Linking urban air pollution with residents' willingness to pay for greenspace: A choice experiment study in Beijing

1 INTRODUCTION

A substantial body of literature seeks to measure the economic value of green amenities such as parks and forests.[1] This literature is by and large intended to inform land-use decision making as to whether the net benefits of green amenities outweigh the benefits of 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 differences in methodology, 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 connections between urban air pollution and the value of green amenities. We consider three possible ways in which these two environmental issues are linked. First, where people choose to live in a city, as reflected by their exposure to air pollution, may indicate their preferences for greenspace through a residential sorting effect (Bayer, Keohane, & Timmins, 2009; Klaiber & Phaneuf, 2010; Roback, 1982; Wu & Plantinga, 2003; Yinger, 2015): residents of heavily polluted neighbourhoods may have a lower appreciation of environmental amenities in general, including greenspace. Further, air pollution may have direct implications for the use value of greenspace. On the one hand, air pollution may devalue green amenities as local recreational resources, 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. On the other hand, residents of severely polluted areas may derive additional benefits from greenspace, as trees are able to enhance air quality by absorbing and diffusing ambient pollutants such as particulate matter (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. The nexus between air pollution and the value of green amenities is hence ambiguous and open to empirical investigation.

[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.

We undertook stated preference choice experiment surveys in different parts of Beijing 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 different types of green amenity whose values might be differently reflected by air pollution exposure: a neighbourhood park near the respondent's home, a city park in central Beijing, and a national park in an outlying location. We then used real-time air pollution data to help explain the spatial heterogeneity in WTP for these three types of green space, whilst controlling for other possible influencing factors.

Neighbourhood parks are likely to provide direct air purification services for communities nearby, and our results indeed suggest that respondents exposed to higher levels of annual pollution are willing to pay more for a new neighbourhood park. In contrast, WTP for the city park and national park is more likely to be linked with pollution levels via the residential sorting and reduced visits mechanisms. Yet our data shows no evidence for such connections.

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. Urban residents' preferences for greenspace are largely context-dependent. It is preferable yet expensive to directly investigate such preferences in every context. In the absence of such information, understanding the main factors that explain or indicate preference heterogeneity takes on pronounced importance, as this would help us more accurately adjust preferences elicited in other settings for the context being considered, and thereby identify the optimal location and timing to create or extend greenspace amenities (Choi & Koo, 2018; Czajkowski et al., 2017). In that sense, this study contributes to the literature on benefit transfer (e.g. 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). Moreover, 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 et al., 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 the data on air pollution. Section 4 reports the methods and results of our main econometric analysis. Section 5 performs a series of ancillary econometric analysis to test the robustness of our findings. The paper concludes in Sections 6 with a summary and discussion of the key findings.

2 CONCEPTUAL LINKAGES BETWEEN AIR POLLUTION AND WILLINGNESS TO PAY FOR GREENSPACE

The 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. This section provides a theoretical discussion of this nexus in a residential sorting framework. Our theoretical framework conforms to the classic residential sorting model of Roback (1982), but is directly adapted from the model's recent variants developed by Bayer et al. (2009), Wu and Plantinga (2003), and Yinger (2015).

Our model assumes that each residential location (s) is characterised by its house price (r_s) and environmental amenities including air quality (Q_s) and greenspace (G_s). A household (i) prefers a location that maximises its utility subject to its budget constraint:

$$max\ U_{is} = Z_{is}^{\alpha_i} H_{is}^{\beta_i} E_s^{\gamma_i}, \tag{2.1}$$

$$s.t.\ pZ_{is} + r_s H_{is} + T_S = I_i - C_{is} = B_{is}. \tag{2.2}$$

In the above expressions, household i's utility in location s (U_{is}) is a combination of the housing floor area H_{is}, and the quantities of a non-housing composite good Z_{is} and a composite environmental amenity $E_s(Q_s,G_s)$.[2] The composite amenity accommodates both site-specific amenities (e.g. air quality and neighbourhood parks in a residential location) and distance-dependent amenities (e.g. city parks and national parks associated with each residential location via distance or proximity), following Wu and Plantinga (2003). We start with a basic model where air quality and greenspace independently enter the utility function. For now, we leave aside the 'direct' connections between air quality and greenspace (namely the air purification effect of greenspace and reduced visits to greenspace due to air pollution), which will be explored later. But this simplification should be particularly applicable to national parks, as presumably there exist no such 'direct' connections between local air pollution loads and national parks outside of the city. To enhance the generality of the model, we only assume that $\frac{\partial E_S}{\partial Q_S} > 0$ and $\frac{\partial E_S}{\partial G_S} > 0$ but do not specify the functional form of E_s.[3]

Positive parameters α_i, β_i and γ_i describe the household's preferences or tastes when making trade-offs among H_{is}, Z_{is} and E_s. Our model describes residential location decision-making within one city, and therefore assumes that all households face the same price of Z_{is} (p) in all locations. Further, for each residential location s, all households take the same house price r_s as exogenous, but can choose different house prices by choosing different locations. The travel cost of park visits $T_s(G_s)$ is assumed to be a location specific function of the characteristics of greenspace G_s, where the travel costs to visit location specific green amenities (such as neighbourhood parks) are assumed to be very small, and for distance-dependent amenities (such as city parks and national parks), both the travel cost per trip and the number of visits are assumed to primarily depend on the distance of parks.[4] Moreover, a

[2] The utility function has standard properties: $\frac{\partial U_{is}}{\partial Z_{is}} > 0$, $\frac{\partial^2 U_{is}}{\partial Z_{is}^2} < 0$, $\frac{\partial U_{is}}{\partial H_{is}} > 0$, $\frac{\partial^2 U_{is}}{\partial H_{is}^2} < 0$, $\frac{\partial U_{is}}{\partial E_s} > 0$, and $\frac{\partial^2 U_{is}}{\partial E_s^2} < 0$.

[3] E_s could include other environmental amenities such as quiet (or lower noise). We have omitted these for brevity. It can be proved that this simplification would not affect the theoretical discussion as long as $\frac{\partial E_s}{\partial Q_s} > 0$ and $\frac{\partial E_s}{\partial G_s} > 0$.

[4] We found in our survey data a strong dependency of the number of visits on the distance of parks. According to our respondents, more than 40% of their park visits in the past year were within a 1km radius of their homes,

household's income I_i is not affected by its residential location within the city, but the cost of commute C_{is} depends on where this household chooses to live. We further assume that C_{is} is fixed once a household decides its residential location. Therefore, C_{is} translates into a shift of a household's budget constraint (B_{is}).

To solve this maximisation problem, we substitute the budget constraint for Z_{is} in the utility function and differentiate the utility function with respect to H_{is}. We then set the resulting expression equal to zero and solve for H_{is}, which yields:

$$H_{is} = \frac{\beta_i}{\alpha_i+\beta_i}\frac{B_{is}-T_S}{r_s}. \tag{2.3}$$

Substituting (2.3) into the budget constraint and solving for Z give:

$$Z_{is} = \frac{\alpha_i}{\alpha_i+\beta_i}\frac{B_{is}-T_S}{p}. \tag{2.4}$$

The indirect utility function can be obtained by substituting (2.3) and (2.4) into the utility function:

$$V_{is} = \phi_{is}[B_{is} - T_S]^{\alpha_i+\beta_i}E_s^{\gamma_i}, \tag{2.5}$$

where $\phi_{is} = \left(\frac{1}{\alpha_i+\beta_i}\right)^{\alpha_i+\beta_i}\left(\frac{\alpha_i}{p}\right)^{\alpha_i}\left(\frac{\beta_i}{r_s}\right)^{\beta_i}$.

The marginal WTP for an amenity equals the marginal rate of substitution between the amenity and the budget (Bayer et al., 2009). For air quality, the marginal WTP can be expressed as:

$$\frac{\frac{\partial V_{is}}{\partial Q_s}}{\frac{\partial V_{is}}{\partial B_{is}}} = \frac{[B_{is}-T_S]\gamma_i}{(\alpha_i+\beta_i)E_s}\frac{\partial E_S}{\partial Q_S}. \tag{2.6}$$

Similarly, the marginal WTP for greenspace can be written as:

$$\frac{\frac{\partial V_{is}}{\partial G_s}}{\frac{\partial V_{is}}{\partial B_{is}}} = \frac{[B_{is}-T_S]\gamma_i}{(\alpha_i+\beta_i)E_s}\frac{\partial E_S}{\partial G_S} - \frac{\partial T_S}{\partial G_S}. \tag{2.7}$$

Suppose households i and j have opted to live in different neighbourhoods, and i's neighbourhood has better air quality. This is because i has a higher marginal WTP for air quality at each location specific level Q_s, otherwise i would not have outbid j and obtained a higher level of air quality (Yinger, 2015), assuming that both households face the same implicit price or cost of air quality at Q_s:

$$\frac{[B_{is}-T_S]\gamma_i}{(\alpha_i+\beta_i)E_s}\frac{\partial E_S}{\partial Q_S} > \frac{[B_{js}-T_S]\gamma_j}{(\alpha_j+\beta_j)E_s}\frac{\partial E_S}{\partial Q_S}. \tag{2.8}$$

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and more than 70% were within a 2km radius. For parks located further than 2km, the number of visits rapidly decline along distance following a steep exponential decay pattern.

Since $\frac{\partial E_S}{\partial Q_S} > 0$ and $\frac{\partial E_S}{\partial G_S} > 0$, the above inequality will remain unchanged if we first multiply both sides by $\left(\frac{\partial E_S}{\partial Q_S}\right)^{-1} \frac{\partial E_S}{\partial G_S}$ and then subtract the same term $\frac{\partial T_S}{\partial G_S}$:

$$\frac{[B_{is} - T_S]\gamma_i}{(\alpha_i + \beta_i)E_s} \frac{\partial E_S}{\partial G_S} - \frac{\partial T_S}{\partial G_S} > \frac{[B_{js} - T_S]\gamma_j}{(\alpha_j + \beta_j)E_s} \frac{\partial E_S}{\partial G_S} - \frac{\partial T_S}{\partial G_S}. \tag{2.9}$$

This suggests that those living in less polluted zones of a city are willing/able to pay more for both local air quality and greenspace. In other words:

Hypothesis 1: willingness to pay for any type of greenspace investment is lower in areas with higher urban air pollution.

Recall that this hypothesis is derived from a simplified model that does not concern the ‘direct’ connections between air quality and greenspace. Therefore, this hypothesis is particularly applicable to national parks that are outside central Beijing and hence less likely to have such connections with air pollution loads in residential locations in the city’s central zones.

We next introduce the ‘direct’ connections between air quality and greenspace into the model. As we discussed above, urban residents’ utility derived from greenspace may depend on air pollution levels. We hence factor in this dependency as a pollution-related multiplier [$\delta(Q_s)$] of greenspace in the utility function. The utility function now becomes:

$$U_{is} = Z_{is}^{\alpha_i} H_{is}^{\beta_i} \{E_s[Q_s, \delta(Q_s)G_s]\}^{\gamma_i}. \tag{2.10}$$

We assume that $\frac{\partial E_S}{\partial \delta(Q_s)} > 0$ for simplicity. But the sign of $\frac{\partial \delta(Q_s)}{\partial Q_s}$ can be ambiguous. On the one hand, residents of more polluted zones may better appreciate local greenspace on account of its air-cleaning functions, which would imply an increase in the utility received from greenspace in response to a decrease in air quality [$\frac{\partial \delta(Q_s)}{\partial Q_s} < 0$]. On the other hand, in those more polluted locations, pollution levels may remain relatively high despite the air-cleaning functions of greenspace. In that case, people may prefer to spend more time indoors to reduce pollution exposure, which would reduce their onsite activities in parks and lead to a decrease in the utility derived from greenspace. Or putting it another way, better air quality would allow people to visit greenspace more often and hence obtain higher utility from greenspace [$\frac{\partial \delta(Q_s)}{\partial Q_s} > 0$]. Therefore, the utility associated with greenspace can be directly affected by pollution in two opposite directions, making it difficult to unambiguously predict the sign of $\frac{\partial \delta(Q_s)}{\partial Q_s}$.

Despite that, households living in less polluted neighbourhoods still have higher marginal WTP for air quality:

$$\frac{\frac{\partial V_{is}}{\partial Q_s}}{\frac{\partial V_{is}}{\partial B_{is}}} > \frac{\frac{\partial V_{js}}{\partial Q_s}}{\frac{\partial V_{js}}{\partial B_{js}}}, \text{ or } \frac{[B_{is}-T_S]\gamma_i}{(\alpha_i+\beta_i)E_s}\Omega > \frac{[B_{js}-T_S]\gamma_j}{(\alpha_j+\beta_j)E_s}\Omega, \tag{2.11}$$

where $\Omega = \left[\frac{\partial E_S}{\partial Q_S} + \frac{\partial E_S}{\partial \delta(Q_S)}\frac{\partial \delta(Q_S)}{\partial Q_S}\right]$.

We can still multiply both sides of this inequality by $\Omega^{-1}\frac{\partial E_S}{\partial G_S}$ and then subtract $\frac{\partial T_S}{\partial G_S}$ to compare the two households' marginal WTP for greenspace. But there exists uncertainty as to which household has a higher WTP for greenspace, since the sign of Ω^{-1} is unknown due to the ambiguous sign of $\frac{\partial \delta(Q_s)}{\partial Q_s}$, given that other derivatives are known to be positive [$\frac{\partial E_S}{\partial G_S} > 0$, $\frac{\partial E_S}{\partial Q_S} > 0$ and $\frac{\partial E_S}{\partial \delta(Q_s)} > 0$].

If $\frac{\partial \delta(Q_s)}{\partial Q_s} > 0$, which suggests that the decisive direct link between pollution and greenspace lies in reduced outdoor activities under severe pollution, it would be certain that $\Omega^{-1} > 0$, and the theoretical prediction would be qualitatively in line with Equation (2.9):

Hypothesis 2: households living in less polluted neighbourhoods should be willing to pay more for greenspace, due to not only residential sorting, but also because higher air quality enables them to visit greenspace more often.

On the contrary, if $\frac{\partial \delta(Q_s)}{\partial Q_s} < 0$, which implies that the utility associated with greenspace is dominantly affected by its air-cleaning functions, there would be the possibility that $\Omega^{-1} < 0$, in which case the inequality would change sign:

$$\frac{[B_{is}-T_S]\gamma_i}{(\alpha_i+\beta_i)E_s}\frac{\partial E_S}{\partial G_S} - \frac{\partial T_S}{\partial G_S} < \frac{[B_{js}-T_S]\gamma_j}{(\alpha_j+\beta_j)E_s}\frac{\partial E_S}{\partial G_S} - \frac{\partial T_S}{\partial G_S}. \tag{2.12}$$

This suggests the possibility that:

Hypothesis 3: if people regard investing in new local green space as a means of reducing their own exposure to air pollution, willingness to pay for new urban greenspace will be higher where local air pollution loads are higher, despite residential sorting.

This situation is most likely to arise in the case of neighbourhood parks, which should be most directly helpful for a neighbourhood's 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 linkages between air pollution and 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).

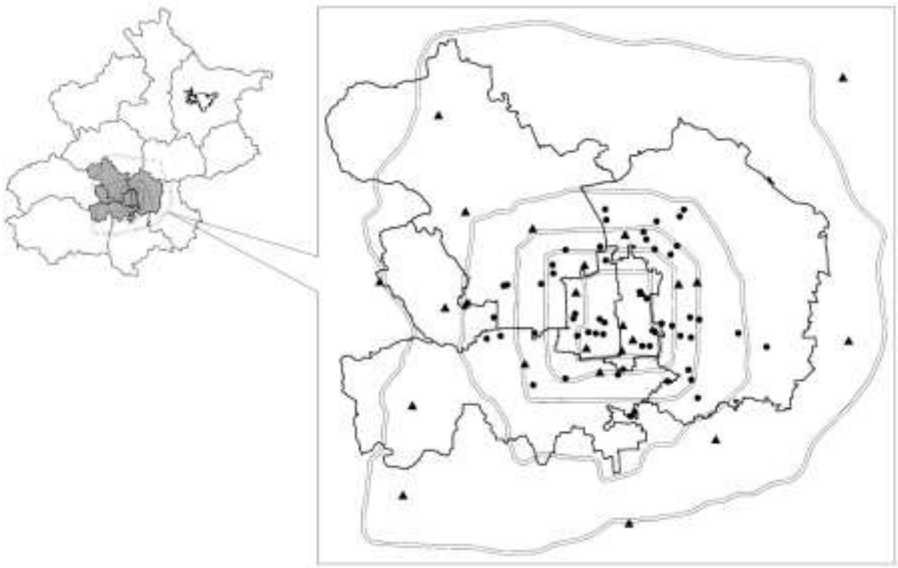

Figure 1 Locations of the surveyed communities and air quality monitoring stations

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 high-income countries. According to the Bloomberg Global City Housing Cost Index 2018, Beijing is positioned within the world's top ten cities with the highest housing costs. 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). Moreover, as can be seen in Figure 2, there exists conspicuous heterogeneity in pollution levels across different zones within Beijing. The spatial distribution of pollution levels appears largely associated with proximity to another city, Baoding, which is considered the most polluted city in China, according to the World Health Organisation. The public's high awareness of the temporal and spatial variations in pollution may have noticeable implications for their perception and utilisation of the city's green infrastructure. Against this background, it is particularly pertinent to investigate the hypothesised connections between air pollution and WTP for greenspace in Beijing noted above.

Figure 2 Pollution distribution around Beijing

Note: Figure 2 uses a grey scale to visualise location-specific average Air Quality Index (AQI) grades from 22 Apr. 2016–22 Apr. 2017, where black represents an average AQI grade above 3 (higher pollution) and white represents an average AQI grade below 1.5 (lower pollution). The AQI is an aggregate measure of the concentrations of six pollutants, which is typically reported in six ordinal grades (1–6). The map was interpolated using the original AQI data and the Kriging method.

3.2 Choice Experiment Valuing Greenspace

This study conducted a choice experiment to elicit Beijing residents' WTP for increases in three types of greenspace, 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 3) 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.

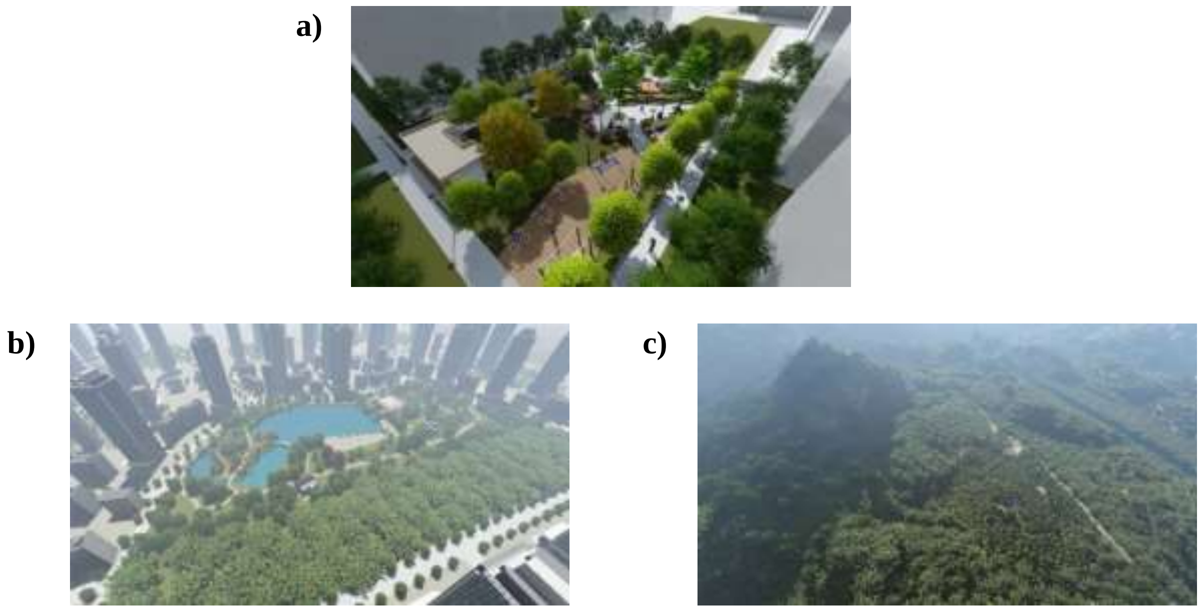

Figure 3 Screenshots of videos of parks

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 distance of parks and the associated travel costs constitute an important determinant of the number of park visits and hence the use value of parks. We have mentioned in Section 2 that over 70% of our respondents' park visits in the past year were within a 2km radius of their homes, and for parks located further than 2km, the number of visits rapidly decline along distance following a steep exponential decay pattern. We therefore explicitly designed different distance levels into the choice experiment. Aside from distance and travel costs, the three types of parks also differ on other aspects such as size and facilities, as described above. The valuation of the three types of parks therefore covers all these differences. 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).[5] 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 selected a subset of all possible choice sets to optimise D-efficiency, 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

[5] We tested the payment mechanism in our focus group meetings and pilot surveys, and did not observe any strong protest responses particularly associated with the payment mechanism. We also tested a voluntary donation payment mechanism, but there were more respondents always choosing the 'no programme' option in the donation scenario than in the tax payment scenario, which is not surprising since a new greenspace would be a nonexclusive public good and a voluntary payment mechanism is likely to induce free-riding. The stated preference literature therefore typically recommends a binding payment mechanism (e.g. a tax or compulsory fee) conditional on majority agreement (Johnston et al., 2017). The payment period was specified to be 3 years because the Chinese government periodically updates its socioeconomic development plans every 5 years and civil servants are expected to achieve these plans. The hypothetical park development programme in our choice experiment was described as a means to achieve the municipal government's 13th five year (2016–2020) plans regarding urban greenspace development. There was 3 years left in the 13th five year period at the time when the choice experiment surveys were conducted. Therefore the payment period was intentionally specified to be 3 years to enhance the credibility of the park development programme.

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.[6] Figure 1 visualises 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.

We conducted mean comparisons between our sample characteristics and government statistics for the population of our study area to assess the representativeness of our sample. As shown in Table A1 in the appendix, we focused on five commonly considered demographic and socioeconomic characteristics at the household level, namely age, education, gender, household size and income. We only found a statistically significant mean difference in age (indicated by a *p*-value below 10%), although the magnitude of the difference (6.10%) is hardly substantial. This implies that on average the sampled households tend to be slightly older than the population of our study area. For the other four variables, the differences between the sample and population means are not only statistically insignificant but also limited in size, since the magnitudes of the differences are all below 5%. These results suggest that on average the sampled households can reasonably represent the population we wish to study in terms of the five characteristics mentioned above. Despite that, we controlled for age in all our regression models to account for potential selection bias.

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 matter ($PM_{2.5}$ 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

[6] 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.

health messages and recommended actions.[7] 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.

As shown in Figure 2, there exists considerable spatial heterogeneity in pollution levels across our study area. The annual average AQI grade of the most polluted residential block that we surveyed (2.84) is 12% higher than that of the least polluted block (2.54). To provide a better sense of the magnitude of this difference, if the sample mean (over all 56 neighbourhoods) of the annual average AQI grade was increased by 12% (a change from 2.64 to 2.96), it would come close to the threshold (3) of whether or not a particular hour/day should be regarded as 'polluted' and whether the public should be advised to reduce or avoid outdoor activities. In fact, the annual number of polluted days (with a daily average AQI above 3) in the most polluted residential block (92 days) is three weeks more than that in the least polluted block (70 days), which provides a more intuitive measurement of the sizeable variation in pollution levels in our sample. Figure A1 in the appendix presents the distributions of the annual average AQI and number of polluted days across different residential blocks.

4 ECONOMETRIC MODELS AND RESULTS

We estimated two mixed logit models to test the hypothesised connections between air pollution and 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 (Table 2) as well as characteristics of respondents and their residential locations (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.

[7] 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.

Table 3 Definition and description of explanatory variables

Variable	Mean	SD	Min	Max
Panel 1: Characteristics of respondents (obs. = 224)				
Age (household mean)	45.60	14.03	19	85
Cars (number of cars owned by a respondent's household)	0.51	0.55	0	2
Elderly & children (whether a respondents' household has members older than 60 or younger than 16, binary: 0 = no; 1 = yes)	0.57	0.50	0	1
Income (household monthly income per capita, CNY 1,000) [a]	4.96	2.73	0.63	15.00
Park-air (whether a respondent considered parks able to clean the air, binary: 0 = no; 1 = yes)	0.43	0.50	0	1
Panel 2: Characteristics of respondents' residential blocks (obs. = 56)				
House price (CNY 1,000/m^2)	77.29	24.52	30	130
Park 1km (number of parks within 1km)	1.17	1.11	0	4
Pollution (average AQI grade in the recent year) [b]	2.64	0.08	2.54	2.84
Population density (1,000 people/km^2) [c]	18.93	10.13	3.09	39.00
Traffic (average time in minutes needed to drive 1km) [d]	1.64	0.13	1.41	1.94

Notes:
[a] CNY 6.75 = USD 1 in 2017.
[b] The variable was measured as the average AQI grades in the recent year leading up to the earliest interview date (22 Apr. 2016–22 Apr. 2017), using data from the closest air quality monitoring station to each respondent's neighbourhood. We used AQI grades (1–6) instead of the original values, as the public are more familiar with the former.
[c] Data source: *Beijing Statistical Yearbook* (Beijing Municipal Bureau of Statistics, 2017).
[d] Data source: Baidu Q-Traffic Dataset (Liao et al., 2018). This dataset contains average traffic speeds on 15,073 geo-referenced road segments for every 15 minutes of the two months when we conducted our surveys (April and May 2017). This allowed us to generate the variable 'Traffic' which measures the average time needed to drive 1km in a 10km radius of each neighbourhood we surveyed, since 10km is the average distance of the city park in our choice experiment. We also explored the average traffic speeds in a 40km radius (which is the average distance of the national park in our choice experiment), but this radius would cover almost all road segments in the traffic dataset, which would lead to very little variation in the average traffic speeds among different neighbourhoods.

The utility function is assumed to be a linear combination of the cost attribute x_{cik} (the 'monthly payment' attribute in Table 2) a vector of non-monetary attributes $\boldsymbol{x}_{nik}$, where choice-makers are indexed by i, alternatives by k:

$$U_{ik} = -\lambda_{ci} x_{cik} + \boldsymbol{\lambda}_{ni} \boldsymbol{x}_{nik} + \varepsilon_{ijt}. \tag{4.1}$$

This utility function underlies the mixed logit model in preference space where the coefficients $-\lambda_{ci}$ and $\boldsymbol{\lambda_{ni}}$ respectively capture the marginal utility of x_{cik} and $\boldsymbol{x_{nik}}$. Since costs usually reduce utility levels, λ_{ci} is assumed to be lognormally distributed among choice-makers, so that $-\lambda_{ci}$ only takes negative values. This can be achieved by estimating a normally distributed parameter $ln\lambda_{ci}$, which can be used to recover λ_{ci}. Each non-monetary attribute in Table 2 is disaggregated into a park attribute and its interaction with distance which respectively indicate whether and where a new park would be created.[8] The coefficients on these non-monetary attributes are assumed to be normally distributed. The marginal WTP estimate for a non-monetary attribute is given by minus one times the marginal utility ratio between this attribute and the cost attribute:

$$\boldsymbol{w_i} = -\frac{\lambda_{ni}}{-\lambda_{ci}} = \frac{\lambda_{ni}}{\lambda_{ci}}. \tag{4.2}$$

The distribution of WTP is simulated by taking a random draw from the estimated distribution of λ_{ni}, dividing it by a random draw from the estimated distribution of λ_{ci}, and repeating the procedure a large number of times (100,000 in this study), as per Train and Weeks (2005) and Hole and Kolstad (2012).

In our mixed logit models, the variable 'pollution' is interacted respectively with the means of the random coefficients on the three park attributes and an alternative specific constant (ASC) 'status quo'.[9] Our primary interest is in the estimated coefficients on these interaction terms, which capture the association between pollution loads near the respondents' residential locations with their mean WTP for the three types of parks.

[8] We coded distance as a continuous variable to facilitate the aggregation of the WTP of households living at different distances of a new park. It would be difficult to derive such an aggregate value without assuming any continuous functional relationship between WTP and distance. However it is certainly not advisable to extrapolate the WTP for a park that has a very different location from the distance levels specified in our choice experiment, such as a national park in one's neighbourhood or a neighbourhood park outside the city, since the distance levels in our choice experiment were purposefully specified according to the nature of each park type. We tested whether assuming the continuity of distance would affect our main results. We recoded distance as an ordinal variable which takes the value –1 for the closest distance of each type of park, 0 for the medium distance and 1 for the longest distance. We next interacted this discrete variable with the number of each type of park and reestimated the choice models. The estimates were found considerably stable regardless of whether distance was coded in a continuous or discrete manner.

[9] The pollution variable (and other characteristics of the respondents and their residential locations listed in Table 3) cannot enter 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 also estimated another two mixed logit models that contain an interaction term between 'pollution' and the logarithm of the random coefficient on the cost attribute (Models A1 and A2 in the appendix). In both models, the coefficient of this interaction term has a *p*-value greater than 0.5 and is therefore statistically indistinguishable from zero. Dropping this interaction term improves both models' goodness of fit, according to the Akaike and Bayesian information criteria. Moreover, we had qualitatively similar findings as to the relationship between pollution and preferences for parks, especially in the preferred specification (Model A2). We have thus opted to drop the interaction term between 'pollution' and the cost attribute to facilitate the estimation of WTP.

We start with a parsimonious specification (Model 1 in Table 4) that only includes the attributes of the choice experiment, the status quo ASC and the aforementioned interaction terms that involve the pollution variable. 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 (Panels 2 and 3 of Table 3) that characterise the respondents and their residential locations. These control variables enter the mixed logit model as interaction terms with the status quo ASC. To avoid over-parameterising the model, we were deliberately selective in adding control variables. We first invoke our theoretical model described in Section 2 to select factors other than pollution which correlate with WTP for additional green amenities. The variables 'income' and 'cars' respectively proxy a household's income I_i and the cost of commute C_{is}, which jointly represent the budget constraint ($B_{is} = I_i - C_{is}$). The variable 'house price' controls for location specific house prices r_s. The price of the non-housing composite good (p) was assumed homogenous across all locations in Beijing and hence can be dropped from the regression model. The travel cost of park visits T_s was assumed to primarily depend on the distance of parks, and therefore has been captured by the distance attributes of the choice experiment. Moreover, Model 2 controls for congestion levels (measured by the variable 'traffic'), which could on the one hand correlate with pollution levels, and on the other, with travel costs and hence the use value of parks. The availability of existing greenspace to each household (G_s) is reflected by the variables 'park 1km' and 'population density' jointly. Turning to the 'direct' connections between pollution exposure and utility derived from greenspace, we consider that whether trees' air-cleaning functions enter a respondent's decision-making process [via the multiplier $\delta(Q_s)$ in our theoretical model] depends on this person's awareness of such effects, which is captured by the variable 'park-air'. Further, although Beijing's residents well understand the necessity to reduce outdoor activities in severe pollution, they are likely to be particularly concerned if there are elderly people or young children in their households, who tend to be more vulnerable to pollution. The presence of such vulnerable household members is indicated by the binary variable 'elderly & children'. Lastly, Model 2 controls for each household's mean age, since the sample mean of this variable was found statistically different from the population mean of our study area. If these factors are not adequately controlled for, they might lead to biased estimates for the association that we wish to assess between air pollution and WTP for green amenities.

The mixed logit models were estimated in R using the simulated maximum likelihood estimation method (Sarrias & Daziano, 2017) with 1,000 Halton draws.[10] We estimated an independent random parameter for the cost attribute, the three park attributes and their interaction terms with distance, and the 'status quo' ASC, to accommodate any remaining unobserved heterogeneity that is unexplained by the observables. The random coefficient of the cost attribute has a lognormal distribution, and all other random coefficients are assumed to be normally distributed.

[10] We progressively increased the number of draws until the estimates stabilised.

4.2 Estimation Results

This section reports the original estimates of the two mixed logit models (Table 4) and the distributions of WTP for the three types of parks evaluated at different pollution levels (Table 5 and Figure 4).

4.2.1 Willingness to pay for a neighbourhood park

Starting with the neighbourhood park, we first find in both Models 1 and 2 (Table 4) that respondents living in a more polluted environment would have a better appreciation of the neighbourhood park, according to the positive and statistically significant estimate on the interaction term ‘Neighbourhood park × Pollution’. We give more weight to the specification of Model 2, as it controls for a number of potential confounders and fits the data better according to the Akaike and Bayesian information criteria. Despite that, comparing Models 1 and 2 offers insights into the impact of adding controls to the model. It can be seen that both models give highly consistent estimates for the ‘neighbourhood park’ attribute and its interaction terms with ‘distance’ and ‘pollution’. We centred the variables ‘distance’ and ‘pollution’ when interacting them with the park attributes and the status quo ASC. Therefore, the coefficient on each park attribute is directly interpretable as the change in utility associated with a new park at the mean distance and pollution level. Our results hence suggest that our respondents’ utility gains of having a new neighbourhood park would be increased by almost six times (7.88/1.35 = 5.8) or become nearly seven times as much [(1.35 + 7.88)/1.35 = 6.8] 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). Yet, this interpretation 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 on the six-point index, so that the public might be advised to reduce or avoid outdoor activities throughout the year according to the interpretation of the AQI grades. We will next present the distributions of WTP for a new neighbourhood park evaluated at the sample minimum, mean and maximum pollution levels, to facilitate a more tangible understanding of the magnitude of the dependence of WTP on pollution exposure.

Table 5 and Figure A2 (Appendix I) illustrate the estimated distributions of WTP evaluated at different pollution levels. As mentioned earlier, Models 1 and 2 allow the coefficient of the cost attribute to vary across individuals following a lognormal distribution, rather than assume it fixed, as it is often unrealistic to assume that all individuals have the same marginal utility of income (Meijer & Rouwendal, 2006). But the resulting WTP distribution can be highly skewed, which implies that many respondents have unreasonably high WTP to have or avoid an attribute (Hole & Kolstad, 2012; Train & Weeks, 2005). Table 5 shows that the WTP distributions for a new neighbourhood park are right-skewed, as the means are substantially higher than the medians. Panel 1 of Figure A2 further reveals that these WTP distributions all have a long and thick right-tail, which becomes more evident at higher pollution levels. This suggests that the means and standard deviations of WTP are likely to be enlarged by extreme values in the positive direction. Moreover, there are implications for using the means to measure the impacts of pollution exposure on WTP, since the WTP distributions appear to have more skewness at higher pollution levels. For comparison, we reestimated the mixed logit models and WTP distributions assuming a fixed cost parameter, which are detailed in the appendix (Tables A2 and A3, and Figure A3). It can be seen from the Akaike and Bayesian information criteria that the mixed logit models with a fixed cost parameter (Models A3 and A4) have a worse fit, which further inclines us to the models with a lognormally distributed random cost parameter (Models 1 and 2). That said, the means and standard deviations of WTP derived from Models 1 and 2 are systematically higher in absolute value than those from Models A3 and A4. Such discrepancies tend to be increasingly sizeable at higher pollution levels.

Despite that, the median WTP estimates produced by the two approaches are closely comparable, as the median is typically more robust to extreme values. We have thus resorted to the median WTP estimates obtained from Model 2 to provide a flavour of the typical magnitude of WTP for a new neighbourhood park and its dependence on pollution loads. These estimates suggest that at the sample mean pollution level, our respondents would typically be willing to pay CNY 13.77 (USD 2.04) per household per month for one additional neighbourhood park. They would be willing to pay an extra CNY 22 (USD 3.26) per household per month had they on average experienced the sample maximum pollution level in the past year (which represents a 7% increase in the average AQI grade). In contrast, the typical WTP would be reduced to CNY 3.95 (USD 0.59) per household per month at the sample minimum pollution level (or a 4% decrease in the average AQI grade).

To obtain an aggregate measure of WTP, we begin with the estimate on the interaction term 'Neighbourhood park × Distance', which implies that only those living within a radius (R = 2.61km at the sample mean pollution level) around the new neighbourhood park would have utility gains. We assume that the typical WTP declines linearly with distance in proportion to the decline in utility gains, integrate the typical WTP per household per month out of its distance decay function over a circle with radius R, and multiply the result by household density times the area of the circle to approximate the aggregate monthly WTP. Lastly, the aggregate monthly WTP is summed over the payment period (three years), where future payments are converted to present values using a discount rate of 8%.[11] The present value of the total WTP for a new neighbourhood park at the sample mean pollution level amounts to CNY 53.72mln (USD 7.96mln). At the sample maximum pollution level, the present value of the total WTP would rise strikingly to CNY 321.51mln (USD 47.63mln), owing to a considerable increase in the typical WTP as well as an extension of the radius where WTP exists. On the other hand, the total WTP would shrink to CNY 9.53mln (USD 1.41mln) at the sample minimum pollution level. As a reference point, Beijing's fixed asset investment in new parks in 2017 averaged at CNY12.42mln (USD 1.84) per hectare (Beijing

[11] The discount rate is recommended by the National Development and Reform Committee of China and the Ministry of Housing and Urban-Rural Development of China (2006).

Municipal Bureau of Statistics, 2017).[12] Recall that the size of the neighbourhood park described in our choice experiment was exactly one hectare. In a cost-benefit line of thinking, the WTP for a new neighbourhood park at the current or a higher pollution level is likely to outweigh the costs of creating such a park. Yet, the conclusion might be reversed if the city's air quality improves.

Taken together, our results lend support to Hypothesis 3 that residents of more polluted zones would be willing to pay more for neighbourhood parks on account of their air cleaning functions. Our attitudinal questions reveal that 43% of our respondents considered parks effective in reducing pollution. As will be seen in the next section, we find evidence that the awareness of this effect is likely to be strengthened under greater pollution exposure, which is explicable by a selective learning mechanism where a more polluted environment tends to draw more attention to pollution-related issues (Chang et al., 2018). The jury is out on the other two hypotheses that postulate an opposite relationship between the extents of pollution exposure and fondness for parks via the residential sorting and reduced visits mechanisms, which might be outweighed by parks' air purification effect and hence become indiscernible. In contrast, the implications of people's pollution exposure for their attitudes towards the city and national parks would be more relevant to Hypotheses 1 and 2, as these parks are assumed to be distant from respondents' homes and thus less instrumental in reducing their pollution exposure.

Table 4 Mixed logit model estimates

	Model 1		Model 2	
	Mean	**SD**	**Mean**	**SD**
Payment: ln(–coef.)	***–2.54******	***1.61******	***–2.64******	***1.23******
	(0.19)	***(0.19)***	***(0.21)***	***(0.19)***
Neighbourhood park	***1.32******	***1.57******	***1.35******	***1.42*****
	(0.33)	***(0.58)***	***(0.34)***	***(0.55)***
Neighbourhood park × Distance	***–0.79******	0.49	***–0.84******	0.64
	(0.26)	(1.02)	***(0.28)***	(0.86)
Neighbourhood park × Pollution	***7.62*****		***7.88*****	
	(3.66)		***(3.64)***	
City park	–0.08	0.20	$–4.35\times10^{-3}$	0.73
	(0.25)	(0.84)	(0.27)	(0.60)
City park × Distance	0.03	3.45×10^{-3}	0.04	3.64×10^{-3}
	(0.03)	(0.09)	(0.03)	(0.09)
City park × Pollution	–0.94		–1.29	
	(2.84)		(3.04)	
National park	***0.74******	0.04	***0.80******	0.35

[12] This does not account for the opportunity costs of land (the foregone benefits of alternative land-use options), as parks in Beijing are typically developed on public land which is freely allocated for public infrastructures and cannot be developed for other purposes.

	(0.22)	(0.89)	***(0.24)***	(0.65)
National park × Distance	–4.92×10^{-3}	***0.03****	–0.01	***0.03*****
	(0.01)	***(0.02)***	(0.01)	***(0.01)***
National park × Pollution	0.56		0.34	
	(2.29)		(2.38)	
Status quo	–0.90	***6.85******	1.36	***4.56******
	(0.79)	***(1.07)***	(1.81)	***(0.82)***
Status quo × Age			0.02	
			(0.03)	
Status quo × Cars			1.30	
			(0.84)	
Status quo × Elderly & children			***1.53****	
			(0.86)	
Status quo × House price			***0.04****	
			(0.02)	
Status quo × Income			***–3.05******	
			(0.72)	
Status quo × Park 1km			***1.29******	
			(0.48)	
Status quo × Park air			***–7.28******	
			(1.47)	
Status quo × Pollution	–9.94		–1.90	
	(8.14)		(7.12)	
Status quo × Population density			***–0.11****	
			(0.05)	
Status quo × Traffic			–5.07	
			(4.05)	
Log–likelihood	–591.68		–528.19	
AIC	1,223.36		1,114.38	
BIC	1,319.32		1,253.52	
Obs. (number of choices)	896		896	

Note:
[a] The estimates for 'payment' refer to the logarithms of the opposite coefficients. All other estimates represent untransformed coefficients.
[b] Asterisks indicate statistical significance: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. Standard errors are in parentheses. Significant results are highlighted in bold italics (up to the 10% significance level).

Table 5 WTP estimates

	Model 1			**Model 2**		
	Mean	**Median**	**SD**	**Mean**	**Median**	**SD**
Neighbourhood park (***min*** pollution)	22.22	2.75	231.43	15.16	3.95	93.27

Neighbourhood park (***mean*** pollution)	60.64	10.24	293.70	40.62	13.77	121.82
Neighbourhood park (***max*** pollution)	128.00	29.31	450.51	86.60	35.77	184.30
City park (***min*** pollution)	0.61	0.06	28.26	4.02	0.98	45.97
City park (***mean*** pollution)	–3.84	–0.49	34.92	–0.27	–0.02	46.49
City park (***max*** pollution)	–12.21	–2.57	48.60	–7.88	–2.08	49.18
National park (***min*** pollution)	30.99	8.57	95.20	22.80	9.60	48.55
National park (***mean*** pollution)	33.69	9.30	103.42	23.99	10.12	51.19
National park (***max*** pollution)	38.64	10.66	118.48	25.95	11.12	53.50

Note:
Unit of measurement: CNY per household per month for three years. CNY 6.75 = USD 1 in 2017.

4.2.2 Willingness to pay for a city park

Turning next to the city park, we can see in both Models 1 and 2 that the negative sign of the coefficient of the interaction term ‘City park × Pollution’ is in line with Hypotheses 1 and 2, which expect that residents of a more polluted neighbourhood would care less about parks because 1) their residential location decisions reflect their lower appreciation of environmental amenities in general, and 2) they may spend more time indoors to mitigate pollution exposure, which would reduce their onsite usage of parks. However, the estimated interaction effect is statistically insignificant (p-value = 0.74 in Model 1 and 0.67 in Model 2) and has a limited size in WTP terms. Table 5 shows that the median WTP derived from Model 2 would only be reduced by CNY 2.06 (USD 0.31) per household per month when the mean pollution level rises to the sample maximum level. As depicted in Panel 2 of Figure A2, such an increase in pollution would shift the WTP distribution to the left, but to a considerably limited extent. These findings suggest no discernible connection between people’s pollution exposure and preferences for city parks.

Another interesting finding is a general lack of willingness to pay for the city park. The marginal utility estimate for the city park is negative, size-wise negligible and statistically insignificant in both models (p-value = 0.73 in Model 1 and 0.99 in Model 2). In addition, the interaction term ‘city park × distance’ has a positive estimate and a p-value (0.13 in Model 2) that comes close to the conventional threshold level for statistical significance (0.10), which somewhat suggests the possibility that the respondents prefer a city park located further away. In our choice experiment, different types of parks were characterised by features such as size, facilities and location which are intrinsically different according to the nature of each park type. Such differences exist not only in the information provided during our choice experiment but also in respondents’ a priori experiences with different types of parks. The estimated WTP is associated with all these features and experiences, and is therefore likely to vary across different park types. For instance, the observed lack of willingness to pay for a new city park is likely attributable to certain dis-amenities associated with city parks in the context of Beijing, such as exacerbated crowdedness, noise and traffic congestion. In comparison, the neighbourhood and national parks are less likely to cause such concerns: the neighbourhood park is small in size and features basic green infrastructures and facilities, which thus would not occupy much space or attract large numbers of visitors; the national park is located at least 20km away and hence may not have a direct effect on the respondents' residential environment.

4.2.3 Willingness to pay for a national park

We find no indication of the dependence of WTP for new national parks on pollution exposure, as shown by the insignificant estimate on the interaction term 'National park × Pollution' in the two mixed logit models (*p*-value = 0.81 in Model 1 and 0.89 in Model 2). Similarly, the WTP distribution is not responsive to changes in pollution, as can be seen in Table 5 and Figure A2. These results are particularly helpful in testing the residential sorting effect described by Hypothesis 1, as the other two hypotheses are less relevant to the national park. 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, WTP for the national park is more likely to be linked with pollution levels via the residential sorting mechanism. If this hypothesis was true, respondents living in more polluted areas would be less enthusiastic about environmental amenities in general and hence have lower WTP for the national park. Yet our results find no evidence for such connection.

Our respondents expressed a sizeable WTP for increases in national parks irrespective of pollution levels. The median WTP for a new national park comes to CNY 10.12 (USD 1.50) per household per month, according to Model 2 which has the preferred specification. Further, the coefficient on the interaction term 'National park × Distance' is indistinguishable from zero in terms of both the magnitude and statistical significance, which implies that WTP would not decline over distance.[13] Therefore, we can aggregate the typical WTP over all households in our study area for the three-year payment period, which amounts to CNY 1.45bln (USD 215.41mln) in total, or CNY 7.27mln (USD 1.08mln) per hectare, since the size of the new national park was set to 200ha. The per hectare WTP estimate, despite its considerable magnitude, is notably lower than the fixed asset investment required for developing new parks (CNY12.42mln or USD 1.84 per hectare), which implies that public spending on additional national parks may not be good value of money. Despite that, it is worth noting that the fixed asset investment estimate is an average over all types of parks and is thus likely to overstate the costs of developing national parks, which typically require far fewer facilities per unit of area compared to neighbourhood and city parks. Lastly, the estimated per hectare WTP for a new neighbourhood park (CNY 53.72mln or USD 7.96mln) is substantially higher than that for a new national park. This is likely because a neighbourhood park would provide higher use values for an urban resident in the Chinese

[13] Despite that, the estimated standard deviation of the marginal utility parameter on the interaction term National park × Distance is statistically significant and much larger in size than the mean estimate. This random parameter (characterised by both the mean and standard deviation estimates) accommodates both observed and unobserved individual heterogeneity in preferences for the distance of a new national park, such as individual heterogeneity in travel costs, since individuals who spend more time travelling the same distance should be more sensitive to the distance of a new national park.

context, where neighbourhood parks are visited far more often than other types of green amenities (Chen & Jim, 2011).

5 ROBUSTNESS TESTS

In this section, we formally probe the robustness of our mixed logit estimates to potential endogeneity of pollution, and the validity of using these estimates to test the hypothesised mechanisms that link pollution exposure with WTP for urban greenspace.

5.1 Robustness tests using instrumental variable estimation

Although we have carefully included a number of control variables in Model 2, it is usually difficult to identify and control for all relevant factors that correlate with both pollution levels and people's preferences for urban greenspace. We performed instrumental variable (IV) estimation to formally assess the impact of potential cofounders. Following Czajkowski et al. (2017), we adopted a two-stage procedure to facilitate the IV estimation, as it is not advisable to directly instrument explanatory variables in mixed logit models (Train, 2009). As detailed in Appendix II, we first derived 'individual specific' parameters for the park attributes and the status quo ASC, or more precisely, the conditional means of these parameters for subgroups of individuals who, when faced with the same alternatives (characterised by the attributes), would make the same choices. In the second stage, we regressed these conditional means in a linear setting against pollution and all other explanatory variables listed in Table 3, where pollution can be instrumented in the usual way.

As discussed earlier in Section 3, Figure 2 reveals that the spatial heterogeneity of Beijing's pollution appears largely associated with proximity to Baoding, the most polluted city in China. We therefore constructed an instrumental variable for pollution using the distance from a respondent's residential location to the borderline between Beijing and Baoding. Aside from pollution, we cannot think of any other particular reasons that Beijing residents would opt to live closer to or further away from Baoding. Studies on inter-city trips [e.g. Liu et al. (2014)] typically found fewer trips from Beijing to Baoding than to other neighbouring cities such as Tianjin. This is not surprising, since Beijing has higher paid employment opportunities and better public services (e.g. healthcare and education), and Baoding is less often considered as a popular holiday destination. Therefore it would be more likely that Baoding residents move towards Beijing, rather than the other way around. Moreover, we tested whether distance to Baoding coincides with certain spatial patterns, such as the spatial distributions of income levels and existing greenspaces (using the 'income' and 'park 1km' variables described in Table 3). The correlation coefficients turned out to be 0.11 and –0.06, respectively, which can hardly be regarded as substantial. In addition, we conducted a placebo test, where we attempted to use distance to Baoding (together with other control variables listed in Table 3) to explain the average AQI grade of the hours (in the past year before our surveys) that had a low wind speed (below 1m/s on average) in the past 8 hours.[14] The reasoning is that local pollution levels in Beijing at these less windy times were less likely affected by intercity pollution transmission. Therefore if the instrument still has a sizeable and statistically significant estimate, this would imply that the instrument has likely picked up the effects of some unobserved factors. We repeated this placebo test using the average AQI grade of the hours that had a low wind speed in the past 12 hours as the dependent variable. The 'less windy hours' defined in the two ways mentioned above respectively represent about 18% and 15% of all the hours of the past year, which are not trivial proportions of the pollution data. As can be seen in Table A4 in Appendix I, the estimate on the instrument is statistically insignificant in both placebo tests (p-value > 0.4), and is much smaller in size compared to that in the actual first stage of our instrumental variable estimation (where the dependent variable is the annual average AQI of all hours). Moreover, both placebo tests have a much smaller R^2 (0.198 and 0.192, respectively) compared to the actual first stage of our instrumental variable estimation (0.52), and the R^2 of the placebo tests would only become marginally lower if the instrument is dropped (0.195 and 0.186, respectively). These results to some extent provide corroborating evidence for the validity of the instrument.

Table A5 in Appendix I presents the IV estimation results. Reassuringly, we find that the estimated effects of pollution on utility changes of having new parks are qualitatively similar to the mixed logit estimates in terms of the sign and statistical significance. For instance, in Model A9, the positive and statistically significant coefficient on 'pollution' implies that respondents exposed to higher pollution levels tend to have higher utility gains from a new neighbourhood park, which provides further corroborating evidence for Hypothesis 3. This echoes the positive and statistically significant coefficient on the interaction term 'Neighbourhood park × Pollution' in our mixed logit models, although the two sets of estimates differ in size. The F statistics from the weak IV tests, which are markedly greater than the frequently invoked rule of thumb (10), provides substantive evidence against the null hypothesis of weak identification. An endogeneity test that compares the estimates given by Models A8 and A9 finds no statistically significant difference (p-value = 0.34), which easies the concern about endogeneity bias. Further, throughout Models A10–A13, the small and statistically insignificant coefficient on 'pollution' provides no evidence for the hypothesised connections between people's pollution exposure and their preferences for city and national parks, which resembles the mixed logit estimates, and the endogeneity tests find no detectable inconsistency between OLS and 2SLS estimates.

The only new finding that slightly deviates from our mixed logit analysis concerns people's inclination for the status quo. We can see in Model A15 that higher pollution exposure would decrease the propensity to choose the status quo option. The estimate is considerably large in magnitude and strongly significant. The 2SLS estimate significantly differs from its OLS counterpart according to the endogeneity test (p-value = 0.02), which indicates that the variable 'pollution' is likely to be endogenous when explaining people's preferences for the status quo. In comparison, the coefficient on the interaction term 'Status

[14] We considered the wind speed in the past 8 hours instead of the wind speed in each hour individually because intercity transmission of pollution takes time. The average distance between the communities we surveyed and the borderline of Baoding divided by the average wind speed equals 8.5.

quo × Pollution' in our mixed logit models has the same negative sign but is statistically insignificant, which is similar to the OLS estimate and prone to endogeneity bias. However, the new evidence would not overturn our findings so far regarding the implications of pollution exposure for preferences of parks. It is thoroughly understandable that individuals living in pollution hotspots are less likely to choose the status quo or 'no park' option because they are found to care more about neighbourhood parks than residents of less polluted zones, whilst have similar tastes for city and national parks. In other words, the reluctance to maintain the status quo simply represents another indication of a stronger demand for a new neighbourhood park.

5.2 Robustness tests using alternative dependent variables

Up to this point, we have been contrasting the results for the three different types of parks to test the hypothesised mechanisms that link pollution exposure with preferences for urban greenspace. To strengthen our hypothesis testing, we conducted econometric analysis that more directly speaks to the hypothesised attitudinal and behavioural rationales behind the heterogenous preferences for parks across locations with different pollution loads. Using our survey data, we constructed: 1) a binary variable that indicates whether the respondent was generally supportive of the creation of additional parks, 2) a censored variable that records the number of the respondent's visits to parks in the past year, and 3) a binary variable that indicates whether the respondent was aware of parks' air-cleaning functions. We regressed the three variables individually on pollution exposure as a direct examination of the hypothesised mechanisms behind the observed nexus between pollution exposure and WTP for parks. The two binary variables were modelled in a probit setting, whereas the censored variable in a tobit setting. Further, we instrumented pollution using the additional instrument introduced above (distance to Baoding) as a precautionary measure against endogeneity bias. The standard errors were clustered at the community/village level.

Table 6 displays the estimation results of these ancillary regressions. As shown in Panel 1, Model 4 gives a positive and statistically significant estimate on 'pollution', which translates into a stronger demand in more polluted zones for new parks. This lends no support to Hypothesis 1 that people's residential location decisions, as reflected by local air pollution loads, indicate their preferences for parks (in which case we should have observed a weaker demand in more polluted zones for new parks). One possibility is that the residential sorting effect is outweighed by the aforementioned higher WTP in more polluted locations for the neighbourhood park and hence cannot be identified. Alternatively, it is possible that residential sorting in Beijing is precluded or hampered by certain constraints such as high costs of moving, since a prerequisite for the validity of the residential sorting theorem is 'full mobility' or 'costless moving' (Bayer & McMillan, 2012), which might clash with Beijing's local contexts. Turning next to Panel 2, we find that long-term pollution exposure has no statistically significant implications for park visitation (p-value = 0.16 in Model 5 and 0.77 in Model 6). Both estimates, albeit sizeable, have a positive sign, which is inconsistent with the expectation of Hypothesis 2 and therefore still provides no evidence that favours Hypothesis 2. Indeed, previous studies that found reduced outdoor activities on heavily polluted days mostly regarded such behaviour as temporary defensive responses to transitory pollution episodes [e.g. Bresnahan et al. (1997) and Graff Zivin and Neidell (2009)]. There might exist a greater degree of uncertainty in extrapolating the short-term impact of pollution episodes on park visitation to a longer period, as people can always reschedule outdoor activities when air quality improves. Lastly, we can see in Panel 3 that a more polluted living environment is indeed able to induce a broader awareness of parks' air-cleaning functions, according to the positive and statistically significant coefficient on 'pollution' in Models 7 and 8. This finding further substantiates Hypothesis 3 and justifies our interpretation of the observed higher WTP in more polluted areas for a new neighbourhood park.

Table 6 Estimation results using alternative dependent variables

Panel 1: Dependent variable: whether support the creation of additional parks		
	Model 3 (Probit)	**Model 4 (Probit-IV)**
Pollution	4.09	***10.63****
	(2.76)	***(2.45)***
Panel 2: Dependent variable: number of visits to parks in the past year		
	Model 5 (Tobit)	**Model 6 (Tobit-IV)**
Pollution	16.56	6.07
	(11.72)	(21.03)
Panel 3: Dependent variable: whether consider parks able to clean the air		
	Model 7 (Probit)	**Model 8 (Probit-IV)**
Pollution	***3.94****	***4.08****
	(1.34)	***(2.30)***
Instrumented variable:		
Pollution	No	Yes
Excluded instrument:		
Distance to Baoding		Yes
Clustered standard errors	Yes	Yes
Obs. (number of respondents)	224	

Note:
[a] These models have controlled for all other explanatory variables in Table 3. For brevity, we have omitted estimates for control variables.
[b] Asterisks indicate statistical significance: * *p*-value < 0.10, ** *p*-value < 0.05, *** *p*-value < 0.01. Standard errors are in parentheses. Significant results are highlighted in bold italics (up to the 10% significance level).

6 DISCUSSION AND CONCLUDING REMARKS

This paper presents the first study that formally explores the linkages between pollution exposure and WTP for green amenities in and around a city. This study builds upon a strand of literature that seeks to discern the spatial patterns of people's preferences about green amenities [e.g. Czajkowski et al. (2017)]. In this study, 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 heterogeneity of WTP using pollution levels measured by air quality monitoring stations, whilst controlling for potential confounders. Our findings provide 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.

We set out 3 hypotheses about the likely links between air pollution and WTP for new green space in and around Beijing. Hypotheses 1 and 2 postulated that willingness to pay for any type of greenspace investment should be higher in areas with lower urban air pollution, because, 1) those who care more about environmental amenities would sort themselves into less polluted residential locations, and 2) better air quality enables people to visit greenspace more often. We did not find any evidence to support either hypothesis, especially in light of the insignificant findings for the national park. Air pollution in Beijing has only recently become a concern in the past decade. It is possible that many households with higher demand for environmental amenities have difficulties relocating to less polluted neighbourhoods if the costs of moving house are considerably high. Alternatively, many households making residential location decisions may prioritise some chiefly important needs, such as affordability of housing and proximity to the workplace (Bayer & McMillan, 2012), which may be less substitutable by environmental amenities. Further, the hypothesised reduced visits to parks on heavily polluted days may be more of a temporary defensive reaction to transitory pollution episodes [e.g. Bresnahan et al. (1997) and Graff Zivin and Neidell (2009)]. In contrast, high average pollution loads over longer periods of time may not necessarily lead to a perpetual decrease in total outdoor activities, since people may increase outdoor activities on unpolluted days as a compensation for being forced indoors during pollution episodes. For instance, in the one-year period prior to our interview dates, the respondents on average experienced 76 polluted days (with an API above three) that are considered unsafe for outdoor activities. This implies that they may still be able to reschedule their outdoor activities in the remaining four fifths of the one-year period. Of course, our statistically insignificant findings pertaining to Hypotheses 1 and 2 are largely inconclusive and should not be over-interpreted, since ‘absence of evidence is not evidence of absence’.

Hypothesis 3 was that willingness to pay for new local greenspace should be higher where local air pollution loads are higher, if people regard investing in new local greenspace as a means of reducing their own exposure to air pollution. But there should be no such link between local air pollution loads and WTP for greenspace outside the city. We found evidence to support this hypothesis, as WTP for the neighbourhood park is significantly higher where local pollution levels are higher. As mentioned above, the equilibrium of residential sorting for air quality may have not been fully achieved in Beijing. In that case, the law of diminishing marginal utility would expect that households living with lower levels of air quality would obtain higher levels of marginal utility from air quality improvements, and hence have higher marginal WTP for measures that improve air quality, such as expanding local greenspace. Moreover, living in neighbourhoods with worse air quality may arouse more attention in pollution’s adverse consequences and parks’ air cleaning functions, a phenomenon explicable in terms of selective learning (Chang et al., 2018).

Admittedly, it is possible that the residential sorting and reduced visits mechanisms described in Hypotheses 1 and 2 indeed exist in our case, but have been outweighed by the effects of parks’ air purification services described in Hypothesis 3 and hence become unobservable. Our empirical results only capture the ‘overall indication’ of preferences about greenspace conveyed by the spatial distribution of pollution loads, after all kinds of connections between the two environmental issues have jointly taken effect. We are thus inclined to place more emphasis on the evidence that favours Hypothesis 3 than on the null results concerning Hypotheses 1 and 2. In addition, the connections between pollution levels and WTP for greenspace in this study involve both use and non-use values. For instance, Hypotheses 2 and 3 concerning park visits and parks' air purification services largely focus on use values, whereas in Hypothesis 1, how much people care about environmental amenities in general could relate to both use and non-use values. Our stated WTP estimates have captured both types of values, which we do not attempt to disaggregate. For instance, we found that our respondents visited neighbourhood parks much more often (more than once a week on average) than national parks (less than once a year on average) in the past year. Moreover, these national parks are located far away outside the city and therefore contribute less to air quality near people's homes in the city. These suggest that the use values of national parks are likely to be rather limited. Yet the estimated median WTP per household for a new national park, although indeed much lower than that for a new neighbourhood park, is still sizeable, as shown in Table 5. On pragmatic grounds, such 'overall indication' (the aggregate implication of different mechanisms for the total value of greenspace which includes both use and non-use values) would suffice to proffer recommendations to urban land-use decision-making, since a cost benefit analysis would primarily consider the total benefits and costs of creating or removing greenspace, and would not need to disaggregate benefits into use and non-use values.

For benefit transfer practitioners, our results show that urban air pollution data contain useful information for helping to explain and predict heterogeneity in the value of new investments in greenspace.

It is worth noting that a few recent studies found that peoples' behaviour and choices with regard to pollution may depend more on their subjective perceptions of pollution levels than on objectively measured pollution levels [e.g. Rousseau, Franck & de Jaeger (2019)]. In this study, we used measured pollution data to partly explain responses to the choice experiment, but it seems likely that for residents of Beijing, variations in measured levels across time and between people will be largely correlated with perceived levels, simply because people in Beijing regularly check data on measured levels. Therefore, potential discrepancies between perceived and measured pollution levels may arguably be a lesser concern in our case.

The hedonic approach would be an alternative way to test whether households with similar tastes in environmental amenities will cluster via residential sorting. For instance, Klaiber & Phaneuf (2010) used housing transaction data to estimate a discrete choice model (amongst different residential locations) which gives the implicit price of open space and its dependency on household characteristics such as income levels and the number of children. If there is a measure of people's preference for air quality (preferably before they choose where to live), it can then be used in a residential location choice model like the model of Klaiber & Phaneuf (2010) to explore whether it has implications for the implicit price of new greenspace, and the marginal benefits of this new greenspace to individuals in different locations.

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APPENDIX I SUPPLEMENTARY TABLES AND FIGURES

Table A1 Comparison of sample characteristics with governmental statistics

Variable	Sample mean	Gov. stats	Diff.	Diff. %	*p*-value
Age (years)	***45.60***	***42.98***	***2.62***	***6.10%***	***0.01***
Education (years)	11.47	11.63	–0.16	–1.38%	0.40
Gender (binary: 0 = female; 1 = male)	0.53	0.51	0.02	3.92%	0.16
Household size (number of household members)	2.808	2.807	0.001	0.04%	0.98
Income (household monthly income per capita, CNY 1,000)	4.96	5.18	–0.22	–4.25%	0.24

Note:
Governmental statistics were sourced from *Beijing Statistical Yearbook 2017* (Beijing Municipal Bureau of Statistics, 2017).

a) b)

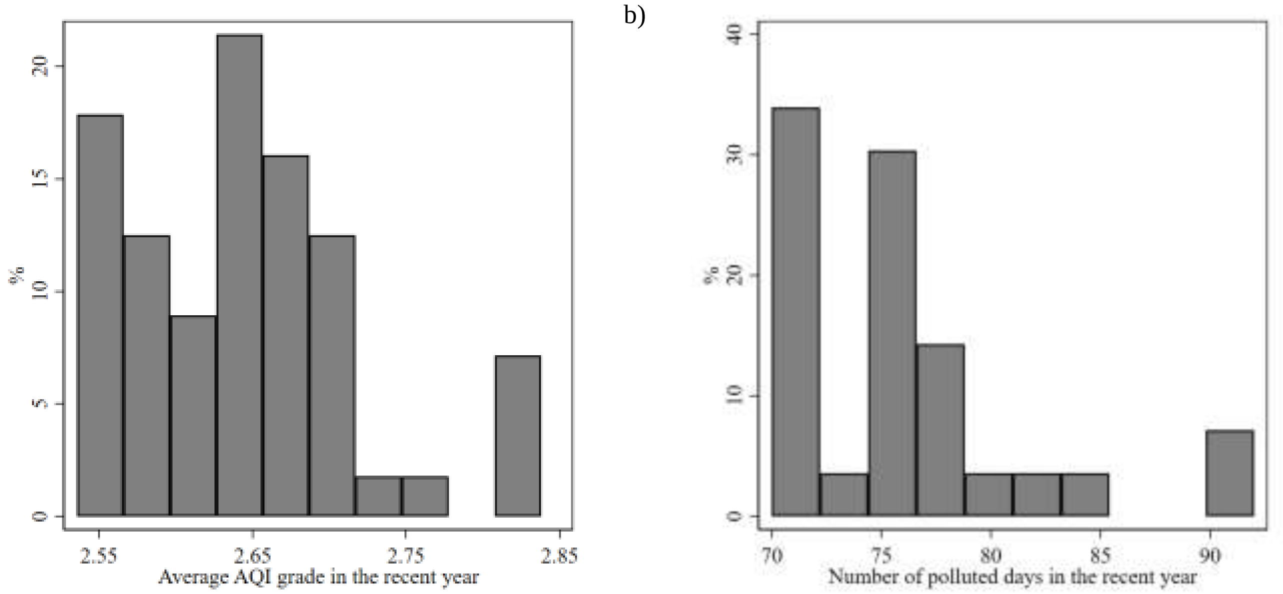
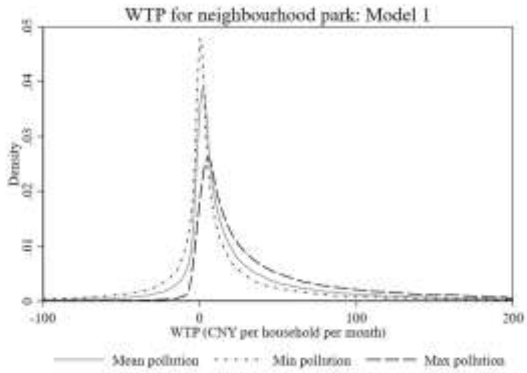


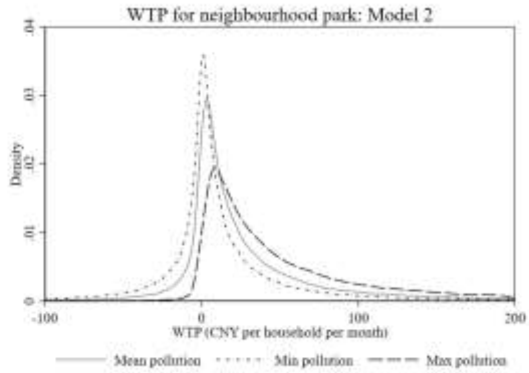
Figure A1 Distribution of pollution levels across residential blocks

Panel 1: Distributions of WTP for a neighbourhood park

a)

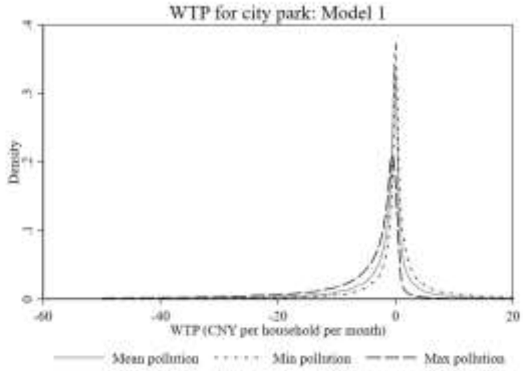


b)

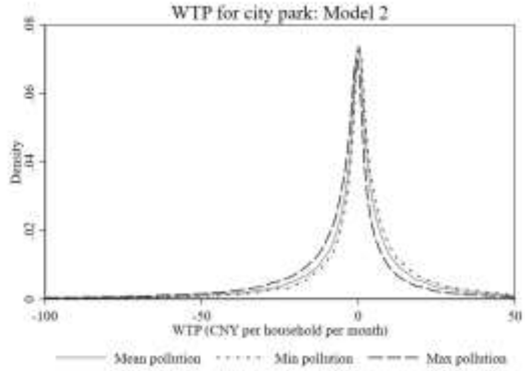


Panel 2: Distributions of WTP for a city park

c)

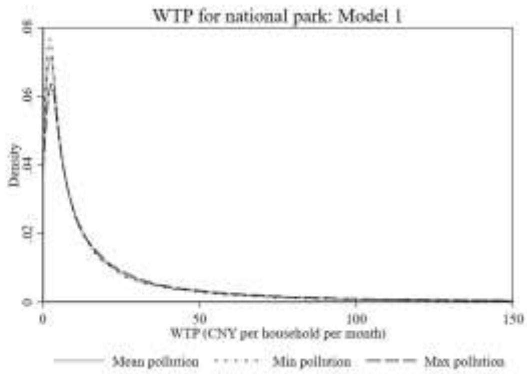


d)



Panel 3: Distributions of WTP for a national park

e)



f)

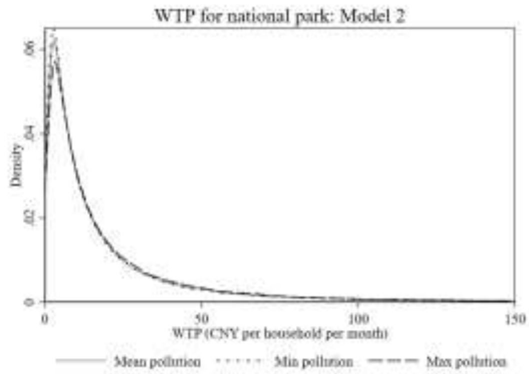


Figure A2 Distributions of WTP estimates

Note:

These are kernel density plots using 100,000 draws from the simulated distributions of WTP.

Table A2 Mixed logit models with different specifications

	Model A1		Model A2		Model A3		Model A4		Model A5	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Payment: ln(–coef.)	***–2.44****	***1.57****	***–2.70****	***1.16****					***–2.49****	***1.67****
	(0.24)	***(0.19)***	***(0.17)***	***(0.17)***					***(0.23)***	***(0.16)***
Payment × Pollution: ln(–coef.)	–2.06		–1.25							
	(3.12)		(1.91)							
Payment: coef.					***–0.06****		***0.05****			
					(0.01)		***(0.01)***			
Neighbourhood park	***1.35****	***1.93****	***1.27****	***1.50****	***1.02****	***2.07****	***1.04****	***1.80****	***1.32****	***1.97****
	(0.39)	***(0.62)***	***(0.33)***	***(0.53)***	***(0.31)***	***(0.44)***	***(0.29)***	***(0.39)***	***(0.36)***	***(0.68)***
Neighbourhood park × Distance	***–0.85****	0.57	***–0.79****	0.34	***–0.82****	0.07	***–0.82****	0.02	***–0.78****	0.18
	(0.30)	(1.08)	***(0.25)***	(1.15)	***(0.22)***	(0.72)	***(0.22)***	(0.72)	***(0.26)***	(2.85)
Neighbourhood park × Pollution	7.04		***6.33****		***7.87****		***7.36****			
	(4.37)		***(3.67)***		***(3.45)***		***(3.22)***			
City park	–0.10	0.81	–0.06	0.14	–0.05	0.08	–0.02	0.03	–0.14	0.14
	(0.27)	(0.83)	(0.25)	(1.47)	(0.23)	(0.50)	(0.22)	(0.50)	(0.25)	(0.85)
City park × Distance	0.04	0.03	0.04	0.02	***0.05****	3.19×10^{-3}	***0.05****	1.74×10^{-3}	0.04	0.01
	(0.03)	(0.10)	(0.02)	(0.07)	***(0.02)***	(0.06)	***(0.02)***	(0.06)	(0.03)	(0.09)
City park × Pollution	–0.92		–1.21		–1.33		–1.54			
	(3.13)		(2.79)		(2.73)		(2.67)			
National park	***0.79****	0.17	***0.78****	0.17	***0.70****	0.01	***0.71****	0.05	***0.76****	0.10
	(0.26)	(0.77)	***(0.22)***	(0.54)	***(0.19)***	(0.58)	***(0.19)***	(0.41)	***(0.22)***	(1.00)
National park × Distance	–0.01	0.02	-4.76×10^{-3}	***0.03****	–0.01	***0.04****	–0.01	***0.04****	-3.63×10^{-3}	0.02
	(0.01)	(0.02)	(0.01)	***(0.02)***	(0.01)	***(0.01)***	(0.01)	***(0.01)***	(0.01)	(0.02)
National park × Pollution	0.54		0.74		0.94		0.92			
	(2.42)		(2.26)		(2.19)		(2.16)			
Status quo	–0.76	***6.91****	1.18	***4.51****	0.49	***6.13****	1.14	***3.91****	–0.96	***6.51****

	(0.70)	***(1.27)***	(2.03)	***(0.74)***	(0.57)	***(0.84)***	(1.60)	***(0.58)***	(0.80)	***(1.04)***
Status quo × Age			0.02				0.03			
			(0.04)				(0.03)			
Status quo × Cars			***1.75****				***1.55****			
			(0.98)				***(0.79)***			
Status quo × Elderly & children			***1.57****				***1.56******			
			(0.88)				***(0.78)***			
Status quo × House price			0.03				0.03			
			(0.02)				(0.02)			
Status quo × Income			***–2.98*******				***–2.73*******			
			(0.69)				***(0.55)***			
Status quo × Park 1km			***1.38*******				***1.08*******			
			(0.48)				***(0.40)***			
Status quo × Park air			***–6.93*******				***–5.85*******			
			(1.33)				***(0.96)***			
Status quo × Pollution	–6.16		0.31		–7.91		–1.84			
	(8.74)		(7.16)		(7.24)		(6.08)			
Status quo × Population density			–0.08				***–0.09******			
			(0.05)				***(0.04)***			
Status quo × Traffic			–4.67				–3.05			
			(4.21)				(3.51)			
Log–likelihood	–591.84		–528.68		–610.94		–545.18		–595.87	
AIC	1,225.67		1,117.37		1,259.89		1,146.35		1,223.74	
BIC	1,326.43		1,261.31		1,351.05		1,280.69		1,300.50	
Obs. (number of choices)	896		896		896		896		896	

Note:
Asterisks indicate statistical significance: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01. Standard errors are in parentheses. Significant results are highlighted in bold italics (up to the 10% significance level).

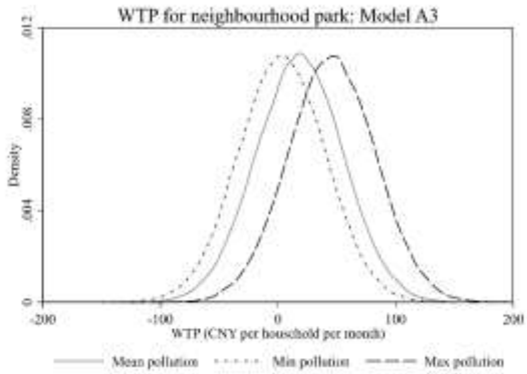
Table A3 WTP estimates assuming a fixed cost parameter

	Model A3			Model A4		
	Mean	**Median**	**SD**	**Mean**	**Median**	**SD**
Neighbourhood park (***min*** pollution)	3.40	3.33	36.99	4.74	4.68	32.94
Neighbourhood park (***mean*** pollution)	18.35	18.45	37.01	19.05	19.01	32.96
Neighbourhood park (***max*** pollution)	45.76	45.78	36.98	45.42	45.44	32.93
City park (***min*** pollution)	1.61	1.61	1.40	2.62	2.62	0.56
City park (***mean*** pollution)	–0.92	–0.91	1.40	–0.41	–0.41	0.56
City park (***max*** pollution)	–5.53	–5.53	1.40	–5.94	–5.94	0.56
National park (***min*** pollution)	10.66	10.66	0.27	13.12	13.12	0.90
National park (***mean*** pollution)	12.46	12.46	0.27	11.31	11.31	0.90
National park (***max*** pollution)	15.75	15.75	0.27	16.40	16.40	0.90

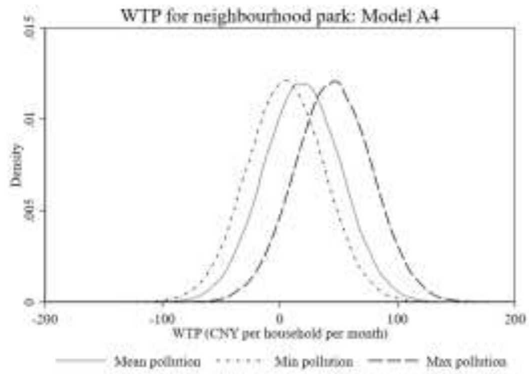
Note:
Unit of measurement: CNY per household per month for three years. CNY 6.75 = USD 1 in 2017.

Panel 1: Distributions of WTP for a neighbourhood park

a)

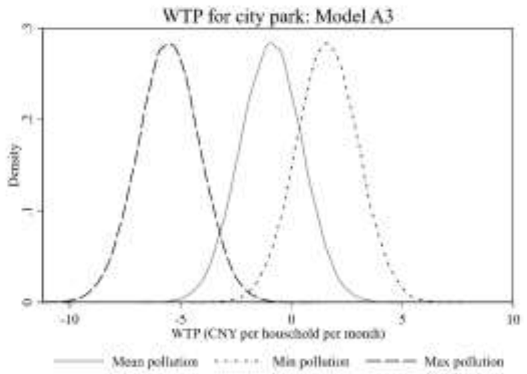


b)

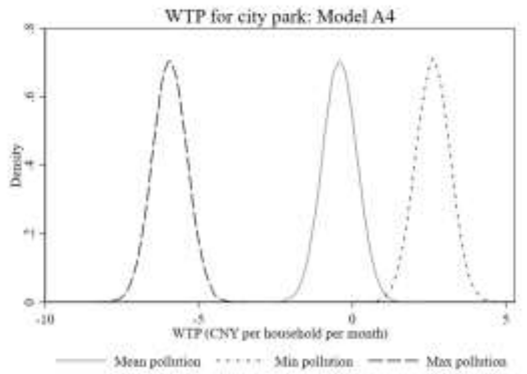


Panel 2: Distributions of WTP for a city park

c)



d)



Panel 3: Distributions of WTP for a national park

e) f)

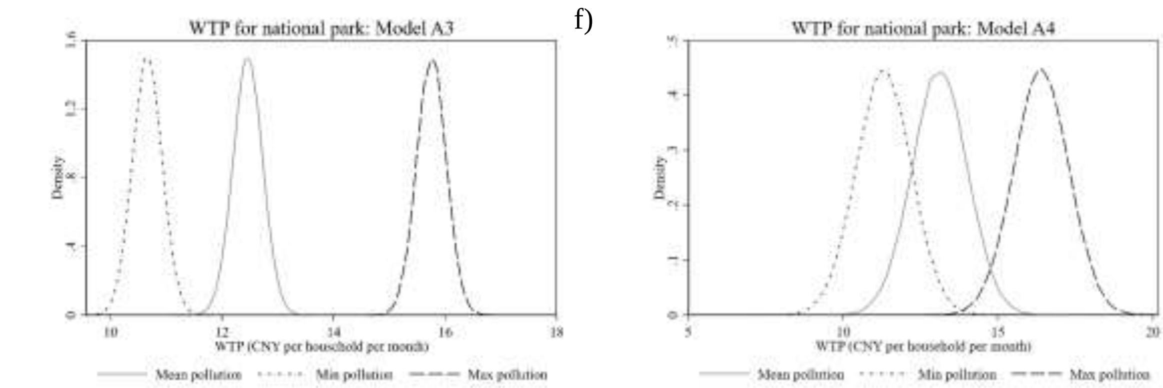


Figure A3 Distributions of WTP estimates assuming a fixed cost parameter

Table A4 Placebo tests of instrument validity

	Model A5	**Model A6**	**Model A7**
	DV: average AQI of 'less windy hrs'		DV: average AQI of all hrs
Distance to Baoding	1.51×10^{-3}	2.41×10^{-3}	***-6.11×10^{-3}******
	(2.40×10^{-3})	(2.90×10^{-3})	***(9.44×10^{-4})***
Control variables (Table 3)	Yes	Yes	Yes
R^2	0.20	0.19	0.52
Clustered standard errors	Yes	Yes	Yes
Obs.	224	224	224

Note:

[a] The dependent variable (DV) of Model A5 is the average AQI grade of the hours (in the past year before our surveys) that had a low wind speed (below 1m/s on average) in the past 8 hours, whereas the DV of Model A6 is the average AQI grade of the hours (in the past year before our surveys) that had a low wind speed (below 1m/s on average) in the past 12 hours. Model A7 is the first stage of the instrument variable models in Table 6.

[b] Standard errors were clustered at the community/village level to address unobserved within-cluster correlation.

[c] Asterisks indicate statistical significance: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01.

Table A5 Estimation results using conditional means of mixed logit coefficients

	OLS Estimates	**2SLS Estimates**
Panel 1: Dependent variable: marginal utility of neighbourhood park		
	Model A8	**Model A9**
Pollution	1.56	***3.12****
	(1.24)	***(1.77)***
Panel 2: Dependent variable: marginal utility of city park		
	Model A10	**Model A11**
Pollution	-4.32×10^{-3}	0.07
	(0.04)	(0.07)
Panel 3: Dependent variable: marginal utility of national park		

	Model A12	Model A13
Pollution	0.02	0.02
	(0.06)	(0.09)
Panel 4: Dependent variable: marginal utility of status quo		
	Model A14	**Model A15**
Pollution	–5.50	***–17.05*****
	(5.30)	***(6.58)***
Instrumented variable:		
Pollution	No	Yes
Excluded instrument:		
Distance to Baoding		Yes
Weak IV test (H_0: Weak IV):		
Cragg–Donald Wald *F* stat.		120.49
Kleibergen–Paap Wald rk *F* stat.		41.96
R^2 from the first stage		0.52
Clustered standard errors	Yes	Yes
Obs. (number of respondents)	224	

Note:
[a] These models have controlled for all other explanatory variables in Table 3. For brevity, we have omitted estimates for control variables.
[b] Standard errors were clustered at the community/village level to address unobserved within-cluster correlation.
[c] Asterisks indicate statistical significance: * *p*-value < 0.10, ** *p*-value < 0.05, *** *p*-value < 0.01. Standard errors are in parentheses. Significant results are highlighted in bold italics (up to the 10% significance level).

APPENDIX II TWO-STAGE PROCEDURES FOR IV ESTIMATION

We first estimated a mixed logit model (Model A5 in Appendix I) that only contains the attributes of our choice experiment and the status quo ASC. The model assumes a lognormally distributed random coefficient for the cost attribute, and a normally distributed random coefficient for all other explanatory variables. The distribution of the coefficient vector $\boldsymbol{\lambda}$ for all individuals is denoted as $g(\boldsymbol{\lambda}|\boldsymbol{\theta})$, where the vector $\boldsymbol{\theta}$ consists of the distribution's parameters, such as the mean and variance. Let $h(\boldsymbol{\lambda}|y, \boldsymbol{x}, \boldsymbol{\theta})$ represent the conditional distribution of $\boldsymbol{\lambda}$ for a subgroup of individuals who, when faced with the same alternatives (characterised by the attribute vector $\boldsymbol{x}$), would make the same choices y. The conditional distribution is given by Bayes' rule:

$$h(\boldsymbol{\lambda}|y_i, \boldsymbol{x}_i, \boldsymbol{\theta}) = \frac{P(y_i|\boldsymbol{x}_i, \boldsymbol{\lambda})g(\boldsymbol{\lambda}|\boldsymbol{\theta})}{P(y_i|\boldsymbol{x}_i, \boldsymbol{\theta})}, \tag{A2.1}$$

where $P(y_i|\boldsymbol{x}_i, \boldsymbol{\lambda})$ represents the probability of the decision-makers' choices. The mean of the conditional distribution can be expressed as:

$$\bar{\boldsymbol{\lambda}}_i = \int \boldsymbol{\lambda} \cdot h(\boldsymbol{\lambda} | y_i, \boldsymbol{x}_i, \boldsymbol{\theta}) d\boldsymbol{\lambda}. \tag{A2.2}$$

$\bar{\boldsymbol{\lambda}}_i$ can be simulated after substituting (A2.2) into (A2.1), which captures each individual's tastes conditional on their choices (Train, 2009).

In the second stage, we regressed these conditional means in a linear setting against pollution and all other explanatory variables listed in Table 3, where pollution can be instrumented in the usual way.