by forcing people to reduce outdoor activities on high pollution days (Bresnahan, Dickie, & Gerking, 1997; Graff Zivin & Neidell, 2009), which may presumably include visits to green amenities. Thirdly, where people choose to locate in a city, as reflected by their exposure to air pollution, may imply their preferences or demand for greenspace which would otherwise be hard to measure. The net effect of air pollution on the value of green amenities is hence ambiguous and open to empirical investigation.

We undertook choice experiment surveys in Beijing at different locations and times to elicit the value of green amenities in the form of the public’s willingness to pay (WTP) for increases in the area of three types of greenspace. We purposefully valued three types of green amenities whose values might be differently reflected by air pollution exposure: a neighbourhood urban park near a respondent’s home, a city park in central Beijing, and a nature reserve type of national park in an outlying location. We then used real-time pollution data to help explain the spatial and temporal variation in WTP, whilst controlling for other possible influencing factors.

[1] Recent systematic reviews have been conducted by Barrio (2010), Brander (2011), D’Amato (2016), Ferraro (2012), Ninan (2013), Perino (2014), Siikamäki (2015) and their co-authors.

Our results suggest that respondents exposed to higher levels of pollution are willing to pay more for neighbourhood parks, which is likely attributable to trees' air purification effect. In contrast, short-term exposure to higher levels of pollution seems associated with lower WTP for a new city park. This finding is possibly due to people's inclination to reduce outdoor activities on heavily polluted days. However, we find no such effect for long-term pollution exposure. Moreover, we find no connection between air pollution levels and WTP for a new national park.

Pursuing this research agenda can offer appealing insights for scientific and policymaking communities from several angles. To start with, it has practical implications for land-use decision making. For instance, it might be economically preferable to situate/retain a green amenity in one location, but the conclusion might be reversed in another location with different air quality. This reasoning aligns with an increasing emphasis on the spatially optimal provision of environmental amenities that seeks to maximise location-specific net benefits (Choi & Koo, 2018; Czajkowski et al., 2017). Further, this study contributes to the literature on benefit transfer (Johnston, Rolfe, Rosenberger, & Brouwer, 2015), since the benefits of urban green amenities can be adjusted for variations in local air pollution levels, similar to adjusting for income and cultural differences (Hynes, Norton, & Hanley, 2013). Lastly, this study adds to a recent yet rapidly growing body of evidence on the non-health impacts of air pollution, such as work productivity (Archsmith, Heyes, & Saberian, 2018; Graff Zivin & Neidell, 2012), labour supply (Hanna & Oliva, 2015), property value (Bayer, Keohane, & Timmins, 2009), demand for health insurance (Chang, Huang, & Wang, 2018), and zoo and observatory visits (Graff Zivin & Neidell, 2009).

The remainder of the paper is structured as follows. Section 2 sets up our proposed conceptual linkages between air pollution and WTP for greenspace. Section 3 describes the study area, the choice experiment and data on air pollution. Section 4 reports the analytical methods and estimation results. The paper concludes in Sections 5 and 6 with a summary and discussion of the key findings.

2 LINKING AIR POLLUTION AND WILLINGNESS TO PAY FOR GREENSPACE

A key message of this paper is that information useful for helping to explain the heterogeneity in WTP for greenspace may be found within air quality data.

The first potential link we investigate is that people may see investing in new urban green space as a means of reducing their own exposure to air pollution, due to the air-cleaning functions of trees and other plants. This means that:

Hypothesis 1: willingness to pay for new urban greenspace should be higher where local air pollution loads are higher. But there should be no link between local air pollution loads and WTP for greenspace outside of the city.

The second potential link is in terms of residential sorting. This implies that those living in more polluted zones of a city are willing/able to pay less to avoid the effects of local air pollution. This would imply:

Hypothesis 2: willingness to pay for any type of greenspace investment is lower in areas with higher urban air pollution.

A third potential link draws on a potential difference between the effects of air pollution levels on or just before the day the survey was undertaken, and longer-term average air pollution levels. Individuals may be less willing to vote for a policy which improves city greenspace if they are interviewed on days when it is too polluted for them to go outside safely to enjoy this greenspace. But if the long-run average pollution load is high even though pollution is low on days when people are interviewed, then their WTP could be increasing in the long run pollution load. This implies a third possible relationship which can be tested:

Hypothesis 3: there is a qualitative difference in how WTP for new greenspace responds to long-term and short-run measures of local air quality.

3 STUDY AREA AND DATA

This section outlines the local context of Beijing where we collected our data. Further, we provide details about our choice experiment survey and air pollution data. This unique dataset has enabled us to empirically explore the impacts of air pollution on WTP for green space.

3.1 Study Area

The geographic scope of this study is the six central districts of Beijing, as shown by Figure 1. The six districts together occupy an area similar in size to London or New York City, accommodate over 12 million people, and had a GDP on a par with Finland in 2016 (Beijing Municipal Bureau of Statistics, 2017).

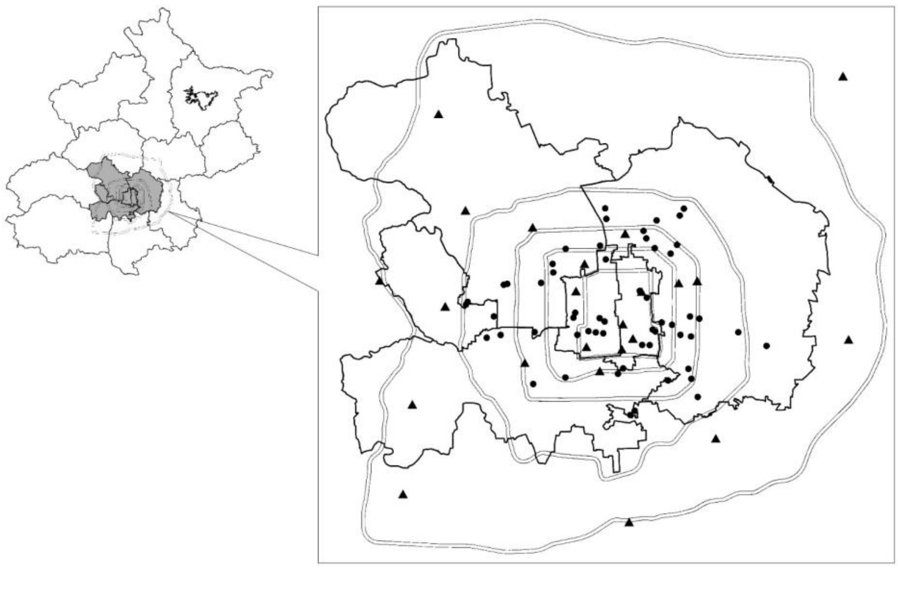

Figure 1 Locations of the surveyed communities and air quality monitoring stations

Notes: spot – community/village; triangle – air quality monitoring station.

In this vibrantly developing and densely populated area, properties are becoming increasingly expensive, even by the standards of the developed world. According to the Bloomberg Global City Housing Cost Index 2018, Beijing has squeezed into the world's top ten cities with the highest housing costs, amid many of the most sought-after places in the developed world such as New York, London and Geneva. This implies considerably high opportunity costs of creating and retaining green amenities within Beijing. Despite this, the city's urban green amenities are surprisingly well developed. Beijing's dry climate and inland location have left greenspaces as one of the few types of environmental amenity available to its residents. In 2016, the per capita area of greenspaces came to $40m^2$, higher than the per capita housing area ($32m^2$).

Air pollution is a serious problem in the city (Guan & Liu, 2014; Zhao et al., 2018; Zhong, Cao, & Wang, 2017). Frequent outbreaks of severe and prolonged pollution episodes have caused widespread concern among the public. Many people pay close attention to real-time pollution reports, which are commonly available in various types of media, and take precautionary actions such as reducing outdoor activities and wearing anti-pollution face masks (Zhang & Mu, 2018). The public's high awareness of pollution may have noticeable impacts on their perception and use of the city's green infrastructure. Against this background, it is particularly pertinent to investigate the hypothesised effects of air pollution on the value of green amenities in Beijing noted above.

3.2 Choice Experiment Valuing Green Amenities

This study conducted a choice experiment to elicit Beijing residents' WTP for increases in three types of green amenities, namely neighbourhood parks, city parks and national parks. Table 1 presents an example choice question, which contains two alternative programmes that hypothetically creates different types of parks at different costs to a respondent's household, and a status quo option that allows the respondent to opt-out.

Table 1 Example choice question

Suppose the municipal government was considering the following 3 options, which option would you prefer the most?

	1 – Programme A	***2 – Programme B***	***3 – No Programme***
Number and distance of neighbourhood parks	*1 additional park 1,500 m away*	*No additional parks*	*No additional parks*
Number and distance of city parks	*1 additional park 15 km away*	*No additional parks*	*No additional parks*
Number and distance of national parks	*1 additional park 60 km away*	*1 additional park 20 km away*	*No additional parks*
Monthly payment of your household (CNY) for the next 3 years.	*80*	*30*	*No payment*

Please choose one:	☐	☐	☐

Prior to the choice tasks, we used 3D architectural animation videos (Figure 2) and narratives to convey the parks' features to our respondents. The *neighbourhood park* would be situated in the respondent's community and hence near their home (500m–1.5km away). It would occupy a small piece of land (1ha, roughly the size of a football pitch) and have green vegetation in 60% of its area. Additionally, it would feature exercise equipment, playgrounds and other basic facilities. The *city park* would be created in central Beijing and was assumed to be 5–15km away from the respondent's home. It would have a larger size (5ha) but the same vegetation cover rate (60%). There would be more attractions and facilities, such as sports grounds, water-based recreational facilities, cafés, dinners and parking places. The *national park* would be developed 20–60km away in outlying areas of Greater Beijing. It would primarily serve nature conservation purposes, but would also be accessible for nature-based and low-impact recreational activities. It would spread over a mountain landscape (200ha) mostly covered by vegetation. It would provide fewer artificial attractions and facilities compared to the other two types of parks, although there would be hotels for overnight stays. When designing these features, we consulted China's Code for the Design of Urban Greenspaces (Ministry of Housing and Urban-Rural Development, 2016) and solicited advice from the Beijing Municipal Bureau of Forestry and Parks.

a)

b)

c)

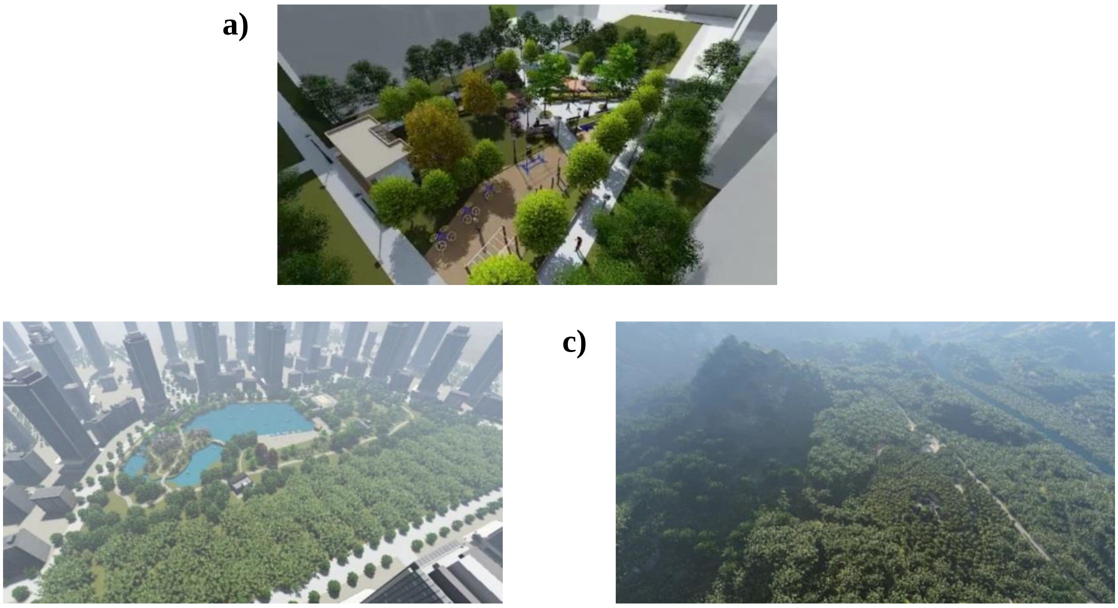

Figure 2 Screenshots of videos of parks

Notes: a) – neighbourhood park, b) – city park, and c) – national park.

As can be seen in Table 2, the first three attributes specify the number and distance of the three types of parks. The fourth attribute represents a special tax payment that would be collected conditional on majority agreement and exclusively used to create those additional parks (Carson & Groves, 2007; Champ, Boyle, & Brown, 2017; Johnston et al., 2017). Attribute levels were derived from focus group meetings and pilot surveys.

Table 2 Attribute levels

Attribute	*Levels*
Number and distance of neighbourhood parks	*No additional parks, 1 additional park 1.5 km away, 1 additional park 1 km away, 1 additional park 500 m away*
Number and distance of city parks	*No additional parks, 1 additional park 15 km away, 1 additional park 10 km away, 1 additional park 5 km away*
Number and distance of national parks	*No additional parks, 1 additional park 60 km away, 1 additional park 40 km away, 1 additional park 20 km away*
Monthly payment (CNY per household)	*5, 10, 20, 30, 50, 80*

Note: CNY 6.75 = USD 1 in 2017.

We used Stata to select a subset of all possible choice sets to optimise D-efficiency (Hole, 2016), which helps enhance the precision of the parameter estimates in the choice models. This approach requires initial input of the choice model estimates (priors), which were obtained from our pilot surveys. This procedure gave rise to 16 choice sets (as exemplified by Table 1), which were randomly sorted into four blocks. Each respondent was presented with four choice sets.

We conducted focus group meetings with residents' representatives of the study area, officers of the Beijing Municipal Bureau of Forestry and Parks, experts and surveyors. The questionnaire was then tested in four rounds of pilot surveys with university students and residents of the study area. The full survey was implemented in April–May 2017 as face-to-face interviews with 224 households at their homes. The sample was randomly drawn from 56 communities/villages via a stratified random sampling procedure that used the study area's administrative divisions as strata.[2] As can be seen in Figure 1, a visual examination would reveal the spatial representativeness of our sample. In addition to the choice experiment, our questionnaire included demographic and attitudinal questions, which allowed us to control for factors that correlate both with pollution exposure and with WTP for green amenities. We will discuss these variables in more detail in Section 4 where we describe our discrete choice models.

[2] The six central districts of Beijing are divided into 103 subdistricts ('*jiedao*') and 31 towns. Below the sub-district (or town) level, the third tire of the administrative hierarchy consists of 1,912 communities ('*shequ*') and 303 villages. We first randomly selected the same proportion of subdistricts/towns in each district, and then two communities/villages in each subdistrict/town. We next obtained the residents' housing numbers, which enabled us to randomly draw 10 households from each community/village. However, the response rate was considerably low – only 25% of the initially sampled households participated in our survey after two attempts. We surveyed non-responding households' neighbours as substitutes, to ensure that we had four responding households evenly in each community/village.

3.3 Data on Air Pollution

Beijing deployed 35 automatic air quality monitoring stations across the municipality in late 2012. Since then, these stations have been measuring and recording the hourly concentrations of a variety of air pollutants, including particulate matters ($PM_{2.5}$ and PM_{10}), sulphur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3) and carbon monoxide (CO). In addition, these stations generate an hourly Air Quality Index (AQI) that aggregates the concentrations of the six pollutants. The AQI values are categorised into six ordinal grades, with accompanying health messages and recommended actions.[3] We extracted these hourly data from the webpage of the Municipal Environmental Monitoring Centre. Moreover, the webpage provides the geographic coordinates of the air quality monitoring stations, which were used to map the air pollution data to the 56 communities that we surveyed for the choice experiment.

4 ECONOMETRIC MODELS AND RESULTS

We estimated two mixed logit models to test the hypothesised effects of air pollution on WTP for green amenities. This section reports the specifications of these models and estimation procedures, followed by estimation results.

4.1 Specifying and Estimating the Mixed Logit Models

We analysed our data using the discrete choice model, which describes choice makers' utility generating process underlying their preferences among the alternatives in each choice question. An alternative is assumed preferable if it gives the highest level of utility. The deterministic part of the utility depends on choice attributes and levels (e.g. Panel 1 of Table 3) as well as characteristics of respondents (e.g. Panel 3 of Table 3). The mixed logit model allows the utility parameters to flexibly vary across choice makers (Greene, 2012; Train, 2009). This implies that the same aspects may induce heterogenous implications for the utility levels of different choice makers.

Table 3 Definition of variables and descriptive statistics

Variable	Mean	SD	Min	Max
Panel 1: Attributes of alternatives (obs. = 2,688 alternatives)				
Neighbourhood park (binary: 0 = no; 1 = yes)	0.52	0.50	0	1
Neighbourhood park × distance [a]	0.00	0.30	-0.52	0.48
City park (binary: 0 = no; 1 = yes)	0.50	0.50	0	1

[3] For instance, Grade 1 indicates excellent air quality that has no adverse implications for human health and hence requires no precautionary actions. At the other end of the scale, Grade 6 indicates severe air pollution, which is likely to pose substantial health threats to all people (children and the elderly in particular), and the public would be advised against outdoor activities.

City park × distance	0.00	2.89	-5	5
National park (binary: 0 = no; 1 = yes)	0.52	0.50	0	1
National park × distance	0.00	12.25	-20	20
Payment (CNY per household per month for the next 3 years) [b]	20.83	25.51	0	80
Status quo (binary: 0 = no; 1 = yes)	0.33	0.47	0	1
Panel 2: Pollution variables (obs. = 224 respondents)				
Pollution 3 ***days*** (average AQI grade in the recent ***three days*** including the interview day) [c]	2.46	1.20	1	4.67
Pollution ***year*** (average AQI grade in the recent ***year*** excluding the recent three days)	2.62	0.09	2.49	2.84
Panel 3: Characteristics of respondents (obs. = 224 respondents)				
Income (household monthly income in intervals: 1 = CNY 0 – 5k; … 7 = CNY 50k – 60k; … 10 = more than CNY 100k)	2.71	1.02	1	7
Children (number of household members younger than 16)	0.33	0.53	0	2
Elderly (number of household members older than 60)	0.57	0.81	0	2
Park air (whether considered parks able to clean the air, binary: 0 = no; 1 = yes)	0.43	0.50	0	1

Notes:

[a] We demeaned the distance variable when constructing this interaction term, so that the variable ‘neighbourhood park’ can be independently interpreted as the main effect of the neighbourhood park at the mean distance. The other two interaction terms in this panel (‘City park × distance’ and ‘National park × distance’) were constructed in the same manner.
[b] CNY 6.75 = USD 1 in 2017.
[c] We used AQI grades instead of the original values, as the public are more familiar with the former.

Our mixed logit models were built around two air pollution variables that reflect respondents’ exposure to air pollution in different periods leading up to the interview dates (Panel 2 of Table 3). Both pollution variables were constructed using data from the closest air quality monitoring station to each respondent’s community. This study seeks to distinguish between the immediate and accumulated effects of pollution exposure, as they are likely to have different implications for people’s purchasing behaviour (Chang et al., 2018). Based on an initial analysis of the pollution data, we have opted for the average AQI grade in the recent three days (including the interview day) as our short-term measure of air quality, and the average AQI grade in the recent year (excluding the recent three days) as our long-term measure. The two pollution variables were respectively interacted with the attributes ‘neighbourhood park’, ‘city park’ and ‘national park’, and the alternative specific constant (ASC) ‘status quo’, giving rise to two sets of interaction terms.[4]

[4] The pollution variables (and the characteristics of the respondents listed in Panel 3 of Table 3) cannot entre a mixed logit model independently. This is because these factors are common to all alternatives and would be cancelled out in the choice process, unless the utility changes induced by an alternative depend on these factors, which would be captured by the interaction terms.

We start with a parsimonious specification (Model 1 in Table 4) that only includes the attributes of the choice experiment (Panel 1 of Table 3) and the two sets of interaction terms that involve the two pollution variables. Further, we tested the robustness of our findings using a richer specification (Model 2 in Table 4) that controls for a number of observed variables (Panel 2 of Table 3) that characterise the respondents. Like the pollution variables, these control variables enter the mixed logit model as interaction terms with the three park attributes and the status quo ASC. To avoid over-parameterising the model, we were deliberately being selective in adding control variables. We only selected those factors that correlate with both pollution exposure and with utility derived from green amenities, according to previous studies (Bertram et al., 2017; Czajkowski et al., 2017; Perino et al., 2014; Schaafsma et al., 2013; Schindler et al., 2018; Thiene et al., 2017; Troy & Grove, 2008). If these factors are not adequately controlled for, they would bias the estimated effects of air pollution on people's preferences about green amenities. For instance, environmental amenities like greenspaces have long been perceived as luxury goods that are better appreciated by higher income groups (Jacobsen & Hanley, 2009). On the other hand, the better-off may have sorted themselves into higher income residential locations that are likely to have better air quality (Bayer et al., 2009). In that case, we would have an observation that greenspaces induce additional utility gains in less polluted locations. However, the additional utility gains may arise from higher income levels, instead of better air quality. More robust lessons can be drawn if the effect of income is ruled out and thereby not mistakenly attributed to air quality. Similarly, other respondent-specific aspects in Panel 3 may also confound the estimated effects of air quality.

In both models, we estimated a random parameter for all the attributes and the 'status quo' ASC listed in Panel 1 of Table 3, to accommodate any remaining unobserved heterogeneity that is unexplained by the observables. All these random parameters were assumed to be independently normally distributed.

The two mixed logit models were estimated in Stata using the simulated maximum likelihood estimation method (Hole, 2007) with 1,000 Halton draws. WTP was measured as the ratio of the marginal utility of a non-pecuniary regressor to that of the 'payment' attribute, where the marginal utility is represented by the estimated coefficients in the mixed logit models. The standard errors of WTP estimates were generated using the delta method. The effects of pollution exposure on WTP for green amenities can be expressed as WTP for the interaction terms between the park attributes and the pollution variables.

4.2 Estimation Results

This section reports the original estimates of the two mixed logit models (Table 4) and the impacts of pollution exposure on WTP for the three types of parks (Table 5). The estimated impacts reflect the changes in WTP for green amenities in response to higher levels of pollution exposure, compared to the current mean level.

4.2.1 Willingness to pay for expanded neighbourhood parks

Starting with the neighbourhood parks, we first find in Model 1 (Table 4) that respondents exposed to higher pollution levels in the past year would have a better appreciation of the neighbourhood parks, according to the positive and statistically significant estimate on the interaction term ‘Neighbourhood park × Pollution year’. In WTP terms, the corresponding estimate in Table 5 suggests that the residents would be willing to pay an extra CNY 166.87 (USD 24.72) per household per month on average for one additional neighbourhood park in their communities/villages, had they experienced a one-unit increase in the average AQI grade in the past year (compared to the actual mean level, which is 2.62). This estimate is statistically significant at the 1% level, and considerably sizeable relative to the ‘baseline’ WTP at the current mean level of pollution exposure, which is given by the estimate on the ‘neighbourhood park’ variable (CNY 18.49 or USD 2.74). This is because the estimated effect of pollution exposure on WTP refers to an extreme scenario: the average AQI grade in the past year would have been greater than three had it been increased by one unit from the actual mean level (2.62). This implies that the entire year would have been moderately polluted on average and the public would be advised to reduce or avoid outdoor activities, according to the interpretation of the AQI grades. As can be seen in Model 2, we have a qualitatively similar finding after adding the control variables.

Table 4 Mixed logit model estimates

	Model 1		**Model 2**	
	Mean	**SD**	**Mean**	**SD**
Neighbourhood park	***1.05******	***2.06******	***1.36******	***1.89******
	(0.31)	***(0.42)***	***(0.39)***	***(0.40)***
Neighbourhood park × Pollution ***3 days***	0.45		0.45	
	(0.28)		(0.29)	
Neighbourhood park × Pollution year	***9.46******		***8.61*****	
	(3.55)		***(3.52)***	
Neighbourhood park × Distance	***-0.82******	0.01	***-0.80******	4.94×10^{-3}
	(0.23)	(0.87)	***(0.23)***	(0.63)
Neighbourhood park × Income			***-0.76*****	
			(0.31)	
Neighbourhood park × Children			0.52	
			(0.61)	
Neighbourhood park × Elderly			0.05	
			(0.39)	
Neighbourhood park × Park air			-0.45	
			(0.63)	
City park	-0.01	0.07	-6.11×10^{-3}	0.06
	(0.23)	(0.44)	(0.29)	(0.39)
City park × Pollution 3 days	***-0.55******		***-0.52*****	
	(0.20)		***(0.22)***	
City park × Pollution ***year***	-4.01		-3.84	
	(2.82)		(2.97)	
City park × Distance	***0.04*****	2.68×10^{-3}	***0.05*****	3.59×10^{-3}

	(0.02)	(0.06)	***(0.02)***	(0.05)
City park × Income			***-0.42****	
			(0.25)	
City park × Children			-0.06	
			(0.43)	
City park × Elderly			***-0.50****	
			(0.27)	
City park × Park air			0.28	
			(0.45)	
National park	***0.69******	0.11	***0.96******	0.06
	(0.19)	(0.57)	***(0.25)***	(0.42)
National park × Pollution ***3 days***	0.04		-0.04	
	(0.18)		(0.19)	
National park × Pollution ***year***	1.27		0.62	
	(2.20)		(2.27)	
National park × Distance	-7.03×10^{-3}	***0.04******	-5.11×10^{-3}	***0.04******
	(6.96×10^{-3})	***(0.01)***	(6.96×10^{-3})	***(0.01)***
National park × Income			-7.04×10^{-3}	
			(0.21)	
National park × Children			-0.22	
			(0.38)	
National park × Elderly			0.05	
			(0.28)	
National park × Park air			***-0.86*****	
			(0.41)	
Status quo	0.48	***6.17******	***-2.80******	***4.39******
	(0.56)	***(0.85)***	***(0.78)***	***(0.63)***
Status quo × Pollution ***3 days***	-0.75		0.05	
	(0.52)		(0.47)	
Status quo × Pollution ***year***	-9.92		-1.88	
	(7.03)		(6.00)	
Status quo × Income			***-3.31******	
			(0.61)	
Status quo × Children			-0.22	
			(0.98)	
Status quo × Elderly			0.45	
			(0.66)	
Status quo × Park air			***5.87******	
			(1.21)	
Payment	***-0.06******		***-0.06******	
	$\boldsymbol{(6.10\times10^{-3})}$		$\boldsymbol{(6.24\times10^{-3})}$	
Model significance	0.00		0.00	
Log-likelihood	-605.92		-540.18	
McFadden's pseudo R^2	0.28		0.20	
AIC	1,257.84		1,158.36	
BIC	1,368.19		1,345.48	
Obs. (number of choices)	896		896	

Note:

[a] Both models were estimated in Stata using the simulated maximum likelihood estimation method with 1,000 Halton draws. We estimated random parameters for the non-pecuniary attributes of alternatives and the ‘status quo’ ASC (namely those variables with both mean and standard deviation estimates). All these random parameters were assumed to be independently normally distributed.

[b] Asterisks indicate statistical significance: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. Standard errors are in parentheses.

Table 5 WTP estimates

	Model 1	**Model 2**
Neighbourhood park	***18.49****	***23.63****
	(5.29)	***(6.43)***
Neighbourhood park × Pollution ***3 days***	8.00	7.80
	(4.93)	(4.96)
Neighbourhood park × Pollution year	***166.87****	***150.02***
	(61.80)	***(60.63)***
City park	-0.21	-0.11
	(4.03)	(5.11)
City park × Pollution 3 days	***-9.73****	***-9.05***
	(3.62)	***(3.82)***
City park × Pollution ***year***	-70.66	-66.98
	(50.27)	(52.12)
National park	***12.09****	***16.80****
	(3.49)	***(4.55)***
National park × Pollution ***3 days***	0.73	-0.65
	(3.12)	(3.30)
National park × Pollution ***year***	22.48	10.73
	(38.84)	(39.50)

Notes:

[a] The WTP values represent payments (in CNY, CNY 6.75 = USD 1 in 2017) per household per month for three years.

[b] Asterisks indicate statistical significance: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. Standard errors are in parentheses.

Both models give statistically insignificant results with respect to the effects of shorter-term pollution exposure on WTP for neighbourhood parks. That said, as shown in Model 1, the estimate on the interaction term ‘Neighbourhood park × Pollution 3 days’ still points towards a positive and sizeable effect (compared to the main effect estimate on the ‘Neighbourhood park’ variable), and the p-value (0.11) is only marginally higher than the conventional significance level (0.10). Model 2 gives a similar result.

Taken together, we find evidence that heavier pollution increases WTP for neighbourhood parks. Our attitudinal questions reveal that 43% of our respondents considered parks effective in reducing pollution. If we use the estimated effect of the past year's pollution exposure in Model 2 as a lower bound, we would find that the total WTP of all the households in our study area would be increased by USD 2.69bln if the average AQI grade in the past year had been increased by one unit. It is worth noting that this aggregate effect represents a change in the total WTP for many neighbourhood parks, rather than one single park. This is because our choice experiment described an additional neighbourhood park *inside* each community. In other words, each respondent was asked to value a neighbourhood park specific to their own community, instead of one common park of the entire city (which characterises the city park and the national park).

4.2.2 Willingness to pay for a city park

Turning next to the city park, our results suggest a sizeable adverse impact of recent pollution exposure on WTP for the city park. For instance, the estimate on the interaction term 'City park × Pollution 3 days' in Model 1 implies that people's WTP for the city park would be lessened by CNY 9.73 (USD 1.44) in response to a one-unit increase in the average AQI grade in the past three days. Nevertheless, we find no discernible effects of pollution exposure in the past year – the corresponding estimates are statistically no different from zero, despite their large magnitude.

These observations present a 'murky' picture of the effects of pollution exposure on WTP for the city park. This may relate to people's tendency to reduce outings to the city's central locations (where the city park would be) when pollution levels are high. In that case, recent experiences of high pollution levels may reduce the perceived immediate use value of the city park, which would explain the observed decrease in WTP of those respondents that were recently exposed to pollution. The concern may be eased in longer terms as people can always visit the city park when air quality picks up. But we are unable to draw robust lessons about the longer-term situation from the insignificant results that we have. Even so, there clearly exist striking disparities between the immediate and longer-term effects of air pollution on WTP for the city park. This implies that recent experiences of pollution may change stated WTP from longer-term preferences about the city park.

Another interesting finding is a general lack of intention to pay for the city park. The baseline WTP for the city park is negligible and insignificant in Models 1 and 2. In addition, the interaction term 'city park × distance' has a positive estimate that is statistically significant at the 5% level, which suggests that the respondents prefer a city park located further away. This is likely attributable to certain dis-amenities associated with city parks in the context of Beijing, such as exacerbated crowdedness, noise and traffic congestion.

4.2.3 Willingness to pay for a national park

Continuing on to the national park, we find no indication of the dependency of WTP on pollution exposure, as shown by the insignificant estimates on all interaction terms between the national park and pollution levels in Models 1 and 2. Admittedly, 'absence of evidence is not evidence of absence'. Yet, the insignificant results are in line with intuition. On the one hand, pollution in central Beijing is less likely to discourage trips to the city's outlying natural areas, where pollution is presumably a lesser concern. On the other hand, the distant location of the national park (20–60km away) would likely preclude it from instantly and continuously providing air purification services for our respondents. In other words, the connections between pollution exposure and use value of green amenities that we discussed above may be less relevant to the national park.

Moreover, the insignificant findings for the national park lend no support to Hypothesis 2, which speculates that people who better appreciate the environment may sort themselves into residential neighbourhoods with better air quality. If so, respondents living in polluted areas would have lower WTP for all types of parks, not due to pollution exposure, but because they are less enthusiastic about environmental amenities in general. However, had that been true, we would have seen a significant negative correlation between pollution exposure and WTP for the national park, which is not what we found.

In addition, our respondents expressed sizeable WTP for the national park in general (irrespective of pollution levels), ranging from CNY 12.09–16.80 (USD 1.79–2.49) per household per month and averaging at CNY 14.45 (USD 2.14). The aggregate WTP (CNY 1.57bln or USD 233.05mln) can be assigned to one single new national park, which differs from the case of the neighbourhood park. Despite that, per capita WTP for a national park is about a third lower than that for a neighbourhood park. This is likely because a neighbourhood park would provide higher use values for an urban resident in the Chinese context, where neighbourhood parks are visited far more often than other types of green amenities (Chen & Jim, 2011).

5 DISCUSSION

Above, we set out 3 hypotheses about the likely links between air pollution and WTP for new green space. We then estimated two mixed logit models, interacting two pollution variables with the mean effects for preferences towards expanding the areas of neighbourhood, city and national parks in and around Beijing. The sign and significance of these interaction terms allow for a test of the 3 hypotheses.

Hypothesis 1 was that willingness to pay for new urban greenspace should be higher where local air pollution loads are higher; but there should be no link between local air pollution loads and WTP for greenspace outside of the city. We found evidence to support this hypothesis in the analysis reported above.

Hypothesis 2 was that, due to residential sorting, willingness to pay for any type of greenspace investment should be lower in areas with higher urban air pollution. We did not find any evidence to support this hypothesis, in light of the insignificant findings for the national park.

Hypothesis 3 was that there is a qualitative difference in how WTP for new greenspace responds to long-term and short-run measures of local air quality. Evidence in support of this was found for a new city park.

There exist a number of psychological mechanisms that could potentially explain the observed discrepancy between the estimated effects of current and longer-term pollution exposure on willingness to pay for new greenspace. One of them is projection bias, which refers to a situation where decision makers systematically overrate the extent to which their future preferences resemble their current preferences, in which case their decisions would be over-influenced by current conditions (Chang et al., 2018; Conlin, O'Donoghue, & Vogelsang, 2007). In our case, people may be less interested in a new city park on a polluted day, but this preference is likely to be 'diluted' in the long term by unpolluted days. Admittedly, projection bias is not the only workable explanation. Yet, this mechanism points to a possibility that the respondents' attitudes towards green amenities may have been over-influenced by their current/recent experiences of air pollution, which may deviate from their future or longer-term preferences.

6 CONCLUDING REMARKS

This paper presents the first study that formally explores the effects of pollution exposure on WTP for green amenities. A choice experiment survey was conducted in Beijing to elicit WTP for three types of green amenities, namely a neighbourhood park within each respondent's community, a city park in central Beijing and a national park in the city's outlying natural areas. We next sought to explain the spatial and temporal heterogeneity of WTP using pollution levels measured by air quality monitoring stations, whilst controlling for potential confounders. We separately tested the impacts of short- and long-term pollution exposure, as they are likely to have different implications for people's purchasing behaviour. Focussing on one measure of short-term pollution and one measure of long-term pollution, we then derived practical insights for land-use decision making, in terms of which kind of investment in greenspace is most valued by people living in different parts of Beijing.

Our main results may be summarised as follows. For neighbourhood parks, WTP is significantly higher when long term measures of air pollution (average levels over the last year) are higher. For city parks in contrast, WTP is significantly lower when short-term measures of local air pollution are higher (average levels over the last 3 days). For national parks, there is no significant relationship between any measure of local air quality and willingness to pay. This contrast in effects on WTP between short- and long-term measures of air quality raises interesting questions as to the behavioural and psychological mechanisms that link local air quality with the value of greenspace. Our results also show that urban air pollution data contain useful information for helping to explain heterogeneity in the value of new investments in greenspace.

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