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Does quantity matter for distance decay? Evidence from two choice experiments on urban green

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ABSTRACT

The value of environmental goods to individuals often depends on spatial features such as distance. The most common approach of accounting for distance decay is to model utility as some function of distance. It has been suggested to instead model the value as a function of the quantity of an environmental good within a certain distance. We develop three novel quantity-within-distance models that may be more suited for evaluating quantity changes in an environmental good. We argue that these models could capture spatial patterns better than distance-based models when i) secondary benefits are a relevant source of welfare, ii) the environmental change is spatially scattered, iii) the distribution of the endowment, i.e. the present availability of the environmental good, matters. Using data from choice experiments on the extension of green space and trees in two urban areas, we compare required assumptions, model fit, and size and precision of aggregated welfare estimates. Our results indicate limited differences in model fit. However, the quantity-within-distance models consistently produce aggregate welfare estimates roughly half of common distance decay models and have narrower confidence intervals. While it is not possible to infer which is more accurate, the large differences can have considerable policy implications.

1. Introduction

To derive valid and reliable value estimates for policy impacts on spatially distinct goods, it is important to account for how individuals' welfare may depend on spatial features (De Valck and Rolfe, 2018; Glenk et al., 2020; Schaafsma, 2015). One such spatial feature that has received a fair amount of attention is distance et al., 2020). Distance decay relationships describe the extent to which utility of individuals diminishes as the distance between their residential location and the good in question increases. From a theoretical point of view, use values in particular should be subject to distance decay since increasing distance correlates with increasing travel costs, search costs and substitute availability. This is supported by several empirical studies (Bateman et al., 2006; Glenk et al., 2020; Hanley et al., 2003).

The most common approach for investigating distance decay is to model utility as a diminishing function of distance between the

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place of residence and the environmental good. Since economic theory is silent with regard to which functional form is correct, the choice is inherently empirical and up to the analyst (Ferrini and Fezzi, 2012). Several functional forms have been applied in the literature, for example a linear, quadratic or logarithmic decay with increasing distance (Concu, 2007; Glenk et al., 2020; Olsen et al., 2020) or combined with fixed effects to capture discontinuities at physical barriers (Bakhtiari et al., 2018).

An approach which may alleviate some limitations of the distance-based models, is the quantity-within-distance (QWD) approach proposed by Holland and Johnston (2017). Instead of modelling utility as a function of the distance to the good, Holland and Johnston model utility from a quality change in riparian land as a function of the quantity of riparian land available within a certain distance of an individual's residence.

The QWD approach has shown promising performance in the context of quality changes, but it has not yet been tested in the context of quantity changes. However, many valuation studies investigate the value of policies or projects that change environmental quantity rather than environmental quality. We use data from choice experiments on such quantity changes in green spaces and trees in two German cities to compare common distance-based models and Holland and Johnston's QWD specification with three novel QWD specifications adapted specifically for quantity changes. The first new QWD model includes the quantity change in the environmental good (that is, the area of green space extension and the number of additional trees) within a certain distance in the utility function. The second new QWD model includes the quantity change both within and beyond this distance cut-off. The third new QWD model combines the best performing of the first two with the QWD specification from Holland and Johnston to capture in our application both distance decay and diminishing marginal utility with increasing endowment, defined as the respondent's initial availability of the environmental good. For all QWD models, the optimal distance cut-off is found in an iterative process, maximizing model fit as suggested by Holland and Johnston. We investigate which of the models are preferable with respect to i) required assumptions, ii) model fit, and iii) the size and precision of aggregated welfare estimates between all models.

We argue that the proposed new QWD specifications may offer a more comprehensive and appropriate way to capture spatial patterns of preferences than the common distance-based approach in some cases of environmental quantity changes. The common distance-based models are based on a plausible mechanism in the case of value from recreational visits: The further the distance between an individual's residence and the visited good, the larger the travel and search cost and the higher the number of available substitutes, and thus, the smaller its net value for the individual. In the case of urban green spaces, a considerable part of the welfare is derived from recreational use, and empirical studies frequently find distance decay (Bertram et al., 2017; Jaung et al., 2020; Liu, Hanley, and Campbell, 2020; Perino et al., 2014; Tibesigwa et al., 2020; Tu et al., 2016).

However, the theoretical foundation of distance decay is less clear for other sources of welfare that individuals enjoy as secondary benefit either at home or when moving around in the neighborhood, instead of utility from a deliberate recreational visit. This includes aesthetic amenities, noise reduction and cooling of air temperature. These benefits are the predominant source of welfare from urban street trees. Generally, individual movement patterns are denser close to one's residence (González et al., 2008). Thus, we would still expect distance decay in these types of values. Nevertheless, if the environmental good is not the destination itself, QWD models based on the quantity of the environmental good in the surrounding of an individual's residence, as a measure of density of the environmental good, may capture distance decay patterns better than models based on individuals' travel distance to the good.

A second limitation of modelling utility as a function of distance is that in order to calculate the distance between the good and individuals' residences, the analyst has to assume that the environmental change for an area is concentrated into a single spatial reference point related to the good, such as its center or its closest point. For some environmental changes, the choice between possible spatial reference points does not considerably impact the calculated distances, e.g. if the change takes place in a small nature area far from individuals' residences. However, at the other end of the spectrum, when the environmental change covers a large area which is close to individuals' residences, the choice of where to locate the single spatial reference point for the common distance decay models will have a large impact on the calculated distances. Thus, when the area of change is large relative to the distance to individuals' residences, there is a greater risk that the analysts' choice of spatial reference point could be decisive for findings and conclusions from common distance decay models. This concern is further exacerbated when the environmental change is patchy or scattered over a large area (henceforth referred to as scattered changes). Extension of urban green distributed over a large residential area is an example of such a scattered environmental change. Assuming that this type of environmental change is concentrated in a single spatial reference point – as required for common distance decay models – is questionable. QWD models avoid the need for such an assumption. This concern is different from the secondary benefit motivation for QWD models, because the reference point is also needed for scattered goods that provide mostly primary recreational value.

Third, modelling utility as a function of distance does not directly account for other spatial features that may affect welfare, such as the endowment in terms of the existing quantity of the environmental good that is available to the individual. This is relevant in the case of urban green, because endowments can vary greatly between different neighborhoods. Some effects of these endowments can be captured indirectly by distance-based models, because endowments are substitutes for new urban green, and as such their location influences distance decay in the value for new urban green. However, QWD models hold the potential to disentangle diminishing marginal utility with increasing distance from increasing quantity of the endowment in the environmental good. QWD variables have already been used in stated preference studies to investigate heterogeneity in marginal utility for an environmental good conditional on variations in its endowment (e.g., De Valck et al., 2017; Nielsen et al., 2016; Sagebiel et al., 2017; Yao et al., 2014). Similar applications to QWD have been used in studies based on hedonic pricing (e.g., Geoghegan et al., 1997; Jensen et al., 2021; Panduro et al., 2018; Sander and Haight, 2012) and studies using the life satisfaction approach (e.g., Bertram and Rehdanz, 2015; Tsurumi and Managi, 2015).

Based on these theoretical arguments and empirical findings, the QWD approach is potentially preferable to the common distance-based models in cases where some of the following conditions apply: a) secondary benefits are a more relevant source of welfare than recreational visits, b) the change is spatially scattered, and c) the distribution of the endowment in the environmental good matters for its valuation. Policies to increase urban green largely match all these conditions.

By comparing new QWD specifications to common distance-based models, we contribute to the literature on spatial welfare effects going beyond conventional distance decay approaches (e.g., Budziński and Czajkowski, 2021; Czajkowski et al., 2017; Johnston and Ramachandran, 2014; Olsen et al., 2020; M. Schaafsma et al., 2013; Toledo-Gallegos et al., 2021), providing a possibly better understanding of the welfare gains from scattered environmental goods with considerable secondary benefits. Based on the comparison we provide recommendations concerning which model specifications may be most suitable for different types of environmental goods.

2. Theoretical frame and model specification

The following subsections describe the seven different models analyzed in this study and define them formally, based on distance interactions and QWD variables for the green space area attribute. The models for the tree attribute are specified in analogous ways. All models are specified as mixed logit models in willingness to pay (WTP) space (Train and Weeks, 2005).

2.1. Baseline model

Serving as a reference for our model comparison, we first compute a baseline model which does not account for distance decay at all (model 1). All models presented in the following, seek to explain the choice of individual *i* between the alternatives *j* in choice task *t*, based on the random utility framework (McFadden, 1973).

Baseline (model 1):

$$U_{ijt} = -\beta_{cost\_i}\left(\omega_{green\_i} * GREEN.CHANGE_{jt} + \omega_i' X_{jt} - COST_{jt}\right) + \varepsilon_{ijt} \tag{1}$$

The utility, U_{ijt}, that an individual *i* gains from alternative *j* in choice task *t* depends on the cost of the alternative, $COST_{jt}$, the vector of non-cost attributes, X_{jt}, with the attribute of particular interest, the change in green spaces $GREEN.CHANGE_{jt}$, singled out for readability, and a stochastic component, ε_{ijt}.

Formulating the model in WTP-space is behaviorally equivalent to a preference space formulation, but allows interpreting estimated parameters as marginal WTP. Hence, ω_{green_i} is the marginal WTP for an additional hectare of green space, and ω_i' is a vector of marginal WTPs for the other non-cost attributes. β_{cost_i} is the cost parameter representing the marginal utility of income. All marginal utility and WTP parameters are individual-specific to allow for heterogenous preferences among individuals. Parameters ω_{igreen} and ω_i' are assumed to be normally distributed, while β_{cost_i} is assumed lognormal to ensure a positive marginal utility of income. The stochastic error term ε_{ijt} follows an i.i.d. type I extreme value distribution (Scarpa et al. 2008; Thiene and Scarpa, 2009).

2.2. Distance-based models

Two of our model specifications follow the common approach to model distance decay. Here utility is defined as a function of the distance between the individual's residence and the location of the change.[1] As discussed above, for the calculation of the distance these models require defining a geographical point where the environmental good is assumed to be located. We use the center point of the policy area described in Section 3.1[2].

Linear distance (model 2.1):

$$U_{ijt} = -\beta_{cost\_i}\left(\omega_{green\_i} * GREEN.CHANGE_{jt} + \omega_{green,distance} * GREEN.CHANGE_{jt} * DISTANCE_i + \omega_i' X_j - COST_{jt}\right) + \varepsilon_{ijt} \tag{2.1}$$

Inverse distance (model 2.2):

$$U_{ijt} = -\beta_{cost\_i}\left(\omega_{green\_i} * GREEN.CHANGE_{jt} + \omega_{green,inversedistance} * GREEN.CHANGE_{jt} * \frac{1}{DISTANCE_i} + \omega_i' X_{jt} - COST_j\right) + \varepsilon_{ijt} \tag{2.2}$$

Eq. (2.1) defines the individual utility for the linear distance model, and Eq. (2.2) defines utility for the inverse distance model. In both specifications, the only difference to the baseline model is the addition of an interaction term between the change in green spaces and the distance variable. The interaction term allows an individual's utility for additional green space to systematically vary with the distance to the policy area. The interaction terms in these and the following models arekept fixed as it would empirically be difficult to separate heterogeneity of the main effect from the interaction effect (see the similar argument for separation of scale and taste

[1] We initially estimated models with linear, inverse, quadratic and logarithmic integration of distance, reflecting the most commonly used functional forms (Olsen, Jensen, and Panduro, 2020). Only the specification and results of the linear and inverse functional forms are reported here, since models specifying the quadratic and logarithmic functional forms performed consistently worse for our data.

[2] We use Euclidian distance for all distance and QWD variables. In reality, individuals cannot travel on a direct line but have to follow streets and pathways. We expect no relevant difference in our case, because the policy areas are in inner city districts with dense street and pathway networks and no major barriers. Furthermore, public transport is unlikely to play a major role because of the short distances. Thus, calculating network distances would not change the distance variables in any relevant way except homogenous scaling them, which does not justify the added complexity.

heterogeneity by Hess and Train, 2017). In the linear distance model, ω_{green_i} is the marginal WTP for an additional hectare of green space for an individual with zero distance to the center of the policy area. The term $\omega_{green,distance}$ captures the distance decay by describing how this marginal WTP changes with each additional unit distance to the center of the policy area. We would thus hypothesize $\omega_{green,distance}$ to be negative. In the inverse distance model, the marginal WTP for an additional hectare of green space approaches ω_{green_i} for individuals with large distance to the policy area. Distance decay in the WTP would be reflected in a positive $\omega_{green,inversedistance}$. Following common practice, we only allow the main effect ω_{green_i} to vary between individuals, while the interaction parameter is kept fixed. None of these two model specifications include the initially available endowment of green spaces and therefore cannot capture changes in marginal utility and WTP with different levels of endowment.

2.3. Endowment QWD model

Model 3 follows the QWD specification proposed by Holland and Johnston (2017). This specification, as described in Eq. (3), differs from the baseline model only in the added interaction term between the change in green spaces, $GREEN.CHANGE_{jt}$, and the green space endowment before the change within the distance d of the individual's residence, $GREEN.SQ_{ijt,0-d}$.

Endowment QWD (model 3):

$$U_{ijt} = -\beta_{cost\_i}\left(\omega_{green\_i} * GREEN.CHANGE_{jt} + \omega_{greensq,0-d} * GREEN.CHANGE_{jt} * GREEN.SQ_{ijt,0-d} + \omega_i' X_{jt} - COST_{jt}\right) + \varepsilon_{ijt} \tag{3}$$

Thus, ω_{green_i} is the marginal WTP for an additional hectare of green space for a hypothetical individual that has no endowment of green spaces within the distance d. The term $\omega_{greensq,0-d}$ captures diminishing marginal utility with endowment by describing how the marginal WTP changes with each additional hectare of green space endowment that is within the distance d of the individual's residence. Endowment in green spaces that is further away than d cannot influence the WTP for new green space. Similar to Holland and Johnston (2017), the optimal distance d is found by iterating and choosing the d that maximizes model fit, as described in section 3.4. Consistent with Holland and Johnston, only ω_{green_i} is allowed to vary between individuals while $\omega_{greensq,0-d}$ is assumed fixed.

Holland and Johnston (2017) applied this specification to a quality change in riparian land. In this case, the QWD variable measured the quantity of riparian land that was improved within the distance d of an individual's home. Thus, the cut-off at distance d captured distance decay in the WTP for a quality change. Applied to our case of a quantity change, this specification cannot capture distance decay in the WTP for the change. The interaction term based on the quantity in endowment captures how utility varies with an individual's endowment, and the cut-off distance d only shows distance decay in this effect of the endowment. Yet, we estimate the model to compare results to the new QWD specifications based on the quantity of the change, as well as the new combined QWD.

2.4. New QWD specifications

When investigating quantity changes such as the extension of green space in our case, the QWD variable can be defined based on the change rather than the endowment. Eq. (4.1) defines one of such specifications. Instead of including the total change in green space in the utility function as the baseline model, $GREEN.CHANGE_{ijt,0-d}$ only includes the quantity of new green space that lies within the distance d of the individual's residence. Thus, $\omega_{green,0-d\_i}$ is the marginal WTP for an additional hectare of green space within the distance d, while the marginal WTP beyond d is zero by assumption. By finding the d that maximizes model fit, this specification can capture distance decay with the same number of parameters as the baseline model.

Policy QWD 1 Buffer (model 4.1):

$$U_{ijt} = -\beta_{cost\_i}\left(\omega_{green,0-d\_i} * GREEN.CHANGE_{ijt,0-d} + \omega_i' X_{jt} - COST_{jt}\right) + \varepsilon_{ijt} \tag{4.1}$$

The next specification, as defined in Eq. (4.2), relaxes the assumption that WTP is zero beyond the distance d by adding the quantity of new green space beyond d as the variable $GREEN.CHANGE_{ijt,d-\max}$ (model 4.2). The distance max is set as the maximum distance a respondent in the sample has from the furthest end of the policy area. That is, for all respondents the full change in green space is included within max, and the sum of $GREEN.CHANGE_{ijt,\ 0-d}$ and $GREEN.CHANGE_{ijt,d-\max}$ is equal to $GREEN.CHANGE_{jt}$ used in the previous models.

Policy QWD 2 Buffers (model 4.2):

$$U_{ijt} = -\beta_{cost\_i}\left(\omega_{green,0-d\_i} * GREEN.CHANGE_{ijt,0-d} + \omega_{igreen,d-\max} * GREEN.CHANGE_{ijt,d-\max} + \omega_i' X_{jt} - COST_{jt}\right) + \varepsilon_{ijt} \tag{4.2}$$

When used for the calculation of the welfare of a population, setting max involves an assumption concerning beyond which distance WTP is zero. In our case, we base max on the sampling area that was defined together with local city administration officials to coincide with the area where substantial valuation for changes in the policy area was expected.

In contrast to the common distance-based models, both policy QWD models can capture distance decay without having to define a single point where all new green space is assumed to be located. Instead, the quantity-based variables capture all of the green spaces that are within a certain distance. However, as in the distance-based models, initial endowment with green space is not included, thus changes in marginal utility with varying endowment cannot be captured.

Finally, we construct a combination of models 3 and 4.1, as defined in Eq. (5), to jointly estimate distance decay and diminishing marginal utility with increasing endowment in a QWD model (model 5).

Combined QWD (model 5):

$$U_{ijt} = -\beta_{cost\_i}\left(\omega_{green,0-d\_i} * GREEN.CHANGE_{ijt,0-d} + \omega_{greensq,0-d} * GREEN.CHANGE_{ijt,0-d} * GREEN.SQ_{ijt,0-d} + \omega_i' X_{jt} - COST_{jt}\right) + \varepsilon_{ijt} \tag{5}$$

This specification includes, as does the policy QWD 1 Buffer model (4.1), the quantity of the change only within the distance *d*, $GREEN.CHANGE_{ijt,0-d}$. As the endowment QWD model (3), it adds an interaction term between the change and the endowment of green spaces within the distance *d*, $GREEN.SQ_{ijt,0-d}$. Thus, $\omega_{green,0-d\_i}$ is the marginal WTP for an additional hectare of green space within the distance *d* for a hypothetical individual that does not have any endowment of green space, and $\omega_{greensq,0-d}$ describes how this marginal WTP varies with each hectare of green space endowment within *d*. In contrast to the endowment QWD model, this specification captures distance decay in the marginal WTP by finding the distance *d* that maximizes model fit, because only the change within the distance *d* is considered and WTP is fixed to zero beyond, as in the policy QWD 1 Buffer model (4.1). As in the endowment QWD model, the second term captures the effect of the endowment on marginal WTP as well as distance decay in this effect of the endowment, as only endowment within the distance *d* affects the marginal WTP.

3. Data and estimation

The analysis is based on data from two online surveys conducted in September and October 2021 in the German cities of Berlin and Leipzig. The surveys elicited preferences towards policy scenarios that would change urban green in a confined policy area close to the respondents' residences. The questionnaires first elicited the location of respondents' residences and provided detailed information about the choice experiment attributes, followed by the choice experiment, and finally follow-up and socio-demographic questions. A translated version of the questionnaire is provided in the supplementary material.

3.1. Discrete choice experiments

The choice experiments considered the change of urban green within a predefined rectangular policy area[3] with a size of 1.4 km^2 in Leipzig and 2.3 km^2 in Berlin. The respondents received a written description of the location of the policy area in their city as well as a map outlining the area, shown as figure 3 and 4 in the appendix.

The policy included six non-cost attributes each taking two to four levels, as shown in Table 1. A detailed description of the attributes as shown to the respondents can be found in the translated questionnaire in the supplementary material. The cost attribute was presented as a compulsory yearly payment that, if the urban green changes were implemented, the city would collect from every adult resident living in the policy area and its vicinity and spend exclusively on the extension and maintenance of urban green in the policy area. The definitions of the attributes were based on an earlier stated preference study with extensive pretesting (Zawojska et al., 2024), and were refined in a pilot study. Besides the choice experiment, the pilot study used additional quantitative and qualitative (open text) questions to test the definitions, descriptions and levels of the attributes. The respondents received detailed explanations of the attributes in the questionnaire, and they were informed about their current level in the policy area before the choice experiment.

Respondents faced a sequence of eight choice tasks, each offering two policy alternatives and one status quo alternative. The status quo alternative displayed current levels in the policy area and no cost. The two policy alternatives displayed changes to the current state in some or all of the attributes and a cost taking one of five levels between 6 and 120 Euros per year. The price vector was chosen based on the pilot study. Most respondents stated in an open text question and the choice experiment that they were not willing to pay 120 Euros or more.

The design had 32 choice tasks in total, split into four blocks such that each respondent received eight choice tasks. The experimental design for the choice experiment was created with the Stata module *dcreate*, based on the modified Fedorov algorithm to maximize the D-efficiency in a multinominal logit model (Hole, 2017), using priors from a pilot study conducted with 183 respondents to test the questionnaire.

3.2. Survey implementation

The online survey was implemented and hosted by the public opinion polling agency Aproxima. Respondents were recruited within and in the vicinity of the policy area by sending physical invitation letters to a random sample from the official registries of the two cities.[4] The letters included a short link to the online survey. All adult residents living inside the policy area or within a certain maximum distance from it were considered eligible. The distance was chosen individually for each city in cooperation with experts from the local city administration to coincide with the area where substantial use values for changes in the policy area were expected. It

[3] In practice, a policy would often be applied within some kind of administrative boundary. However, utility of urban green is unlikely to follow administrative boundaries. For the research project, the policy areas were chosen jointly with local administration officials. The areas were located in city quarters where the local administration planned future changes in urban green, and the simple rectangular shape was chosen for easy communication to the public in maps and the survey.

[4] The survey complies with all relevant laws and institutional guidelines. At the beginning of the survey the respondents were informed how the survey data will be used and they needed to consent by voluntarily proceeding to the survey. The Data Protection Officer of the Institute of Ecological Economy Research verified that all personal data was collected and processed in accordance with the European General Data Protection Regulation (GDPR).

Table 1
Choice experiment attributes and levels.

Attribute	Levels Berlin	Levels Leipzig
Trees	11,000 (as today)	2700 (as today)
	10,500	2200
	11,500	3200
	12,000	3700
Green roofs	1 % of suitable roofs (as today)	1 % of suitable roofs (as today)
	10 % of suitable roofs	10 % of suitable roofs
	20 % of suitable roofs	20 % of suitable roofs
Green facades	1 in 100 facades (as today)	1 in 100 facades (as today)
	25 in 100 facades	25 in 100 facades
	50 in 100 facades	50 in 100 facades
Green spaces	120 ha (as today)	38 ha (as today)
	110 ha	30 ha
	130 ha	46 ha
	140 ha	54 ha
Management	Standard (as today)	Standard (as today)
	Intensified care	Intensified care
Near-natural green spaces	10 % of green spaces (as today)	10 % of green spaces (as today)
	5 % of green spaces	5 % of green spaces
	15 % of green spaces	15 % of green spaces
	20 % of green spaces	20 % of green spaces
Yearly contribution per person	6 Euros	6 Euros
	12 Euros	12 Euros
	36 Euros	36 Euros
	60 Euros	60 Euros
	120 Euros	120 Euros

also corresponds to empirical findings from the hedonic house price literature, where distance effects within a couple of hundred meters are often identified. This is for example the case for the studies included in the meta-analysis of Brander and Koetse (2011). Liu et al. (2024) and Panduro and Veie (2013) explicitly investigate a cut-off distance after which values are negligible and find a cut-off around 1000 meter to be reasonable. While hedonic pricing studies only capture values close by, stated preference studies can capture values further away. But the nature of the good we are investigating – with co-benefits and a scattered structure – suggests that similar utility components are identified in our study as in hedonic pricing. The maximum distance we chose for our study in Leipzig, resulted in a range of distances of a respondent's residence to the center of the policy area between 31 and 2577 m, with 1012 m as the average. In Berlin, the distance ranged between 484 and 2995 m, with 1810 m as the average.[5]

A pilot study was conducted including additional qualitative (open text) questions for pretesting. For the pilot study, in each city, 1000 invitation letters were sent in May 2021. For the final survey, in each city, 10,000 letters were sent in September 2021. The number of completed questionnaires in the pilot was 88 in Berlin and 95 in Leipzig, and in the final survey 776 in Berlin and 1027 in Leipzig. After removing respondents who did provide no or an implausible location of their residence, 750 and 945 respondents of the main survey are used for the empirical analysis. Table 2 shows socio-demographic characteristics of these respondents. The sample skewed towards higher educated people.

3.3. Spatial data

As part of the questionnaire, respondents marked the place of their residence on a zoomable and movable map of their city based on OpenStreetMap that included an address search function. To calculate the endowment of green spaces in the respective policy areas, we use the land use class green urban areas from Urban Atlas 2018 (European Environment Agency (EEA), 2020). For the endowment of trees in the policy areas, we use tree inventories provided by the two cities. A respondent's QWD variables for endowment were calculated by summing the green space area or number of trees within a buffer with radius *d* around the reported place of residence of the respondent. The data for the change scenarios was generated by adding trees or patches of green space evenly spread across the policy area, based on the verbal description of the scenario in the questionnaire. A respondent's QWD variables for the change in urban green were calculated by summing the added trees or patches of green spaces within a buffer with radius *d* around the reported place of residence of the respondent. Since the added urban green was evenly spread in the policy area, the QWD variables for change are directly correlated with the share of the policy area overlapping with the buffer.

[5] This distance to the center is of course smaller than the distance to the furthest edge of the policy area which we use as the maximum when optimizing the size of the buffers of the QWD models. The maximum distance to the furthest edge of the policy area is 3340 m in Leipzig and 4110 m in Berlin.

Table 2
Socio-demographic characteristics of respondents.

Characteristic	Berlin	Leipzig
Age	43.5 (12.6)	37.1 (13.9)
Gender		
Female	51.1 %	47.2 %
Male	42.7 %	48 %
Diverse	2.7 %	1.9 %
Household size	2.3 (1.5)	2.4 (1.4)
Number of children under 18	0.4 (0.8)	0.4 (0.8)
Household monthly income [EUR]		
Less than 3000	47.1 %	61.1 %
3000 or more	43.7 %	32.2 %
University education		
University degree	74.7 %	59.8 %
No university degree	23.7 %	38.4 %
Number of respondents	750	945

Note: For age, household size and the number of children under 18, the table shows means (and standard deviations in parentheses). For gender, household monthly income and university education, shares of participants are reported. The shares do not sum up to 100 % because some respondents chose not to answer these questions.

3.4. Model estimation

For all specifications, we first estimate a preference space version of the mixed logit models followed by WTP space versions (Train and Weeks, 2005), using the estimates from the preference space version as priors. For the QWD specifications, we follow a similar approach to Holland and Johnston (2017) and estimate two sets of preference space models to find the optimal distance *d*. First, we estimate several models in 500-meter steps for *d*, ranging from 0 m to the city specific distance *max*. The distance *max* is the maximum distance that a respondent included in the sample has to the furthest end of the policy area. This is logically based on the sampling area, which was chosen in collaboration with experts from the city administration to coincide with the maximum distance where substantial use value from the policy scenario was expected. Second, the two models with the largest Log-likelihood at convergence were chosen and a second set of models estimated in 50-meter steps between them. For the QWD specifications, we estimated the WTP space versions using the 50-meter step for the distance *d* with the largest Log-likelihood at convergence. All models were estimated in R 4.1.0 with the Apollo package version 0.2.4 (Hess and Palma, 2019), using 1000 Sobol draws.

We calculate the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to evaluate how well each model specification fits our data (see for example, Greene, 2018). To test statistical significance of differences in the AIC measure between specifications, we use the test proposed by Ben-Akiva and Swait (1986).

3.5. Welfare aggregation

We use the WTP results from the seven models to aggregate for each one an estimate of the total welfare effect of a scenario measured as compensating surplus. For the scenarios, we use the intermediate attribute levels for two of the urban green attributes presented in the choice experiment, namely an additional eight hectares of green space and an additional 500 trees, respectively. We divide the area in and around the policy area into one-hectare (100x100 meter) grid cells. For all center points of the one-hectare cells, we calculate the distance and QWD variables used in the model specifications.

As a first step in the aggregation, we calculate the mean estimate and standard error of the WTP for the scenario by an average individual in a grid cell, using the relevant parameter estimates from each model and the distance or QWD variables for the center of the cell. Second, in each cell we multiply the means and standard errors by the number of inhabitants. Third, we add up the means and standard errors over all cells. The resulting sum of means is the mean estimate of the aggregate welfare measure of the scenario. We use the standard errors to calculate 95 % confidence intervals for these means.

4. Results

For conciseness, the following three subsections first present results from our main analysis where the seven models specified above are applied to the data from Leipzig with the attribute green spaces treated as the variable of interest. We chose Leipzig over Berlin because the larger sample likely holds more statistical power. We first look at WTP, then the model fit, and then derived welfare effects. Section 4.4 summarizes and compares results obtained for the seven models equivalently applied to the data from Berlin and the attribute trees as the variable of interest, with respective tables and figures available in the appendix.

Table 3
Results of mixed logit models in WTP space for green spaces in Leipzig. Numbers are WTP in euros per individual and year.

	Model 1 Baseline	**Model 2.1 Linear distance**	**Model 2.2 Inverse distance**	**Model 3 Endowment QWD**	**Model 4.1 Policy QWD 1 Buffer**	**Model 4.2 Policy QWD 2 Buffer**	**Model 5 Combined QWD**
Means							
ASC	−114.85 (11.32) ***	−116.01 (12.99) ***	−115.79 (12.98) ***	−115.53 (11.19) ***	−113.19 (12.11) ***	−119.27 (11.85) ***	−115.38 (11.39) ***
ω_{green_i}(per 1 ha)	1.44 (0.17) ***	1.94 (0.37) ***	1.20 (0.22) ***	1.14 (0.42) ***			
$\omega_{green,distance}$(per 1 ha)		−0.49 (0.32)					
$\omega_{green,inversedistance}$(per 1 ha)			0.17 (0.10)				
$\omega_{green,0-d\_i}$(per 1 ha)					1.44 (0.17) ***	1.39 (0.18) ***	5.35 (1.77) ***
$\omega_{green,d-\max\_i}$(per 1 ha)						1.17 (0.75)	
$\omega_{greensq,0-d}$(per 1 ha)				0.00 (0.00)			−0.01 (0.00) **
trees (per 100)	4.34 (0.34) ***	4.32 (0.34) ***	4.32 (0.34) ***	4.33 (0.34) ***	4.30 (0.34) ***	4.33 (0.34) ***	4.33 (0.34) ***
natural spaces (per 1 %)	2.90 (0.31) ***	2.93 (0.30) ***	2.93 (0.30) ***	2.91 (0.31) ***	2.91 (0.31) ***	2.88 (0.31) ***	2.89 (0.31) ***
green roofs (per 1 %)	0.54 (0.06) ***	0.54 (0.06) ***	0.54 (0.06) ***	0.55 (0.06) ***	0.54 (0.06) ***	0.54 (0.06) ***	0.54 (0.06) ***
green facades (per 1 %)	0.54 (0.07) ***	0.55 (0.07) ***	0.55 (0.07) ***	0.54 (0.07) ***	0.54 (0.07) ***	0.55 (0.07) ***	0.54 (0.07) ***
management	−0.57 (2.33)	−0.65 (2.30)	−0.70 (2.31)	−0.83 (2.33)	−0.62 (2.33)	−0.69 (2.31)	−0.54 (2.33)
cost	−3.99 (0.07) ***	−4.00 (0.07) ***	−4.00 (0.07) ***	−4.01 (0.07) ***	−3.99 (0.07) ***	−3.99 (0.07) ***	−3.99 (0.07) ***
Standard Deviations							
ASC	173.99 (18.06) ***	175.27 (19.09) ***	175.40 (19.06) ***	177.45 (16.45) ***	174.65 (17.75) ***	178.87 (17.44) ***	174.19 (18.03) ***
ω_{green_i}(per 1 ha)	2.47 (0.28) ***	2.42 (0.27) ***	2.42 (0.27) ***	2.40 (0.28) ***			
$\omega_{green,0-d\_i}$(per 1 ha)					2.44 (0.28) ***	2.48 (0.28) ***	2.46 (0.28) ***
$\omega_{green,d-\max\_i}$(per 1 ha)						−2.96 (1.52) *	
trees (per 100)	2.55 (0.49) ***	2.50 (0.54) ***	2.49 (0.54) ***	2.39 (0.55) ***	2.54 (0.49) ***	2.44 (0.54) ***	2.55 (0.50) ***
natural spaces (per 1 %)	2.04 (0.71) ***	1.87 (0.71) ***	1.89 (0.71) ***	2.18 (0.62) ***	1.96 (0.65) ***	1.75 (0.73) **	2.04 (0.70) ***
green roofs (per 1 %)	0.78 (0.08) ***	0.75 (0.09) ***	0.75 (0.09) ***	0.78 (0.08) ***	0.78 (0.08) ***	0.75 (0.08) ***	0.78 (0.08) ***
green facades (per 1 %)	0.92 (0.11) ***	0.90 (0.12) ***	0.90 (0.12) ***	0.89 (0.11) ***	0.93 (0.12) ***	0.88 (0.11) ***	0.92 (0.11) ***
enhanced management	31.87 (4.53) ***	32.35 (4.36) ***	32.37 (4.35) ***	31.25 (4.46) ***	31.52 (4.64) ***	31.58 (4.55) ***	31.79 (4.56) ***
cost	0.39 (0.07) ***	0.40 (0.07) ***	0.40 (0.07) ***	0.38 (0.07) ***	0.41 (0.07) ***	0.44 (0.08) ***	0.40 (0.07) ***
Number of respondents	945	945	945	945	945	945	945
Number of parameters	16	17	17	17	16	18	17
buffer boundaries	n.a	n.a	n.a	1350 m	2500 m	2000 m	3000 m
Log-likelihood (converg.)	−6086.21	−6084.90	−6084.80	−6087.40	−6087.10	−6085.22	−6084.06
AIC	12204.42	12203.81	12203.61	12208.80	12206.21	12206.43	12202.13
BIC	12315.31	12321.63	12321.43	12326.62	12317.10	12331.19	12319.95
Adj. rho square	0.2653	0.2653	0.2653	0.2650	0.2652	0.2652	0.2654

Notes: ***, **, and * indicate 1 %, 5 %, and 10 % significance levels, respectively. Standard errors are given in brackets.

4.1. Willingness to pay

Table 3 reports results of the seven estimated models focusing on green spaces in Leipzig. The upper part shows parameter estimates for means and standard deviations of marginal WTP for each of the attributes per individual and per year. In the baseline model, respondents are on average willing to pay 1.44 euros per year for an increase of green spaces by one hectare, 4.34 euros per year for an increase of city trees by 100 trees, 2.90 euros per year for an increase of the share of natural spaces by one percentage point, 0.54 euros per year for an increase of green roofs by 1 % of roof area, and 0.54 euros per year for an increase of green facades by 1 % of facades. The coefficient for management is small and not statistically significant. All estimated standard deviations are statistically significant and for some attributes even larger than the estimated means. This indicates substantial heterogeneity among respondents, with a share of respondents exhibiting negative WTP.[6]

The two distance-based models yield overall similar means and standard deviations. In the linear distance model (2.1), the average WTP for an additional hectare of green spaces for respondents in the immediate vicinity is 1.94 euros per year. It decreases by 0.49 euros per kilometer distance between the respondent's residence and the center of the policy area, although not significantly. That is, this model predicts the same 1.44 euros WTP as the baseline model for respondents that live one kilometer from the center. In the inverse distance model (2.2), the WTP for an additional hectare of green space approaches the baseline coefficient of 1.20 euros for respondents far from the policy area. Estimates increase hyperbolically with closer distance to the policy area, with for example 1.37 euros at one kilometer distance, slightly smaller than for the baseline and linear model, and 2.05 euros at 200 m distance. However, also in the inverse distance model, the distance interaction coefficient is not significantly different from zero. In conclusion, using the common approach, we are not able to find significant distance decay for the scattered change in green spaces.

The endowment QWD model (3) yields a WTP for an additional hectare of green space of 1.14 euros per year for a hypothetical respondent with no endowment of green spaces in 1350 m radius around their residence. This WTP is independent of the distance to the change in green spaces, as the model applied to quantity changes cannot capture distance decay. The relation between marginal WTP and the endowment of green space within 1350 m is small and not statistically significant, contrary to the diminishing marginal utility that was expected.

In the QWD model based on the quantity of green space extension with one buffer (4.1), the iteration yielded 2500 m as the optimal buffer boundary: The marginal WTP is 1.44 euros per year for an additional hectare of green space within this distance of a respondent's residence, and by assumption zero for any new green space beyond this distance. That is, the models predict WTP to be identical to the baseline model for new green spaces within 2500 m. In the QWD model based on the quantity of green space extension with two buffers (4.2), the marginal WTP is 1.39 euros for an additional hectare of green space within 2000 m, and 1.17 euros beyond. However, the latter coefficient is not significantly different from zero.

The combined QWD model (5) estimates a marginal WTP of 5.35 euros per year for an additional hectare of green space within 3000 m of the residence of a hypothetical respondent who does not have any endowment of green space. For each hectare endowment within 3000 m, the marginal WTP decreases by 0.006 euros. This yields a marginal WTP of 1.44 euros, identical to the baseline model and the policy QWD model with one buffer, for a respondent with an average endowment of 686 ha of green space. For additional green space beyond the buffer boundary of 3000 m, the WTP in this model is zero by assumption. Both parameters are statistically significant, thus indicating both a distance decay and a diminishing marginal utility with increasing endowment.[7]

4.2. Model fit

All differences in model fit between the baseline model and both the QWD and the distance-based models are small. A considerable share of the differences in model fit between the specifications is within the range one would expect from typical simulation errors in the maximum likelihood estimation without true differences in model fit (Czajkowski and Budziński, 2019). The combined QWD model (5) is the only one with a significantly superior AIC in a Ben-Akiva & Swait test (p-value = 0.003) compared to the baseline model. Measured in BIC, which penalizes stronger for additional parameters, no model is superior to the baseline model. A bootstrapping analysis with 1000 simulated samples, as described in Appendix 8.4, produces similar results: Measured in AIC, only the combined QWD model (5) and the inverse distance model (2.2) have statistically significant ($p<0.01$) superior model fit compared to the baseline model. Measured in BIC, none are superior.

4.3. Welfare effects

Table 4 reports means and 95 % confidence intervals of the total welfare effect of the change in green spaces implied by the seven models. The baseline model yields a mean estimate of 2.6 million euros per year for extending green space in the policy area by eight

[6] There may be some interaction between preferences for the quantity of green spaces (captured in the green spaces attribute) and preferences for their quality (e.g., captured in the management attribute). Additional models showed that these interactions are not significant nor substantially change the results of the simpler models used for this analysis. The experimental design did not ensure that this kind of interaction analysis is possible.

[7] The distance patterns picked up by some of the models might generally also be explained by spatial differences in socio-demographic characteristics instead of distance decay in individual preferences. However, in our data we found virtually no correlation between distance and age, income or education (R^2 below 0.01).

Table 4
Means and 95 % confidence intervals of aggregated welfare effects for green spaces in Leipzig. Numbers are euros per year.

	Model 1 Baseline	Model 2.1 Linear distance	Model 2.2 Inverse distance	Model 3 Endowment QWD	Model 4.1 Policy QWD 1 buffer	Model 4.2 Policy QWD 2 buffers	Model 5 Combined QWD
welfare mean	2628,021	1312,138	2377,442	2771,198	1221,118	1754,048	922,213
lower CI boundary	2003,822	−565,028	1657,836	1814,412	929,479	424,215	−103,358
upper CI boundary	3252,219	3189,304	3097,048	3727,985	1512,757	3083,881	1947,786
Individuals with positive WTP	228,847	214,846	228,847	228,847	150,802	228,847	144,101
Average WTP per individual with positive WTP	11.48	6.11	10.39	12.11	8.10	7.66	6.40

hectares. The inverse distance model (2.2) and endowment QWD model (3) yield very similar mean estimates with 2.4 and 2.8 million euros per year, respectively. All other models produce lower welfare estimates, ranging from 0.9 million euros per year for the combined QWD model (5) to 1.8 million euros per year for the policy QWD model with two buffers (4.2).

The confidence interval of the welfare estimates yielded by the baseline model spans from 2 million to 3.3 million euros per year. For the inverse distance model (2.2), the endowment QWD model (3) and the policy QWD model with two buffers (4.2), the confidence intervals are slightly larger. The welfare estimates yielded by the linear distance model (2.1) are the least precise, the very large confidence interval spans from −0.6 to +3.2 million euros per year. The policy QWD model with one buffer (4.1) yields the smallest confidence interval, ranging from 0.9 to 1.5 million euros per year. While the confidence intervals of several of the models overlap with the baseline model, this is not the case for model 4.1 because of its considerably lower welfare estimate and its narrow confidence interval. The mean of the aggregated welfare estimate can be seen as the product of the number of individuals that a model predicts to have positive WTP, and their average WTP. Both QWD models with just one buffer (4.1 and 5) predict WTP to be zero beyond the iteratively optimized buffer boundary, which reduces the number of individuals with positive WTP around one third in both cases. In addition, the policy and combined QWD models as well as the linear distance model predict smaller average WTP per person.

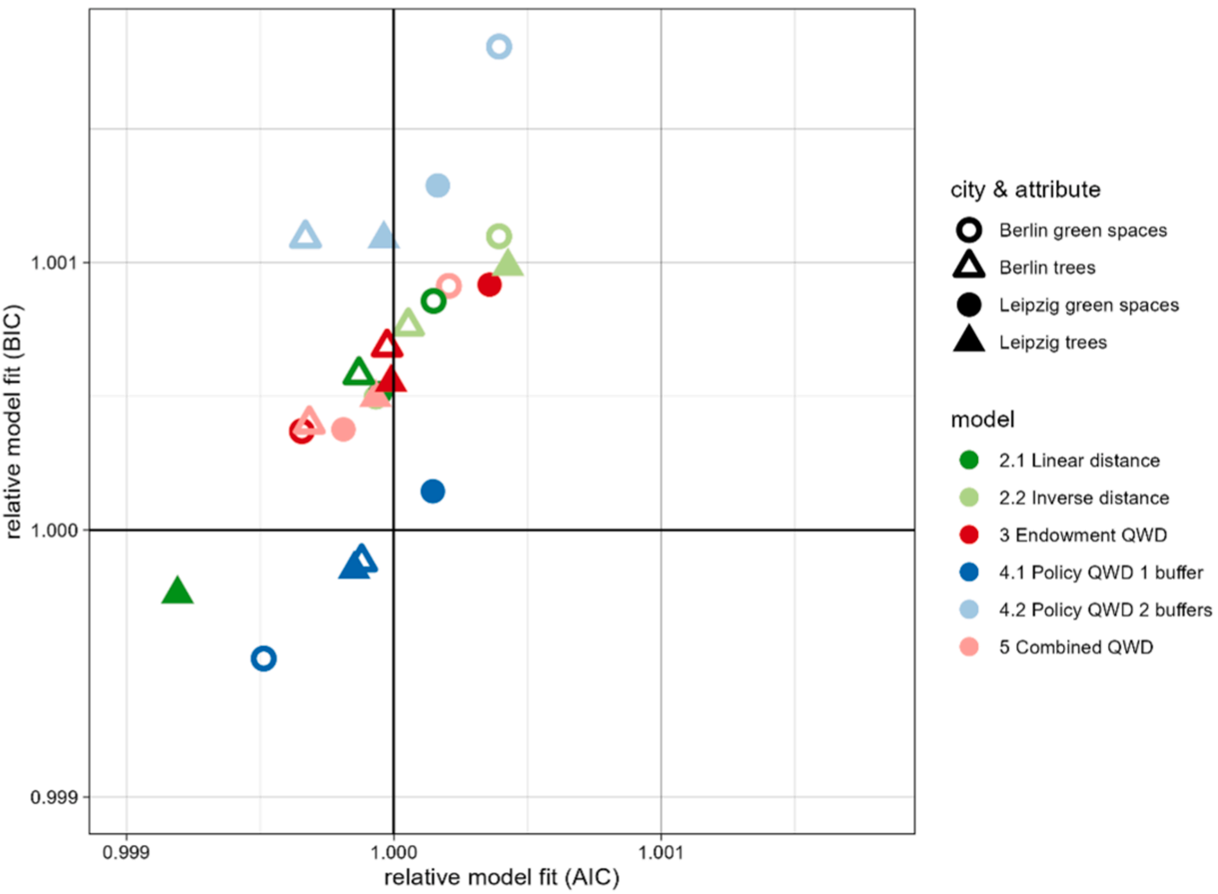

Fig. 1. AIC and BIC compared to the baseline model.

The bootstrapping analysis described in appendix 8.4 indicates that these differences between the models are statistically significant. The policy QWD model with one buffer (4.1) and the combined QWD model (5) yield lower welfare estimates than the baseline model in all 1000 redrawn samples. The average welfare estimates over the 1000 samples for these two QWD models is significantly smaller than for the baseline and both distance-based models, with p-values below 0.01 based on pairwise Student's *t*-tests. In all 1000 samples, the policy QWD model with one buffer (4.1) also yields a smaller confidence interval of the welfare estimates with a p-value below 0.01.

4.4. Sensitivity to different cities and attributes

The previous sections described results for the application of the seven models focusing on an extension in green spaces in Leipzig. We applied the same models also to the city of Berlin and to the attribute trees. Applying the same models to city trees gives an indication of how generalizable results are as they provide a larger share of secondary benefits relative to recreational value in comparison to green spaces, and they are also generally more scattered. Tables showing the remaining results of model estimation and welfare aggregation can be found in the appendix. Fig. 1 summarizes the results of all estimated models for both Berlin and Leipzig regarding the two model fit measures AIC and BIC. All reported values are normalized to the values of the baseline model for the respective city and attribute. That is, the baseline models are not marked by shapes but located in the intersection of the two lines in the middle of the diagrams. Models in the lower left quadrant of Fig. 1 perform better in AIC and BIC than the baseline model, models in the upper right quadrant perform worse in both measures.

In Fig. 1, some points are to the left and some are to the right of the middle line, reflecting the mixed results regarding improvement in AIC model fit compared to baseline. The linear distance model (2.1), the policy QWD model with one buffer (4.1), and the combined QWD model (5) have a better AIC compared to the baseline model in three out of four applications, but the improvements are small. Each model performs worse than the baseline in one of the four applications. Measured in BIC, most model applications result in a worse model fit than the baseline model. This reflects the small improvements in AIC while requiring additional parameters which are

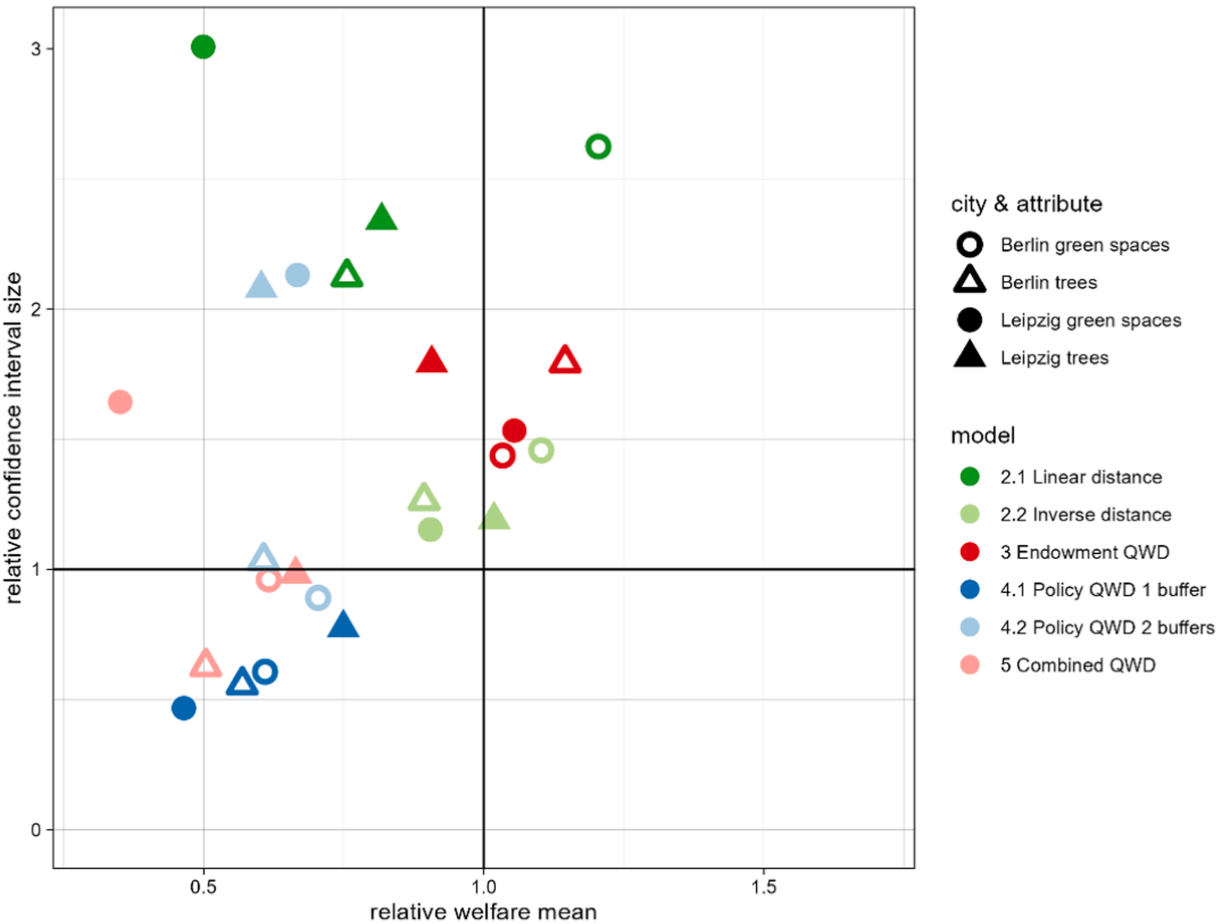

Fig. 2. Mean and size of 95 % confidence intervals of aggregated welfare compared to the baseline model:.

stronger penalized in the BIC measure. The policy QWD model with one buffer (4.1) has a better BIC than the baseline model in three out of four applications because it does not require additional parameters.

Fig. 2 shows in an analogous way the mean welfare estimates and the size of its 95 % confidence interval implied by the results of the models. Models in the lower left quadrant have a smaller mean estimate and confidence interval width than the baseline model, models in the upper right quadrant have larger mean estimates and confidence intervals. The models show consistent patterns over all four applications. The size of the confidence intervals of the welfare estimates is smallest for the policy QWD model with one buffer (4.1). Also, the inverse distance model (2.2) and the combined QWD model (5) generally yield relatively small confidence intervals comparable to the baseline model. In contrast, the confidence intervals produced by the linear distance model (2.1) are more than twice as large as the baseline confidence intervals in all applications. All three new QWD specifications yield relatively small welfare means, generally around half the size of those obtained from the baseline model. The welfare mean estimates produced by the inverse distance model (2.2) and the endowment QWD model (3) are consistently similar to the baseline model. The welfare means based on the linear distance model are highly variable over the four applications, reflecting the imprecise estimation indicated by their large confidence intervals.

5. Discussion

Contrary to our expectations, we only find small differences in model fit measured by AIC and BIC between the baseline model, the QWD models, and the more common distance-based models. No model performs consistently better in all four applications (trees and green spaces in Berlin and Leipzig). One likely reason for the limited difference is, that both the distance from the policy area and the quantity of change within a certain distance play only a small role for the respondents' choices, and thus only explain a small share of preference heterogeneity in our case study. This is indicated by the remaining large standard deviations in all distance decay models, the inconsistent statistical significance of the distance decay parameters, and the generally good performance of the baseline model that does not account for any spatial patterns.

This limited role of distance decay is in contrast to expectations based on the theory of increasing travel costs and substitute availability, as well as decreasing secondary benefits with distance. It is also in contrast to previous empirical results for green spaces, parks and urban forests in empirical studies using both stated preference (e.g., Bertram et al., 2017; Tu et al., 2016) and revealed preference (e.g., Perino et al., 2014) approaches. While we can only speculate about the reason, the limited role of distance decay may be an indication that more pronounced decay only occur beyond the maximum distance sampled from the policy change (3.3 km for Leipzig and 4.1 km for Berlin), although hedonic house price studies indicate substantial distance decay in urban settings within these distance ranges (e.g., Liu et al., 2024). The limited role of distance decay may also be exacerbated by our modelling approach that focuses only on distance decay in one urban green attribute, either green spaces or city trees. This can only capture spatial heterogeneity for the attribute in focus, while there could also be spatial patterns in the preferences for the other attributes. Finally, the role of distance decay may be limited because city residents derive a substantial share of utility from urban green via non-use or indirect values that do not depend on where it is located relative to their location of residence, such as the overall image of the city or biodiversity. We cannot disentangle these potential reasons based on our data and thus leave this for future research.

The differences to the study by Holland and Johnston (2017) may also be explained by the different constructs that the QWD variables capture in the different applications. Holland and Johnston's QWD variable measured the quantity of riparian land that would be affected by a quality change. In our application of their specification, the QWD variable measured the quantity of endowment in urban green. Hence, in our application it could capture diminishing marginal utility with endowment and its spatial patterns, but not distance decay in the value for the quantity change. Our new model specifications capture a further construct in our case. The QWD variables measure the added quantity of urban green within a certain distance. This is a direct measure of the quantity change, hence the models capture distance decay in the value for this change, but in a different way than the original approach by Holland and Johnston.

We found considerable differences in the resulting estimates for the aggregate welfare effect of the change in urban green, depending on which model is applied. The QWD models based on the quantity of change in urban green consistently produce estimates that are roughly half in size compared to the baseline model, the common distance-based models, and the endowment QWD specification. As we do not know the true welfare effect, there is no direct indication which model is the most accurate. Notwithstanding this, the differences in the welfare values appear noteworthy, especially since policy recommendations are usually based on these measures.

Differences between the models in the precision of welfare estimates are also considerable. The commonly used linear distance decay model (2.1) produces estimates with a confidence interval more than twice the width of the baseline model, which is reflected in its highly variant mean estimates for the welfare effects. This is caused by large standard errors of the distance interaction term, which lead to high statistical uncertainty in large distances from the policy area. By construction, this would typically be where a large part of the population lives, as the area increases quadratically with distance. In contrast, the QWD models with one buffer (4.1 and 5) produce smaller confidence intervals of welfare estimates than the baseline model. This is desirable, since policy recommendations can be given with less statistical uncertainty.

Beyond these empirical findings, some theoretical considerations are important for the choice of model. Some assumptions underlying the different modelling approaches are more pertinent to different kinds of environmental goods. We argued in the introduction that QWD may be more suitable if secondary benefits are a dominant source of value compared to the primary recreational benefit. In the context of urban green, recreational activities would be expected to be a more dominant value component for green spaces, while secondary benefits would be more dominant for trees. This led to the expectation that QWD models would perform relatively better in the application to trees. However, we do not find such patterns consistently across models and the two cities. Another assumption underlying common distance-based models is that the environmental good is concentrated in one single point to be defined by the researcher. QWD models are less restrictive as they capture the spatial distribution of the environmental good. Thereby, in principle, they are more suited for applications where the good is spatially scattered across some geographical area.

Further, QWD models may be an effective way to jointly model diminishing marginal utility with distance and with increasing endowment of the environmental good. In principle, also the common approach of modelling utility as a function of distance can capture diminishing marginal utility with endowment directly. However, the combined QWD model (5) allows for this with less parameters. Our empirical results do not show a consistent change in model fit when adding these endowment components. Furthermore, the coefficients show a statistically significant relation between marginal utility and endowment only in a few of the applications. This indicates that the endowment in green spaces or trees explains only a small part of preference heterogeneity in our data.

Finally, some pragmatic considerations are pertinent for the choice between modelling approaches. All distance decay models have additional data requirements compared to the baseline model. The location of the residence of the respondents is needed both for the common distance-based and the QWD models. For the distance-based models, a point related to the change in the environmental good has to be defined to calculate the distances. For the QWD models, the full spatial distribution of the change or endowment of the environmental good is needed to calculate the QWD variables. In the computation of models, the QWD approach has considerably higher requirements due to the iterative optimization.

For policy use, also the ease of interpretation is an important factor. It can be helpful to communicate not only aggregated welfare effects to policy makers, but also the spatial pattern of individual WTP values they are derived from. For the common distance-based models, this is possible for simple functional forms, such as a linear decrease of WTP with distance from the policy area. Other functional forms are likely more difficult to communicate and be understood by policy makers. The QWD models can be communicated in a relatively easy way: There is a constant WTP for a change within a certain distance, dropping to zero (one-buffer models) or a lower value (two-buffer models) beyond this distance. This contrasts other approaches that try to capture spatial characteristics of WTP with more complex models. For example, nonparametric generalized additive models relax some assumptions of the common distance-based models, but cannot be readily interpreted (see e.g., Olsen et al., 2020). When using results from the analysis of spatial heterogeneity for policy, it may be relevant to consider that people can benefit from public goods such as urban green regardless of whether they pay for it. In the small scale case of urban public goods, it may be relevant to which extent the inhabitants of the administrative unit that decides on and funds the policy and those of other units benefit.

An obvious question is how generalizable the results are. We investigate two cities of different sizes and two attributes that differ in the type of value they provide to citizens. This gives more insight into how general the empirical results are than if only one application had been investigated. As discussed, we find some common patterns in welfare estimates over all four applications. However, the variation between the applications indicates that distance decay patterns may have substantial context dependency. For example, the size of a city may make substitutes in and out of the city more or less important. Also, distance decay patterns may deviate between different sociodemographic groups and, consequently, between cities with a different sociodemographic structure. Substantial sociodemographic differences between the two cities of our investigation are visible in Table 2. Urban green frequently fulfills the conditions of scattered goods and secondary benefits. Based on our theoretical arguments, the advantages of QWD models should also hold in larger scale cases that fulfill these conditions, but future empirical research would have to confirm how our findings generalize beyond the urban setting.

6. Conclusion

This study develops three new QWD model specifications and investigates whether QWD models are preferable to the common distance-based approach in an urban green case study. We suggest that these models may be superior in applications when secondary benefits are a relevant source of welfare, the change in the environmental good is spatially scattered, or the distribution of the endowment in the environmental good matters for its valuation. We estimate seven mixed logit models in WTP space for two urban green attributes in two cities: a baseline model not capturing distance decay, two common distance decay models with linear and inverse distance in the utility functions, Holland and Johnston's (2017) QWD specification applied to a different quantity change scenario, as well as three novel QWD specifications.

We find only limited differences between the models regarding model fit. However, the novel QWD models generally produce aggregated welfare estimates that are roughly half in size compared to the common distance-based models and Holland and Johnston's QWD specification. As we do not know the true values, we cannot conclude which is more accurate. Yet, the large differences can have considerable policy implications. The welfare estimates produced by most of the novel QWD models have smaller confidence intervals, which is desirable as policy recommendations can be given with less statistical uncertainty.

Our analysis informs recommendations for the choice of model when investigating distance decay in quantitative environmental changes. If the environmental good to be valued is spatially scattered or provides important secondary benefits, our proposed policy QWD model with one buffer (4.1) seems a viable option. For these kinds of environmental goods, the assumptions for this model are more realistic and less restrictive than for the common distance-based models that need to define a single point where the environmental good is concentrated. Thus, it may capture some patterns in individuals' valuation that cannot be captured by distance alone. This is reflected in the favorable empirical results, as it produces more precise welfare estimates while obtaining a similar model fit as compared to the common distance-based models.

The proposed combined QWD model (5) is another viable option in cases when diminishing marginal utility with endowment in the environmental good is relevant. It adds an endowment component to the policy QWD model, with the same underlying assumptions about the area of the environmental good. In some of our empirical cases we find a statistically significant relation between individuals' valuation and their endowment in urban green. This aspect of spatial heterogeneity could not have been captured by distance alone. When comparing the combined QWD model to the common distance-based models, we find similar-to-superior model fit and precision of welfare estimates.

For practical applications, the empirical advantages we find for the proposed QWD models have to be balanced with the higher requirements regarding data and computation. It is particularly noteworthy that the choice between distance and QWD models may have substantial impacts on welfare estimates, which can have considerable policy implications. This makes a sensitivity analysis with QWD models advisable, in particular in applications where the assumptions underlying QWD are more realistic, such as environmental goods that are scattered, provide considerable secondary benefits or have a heterogeneous distribution of endowment, which may matter for individual valuation.

Future research can further illuminate the potentials and drawbacks of applying QWD models in the valuation of environmental goods where the value to individuals depends on spatial features. It may be interesting to compare additional model specifications that integrate quantity-within-distance components into the utility function in a different way. In addition, applying our new QWD models to different types of environmental goods may provide additional insight. Cases where distance and QWD explain larger parts of preference heterogeneity than in our data would make the comparison of models clearer.

CRediT authorship contribution statement

Malte Welling: Writing – review & editing, Writing – original draft, Resources, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Jette Bredahl Jacobsen:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Conceptualization. **Søren Bøye Olsen:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Formal analysis, Conceptualization. **Thomas Lundhede:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare no conflicts of interest related to this research or its publication.

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Appendix A

Maps of study areas in Leipzig and Berlin

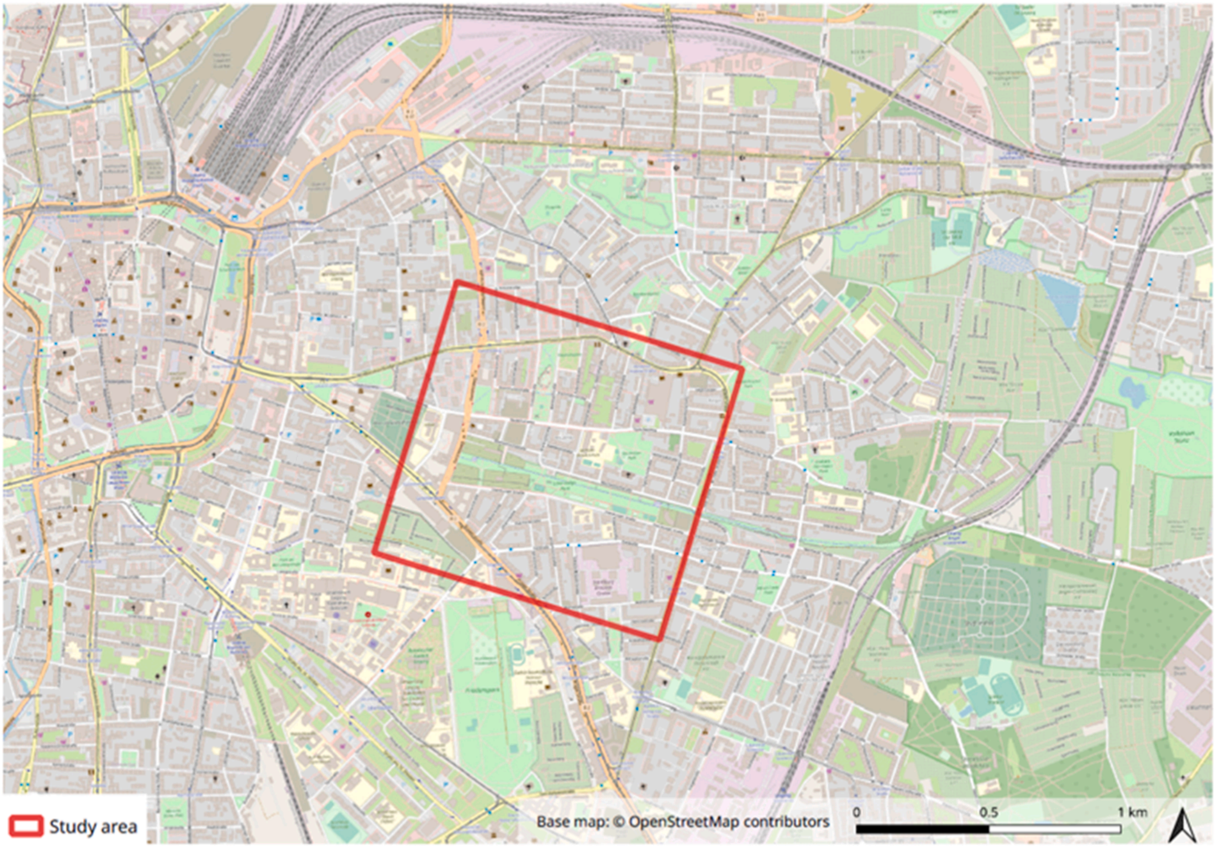

Fig. 3. Map displayed in the Leipzig questionnaire (translated from German).

Fig. 4. Map displayed in the Berlin questionnaire (translated from German).

Model results for Berlin and for trees

Table 5
Results of mixed models for trees in Leipzig

	Model 1 **Baseline**	**Model 2.1** **Linear distance**	**Model 2.2** **Inverse distance**	**Model 3** **Endowment QWD**	**Model 4.1** **Policy QWD** **1 Buffer**	**Model 4.2** **Policy QWD** **2 Buffer**	**Model 5** **Combined QWD**
Means							
ASC	−114.85 (11.32) ***	−112.56 (10.82) ***	−116.57 (12.69) ***	−113.93 (11.22) ***	−118.01 (12.78) ***	−116.37 (12.36) ***	−112.66 (12.19) ***
ω_{green_i}(per 1 ha)	4.34 (0.34) ***	4.79 (0.56) ***	4.47 (0.44) ***	2.10 (2.21)			
$\omega_{green,distance}$(per 1 ha)		−0.50 (0.44)					
$\omega_{green,inversedistance}$(per 1 ha)			−0.09 (0.17)				
$\omega_{green,0-d\_i}$(per 1 ha)					4.29 (0.34) ***	4.31 (0.35) ***	1.34 (2.20)
$\omega_{green,d-\max\_i}$(per 1 ha)						2.61 (1.57) *	
$\omega_{greensq,0-d}$(per 1 ha)				0.01 (0.01)			0.01 (0.01)
trees (per 100)	1.44 (0.17) ***	1.45 (0.17) ***	1.42 (0.18) ***	1.41 (0.17) ***	1.41 (0.17) ***	1.42 (0.17) ***	1.41 (0.18) ***
natural spaces (per 1 %)	2.90 (0.31) ***	2.87 (0.31) ***	2.96 (0.30) ***	2.90 (0.31) ***	2.88 (0.31) ***	2.92 (0.30) ***	2.89 (0.31) ***
green roofs (per 1 %)	0.54 (0.06) ***	0.53 (0.06) ***	0.54 (0.06) ***	0.54 (0.06) ***	0.54 (0.06) ***	0.54 (0.06) ***	0.54 (0.06) ***
green facades (per 1 %)	0.54 (0.07) ***	0.54 (0.07) ***	0.55 (0.07) ***	0.54 (0.07) ***	0.54 (0.07) ***	0.53 (0.07) ***	0.55 (0.07) ***
management	−0.57 (2.33)	−0.90 (2.28)	−0.99 (2.32)	−0.89 (2.31)	−0.94 (2.30)	−0.63 (2.30)	−0.92 (2.30)
cost	−3.99 (0.07) ***	−3.97 (0.08) ***	−4.01 (0.07) ***	−3.99 (0.07) ***	−3.99 (0.08) ***	−4.00 (0.07) ***	−3.98 (0.08) ***
Standard Deviations							
ASC	173.99 (18.06) ***	176.02 (16.27) ***	177.69 (17.48) ***	173.35 (18.28) ***	176.40 (18.55) ***	175.88 (17.95) ***	171.23 (19.09) ***
ω_{green_i}(per 1 ha)	2.55 (0.49) ***	2.64 (0.42) ***	2.46 (0.53) ***	2.59 (0.55) ***			
$\omega_{green,0-d\_i}$(per 1 ha)					2.56 (0.48) ***	2.60 (0.48) ***	2.67 (0.57) ***
$\omega_{green,d-\max\_i}$(per 1 ha)						4.65 (2.93)	
trees (per 100)	2.47 (0.28) ***	2.53 (0.26) ***	2.46 (0.28) ***	2.45 (0.27) ***	2.43 (0.27) ***	2.49 (0.27) ***	2.47 (0.26) ***
natural spaces (per 1 %)	2.04 (0.71) ***	2.04 (0.52) ***	1.85 (0.66) ***	2.04 (0.67) ***	1.71 (0.85) **	1.94 (0.55) ***	1.93 (0.63) ***
green roofs (per 1 %)	0.78 (0.08) ***	0.77 (0.07) ***	0.75 (0.09) ***	0.77 (0.08) ***	0.75 (0.09) ***	0.77 (0.07) ***	0.79 (0.08) ***
green facades (per 1 %)	0.92 (0.11) ***	0.94 (0.10) ***	0.90 (0.11) ***	0.93 (0.10) ***	0.92 (0.12) ***	0.90 (0.11) ***	0.95 (0.11) ***
enhanced management	31.87 (4.53) ***	31.02 (4.19) ***	32.23 (4.33) ***	31.79 (4.38) ***	31.94 (4.17) ***	32.19 (4.45) ***	32.15 (4.45) ***
cost	0.39 (0.07) ***	−0.46 (0.07) ***	0.37 (0.07) ***	0.41 (0.07) ***	0.42 (0.07) ***	0.40 (0.07) ***	0.41 (0.07) ***
Number of respondents	945	945	945	945	945	945	945
Number of parameters	16	17	17	17	16	18	17
buffer boundaries	X	X	X	2600 m	3350 m	2200 m	3200 m
Log-likelihood (converg.)	−6086.21	−6080.28	−6087.82	−6085.15	−6085.31	−6083.99	−6084.80
AIC	12204.42	12194.55	12209.64	12204.30	12202.61	12203.97	12203.59
BIC	12315.31	12312.37	12327.46	12322.12	12313.50	12328.72	12321.41
Adj. rho square	0.2653	0.2659	0.2650	0.2653	0.2654	0.2653	0.2653

Notes: ***, **, and * indicate 1 %, 5 %, and 10 % significance levels, respectively. Standard errors are given in brackets

Table 6
Results of mixed models for green spaces in Berlin

	Model 1 **Baseline**	**Model 2.1** **Linear distance**	**Model 2.2** **Inverse distance**	**Model 3** **Endowment QWD**	**Model 4.1** **Policy QWD** **1 Buffer**	**Model 4.2** **Policy QWD** **2 Buffer**	**Model 5** **Combined QWD**
Means							
ASC	−179.72 (26.04) ***	−174.38 (24.59) ***	−183.00 (27.34) ***	−185.27 (25.61) ***	−184.91 (25.51) ***	−187.80 (25.76) ***	−179.27 (25.89) ***
ω_{green_i}(per 1 ha)	1.44 (0.20) ***	0.92 (0.56)	1.95 (0.44) ***	1.97 (0.69) ***			
$\omega_{green,distance}$(per 1 ha)		0.27 (0.30)					
$\omega_{green,inversedistance}$(per 1 ha)			−0.84 (0.57)				
$\omega_{green,0-d\_i}$(per 1 ha)					1.43 (0.20) ***	−0.09 (0.91)	1.54 (1.27)
$\omega_{green,d-\max\_i}$(per 1 ha)						1.60 (0.24) ***	
$\omega_{greensq,0-d}$(per 1 ha)				−0.00 (0.00)			−0.00 (0.00)
trees (per 100)	4.23 (0.44) ***	4.24 (0.44) ***	4.23 (0.44) ***	4.17 (0.44) ***	4.16 (0.44) ***	4.20 (0.44) ***	4.24 (0.45) ***
natural spaces (per 1 %)	4.79 (0.47) ***	4.82 (0.47) ***	4.85 (0.47) ***	4.73 (0.46) ***	4.72 (0.46) ***	4.82 (0.47) ***	4.80 (0.47) ***
green roofs (per 1 %)	1.01 (0.11) ***	1.04 (0.11) ***	1.03 (0.11) ***	1.00 (0.10) ***	1.00 (0.10) ***	1.03 (0.11) ***	1.01 (0.11) ***
green facades (per 1 %)	0.96 (0.10) ***	0.96 (0.10) ***	0.97 (0.10) ***	0.95 (0.10) ***	0.95 (0.10) ***	0.96 (0.10) ***	0.96 (0.10) ***
management	14.10 (3.56) ***	13.99 (3.64) ***	14.41 (3.64) ***	13.97 (3.62) ***	13.91 (3.60) ***	14.08 (3.57) ***	14.17 (3.57) ***
cost	−4.20 (0.10) ***	−4.21 (0.10) ***	−4.22 (0.09) ***	−4.18 (0.09) ***	−4.18 (0.09) ***	−4.22 (0.09) ***	−4.20 (0.10) ***
Standard Deviations							
ASC	252.89 (29.59) ***	246.14 (30.12) ***	251.66 (31.47) ***	256.03 (29.92) ***	255.54 (29.81) ***	251.89 (30.25) ***	252.62 (29.51) ***
ω_{green_i}(per 1 ha)	2.49 (0.32) ***	2.51 (0.33) ***	2.46 (0.34) ***	2.44 (0.32) ***			
$\omega_{green,0-d\_i}$(per 1 ha)					2.46 (0.32) ***	−1.59 (2.18)	2.50 (0.32) ***
$\omega_{green,d-\max\_i}$(per 1 ha)						2.72 (0.38) ***	
trees (per 100)	3.51 (0.71) ***	−3.51 (0.73) ***	3.46 (0.72) ***	3.43 (0.67) ***	3.44 (0.66) ***	3.47 (0.76) ***	3.52 (0.71) ***
natural spaces (per 1 %)	2.13 (1.01) **	2.43 (0.89) ***	2.25 (0.87) ***	2.64 (0.77) ***	2.63 (0.76) ***	2.47 (0.78) ***	2.14 (1.00) **
green roofs (per 1 %)	0.97 (0.11) ***	1.00 (0.12) ***	0.94 (0.13) ***	0.96 (0.11) ***	0.95 (0.11) ***	0.94 (0.13) ***	0.97 (0.11) ***
green facades (per 1 %)	1.02 (0.16) ***	1.04 (0.16) ***	1.00 (0.16) ***	−0.98 (0.13) ***	0.98 (0.13) ***	0.98 (0.15) ***	1.02 (0.16) ***
enhanced management	58.35 (5.79) ***	59.16 (6.00) ***	59.21 (5.86) ***	57.67 (5.66) ***	57.61 (5.65) ***	58.74 (5.92) ***	58.42 (5.80) ***
cost	0.36 (0.07) ***	0.29 (0.09) ***	0.31 (0.11) ***	0.42 (0.07) ***	0.42 (0.07) ***	0.31 (0.10) ***	−0.36 (0.07) ***
Number of respondents	750	750	750	750	750	750	750
Number of parameters	16	17	17	17	16	18	17
buffer boundaries	X	X	X	2500 m	3700 m	800 m	3700 m
Log-likelihood (converg.)	−4652.15	−4651.85	−4652.99	−4649.55	−4649.88	−4651.99	−4652.11
AIC	9336.30	9337.69	9339.98	9333.09	9331.76	9339.98	9338.23
BIC	9443.49	9451.59	9453.87	9446.99	9438.95	9460.57	9452.12
Adj. rho square	0.2918	0.2917	0.2915	0.2921	0.2922	0.2915	0.2917

Notes: ***, **, and * indicate 1 %, 5 %, and 10 % significance levels, respectively. Standard errors are given in brackets.

Table 7
Results of mixed models for trees in Berlin

	Model 1 Baseline	**Model 2.1 Linear distance**	**Model 2.2 Inverse distance**	**Model 3 Endowment QWD**	**Model 4.1 Policy QWD 1 Buffer**	**Model 4.2 Policy QWD 2 Buffer**	**Model 5 Combined QWD**
Means							
ASC	−179.72 (26.04) ***	−185.31 (24.97) ***	−181.51 (24.37) ***	−183.34 (27.28) ***	−187.12 (25.36) ***	−191.37 (27.31) ***	−182.88 (28.91) ***
ω_{green_i}(per 1 ha)	4.23 (0.44) ***	5.60 (1.13) ***	3.03 (0.82) ***	11.55 (4.24) ***			
$\omega_{green,distance}$(per 1 ha)		−0.78 (0.54)					
$\omega_{green,inversedistance}$(per 1 ha)			1.76 (1.16)				
$\omega_{green,0-d\_i}$(per 1 ha)					4.22 (0.43) ***	4.61 (0.54) ***	12.14 (4.73) **
$\omega_{green,d-\max\_i}$(per 1 ha)						2.88 (0.98) ***	
$\omega_{greensq,0-d}$(per 1 ha)				−0.02 (0.01) *			−0.02 (0.01)
trees (per 100)	1.44 (0.20) ***	1.41 (0.20) ***	1.43 (0.21) ***	1.40 (0.21) ***	1.39 (0.21) ***	1.46 (0.21) ***	1.42 (0.21) ***
natural spaces (per 1 %)	4.79 (0.47) ***	4.73 (0.47) ***	4.83 (0.46) ***	4.79 (0.47) ***	4.75 (0.46) ***	4.77 (0.46) ***	4.82 (0.46) ***
green roofs (per 1 %)	1.01 (0.11) ***	1.02 (0.11) ***	1.03 (0.10) ***	1.04 (0.11) ***	1.02 (0.10) ***	1.02 (0.10) ***	1.02 (0.10) ***
green facades (per 1 %)	0.96 (0.10) ***	0.95 (0.10) ***	0.96 (0.10) ***	0.96 (0.10) ***	0.96 (0.10) ***	0.96 (0.10) ***	0.96 (0.10) ***
management	14.10 (3.56) ***	14.49 (3.52) ***	14.47 (3.55) ***	14.17 (3.64) ***	14.40 (3.61) ***	14.18 (3.54) ***	14.21 (3.61) ***
cost	−4.20 (0.10) ***	−4.17 (0.10) ***	−4.20 (0.09) ***	−4.20 (0.09) ***	−4.20 (0.09) ***	−4.20 (0.09) ***	−4.20 (0.09) ***
Standard Deviations							
ASC	252.89 (29.59) ***	250.48 (32.07) ***	256.82 (31.04) ***	253.65 (31.19) ***	253.69 (32.04) ***	258.80 (34.82) ***	249.28 (30.22) ***
ω_{green_i}(per 1 ha)	3.51 (0.71) ***	3.40 (0.68) ***	3.51 (0.61) ***	3.30 (0.79) ***			
$\omega_{green,0-d\_i}$(per 1 ha)					3.42 (0.74) ***	3.86 (0.91) ***	3.60 (0.75) ***
$\omega_{green,d-\max\_i}$(per 1 ha)						2.75 (4.45)	
trees (per 100)	2.49 (0.32) ***	2.55 (0.32) ***	2.46 (0.32) ***	2.54 (0.33) ***	2.46 (0.31) ***	2.54 (0.32) ***	2.48 (0.32) ***
natural spaces (per 1 %)	2.13 (1.01) **	−2.56 (0.68) ***	2.09 (0.77) ***	2.72 (0.82) ***	−2.35 (0.82) ***	2.37 (0.68) ***	−2.48 (0.68) ***
green roofs (per 1 %)	0.97 (0.11) ***	0.92 (0.11) ***	0.91 (0.12) ***	0.96 (0.12) ***	0.95 (0.12) ***	0.91 (0.11) ***	0.95 (0.12) ***
green facades (per 1 %)	1.02 (0.16) ***	0.99 (0.14) ***	0.99 (0.15) ***	1.04 (0.16) ***	0.98 (0.14) ***	0.98 (0.15) ***	0.99 (0.14) ***
enhanced management	58.35 (5.79) ***	58.02 (5.56) ***	58.46 (5.79) ***	58.82 (6.00) ***	57.27 (5.65) ***	58.37 (5.88) ***	57.50 (5.78) ***
cost	0.36 (0.07) ***	0.41 (0.10) ***	−0.36 (0.08) ***	0.35 (0.08) ***	0.38 (0.08) ***	0.39 (0.08) ***	0.35 (0.08) ***
Number of respondents	750	750	750	750	750	750	750
Number of parameters	16	17	17	17	16	18	17
buffer boundaries	X	X	X	2750 m	3500 m	2450 m	3000 m
Log-likelihood (converg.)	−4652.15	−4650.54	−4651.41	−4651.03	−4651.59	−4648.61	−4649.68
AIC	9336.30	9335.09	9336.81	9336.07	9335.18	9333.22	9333.35
BIC	9443.49	9448.98	9450.70	9449.96	9442.37	9453.81	9447.24
Adj. rho square	0.2918	0.2919	0.2918	0.2918	0.2919	0.2920	0.2920

Notes: ***, **, and * indicate 1 %, 5 %, and 10 % significance levels, respectively. Standard errors are given in brackets.

Welfare estimates for Berlin and for trees

Table 8
Means and 95 % confidence intervals of aggregated welfare effects for trees in Leipzig

	Model 1 Baseline	Model 2.1 Linear distance	Model 2.2 Inverse distance	Model 3 Endowment QWD	Model 4.1 Policy QWD 1 Buffer	Model 4.2 Policy QWD 2 Buffer	Model 5 Combined QWD
welfare mean	4966,456	4060,635	5058,444	4506,003	3721,814	2993,657	3299,889
lower CI boundary	4211,724	2294,234	4159,716	3153,719	3135,898	1424,020	2558,958
upper CI boundary	5721,188	5827,037	5957,171	5858,287	4307,729	4563,294	4040,820
Individuals with positive WTP	228,847	228,847	228,847	228,847	224,942	228,847	211,845
Average WTP per individual with positive WTP	21.70	17.74	22.10	19.69	16.55	13.08	15.58

Table 9
Means and 95 % confidence intervals of aggregated welfare effects for green spaces in Berlin

	Model 1 Baseline	Model 2.1 Linear distance	Model 2.2 Inverse distance	Model 3 Endowment QWD	Model 4.1 Policy QWD 1 Buffer	Model 4.2 Policy QWD 2 Buffer	Model 5 Combined QWD
welfare mean	9397,813	11,321,892	10,363,684	9714,107	5729,101	6618,660	5791,292
lower CI boundary	6801,537	4510,252	6579,955	5983,037	4153,377	4306,106	3295,657
upper CI boundary	11,994,089	18,133,531	14,147,412	13,445,178	7304,824	8931,214	8286,927
Individuals with positive WTP	650,884	650,884	650,267	650,884	535,554	650,884	535,554
Average WTP per individual with positive WTP	14.44	17.39	15.94	14.92	10.70	10.17	10.81

Table 10
Means and 95 % confidence intervals of aggregated welfare effects trees in Berlin

	Model 1 Baseline	Model 2.1 Linear distance	Model 2.2 Inverse distance	Model 3 Endowment QWD	Model 4.1 Policy QWD 1 Buffer	Model 4.2 Policy QWD 2 Buffer	Model 5 Combined QWD
welfare mean	13,769,308	10,408,072	12,304,389	15,770,278	7833,613	8358,182	6936,412
lower CI boundary	10,933,981	4385,313	8718,262	10,686,651	6254,260	5427,880	5157,739
upper CI boundary	16,604,635	16,430,831	15,890,515	20,853,905	9412,966	11,288,485	8715,085
Individuals with positive WTP	650,884	650,884	650,884	650,884	520,869	650,884	434,546
Average WTP per individual with positive WTP	21.15	15.99	18.90	24.23	15.04	12.84	15.96

Approach and results of bootstrapping analysis for Leipzig green spaces

To test hypotheses about differences in model fit and welfare estimates between the different models, we carried out a bootstrapping analysis for the attribute of green spaces in Leipzig. First, we simulated 1000 synthetic samples with an identical sample size to our main sample. For this, we resampled respondents from our main sample with replacement. Second, we ran each of the seven models with each of the 1000 synthetic samples. To achieve a feasible run time, we did not iteratively optimize the buffer size of the QWD models for this analysis. Instead, we used for each model the optimal buffer size identified in the main sample. Third, we calculated the indicators AIC, BIC, mean welfare estimates and welfare estimates confidence intervals for each model and sample. The following pages first provide tables that show how the mean over the 1000 samples of these indicators differs between models. The subsequent pages include histograms that show how the difference between models in these indicators is distributed over the 1000 samples.

Table 11
Pairwise differences (row – column) in AIC between models in the 1000 simulated samples

	Model 1 **Baseline**	**Model 2.1** **Linear distance**	**Model 2.2** **Inverse distance**	**Model 3** **Endowment QWD**	**Model 4.1** **Policy QWD** **1 Buffer**	**Model 4.2** **Policy QWD** **2 Buffer**	**Model 5** **Combined QWD**
1 Baseline	0 (0)	−2.42 (2.77)	2.03 (0.2) ***	−0.34 (0.13) **	−3.13 (0.15) ***	−0.18 (0.19)	3.29 (0.19) ***
2.1 Linear distance	2.42 (2.77)	0 (0)	4.46 (2.77)	2.08 (2.78)	−0.71 (2.77)	2.24 (2.79)	5.71 (2.77) **
2.2 Inverse distance	−2.03 (0.2) ***	−4.46 (2.77)	0 (0)	−2.37 (0.22) ***	−5.17 (0.22) ***	−2.22 (0.22) ***	1.25 (0.25) ***
3 Endowment QWD	0.34 (0.13) **	−2.08 (2.78)	2.37 (0.22) ***	0 (0)	−2.79 (0.18) ***	0.16 (0.19)	3.63 (0.19) ***
4.1 Policy QWD 1 Buffer	3.13 (0.15) ***	0.71 (2.77)	5.17 (0.22) ***	2.79 (0.18) ***	0 (0)	2.95 (0.22) ***	6.42 (0.21) ***
4.2 Policy QWD 2 Buffer	0.18 (0.19)	−2.24 (2.79)	2.22 (0.22) ***	−0.16 (0.19)	−2.95 (0.22) ***	0 (0)	3.47 (0.24) ***
5 Combined QWD	−3.29 (0.19) ***	−5.71 (2.77) **	−1.25 (0.25) ***	−3.63 (0.19) ***	−6.42 (0.21) ***	−3.47 (0.24) ***	0 (0)

Notes: ***, **, and * indicate 1 %, 5 %, and 10 % significance levels, respectively. Standard errors are given in brackets

Table 12
Pairwise differences (row – column) in BIC between models in the 1000 simulated samples

	Model 1 Baseline	Model 2.1 Linear distance	Model 2.2 Inverse distance	Model 3 Endowment QWD	Model 4.1 Policy QWD 1 Buffer	Model 4.2 Policy QWD 2 Buffer	Model 5 Combined QWD
1 Baseline	0 (0)	−9.35 (2.77) ***	−4.9 (0.2) ***	−7.27 (0.13) ***	−3.13 (0.15) ***	−14.04 (0.19) ***	−3.64 (0.19) ***
2.1 Linear distance	9.35 (2.77) ***	0 (0)	4.46 (2.77)	2.08 (2.78)	6.22 (2.77) **	−4.69 (2.79) *	5.71 (2.77) **
2.2 Inverse distance	4.9 (0.2) ***	−4.46 (2.77)	0 (0)	−2.37 (0.22) ***	1.77 (0.22) ***	−9.15 (0.22) ***	1.25 (0.25) ***
3 Endowment QWD	7.27 (0.13) ***	−2.08 (2.78)	2.37 (0.22) ***	0 (0)	4.14 (0.18) ***	−6.77 (0.19) ***	3.63 (0.19) ***
4.1 Policy QWD 1 Buffer	3.13 (0.15) ***	−6.22 (2.77) **	−1.77 (0.22) ***	−4.14 (0.18) ***	0 (0)	−10.91 (0.22) ***	−0.51 (0.21) **
4.2 Policy QWD 2 Buffer	14.04 (0.19) ***	4.69 (2.79) *	9.15 (0.22) ***	6.77 (0.19) ***	10.91 (0.22) ***	0 (0)	10.4 (0.24) ***
5 Combined QWD	3.64 (0.19) ***	−5.71 (2.77) **	−1.25 (0.25) ***	−3.63 (0.19) ***	0.51 (0.21) **	−10.4 (0.24) ***	0 (0)

Notes: ***, **, and * indicate 1 %, 5 %, and 10 % significance levels, respectively. Standard errors are given in brackets

Table 13
Pairwise differences (row – column) in mean welfare estimates between models in the 1000 simulated samples

	Model 1 Baseline	Model 2.1 Linear distance	Model 2.2 Inverse distance	Model 3 Endowment QWD	Model 4.1 Policy QWD 1 Buffer	Model 4.2 Policy QWD 2 Buffer	Model 5 Combined QWD
1 Baseline	0 (0)	1307,517 (28,081) ***	253,399 (5392) ***	−175,886 (6811) ***	1392,744 (5305) ***	914,253 (19,000) ***	1707,451 (11,834) ***
2.1 Linear distance	−1307,517 (28,081) ***	0 (0)	−1054,117 (25,563) ***	−1483,404 (26,916) ***	85,227 (28,310) ***	−393,264 (21,176) ***	399,933 (29,143) ***
2.2 Inverse distance	−253,399 (5392) ***	1054,117 (25,563) ***	0 (0)	−429,286 (7947) ***	1139,345 (7417) ***	660,853 (18,580) ***	1454,051 (12,583) ***
3 Endowment QWD	175,886 (6811) ***	1483,404 (26,916) ***	429,286 (7947) ***	0 (0)	1568,631 (8498) ***	1090,140 (17,758) ***	1883,338 (14,603) ***
4.1 Policy QWD 1 Buffer	−1392,744 (5305) ***	−85,227 (28,310) ***	−1139,345 (7417) ***	−1568,631 (8498)	0 (0)	−478,491 (18,822) ***	314,706 (11,335) ***
4.2 Policy QWD 2 Buffer	−914,253 (19,000) ***	393,264 (21,176) ***	−660,853 (18,580) ***	−1090,140 (17,758) ***	478,491 (18,822) ***	0 (0)	793,198 (22,143) ***
5 Combined QWD	−1707,451 (11,834) ***	−399,933 (29,143) ***	−1454,051 (12,583) ***	−1883,338 (14,603) ***	−314,706 (11,335) ***	−793,198 (22,143) ***	0 (0)

Notes: ***, **, and * indicate 1 %, 5 %, and 10 % significance levels, respectively. Standard errors are given in brackets

Table 14
Pairwise differences (row – column) in span of confidence interval of welfare estimates between models in the 1000 simulated samples

	Model 1 Baseline	**Model 2.1 Linear distance**	**Model 2.2 Inverse distance**	**Model 3 Endowment QWD**	**Model 4.1 Policy QWD 1 Buffer**	**Model 4.2 Policy QWD 2 Buffer**	**Model 5 Combined QWD**
1 Baseline	0 (0)	−2603,246 (9151) ***	−202,116 (1767) ***	−674,906 (2230) ***	663,259 (1416) ***	−1569,463 (12,612) ***	−817,278 (3943) ***
2.1 Linear distance	2603,246 (9151) ***	0 (0)	2401,130 (9128) ***	1928,340 (7910) ***	3266,505 (9933) ***	1033,783 (8429) ***	1785,968 (9285) ***
2.2 Inverse distance	202,116 (1767) ***	−2401,130 (9128) ***	0 (0)	−472,790(2524) ***	865,375 (2212) ***	−1367,347 (12,493) ***	−615,161 (4218) ***
3 Endowment QWD	674,906 (2230) ***	−1928,340 (7910.) ***	472,790 (2524) ***	0 (0)	1338,165 (3193) ***	−894,557 (11,641) ***	−142,371 (4153) ***
4.1 Policy QWD 1 Buffer	−663,259 (1416) ***	−3266,505 (9933) ***	−865,375 (2212) ***	−1338,165 (3193) ***	0 (0)	−2232,722 (13,058) ***	−1480,537 (4518) ***
4.2 Policy QWD 2 Buffer	1569,463 (12,612) ***	−1033,783 (8429) ***	1367,347 (12,493) ***	894,557 (11,641) ***	2232,722 (13,058) ***	0 (0)	752,185 (13,072) ***
5 Combined QWD	817,278 (3943) ***	−1785,968 (9285) ***	615,161 (4218) ***	142,371 (4153) ***	1480,537 (4518) ***	−752,185 (13,072) ***	0 (0)

Notes: ***, **, and * indicate 1 %, 5 %, and 10 % significance levels, respectively. Standard errors are given in brackets.

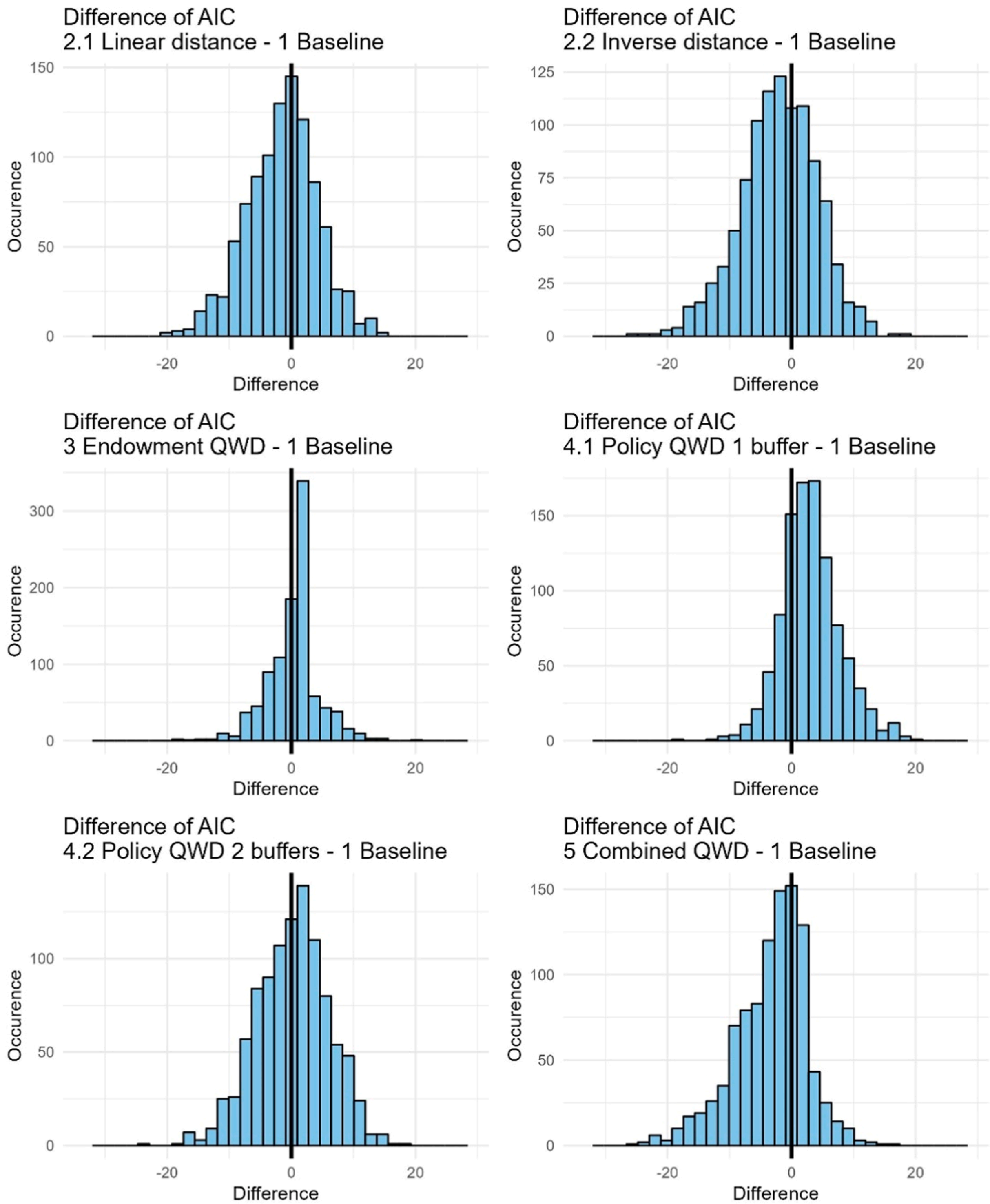

Fig. 5. Distribution of differences in AIC compared to the baseline model over the 1000 simulated samples.

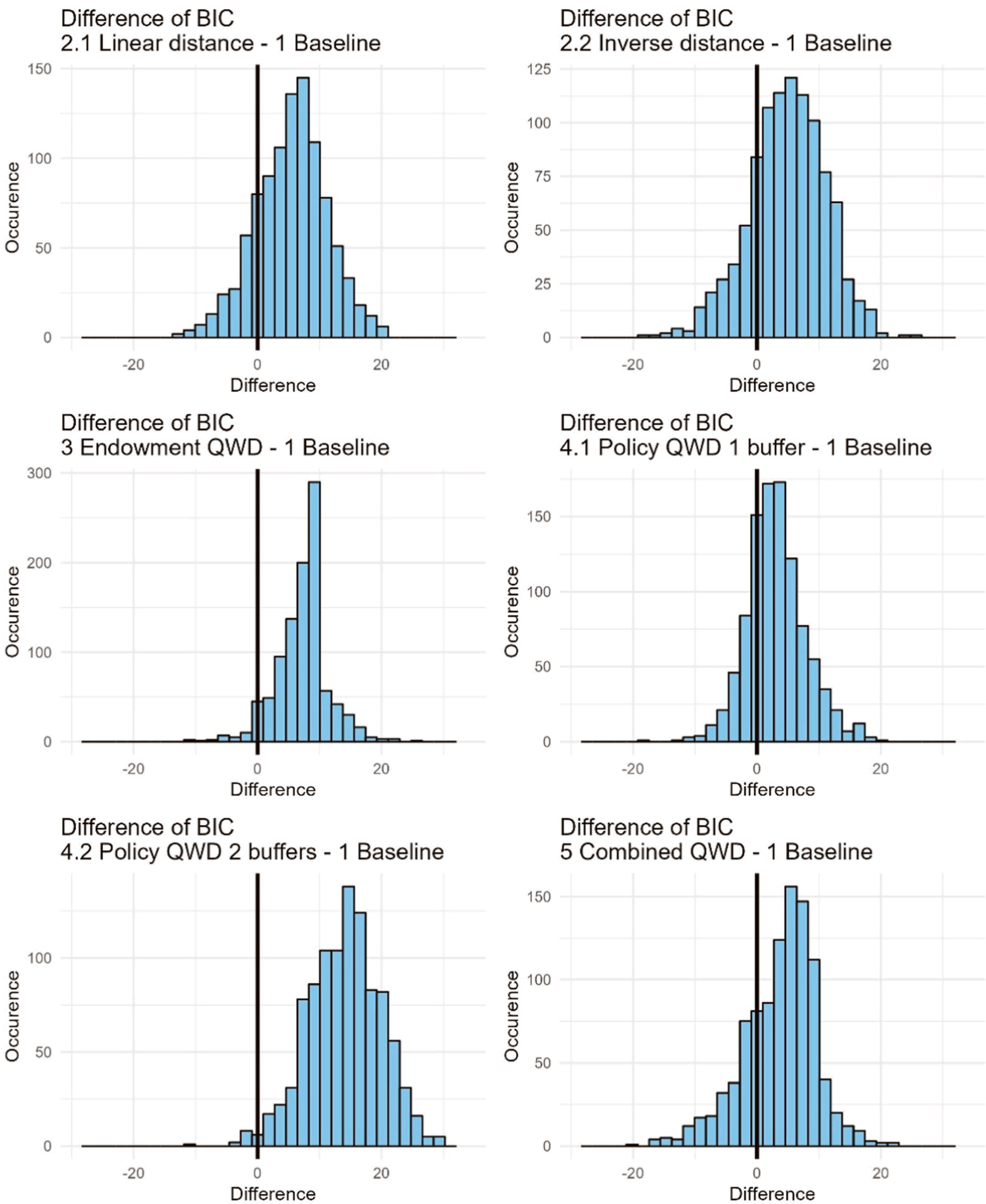

Fig. 6. Distribution of differences in BIC compared to the baseline model over the 1000 simulated samples.

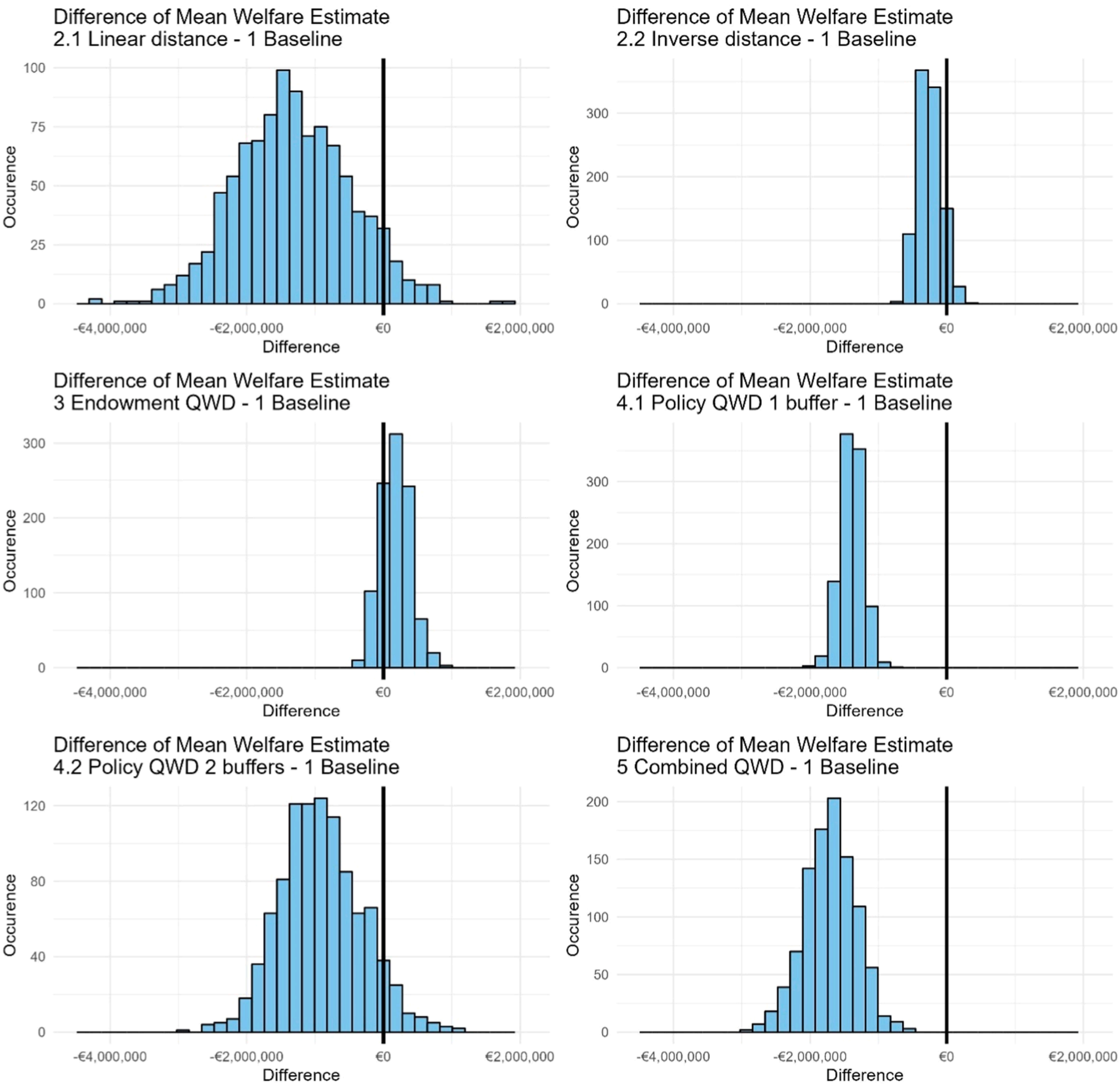

Fig. 7. Distribution of differences in mean welfare estimates compared to the baseline model over the 1000 simulated samples.

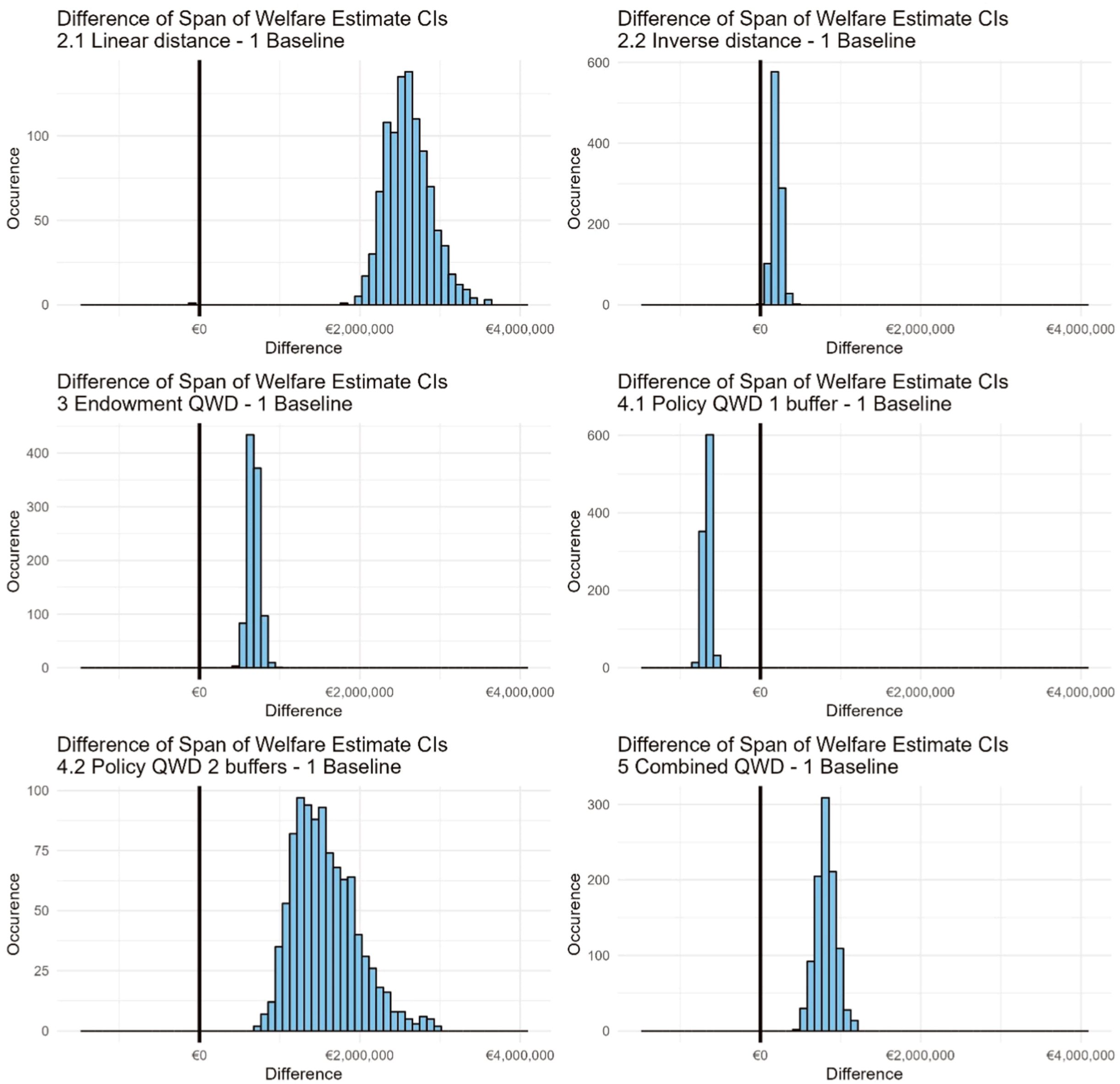

Fig. 8. Distribution of differences in span of confidence interval for welfare estimates compared to the baseline model over the 1000 simulated samples.

Appendix B. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.reseneeco.2024.101472.

Data Availability

Data will be made available on request.

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