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Preferences for Biodiversity-Promoting Private Garden Designs: A Basket-Based Choice Experiment

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Abstract

This study introduces the basket-based choice experiment (BBCE) as suggested by Caputo and Lusk (2022) into the field of environmental economics and management. The application is a survey to assess garden owners' preferences for installing design elements conducive to biodiversity conservation in private gardens. In addition to showcasing this approach in the context of environmental management, the present application of the BBCE adds two new methodological features to this approach. First, an experimental design is used to provide context attributes for each basket-based choice task to assess the extent to which policy levers set by local councils can affect how garden owners design their gardens. Second, the econometric model to analyse the resulting basket-based choice data is augmented by a latent class structure to accommodate the empirical finding that a substantial share of respondents never chose to add any new element to their gardens (i.e. chose an empty basket). Results show that the policy instruments have mixed effects on the element-specific choice probabilities, with financial support for new garden elements exhibiting the strongest effect on demand. Furthermore, it is demonstrated how prediction can be used to assess the uptake of biodiversity friendly garden elements as a function of policy instruments.

Keywords Biodiversity · Basket-based choice experiment · Private gardens · Policy instruments · Wildlife gardening

JEL Classification D12 · Q57 · Q58

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1 Introduction

Private gardens are an important source of enjoyment, well-being and subsistence (Cameron et al. 2012). Yet private gardens can also be an important element in biodiversity conservation (Delahay et al. 2023). Their total share of landcover may seem small. In Germany, for example, the approximately 16 million private gardens only cover 0.84% of the country's total area. However, in biodiversity-poor settings such as urban or argicultural landscapes their importance for biodiversity conservation may be substantial due to their large number. In the United States, lawns account for a large share of garden areas, particularly in single-household residential properties. In total, lawns are the single biggest land cover type amongst all irrigated crops in the country (Wheeler et al. 2017). These numbers demonstrate the potential of private gardens to contribute to biodiversity conservation at scale. In urbanised areas in particular, private gardens can provide habitat for plant and animal species and function as stepping stones in a larger network of green infrastructure (Delahay et al. 2023).

Wildlife gardening, an often-used term for managing gardens with the aim to improve species diversity and ecosystem processes (van Heezik 2020), entails alternative management and design choices carried out by each garden owner (García-Antúnez et al. 2023). This practice includes avoiding the use of pesticides in the garden, applying less or no chemical fertiliser, or no or much less frequent mowing of lawns, among other things. In addition, design choices concern the question of which elements are installed in a garden and how these are arranged spatially. Such design choices influence the presence of land-use types (e.g. a flowering meadow instead of lawn) and of elements that positively impact on biodiversity, such as a drywall or a pond.

Against this background, the present study addresses the following research questions which are relevant for any conservation policy aiming to activate the potential of private gardens for biodiversity conservation: (1) How do a set of policy instruments affect the demand for garden elements supporting biodiversity conservation? (2) How do the current design of the garden, and respondent and garden characteristics affect demand? Answering the first question in particular would contribute to what Dewaelheyns et al. (2016) presented as a toolbox for garden governance. The starting point for their considerations is that each individual private garden may look insignificant, but the aggregation of actions in many gardens could result in significant habitat changes promoting biodiversity conservation. Thus, referring to 'the tyranny of small decisions', they suggest considering private gardens as a 'resource by small gardening actions'. This turns the question of policy design into an economic question of incentives: Many decentralised individuals (private garden owners) take decisions at a small scale (their garden) resulting in potentially significant outcomes on the aggregated level (the landscape level). Wildlife gardening may entail private costs to the garden owner, which results in benefits (in terms of species conservation, for instance), which are – at least partly – public. So it is likely that policy intervention is necessary to further incentivise private garden owners to increase the wildlife friendliness of their gardens beyond the level enjoyed privately. In this context, it is important not only to incentivise gardeners already engaged in such practices but also to examine whether previously unengaged gardeners could be mobilised (Shaw et al. 2016). The formation of green infrastructure networks via domestic gardens requires that a larger number of gardens contain biodiversity-promoting elements. Individual gardens in isolation lack the capacity to enhance biodiversity at larger spatial scales (Goddard et al. 2010; Ellis and Wilkinson 2021).

The literature indicates that many private garden owners perceive wildlife gardening to be important (Goddard et al. 2013; García-Antúnez et al. 2023). However, despite such potential intrinsic motivation for wildlife gardening, little is known about how garden owners can be motivated to adopt this practice. While some studies suggest possible instruments to incentivise wildlife gardening, such as the 'Homes for Wildlife' scheme of the Royal Society for the Protection of Birds (RSPB) in the UK (Goddard et al. 2017), systematic evaluations of the effectiveness of such programmes are rare (see also Fogel et al. 2023). Among the few studies that do evaluate incentives, Kerr and Harricharan (2021) tested the impact of complimentary wildflower seed packets as a way to facilitate native plant gardening and promote pollinator conservation. Lange et al. (2022) used field experiments to investigate whether information treatments are effective in increasing the probability of customers of a Belgian wholesale store to buy pollinator-friendly seed mixtures. Beyond these two, the authors are not aware of other studies that have examined the extent to which private garden owners would respond to policy instruments aiming to promote wildlife gardening in the face of private implementation costs and (partly) public conservation benefits.

To address the above research questions, we employed a novel version of the basket-based choice experiment (BBCE) (Caputo and Lusk 2022) to assess private garden owners' preferences for biodiversity-promoting garden elements in the presence of policy interventions. For the purposes of this study private gardens are defined as an enclosed area around, and associated with, a residential property in which plants are organised under human control (Cameron 2023; Coisnon et al. 2019). Such properties include single, semi-detached, terraced and multistory houses in which the owners or tenants manage the adjacent garden area. The BBCE was implemented as part of an online survey among 2000 private garden owners across Germany. Using a list of land-use types and design elements that commonly occur in gardens, garden owners were requested to indicate the current configuration of their garden. Such information can be used to assess the suitability of private gardens for biodiversity protection (Young et al. 2019; Felgentreff et al. 2025). According to these authors, information on the presence or absence of an element rather than on the quantity of units of a specific element may already serve as an indicator of gardens' biodiversity levels. Subsequently, respondents were asked to complete the BBCE comprising all the land-use types and elements that were previously queried. In a series of basket-based choice tasks, respondents were asked which garden elements, each being offered at a varying price, they would install in their garden within the next year. In the spirit of the biodiversity assessment in Young et al. (2019), respondents could only add one single unit of an element.

In addition to assessing preferences for a certain type of wildlife friendly gardening, i.e., biodiversity conservation through design choices in private gardens, this paper advances the literature on stated preference assessment in three ways. *First*, it adapts the BBCE, so far applied in the field of food choice (Caputo and Lusk 2022; Neill and Lahne 2022; Kilders et al. 2024; Ma et al. 2024; Neill and Britton 2024), for the use in environmental economics and management. This approach is similar to an analysis of purchase data in consumer research (e.g. Song and Chintagunta 2006; Kwak et al. 2015; Richards et al. 2018) yet using a bespoke survey to collect experimental data. The advantage of a BBCE for the present application is that respondents are free to select into the "shopping basket" any combination of garden elements on the menu, each with a specific price, instead of confining their choice to predefined discrete alternatives. Consequently, compared to a standard discrete choice experiment the BBCE allows for a better understanding of the trade-offs garden owners make between garden elements and whether they are demand substitutes or complements.[1] *Second*, the present study augments the BBCE as previously proposed in food choice by combining it with a set of context attributes describing policy instruments aiming to incentivise the installation of elements promoting biodiversity conservation.[2] These context attributes are policy levers that can be set by local councils, and which are varied over a series of basket-based choice tasks according to an experimental design. This allows for an analysis of the demand for different garden elements in the presence of specific combinations of policy instruments and eventually the determination of the effectiveness of these instruments to foster biodiversity-promoting garden design. *Third*, the econometric model to analyse the resulting basket-based choice data is augmented by a latent class (LC) structure to accommodate the empirical finding that a substantial share of respondents submitted an empty basket in every choice task. The argument is made that the composite likelihood model employed by Caputo and Lusk (2022) is unable to accommodate the resulting choice probabilities. The superiority of the proposed LC model in this case is demonstrated by comparing it to the standard approach using the data collected in the present study.

Empirical results show that all garden elements on offer are demand complements, a result which would have been practically impossible to ascertain using a standard discrete choice experiment. Results regarding the context attributes further suggest that only monetary instruments, i.e. a subsidy on maintenance costs and, in particular, a rebate on new garden elements, affect demand. Different types of information provision have little effect. Having a specific element already in their garden increases the probability of selecting it in the BBCE for all but two elements. Additional systematic variation of demand driven by respondent and garden characteristics can be detected. The remainder of the paper is structured as follows. "Methods" section sets out the methods. Results are presented in "Results" section. "Discussion and Conclusions" section discusses these results and concludes.

[1] A small number of studies in environmental valuation have examined possible substitution *and* complementary relationships between, for instance, ecosystem conservation or environmental programmes (Hailu et al. 2000; Hoehn and Loomis 1994). Note that, in theory, it is possible for a standard discrete choice experiment to elicit the same information by including mutually exclusive alternatives each presenting different combinations of garden elements. With a sufficiently high number of choice responses a multinomial choice model is able to study both marginal and interaction effects and could produce information regarding the substitution or complementary relationship between elements. In practice, however, the data requirements are prohibitive. With, for example, 14 elements as in the present study, there would be $2^{14} = 16,384$ possible baskets. With more elements in the basket-based choice experiment, the number of combinations in the full factorial design increases accordingly. Offering respondents different element-specific prices then requires another dimension of variation. So even the use of a fractional factorial design quickly results in an intractable number of potential baskets (and hence choice sets) even in BBCE with relatively few elements.

[2] Previous applications of context attributes include, for instance, the elicitation of preferences for fresh fruit (Jaeger and Rose 2008) and characteristics of urban parks (Bertram et al. 2017).

2 Methods

2.1 A Context-Augmented Basket-Based Choice Experiment

To investigate whether policy instruments set incentives for private garden owners to add elements to their gardens in the face of private costs, we employ a basket-based choice experiment (BBCE) as part of an online survey among garden owners across Germany. The BBCE is an item-based choice format eliciting preferences (and essentially demand curves) for a list of 14 garden elements (also referred to as items). For this application, the BBCE is augmented by the addition of context attributes which describe different policy instruments set by the local authority. The context attributes consist of a set of instruments promoting wildlife-friendly garden design which are varied between basket-based choice tasks following an orthogonal design. In the following, the BBCE is introduced followed by a description of the context attributes.

2.1.1 The Basket-Based Choice Experiment (BBCE)

At the core of the experiment, the BBCE section showed respondents definitions of 14 garden elements (Table 1). During the BBCE, respondents could recall the definitions by hovering the computer mouse over the names of the elements in the choice task. Before the BBCE section in the questionnaire, respondents had been asked to indicate whether each of these elements was already present in their respective garden.

The subsequent basket-based choice tasks combined the context (as described by the policy instruments, see below) and the prompt to select elements from the menu of 14 elements. Respondents were asked “Which elements in the table would you add to your garden in the next 12 months?”. By ticking a specific element, respondents could indicate that they would install one unit of this element. As such, the experiment does not have a quantity dimension which follows most applications of the BBCE in the food choice literature, and is also consistent with the evaluation of the effects of the mere presence or absence of garden elements on biodiversity levels (Young et al. 2019). The period of one year was further emphasised in a question asking for confirmation of each basket-based choice. In these basket-based choice tasks, each element was further characterised by a specific purchase price (in Euro) and space requirement (in sqm). While the prices were varied according to an orthogonal experimental design (over a set of four element-specific price amounts, Table 1), the space requirement of each element was kept constant across all choices. Three elements (Deadwood; Leaves and branches; Wild corner) were always displayed at zero price to ensure scenario realism. The design consisted of 36 price combinations from which one was drawn randomly without replacement for each basket-based choice task. The order of appearance of the garden elements in the list was randomised to mitigate potential ordering effects.

The structure of the basket-based choice task in the online survey extended over two consecutive webpages (Fig. A.1 and A.2 in the online Appendix). Respondents had the opportunity to move back and forth between these pages. The first webpage started with the introductory sentence, “Imagine your city/municipality offers a support programme with the following measures” followed by a combination of the policy instruments (Table 2), the prompt to select the elements one would like to install in the next 12 months and the menu

Table 1 Elements promoting biodiversity in private gardens

Element	Descriptions given in the questionnaire	Prices (in EUR)	Space required (m^2)
Berry patch	By berry patches we mean all plants including shrubs that have berries as fruits. Examples are blueberries, currants, rock pears and sloes.	5, 10, 25, 50	1 to 3
Compost heap	By a compost heap we mean a place in the garden that is used to decompose organic material from your own garden or kitchen and is at least half a metre by one metre in size.	30, 70, 100, 150	2 to 4
Deadwood	By deadwood we mean dead trunk parts or trunks that have a diameter of at least 20 cm and are at least one metre long.	0	0.5
Drinking aid	By a drinking aid we mean a place in the garden that is regularly filled with water and can be visited by birds without danger.	5, 10, 15, 20	-
Drywall	By a drywall we mean a wall made of natural stone. There are spaces between the stones that have not been firmly grouted. Plants take root in them and insects or reptiles can hide in them. Please only enter the wall if it is at least 30 cm high and one metre long.	150, 300, 500, 800	1.5 to 4
Flowering lawn	By a flowering lawn we mean a lawn that is not fertilised and is only mowed every few weeks, allowing some types of flowers and herbs to grow.	5, 12, 18, 28	10
Native shrubs	By native shrubs we mean woody plants that have several trunks and are at least one metre high. Trees, on the other hand, only have one trunk. Native shrubs are often planted as a hedge.	20, 40, 80, 120	2 to 6
Nesting aid	By nesting aids we mean artificially created places such as a bird nesting box, a hedgehog hotel or a bat box.	15, 35, 60, 90	-
Open space	By an open space we mean an area that can be filled with sand or clay of at least 40 by 40 cm or a former open sandpit that is no longer used by children.	5, 10, 15, 25	0.2
Perennial bed	By a perennial bed we mean a bed of perennials that have their natural habitat in the area where you live. Herbaceous plants do not become woody like trees and shrubs and do not thicken as they grow. Examples of these plants are forget-me-nots, daisies, columbine, deadnettle, wild mallow, lily of the valley, ground ivy or nettle.	50, 120, 200, 300	5 to 10
Pile of leaves and branches	By these piles we mean places in the garden where cut branches from trees or shrubs lie on top of each other, often with leaves in between.	0	0.5
Pond	By a pond we mean a water body that is usually filled with water all year round and contains soil substrate on which organisms can live, especially in the bank area. This allows typical vegetation to develop in the bank area and in the pond (with pond lilies in the middle, for example).	500, 1100, 1800, 2600	5 to 10
Tree	*[No definition was given for trees.]*	25, 40, 65, 90	10 to 15
Wild corner	By a wild corner we mean an area in the garden that is left to its own devices and is very rarely entered. Interventions in these areas are only carried out to remove emerging young wood so that the natural corner does not become "overgrown".	0	1 to 2

of elements. Two additional pieces of information were presented before each basket-based choice task:

- "For each element you will find details of the **area required in square metres** and the **cost in Euros**. Both figures represent an order of magnitude. The amounts **do not yet include** possible subsidies." [emphasis in the original]

Table 2 Policy instruments

Instrument	Description	Levels
Free consultation	A consultant comes to your garden and advises you for up to 2 hours. There are one or two appointments per household and year.	*No consultation*; One session up to two hours; Two sessions, each up to two hours
Free telephone helpline	Your city/municipality offers regular consultation hours where you can visit or call an expert on the subject of garden design and maintenance.	*No*; Yes
Financial support for new elements	A financial subsidy is paid in proportion to the cost of new elements.	*0%*; 30%; 60%; 90%
Financial support for maintenance	A financial subsidy is paid in proportion to the costs of maintenance measures. The subsidy is initially promised for 10 years.	*0%*; 30%; 70%; 100%

Notes: Levels were combined into packages using an orthogonal design with 96 combinations. Status-quo levels are indicated in italics

- "Please select the elements that you would like to add to your garden with the above support package. You can also select elements that already exist in your garden. If you do not want to add any elements, go to the bottom of the page."

At the bottom of the page another response option "I do not (want to) add any other elements to my garden" was provided. Not choosing any items could have alternatively been indicated by simply not selecting any element from the basket choice task. However, to make clear that not choosing anything is the intended choice, respondents were asked to use this separate response option.

After clicking the "Proceed" button, the subsequent page showed the policy instruments again as well as the total purchase price of the selected basket of elements and the amount payable after applying the subsidy for new elements as displayed (0%, 30%, 60% or 90%). Afterwards, the respondent was asked: "Would you add the selected elements to your garden with the support offered?". Two response options were given: a) "Yes, I would add the selected elements to my garden in the next 12 months"; b) "No, I would like to make changes". If choosing b), the respondent was redirected to the basket-based choice task on the previous webpage. If choosing a), she went ahead to the next basket-based choice or the question that followed the basket section if this was the sixth and last basket-based choice.

2.1.2 Context Attributes: Policy Instruments

As part of each basket-based choice task, respondents were given some context information, specifically whether a set of supporting policy instruments would be provided by the local council (Table 2). A particular combination of these instruments, which changed over choice tasks, was shown on top of each basket-based choice task. The first of these instruments was a one- or two-hour free consultation session in the respondent's own garden provided by a gardening expert sent and paid for by the council. The next instrument was a free-of-charge telephone helpline for all questions concerning gardening and the installation and maintenance of the different elements. The last two instruments both offer financial support for respondents who decide to add new elements to their garden. While the third instrument was financial support for adding new features to the respondents' garden, the fourth instrument was a financial support for maintaining the new garden element. The subsidy for new elements varied across the levels 0%, 30%, 60% and 90% of the price of the whole basket of elements chosen. The maintenance subsidy could assume values of 0%, 30%, 70% and 100% of the (monetary) costs a household would incur to maintain the garden elements for ten years.

These instruments and their levels were developed in an iterative process involving discussions with local policy makers (of the city of Gütersloh, Germany) and biodiversity experts (Nature and Conservation Union of Germany – NABU e.V., Naturgarten e.V.). They were further evaluated in two online-communities sampling garden owners from across Germany and conducted two months before the main survey took place.[3] The levels were combined into packages using an orthogonal design with 48 combinations. One of these packages was selected randomly to be displayed on top of each basket-based choice task. Since the garden elements offered at different prices and the context attributes were each drawn randomly from different orthogonal designs, the effects of both price and the policy instruments are identified.

2.2 Survey Instrument and Sampling

In the online survey, a set of screening questions at the beginning of the questionnaire (see below) was followed by a section with questions about the respondent's garden (size of the garden, share of land-use types, time spent in the garden, etc.). A knowledge quiz consisting of eight questions followed. Questions concerned topics such as lawn management or the use of pesticides. In the subsequent section, respondents were asked which of the 14 elements used in the BBCE were already present in their garden. This follows Young et al. (2019) who, in a survey in Switzerland, recorded which elements can be found in domestic gardens. Expanding their work, additional questions were asked to obtain further details about the elements. After the subsequent BCEE, the questionnaire proceeded by asking for information about the respondent's neighbours, attitudes toward gardening, among others, and a best-worst scaling exercise about the effectiveness of policy instruments that aim at promoting wildlife gardening. Finally, socio-demographics and further details about the residential property and the associated garden were requested.

Respondents were recruited from the online panel GapFish (https://gapfish.com; around 470,000 sample able users across Germany, active panel management). As part of the initial screening questions, the questionnaire started with questions about the respondent's garden. The rationale behind those questions was to ensure that only people who have a garden associated to their residential property and who have a say about how the garden is maintained and designed could participate in the interview. Quotas were not used to select respondents based on socio-demographic characteristics as the target population is unknown. No official statistics are available about people who own or rent a house with an associated garden. The online survey took place in June and July 2023.

[3] In contrast to focus groups, online-communities gather participants not only for a single meeting but for a sequence of tasks and meetings across a series of days. In the present case, the online-communities lasted ten days. Tasks to be completed included short surveys, descriptions of their own garden or ranking of photos. Intermittently, chat-based meetings in which participants discussed topics such as garden design or could put questions to a garden expert were held. In total, 28 people actively participated in each of the two online-communities, they received an incentive of EUR 50. The online-communities were implemented on a software platform tailored for qualitative research (http://www.kernwert.de).

2.3 Data Analysis

This section introduces the multivariate logistic (MVL) model to analyse the data resulting from the basket-based choice tasks. Theoretically, an MNL model to examine the discrete choice between all possible baskets could be used for analysis. However, due to the large number of alternatives (cf. Footnote 2) this is numerically infeasible. Therefore, the first part of the MVL model follows Caputo and Lusk (2022). In the second part, we propose a modification to this basket-based choice model accommodating the empirical result of a high share of respondents who, in their series of basket-based choices, never select any element into their baskets.

Following e.g. Song and Chintagunta (2006), the observable utility V_{bt} an individual derives from a basket b consisting of a number of elements $j \in \{1, \ldots, j, \ldots J\}$ in task t is assumed to be

$$V_{tb} = \sum_{j=1}^{J} \alpha_j \, y_{jt} + \sum_{j=1}^{J} \sum_{k \neq j}^{J} \gamma_{jk} \, y_{jt} \, y_{kt}, \tag{1}$$

where y_{jt} takes value of one if element j is included in this basket and zero otherwise. In Eq. (1), α_j indicates the baseline utility of element j and can be expressed as a function of price p_{jt}[4] and other variables, X and/or X_t (depending on if they are task-specific or not), i.e., $\alpha_j = \alpha_{0j} + \beta p_{jt} + X_t \delta_j$; and γ_{jk} denotes the relationship between different elements in terms of their effect on utility. In the present study, the policy instruments (Table 1) are task-specific variables, i.e. they vary across choice tasks, and are therefore indexed t. All other variables are respondent-specific (i.e. constant across the series of choice tasks of one respondent) and therefore not indexed. These latter variables are an indicator if the element is already present in a garden[5], and indicate garden size, share of lawn cover and respondent age. Garden size is included because all elements have space requirements which were also indicated in the choice task. It is expected that owners of bigger gardens have a higher chance of adding an element, ceteris paribus. The share of lawn cover in the garden serves as a proxy for the level of engagement in gardening. The higher this share, the lower the supposed willingness of the respondent to actively work in and shape their garden. Respondent age is the only demographic variable included as a covariate with the expectation that older respondents will be less willing to add elements to their garden.

Since the application of a BBCE in Caputo and Lusk (2022) contained only respondent-specific variables, a distinction between X and X_t as in the present study was not necessary in that context. If $\gamma_{jk} > 0$, elements j and k are complements in utility, whereas for $\gamma_{jk} < 0$ they are substitutes in utility. $\gamma_{jk} = 0$ indicates that the utility of element j is invariant to the presence or absence of element k in basket b. It is assumed that $\gamma_{jj} = 0$ and $\gamma_{jk} = \gamma_{kj}$. Given that the total utility of a specific basket of elements is $U_{tb} = V_{tb} + \varepsilon_{tb}$, where ε_{tb} is assumed to be Extreme Value Type I distributed, the probability of choosing a specific bundle of elements into the basket can in principle be obtained using the standard conditional

[4] We let p_{jt} enter the model in its logarithmic form (using $\log_{10}$) to accommodate the differences in the absolute amounts between garden elements (Table 2).

[5] In addition to being respondent-specific this variable is also element-specific, i.e. for a specific respondent, a particular element can currently be present in their garden or not.

logit (Ben-Akiva and Lerman 1985).[6] The issue with this approach in practice, however, is that the number of possible combinations of garden elements is large. In the present case, with $J = 14$ elements, there are $B = 2^{14} = 16,384$ possible combinations, which makes estimation using conditional logit difficult if not impossible.

As a compromise, in a composite conditional likelihood function a series of binary probabilities of including an element in the basket are specified. The probability of picking element j into the basket-based choice task t conditional on other elements k also selected into the basket (or not) is

$$Pr\left(j_t\right) = \frac{\exp\left(z_{tj}\right)}{1 + \exp\left(z_{tj}\right)} \quad \forall j \in J, \tag{2}$$

where $z_{jt} = \alpha_j + \sum_{k \neq j}^{J} \gamma_{jk} y_{tk}$. Note that the parameters α_j and γ_{jk} in Eq. (1) are equal to those in Eq. (2) (Bel et al. 2018). This is ensured by assuming $\gamma_{jj} = 0$ and the symmetry restriction on the cross-utility effects, i.e. $\gamma_{jk} = \gamma_{kj}$ (Besag 1974; Kwak et al. 2015). In other words, with these assumptions in place the system of J element-specific (binary) probability expressions in Eq. (2) implies the choice of a basket with the corresponding elements and the indirect utility as defined in Eq. (1) for all 2^J possible baskets. With this specification, the probability of an individual's choice is then

$$Pr\left(j_t | y_{tj}\right) = Pr\left(j_t\right) y_{tj} + \left(1 - Pr\left(j_t\right)\right)\left(1 - y_{tj}\right). \tag{3}$$

Therefore, the composite probability C over the sequence of $t = 1, \ldots, T$ basket-based choice tasks by a respondent is

$$Pr\left(C\right) = \prod_{t=1}^{T} \prod_{j=1}^{J} Pr\left(j_t | y_{tj}\right) \tag{4}$$

Note that this is the standard composite model as set out and applied by Caputo and Lusk (2022) and Kilders et al. (2024). However, this model may be inappropriate whenever there is a high share of individuals serially choosing an empty basket.[7] The model is unlikely to perform well in predicting these probabilities as can be illustrated as follows. Suppose $Pr\left(j_t\right) = 0.05 \forall j$. This leads to a relatively high probability of not selecting any one element j in any one particular choice task, i.e. $1 - Pr\left(j_t\right) = 0.95 \forall j$. In a BBCE with 14 elements and with six consecutive choice tasks as in the present application, this yields a probability of choosing an empty basket in all tasks of $\left[1 - Pr\left(j_t\right)\right]^{14 \times 6} = 0.95^{84} = 0.013$. This shows that even with a very high probability of not selecting each of the elements on

[6] An example of this is the portfolio site choice model by Parsons et al. (2021) in which respondents could have visited any combination of seven national parks in the United States. The resulting data of their actual itinerary can be modelled as a discrete choice between $2^7 - 1 = 127$ possible combinations of visited sites using conditional logit.

[7] Or indeed consistently choosing any other possible combination of elements, such as a full basket comprising all elements on the menu a relatively large number of times. As a result, the latent class model proposed below will be superior to the standard model in any situation where there are a substantial number of decision-makers exhibiting any of the above choice behaviour.

offer in a basket-based choice task, the resulting likelihood of serially doing so for all elements in all tasks is quite low. Note that in the empirical application presented below, 23.9% of individuals never choose a single element (Fig. 5, Panel B), which, assuming the same probabilities for all elements, would require the probability of choosing any element to be equal to $1 - 0.2385^{1/(14x6)} = 0.017$, which in the present empirical study is unexpectedly much too low given the empirical choice probabilties.[8]

As a consequence, not accounting for this empirical characteristic of the basket-based choice data at hand likely leads to biased parameter estimates and poor predictions of choice probabilities. To circumvent this problem, a model with a latent class (LC) structure is employed. In the class where respondents never select an element in any of the T choice tasks, the choice probability is expressed as

$$\begin{aligned} Pr\left(C_{q=1}\right) &= \prod_{t=1}^{T}\prod_{j=1}^{J}\left(1 - y_{tj}\right) \\ &= 1 \quad \text{if basket is empty in every task } t \\ &= 0 \quad \text{otherwise.} \end{aligned} \tag{5}$$

In a second class, this choice probability is as defined by the composite probability of a series of basket-based choices according to Eq. (4), i.e. $Pr\left(C_{q=2}\right) = Pr\left(C\right)$. In effect this LC specification is similar to a zero-inflated model where the observation of zero is given additional probability mass.

With this the overall sequence of basket-based choice probabilities, which better accounts for serial empty baskets is

$$Pr\left(C|\pi\right) = \pi Pr\left(C_{q=1}\right) + \left(1 - \pi\right) Pr\left(C_{q=2}\right). \tag{6}$$

whereπ is the unconditional probability of belonging to the class with the serial empty baskets. It is modelled at the respondent level and can be expressed as a logit:

$$\pi = \frac{\exp\left(\theta Z\right)}{1 + \exp\left(\theta Z\right)}. \tag{7}$$

In Eq. (7), Z contains respondent- (and garden-) specific characteristics which may account for systematic differences in the probability of returning a series of T empty baskets. In the present study, these are garden size, the share of lawn cover and respondent age.[9] The likelihood model as set out above is coded and estimated using R (R Core Team 2023).

With the estimated parameters in hand it is possible to do scenario evaluations of changes in the probability of selecting a specific element j into the basket, i.e. changes in demand for that element. Such changes can be the result of a change in policy, i.e. the implementation of a specific instrument, *ceteris paribus*. We calculate this change as

[8] As indicated in the right-hand panel of Fig. 4, the individual elements were selected in between 10 and 30 percent of all basket-based choice tasks.

[9] Note that it is generally possible to also include in Z element-specific variables, such as already-in-garden. However, we decided against this approach to avoid the estimation of an additonal 14 parameters.

$$\Delta P_j = \frac{\widehat{P_j} - \overline{P_j}}{\overline{P_j}}. \tag{8}$$

where $\overline{P_j}$ and $\widehat{P_j}$ are the probabilities of choosing element j before and after implementation of the instrument, respectively. Alternatively, a change in the selection probability of element j may be the result of a price change of element k (or a set of multiple elements). If the price change is one percent, this is equal to the arc price elasticity of demand between these two elements, E_{jk}, calculated as

$$E_{jk} = \frac{\widehat{P_{jk}} - \overline{P_{jk}}}{\overline{P_{jk}}}. \tag{9}$$

where $\overline{P_{jk}}$ and $\widehat{P_{jk}}$ are the probabilities of choosing element j before and after the price change of element k, respectively. For $k = j$ these are own-price elasticities, and for $k \neq j$ they are cross-price elasticities of demand.

3 Results

3.1 Sample Characteristics

The realised sample is $N = 2,000$. Average respondent age is 49.7 years (Table 3), which is approximately five years older than the mean of the resident population of Germany as a whole. 51 percent of respondents are female; 22 percent are tenants. This low share compared to the national average of 52 percent of household living as tenants is plausible given that we expect the majority of people in our target population to own their properties. However, no official statistics are available that describe exactly the target population of this study. This prevents statements about representativeness.

Garden size is recorded in size brackets, with 19 percent of gardens in the sample being smaller than $100\,\mathrm{m}^2$, 32 percent ranging between 100 and $300\,\mathrm{m}^2$ and a respective quarter of gardens being large (between 300 and $500\,\mathrm{m}^2$) and very large (more than $500\,\mathrm{m}^2$) (Table 3).[10] The dominating (self-reported) land use type in the gardens is lawn with an average share of 31 percent of the respective garden area. The second largest share are flower and herbaceous areas with around 16.5 percent followed by land covered by trees and shrubs with nearly 15.7%. Next both sealed surfaces and vegetable beds each cover approximately 12 percent of the garden areas. Lawns or meadows with wildflowers and herbs cover an average area of just below 10 percent while water surfaces only cover around 3 percent of the average garden size.

The total number of elements installed in the garden also varies considerably (Fig. 1). There are gardens (0.2 percent of gardens) which contain none or all of the elements (1.8%) available in the BBCE. Gardens with 6, 7, 8, 9 or 10 elements each account for more than 10% of the surveyed respondent gardens. The left-hand panel of Fig. 2 displays the share of gardens containing each of the elements. Trees are most ubiquitous, being present in 87.5%

[10] Note that this variable is used in continuous form in the choice model (Table 4) and computed using the mid-points of each size bracket, $50\,\mathrm{m}^2$, $200\,\mathrm{m}^2$, $400\,\mathrm{m}^2$, and $600\,\mathrm{m}^2$ for the category "Very large (more than $500\,\mathrm{m}^2$)".

Table 3 Sample characteristics

	Mean	Std. dev.	Min	Max
Age (years)	49.70	14.03	18	92
Gender (1 = female)	0.51	0.49	0	1
I live for rent (1 = yes)	0.22	0.42	0	1
Garden size categories (in percent)[a]				
Small (less than 100 m^2)	19.00			
Medium (100 to 300 m^2)	31.95			
Large (301 to 500 m^2)	23.80			
Very large (more than 500 m^2)	25.25			
Share of self-reported garden area (in percent)				
Size of the lawn[b]	31.06	22.15	0	100
Lawn with wildflowers and herbs	9.87	15.14	0	85
Meadow with wildflowers and herbs	9.76	16.01	0	100
Sealed surfaces	11.62	11.77	0	100
Trees and shrubs	15.70	11.48	0	100
Vegetable beds	10.51	11.27	0	100
Water surfaces	3.17	5.99	0	100
Flower and herbaceous areas	16.48	11.95	0	100
Other land-type uses	5.12	9.38	0	100

Notes: N = 2,000; Whilst the characteristics of the whole population with access to a garden are unknown, the respective averages of age, share of females and share of those who live for rent in Germany in 2023 were 45, 0.506, and 0.542

[a]For size of the garden, 25 missing values were replaced by the median of the non-missings (200 m^2). The estimation models below use this variable in continuous form, computed using the mid-points of each size bracket, 50 m^2, 200 m^2, 400 m^2, and 600 m^2 for the category "Very large (more than 500 m^2)"

[b]For share of lawn, 149 missing values were replaced by the median of the non-missings (30%)

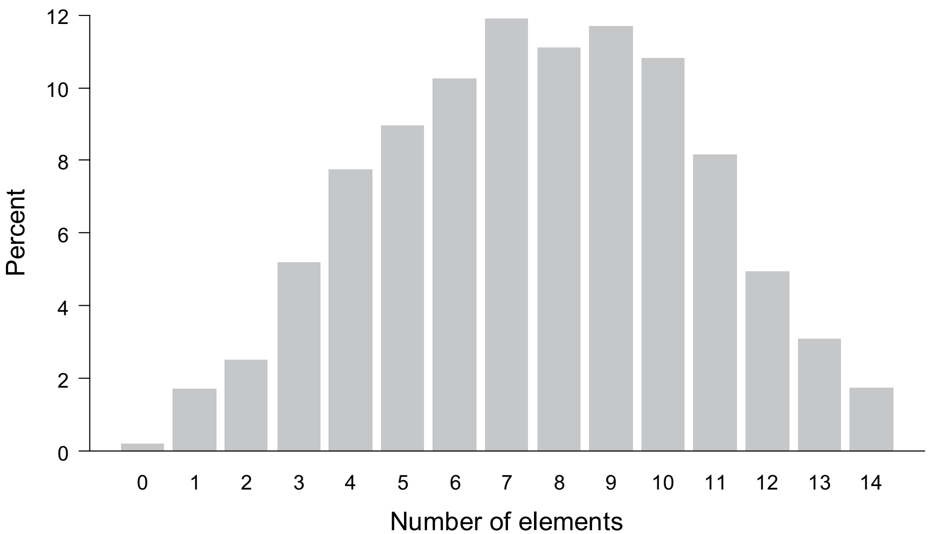

Fig. 1 Number of garden elements already in present in respondents' gardens (share of 2,000 respondent gardens)

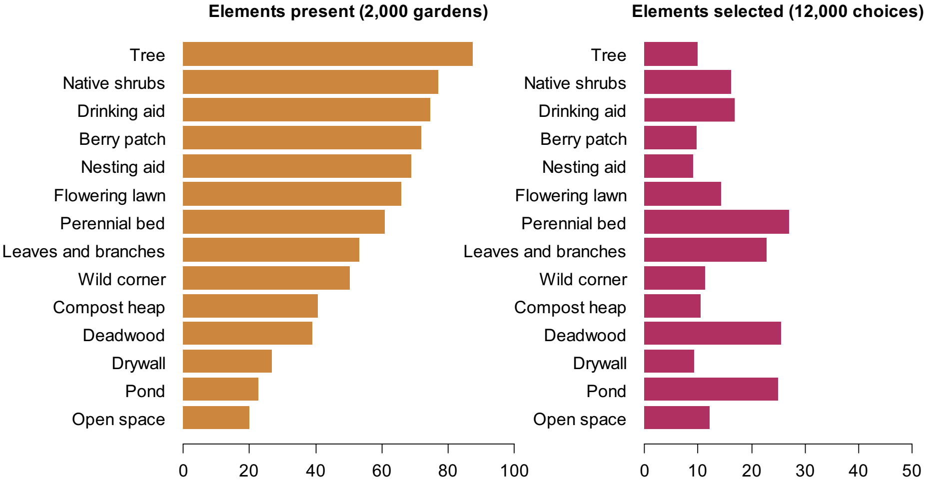

Fig. 2 Percentage shares of garden elements present in private gardens (left-hand panel) and percentage shares of those selected into the baskets (right-hand panel) in percent

of gardens, whereas drywalls, ponds and open spaces are only present in 26.8, 22.7 and 20.0%, respectively. The right-hand panel of Fig. 2 reports how often each of these elements was selected across all basket-based choice tasks. Among the most popular are trees, drinking and nesting aids and berry-bearing plants. All of them are already among those elements that are most frequent in current gardens. In contrast, drywalls and ponds were selected less frequently as new elements for the private garden.

In 43.9 percent of the 12,000 basket-based choice tasks, no element was selected into the basket (Fig. 3, Panel A). Baskets with one, two or three elements each account for approx. 10 percent of all choice tasks. Baskets with more elements were recorded increasingly rarely, with baskets having more than nine elements appearing only in altogether 2 percent of all choices. On the number of empty baskets, Panel B in Fig. 3 shows that approx. 33 percent of respondents never made this choice, i.e. their number of empty baskets is zero. At the other end, approx. 24 percent of respondents always (i.e. six times out of six) selected the no-purchase option. This reflects that a substantial share of garden owners may not be interested in wildlife gardening, a result also found elsewhere (García-Antúnez et al. 2023), and are therefore not willing to add elements to their garden which support biodiversity conservation in this way. This situation is the reason for introducing the LC structure into the composite likelihood model as set out in the previous section.

3.2 Preferences for Garden Elements

Tables 4, 5 and 6 display the estimates of the composite conditional likelihood model in three parts. Table 4 reports the estimates of all baseline utility parameters α_{0j}, the price parameter p_{jt} and the effects of the instruments and garden- and respondent-specific characteristics δ_j. Table 5 shows the estimates of the cross-utility effects γ_{jk}. Finally, Table 6 displays the effects of the covariates in the class membership function θ (cf. Eq. 8). Starting with Table 4, the leftmost column indicates the element-specific constants. These are

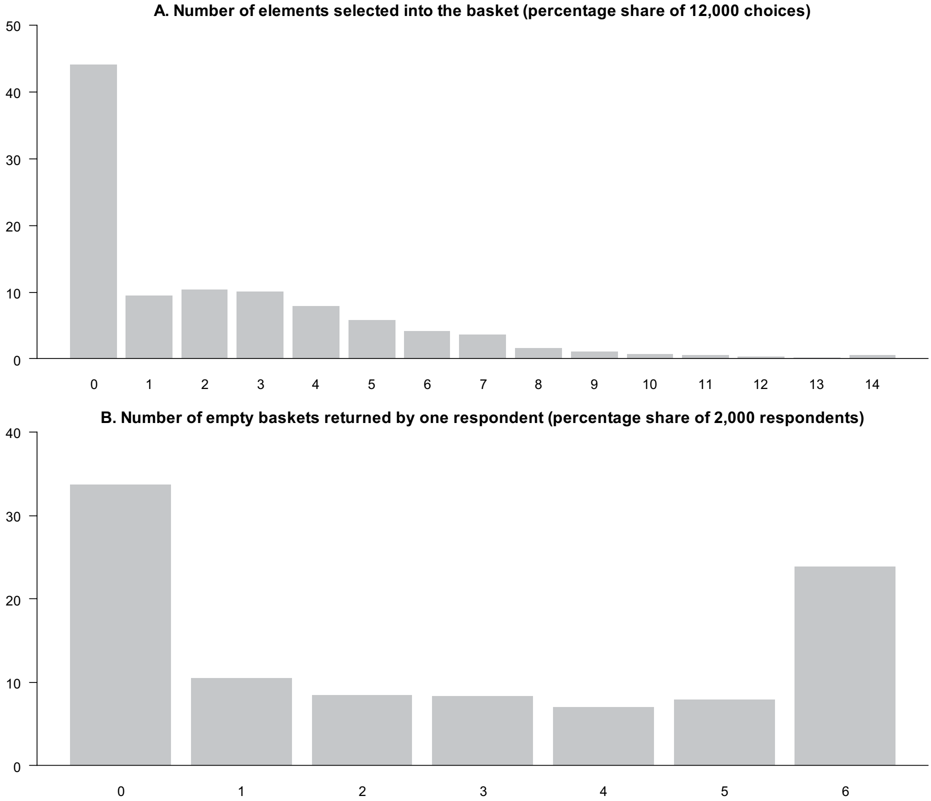

Fig. 3 Number of elements selected into one basket (panel **A**); number of empty baskets returned by one respondent (panel **B**)

all negative, which, in a binary logit model means that the probability of any one element being in the basket is smaller than 0.5. This matches the observed choice frequencies in Fig. 2. The coefficient on price p_{jt} in Column 2 is negative and significant, implying that more expensive elements are less likely selected into a basket, *ceteris paribus*. Note that this coefficient is modelled as constant across elements to reflect the assumption of equal sensitivity to price. In other words, one Euro spent on any of the elements is assumed to cause the same extent of disutility. While this model had the best fit to the data relative to alternative model specifications with three (for cheap, medium-priced and expensive elements) or eleven price coefficients (for each element with non-zero price), such alternatives (available from the authors on request) served as robustness checks. The effects of all other variables in the model, as presented below, remain unchanged.

Columns 3 through 7 report the element-specific effects of the policy instruments. The basic picture emerging from these results is that the set of non-financial instruments have virtually no effect on the purchase decisions of garden owners. The effects of these instruments are mostly small compared to the differences garden and gardener characteristics make (Columns 8 through 11), and mostly insignificant.

Exceptions are the subsidy for new elements (Column 7) and the financial subsidy for maintaining the new elements (Column 6). The effect of the former is demonstrated both by

Table 4 Composite conditional likelihood model – part I: baseline utility, price, instruments, garden- and respondent-specific characteristics

	1	2	3	4	5	6	7	8	9	10	11
	Constant	Price	AdviserI	AdviserII	Callcenter	Money_main	Rebate_new	Size_garden	Share_lawn	Already_in_garden	Age
Tree	−1.61***	−0.18***	−0.05	0.05	0.06	0.07	−0.01	0.08***	0.36***	0.47***	−2.08***
	(0.14)	(0.04)	(0.08)	(0.07)	(0.06)	(0.08)	(0.09)	(0.01)	(0.08)	(0.05)	(0.13)
Nesting aid	−2.35***	−0.18***	0.12	0.08	−0.09	0.04	0.20**	0.01	−0.71***	0.29***	1.06***
	(0.13)	(0.04)	(0.08)	(0.08)	(0.06)	(0.09)	(0.09)	(0.01)	(0.08)	(0.04)	(0.13)
Open space	−3.37***	−0.18***	0.05	0.10	−0.13	0.01	−0.20*	0.02**	−0.42***	0.33***	0.91***
	(0.17)	(0.04)	(0.10)	(0.10)	(0.08)	(0.11)	(0.12)	(0.01)	(0.12)	(0.06)	(0.18)
Drywall	−2.59***	−0.18***	0.04	0.02	0.09	0.22**	0.49***	0.10***	−0.92***	−0.01	−0.48***
	(0.18)	(0.04)	(0.09)	(0.09)	(0.08)	(0.10)	(0.12)	(0.01)	(0.10)	(0.05)	(0.17)
Berry patch	−2.05***	−0.18***	0.11	0.16**	0.00	0.05	0.19**	−0.03***	0.17**	0.38***	−0.63***
	(0.13)	(0.04)	(0.08)	(0.08)	(0.06)	(0.08)	(0.09)	(0.01)	(0.08)	(0.04)	(0.14)
Flower lawn	−2.21***	−0.18***	−0.01	0.06	0.04	0.00	−0.31***	−0.02***	−0.28***	0.29***	−0.17
	(0.13)	(0.04)	(0.08)	(0.08)	(0.07)	(0.09)	(0.10)	(0.01)	(0.08)	(0.04)	(0.13)
Compost	−2.41***	−0.18***	−0.13	−0.19*	−0.02	0.01	−0.01	0.02	−0.05	0.66***	−1.66***
	(0.17)	(0.04)	(0.10)	(0.10)	(0.08)	(0.11)	(0.12)	(0.01)	(0.11)	(0.05)	(0.18)
Native shrubs	−2.03***	−0.18***	−0.01	−0.01	−0.02	0.25**	0.15	0.01	0.21**	0.16***	−2.41***
	(0.16)	(0.04)	(0.10)	(0.09)	(0.08)	(0.10)	(0.12)	(0.01)	(0.11)	(0.06)	(0.17)
Drinking aid	−2.37***	−0.18***	−0.03	−0.03	0.00	0.06	−0.08	−0.07***	0.71***	−0.01	0.35**
	(0.14)	(0.04)	(0.08)	(0.08)	(0.07)	(0.09)	(0.10)	(0.01)	(0.09)	(0.04)	(0.14)
Perennial bed	−3.03***	−0.18***	0.04	−0.01	−0.07	0.16*	0.22**	−0.01	0.20**	0.35***	0.68***
	(0.15)	(0.04)	(0.09)	(0.09)	(0.07)	(0.09)	(0.10)	(0.01)	(0.09)	(0.05)	(0.15)
Deadwood	−3.32***	−0.18***	0.08	0.02	−0.10	−0.05	−0.24	−0.09***	−0.25*	0.73***	−0.64***
	(0.21)	(0.04)	(0.13)	(0.14)	(0.11)	(0.14)	(0.16)	(0.01)	(0.13)	(0.06)	(0.22)
Pond	−2.27***	−0.18***	0.03	0.03	0.07	0.05	0.35***	0.05***	0.05	0.62***	−2.01***
	(0.19)	(0.04)	(0.10)	(0.11)	(0.09)	(0.10)	(0.13)	(0.01)	(0.11)	(0.05)	(0.18)
Wild corner	−2.72***	−0.18***	−0.01	0.03	0.03	−0.09	−0.10	−0.03***	0.42***	0.16***	−0.35**
	(0.15)	(0.04)	(0.10)	(0.10)	(0.09)	(0.11)	(0.12)	(0.01)	(0.11)	(0.04)	(0.17)

Table 4 (continued)

	1	2	3	4	5	6	7	8	9	10	11
	Constant	Price	AdviserI	AdviserII	Callcenter	Money_main	Rebate_new	Size_garden	Share_lawn	Already_in_garden	Age
Leaves and branches	−4.04***	−0.18***	0.00	−0.08	−0.03	0.14	−0.08	0.01	0.31***	0.51***	0.39*
	(0.18)	(0.04)	(0.11)	(0.12)	(0.10)	(0.12)	(0.14)	(0.01)	(0.12)	(0.05)	(0.21)

Notes: Model based on 12,000 observations; 236 parameters estimated; log-likelihood: −49,835; adj. Rho^2: 0.570; BIC: 101,463. Standard errors in parentheses. *, ** and *** indicate significance at the 10%-, 5%- and 1%-level. Note that the price of deadwood, a pile of leaves and branches and a wild corner is always zero. Therefore, the effect of price in Column 2 is estimated based on the price variations of the remaining elements

Table 5 Composite conditional likelihood model – part II: cross-utility effects

	Tree	N.A.	O.S.	DW	B.P.	F.L.	C.H.	N.S.	D.A.	P.B.	Deadw.	Pond	W.C.	L.B.
Tree	0	0.26***	−0.03	0.21***	1.19***	0.30***	0.61***	0.46***	0.47***	0.47***	0.28***	0.18***	−0.15***	−0.20***
		(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)
Nesting aid (N.A.)	0.26***	0	0.45***	0.66***	0.44***	0.50***	−0.09***	0.08***	1.47***	0.39***	−0.28***	0.47***	0.07***	0.41***
	(0.02)		(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)
Open space (O.S.)	−0.03	0.45***	0	0.26***	0.22***	0.18***	0.60***	0.53***	0.34***	0.08***	0.93***	0.44***	0.66***	0.16***
	(0.03)	(0.03)		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
Drywall (DW)	0.21***	0.66***	0.26***	0	−0.22***	0.12***	0.38***	0.67***	−0.03	0.84***	0.09**	0.92***	0.32***	0.13***
	(0.03)	(0.03)	(0.03)		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
Berry patch (B.P.)	1.19***	0.44***	0.22***	−0.22***	0	0.42***	0.50***	0.18***	0.93***	0.65***	−0.04	0.02	0.44***	0.10***
	(0.02)	(0.02)	(0.03)	(0.03)		(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)
Flower lawn (F.L.)	0.30***	0.50***	0.18***	0.12***	0.42***	0	0.22***	0.47***	0.45***	0.67***	0.37***	0.11***	0.31***	0.42***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)		(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Compost heap (C.H.)	0.61***	−0.09***	0.60***	0.38***	0.50***	0.22***	0	0.19***	0.45***	0.35***	0.59***	0.75***	−0.10***	0.27***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)		(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
Native shrubs (N.S.)	0.46***	0.08***	0.53***	0.67***	0.18***	0.47***	0.19***	0	0.33***	0.71***	0.29***	0.47***	0.16***	−0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)		(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
Drinking aid (D.A.)	0.47***	1.47***	0.34***	−0.03	0.93***	0.45***	0.45***	0.33***	0	−0.09***	0.49***	0.12***	0.63***	0.55***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)		(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Perennial bed (P.B.)	0.47***	0.39***	0.08***	0.84***	0.65***	0.67***	0.35***	0.71***	−0.09***	0	0.27***	0.58***	−0.04	0.14***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)		(0.04)	(0.03)	(0.03)	(0.03)
Deadwood	0.28***	−0.28***	0.93***	0.09**	−0.04	0.37***	0.59***	0.29***	0.49***	0.27***	0	−0.68***	1.77***	1.81***
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)		(0.05)	(0.03)	(0.03)

Table 5 (continued)

	Tree	N.A.	O.S.	DW	B.P.	F.L.	C.H.	N.S.	D.A.	P.B.	Deadw.	Pond	W.C.	L.B.
Pond	0.18***	0.47***	0.44***	0.92***	0.02	0.11***	0.75***	0.47***	0.12***	0.58***	−0.68***	0	0.31***	−0.10**
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)		(0.04)	(0.04)
Wild corner (W.C.)	−0.15***	0.07***	0.66***	0.32***	0.44***	0.31***	−0.10***	0.16***	0.63***	−0.04	1.77***	0.31***	0	1.48***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)		(0.03)
Leaves & branches (L.B.)	−0.20***	0.41***	0.16***	0.13***	0.10***	0.42***	0.27***	−0.01	0.55***	0.14***	1.81***	−0.10**	1.48***	0
	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	

Notes: Standard errors in parentheses. *, ** and *** indicate significance at the 10%-, 5%- and 1%-level

Table 6 Composite conditional likelihood model – part III: class membership function (for class 2 – serial empty baskets)

	Coef.		se
Constant	−3.130	***	(0.259)
Size_garden	−0.080	***	(0.025)
Share_lawn	0.750	***	(0.249)
Age	3.765	***	(0.421)

Notes: *** indicate significance at the 1%-level

the selective significant effects of the variable *rebate_new*, which is a continuous variable taking on the value 0, 0.3, 0.6 or 0.9, as well as by the significant price effect. In other words, respondents react to changes in prices, with lower, i.e. discounted prices, increasing the chances of any one element to be selected into the basket and – at least for some elements – to the rebate as a signal. The latter effect can be found for some expensive and medium-priced elements, such as the nesting aid, the drywall, the perennial bed and the pond. The financial subsidy for maintenance (*money_main*) is included as a continuous variable taking on the value 0, 0.3, 0.7 or 1. It has a positive and significant effect on the probability of choosing three elements (drywall, native shrubs, perennial bed), which are rather long-term installations in the garden.

Moving on, Columns 8 and 9 display the effect of garden characteristics on the probability to select each of the 14 elements. Respondents managing larger gardens, where garden size is modelled as a continuous variable (*size_garden*), are more likely to install a tree, a drywall and a pond. In contrast, this variable makes the selection of a berry patch, a flowering lawn, a drinking aid for birds, deadwood and a wild corner less likely. The effects of the share of lawn of the total garden area (*share_lawn*) are similarly heterogeneous. The probabilites of selecting a tree or drinking aid into the basket increase with higher shares of lawn; the chances of picking a nesting aid, open space or a drywall decrease. Column 10 depicts the effect of the respective elements already being present in a respondent's garden on choosing it in the basket-based choice task. This effect is positive and significant for all but two elements, indicating that many respondents who add elements to their baskets like adding more units of elements they already have instead of installing genuinely new garden features.[11] The inclusion of this variable is also important because the present application of the BBCE deals with durable goods (in contrast to those applications in food choice). Since a garden element may potentially stay in a garden for a long time, this aspect of choice needs to be controlled for.

The fact that most estimates of γ_{jk} reported in Table 5 are positive and significant indicates that almost all pairwise relationships are characterised by a utility-increasing effect. In other words, selecting element j into the basket increases the probability that element k is chosen, as well. It is notable that the cross-utility coefficients between a few pairs of very similar elements is particularly large, such as between a tree and a berry patch, a drinking and a nesting aid, or a wild corner leaves and branches and deadwood. There are very few cases of element pairs for which cross-utility effects are negative and significant, albeit very small, such as between a tree and a wild corner.

The estimates in Table 6 are the covariates in the class membership function indicating effects on the probability of a respondent to choose the no-purchase option in all six basket-

[11] While the model does not allow us to examine conclusively the reason behind these effects, they may be a result of perceived availability and increased realism. We thank one anonymous reviewer for suggesting this explanation.

based choice tasks. Older respondents (*age*), those with smaller gardens (*size_garden*) and those with higher shares of lawn (*share_lawn*) are all more likely to be in this serial opt-out class.

To explore the appropriateness of the explicit modelling of a probability to return an empty basket in each of the six choice tasks, we compare the fit of this model (Tables 4, 5 and 6) against that of an alternative model where the LC structure is missing (henceforth referred to as 'naïve model' and reported in Tables A.1 and A.2 in the online Appendix). The LC model converges at a log-likelihood value of −49,835, whereas the naïve model at −50,970. However, the naive model has five fewer parameters to estimate (232 vs. 236), so it is appropriate to compare the Bayesian Information Criterion (BIC). This indicator is also in favour of the model with LC structure ($BIC_{LC} = 101,463$ vs. $BIC_{naive} = 103,704$). A likelihood ratio test with 4 degrees of freedom is highly significant ($p < 0.001$). This comparison demonstrates that, given the data at hand, it is beneficial to account for the relatively high share of respondents who leave their baskets empty in every single choice task.

3.3 Price Elasticities of Demand

With the estimates presented in Tables 4, 5 and 6 in hand, the analyst can predict probabilities of the different elements to be selected into a basket. Using this prediction, Table 7 presents the price elasticity of demand for the different elements, i.e. the percentage change in selection probability following a one-percent increase in the element-specific price (Eq. 9). Note the absence of columns for the elements *Deadwood*, *Leaves and branches* and *Wild corner* because these elements have a price of zero. Results show that own-price elasticities (the diagonal elements in the table) are all negative and significant as expected. However, their magnitude is very small. For instance, a one-percent increase in the price of a tree will lead to only a reduction of demand of 0.0578 percent. Own-price elasticities for other elements are in a similar range. All cross-price elasticities are negative and significant, too, effectively making the 14 garden elements in the experiment demand complements.[12] Therefore, making any one element more expensive will reduce demand for all other elements, albeit with very small effect sizes.

3.4 Predictions and Simulations

The prediction of choice probabilities based on estimated parameters also allows for a comparison of the suggested LC model to accommodate respondents who serially return an empty basket and the naïve model. Note that choice probabilities based on the LC model can be made either for all respondents (i.e. also for those who returned an empty basket in each choice task – those 'outside the market') or only those who bought a basket at least once (i.e. those 'in the market', i.e., those in Class 2 of the LC model). In the former case, the choice probabilities of those in the market are scaled down using the average probability of belonging to the serial empty basket class. Figure 4 indicates that the naïve model slightly

[12] This is despite the fact that not all cross-utility effects in Table 5 are positive. As Caputo and Lusk (2022) explain, only in the case of a choice of two possible items into the basket will there be a straightforward relationship between the cross-utility parameters γ_{jk} and the cross-price elasticities. As soon as there are more than two items to choose from, the cross-price elasticity between any two items j and k may depend on the utility parameters of some or all other items on offer, too.

underestimates the chances that a specific element is selected into the basket. Yet, 95% confidence intervals overlap in the case of all elements, so the differences between models – in the case of the present dataset – are likely insignificant. The same applies to the chances of returning an empty basket.

Predictions can further be used to examine the effectiveness of different policy scenarios in terms of shifting the probabilities of the different elements to be installed in a garden according to Eq. (8). While such an evaluation of many different (policy) scenarios is possible, we focus here on the effect of financial support for maintenance and for the purchase of new elements, since none of the other instruments show significant effects (Table 4). Figure 5 presents percentage changes in choice probability resulting from the introduction of, for example, a 30 percent subsidy on garden maintenance costs. It shows that the changes in choosing a drywall, native shrubs and a perennial bed are significant, i.e. have a confidence interval not including zero. This confirms findings in Table 4. None of the other choice probabilities are affected significantly by this policy instrument.

Figure 6 similarly depicts percentage changes of choice probabilities, now resulting from an exemplary 30 percent rebate on the purchase price of all elements on offer. Note that the predicted effects are a combination of a price reduction of 30% (which works through the parameter on price) and the fact that there is a rebate announced for all elements (which affects choice probabilities through the variable *money_new*). The strongest effects can be seen for some of the most expensive elements, the drywall and the pond. Yet also medium-price elements, such as the tree, the nesting aid, native shrubs and the perennial bed are between 6 and 14 percent more likely to be chosen with the rebate in place. The prediction finds no effect for the zero-price elements (deadwood, wild corner and branches and leaves) as well as for a selection of low-price elements. Note further that the effect of uniform price changes (e.g. a blanket rebate on the whole basket) are not identical across garden elements not only because of the element-specific effects of *money_new*. Another reason is the pattern of complementary utility effects which are captured by the estimates of γ_{jk} reported in Table 5. These cross-utility effects partly explain why the selection probabilities of the three elements with zero price (Deadwood, Leaves and branches and Wild corner) also change as a result of the blanket rebate, albeit insignificantly.

Finally, note that these predictions are based on the composite likelihood model with LC structure to accommodate the substantial share of respondents returning a series of empty basket. If, however, these predictions are done based on the estimates of the naïve model, similar changes of element-specific choice probability are computed at the sample level (Fig. A.3 and A.4 in the online Appendix). The difference, however, is in the level of the precision of the predicted probabilities – predictions based on the naïve model have much larger confidence intervals, which in many cases encompass zero. This is the result of the biased estimates produced by the naïve model since it is less able to accommodate the high share of respondents with a series of empty baskets.

4 Discussion and Conclusions

This study introduces the basket-based choice experiment (BBCE) as suggested by Caputo and Lusk (2022) to the field of environmental economics and management. The application is a survey to assess preferences of private garden owners for the installation of elements

Table 7 Price elasticities of demand of the LC model (Tables 4, 5 and 6)

	tree.adj	nest.adj	open.adj	dryw.adj	berry.adj	flaw.adj	comp.adj	shrub.adj	drink.adj	pere.adj	pond.adj
Tree	−0.0578	−0.0114	−0.0040	−0.0049	−0.0191	−0.0085	−0.0066	−0.0065	−0.0131	−0.0097	−0.0037
	(0.0122)	(0.0022)	(0.0007)	(0.0009)	(0.0037)	(0.0016)	(0.0012)	(0.0012)	(0.0025)	(0.0018)	(0.0007)
Nesting aid	−0.0093	−0.0537	−0.0056	−0.0065	−0.0125	−0.0092	−0.0038	−0.0048	−0.0194	−0.0080	−0.0044
	(0.0018)	(0.0115)	(0.0010)	(0.0012)	(0.0024)	(0.0017)	(0.0007)	(0.0009)	(0.0039)	(0.0015)	(0.0008)
Open space	−0.0099	−0.0171	−0.0642	−0.0090	−0.0142	−0.0120	−0.0106	−0.0109	−0.0177	−0.0103	−0.0071
	(0.0018)	(0.0033)	(0.0133)	(0.0016)	(0.0027)	(0.0022)	(0.0019)	(0.0020)	(0.0034)	(0.0019)	(0.0013)
Drywall	−0.0100	−0.0164	−0.0073	−0.0676	−0.0079	−0.0091	−0.0075	−0.0109	−0.0102	−0.0160	−0.0102
	(0.0019)	(0.0031)	(0.0013)	(0.0140)	(0.0015)	(0.0017)	(0.0013)	(0.0020)	(0.0019)	(0.0029)	(0.0019)
Berry patch	−0.0173	−0.0139	−0.0051	−0.0035	−0.0541	−0.0095	−0.0061	−0.0055	−0.0169	−0.0101	−0.0031
	(0.0034)	(0.0027)	(0.0010)	(0.0006)	(0.0115)	(0.0018)	(0.0011)	(0.0010)	(0.0033)	(0.0019)	(0.0006)
Flower lawn	−0.0120	−0.0160	−0.0068	−0.0063	−0.0149	−0.0596	−0.0064	−0.0084	−0.0159	−0.0129	−0.0043
	(0.0022)	(0.0031)	(0.0013)	(0.0011)	(0.0028)	(0.0125)	(0.0012)	(0.0015)	(0.0031)	(0.0024)	(0.0008)
Compost	−0.0180	−0.0127	−0.0115	−0.0100	−0.0183	−0.0122	−0.0690	−0.0095	−0.0174	−0.0137	−0.0096
	(0.0034)	(0.0024)	(0.0021)	(0.0018)	(0.0035)	(0.0023)	(0.0143)	(0.0017)	(0.0033)	(0.0025)	(0.0017)
Shubs	−0.0149	−0.0135	−0.0100	−0.0123	−0.0140	−0.0136	−0.0080	−0.0676	−0.0149	−0.0165	−0.0080
	(0.0028)	(0.0026)	(0.0018)	(0.0023)	(0.0027)	(0.0025)	(0.0014)	(0.0140)	(0.0028)	(0.0031)	(0.0015)
Drinking aid	−0.0123	−0.0224	−0.0066	−0.0047	−0.0175	−0.0105	−0.0060	−0.0061	−0.0524	−0.0071	−0.0036
	(0.0024)	(0.0045)	(0.0012)	(0.0009)	(0.0034)	(0.0020)	(0.0011)	(0.0011)	(0.0112)	(0.0013)	(0.0007)
Perennial bed	−0.0141	−0.0143	−0.0060	−0.0114	−0.0162	−0.0132	−0.0073	−0.0105	−0.0110	−0.0640	−0.0071
	(0.0027)	(0.0027)	(0.0011)	(0.0021)	(0.0031)	(0.0025)	(0.0013)	(0.0019)	(0.0021)	(0.0134)	(0.0013)
Deadwood	−0.0125	−0.0141	−0.0170	−0.0085	−0.0157	−0.0165	−0.0115	−0.0104	−0.0225	−0.0123	−0.0026
	(0.0023)	(0.0026)	(0.0031)	(0.0015)	(0.0029)	(0.0030)	(0.0020)	(0.0019)	(0.0043)	(0.0022)	(0.0006)
Pond	−0.0106	−0.0156	−0.0083	−0.0147	−0.0101	−0.0089	−0.0103	−0.0101	−0.0113	−0.0143	−0.0702
	(0.0020)	(0.0030)	(0.0015)	(0.0027)	(0.0019)	(0.0017)	(0.0018)	(0.0018)	(0.0022)	(0.0026)	(0.0145)
Wild corner	−0.0077	−0.0132	−0.0115	−0.0071	−0.0142	−0.0121	−0.0063	−0.0072	−0.0188	−0.0080	−0.0042
	(0.0014)	(0.0024)	(0.0020)	(0.0013)	(0.0026)	(0.0022)	(0.0011)	(0.0012)	(0.0036)	(0.0014)	(0.0008)
Leaves	−0.0085	−0.0173	−0.0119	−0.0076	−0.0144	−0.0152	−0.0087	−0.0077	−0.0216	−0.0102	−0.0035
	(0.0016)	(0.0033)	(0.0021)	(0.0014)	(0.0026)	(0.0028)	(0.0015)	(0.0014)	(0.0041)	(0.0018)	(0.0007)

Table 7 (continued)

	tree.adj	nest.adj	open.adj	dryw.adj	berry.adj	flaw.adj	comp.adj	shrub.adj	drink.adj	pere.adj	pond.adj
Empty basket	0.0082	0.0101	0.0033	0.0040	0.0091	0.0058	0.0030	0.0036	0.0088	0.0057	0.0028
	(0.0016)	(0.0019)	(0.0006)	(0.0008)	(0.0017)	(0.0011)	(0.0005)	(0.0006)	(0.0017)	(0.0010)	(0.0005)

Notes: [a]Elements with zero price. Elasticities reported in percent. Robust standard errors simulated using 1,000 draws and reported in parentheses. All simulated parameters are different from zero at the 1%-level of significance

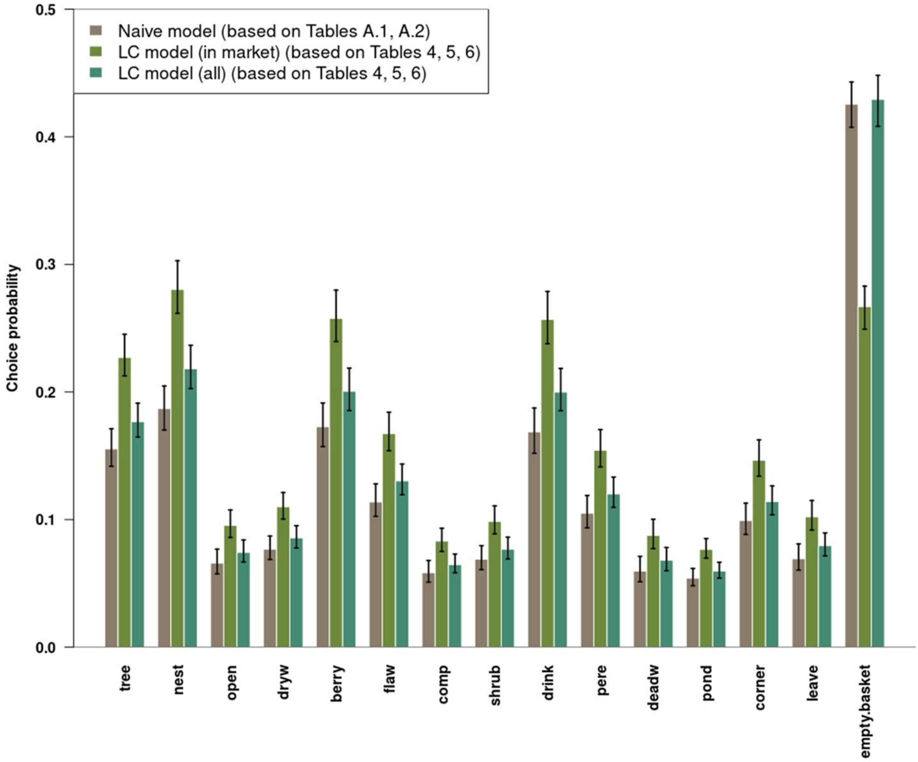

Fig. 4 Choice probabilities of garden elements (and empty basket) in the different basket-based choice models

conducive to biodiversity conservation, i.e. a form of wildlife gardening. Before the experiment, the current situation in gardens was assessed using a predefined list of 14 elements that have been shown to promote biodiversity in gardens (Young et al. 2019; Felgentreff et al. 2025). Results show a very heterogeneous distribution of elements among a sample of 2000 private garden owners in Germany. Between six to ten elements are present in at least 10 percent of the gardens in the sample. There are, however, also a few gardens with none of these elements as well as gardens with all 14 elements (0.2 and 1.8%, respectively). Among the elements chosen to be installed, the most popular were trees, drinking and nesting aids and berry-bearing plants.

The model used to analyse the basket-based choice responses suggests that the policy instruments employed in this study are partly ineffective in shifting demand for biodiversity promoting garden elements. Information provision by means of free on-site consultation and a telephone helpline do not affect choice probabilities of garden elements as suggested by the lack of significant effects of these instruments (Table 4, columns 3 to 5). In contrast, a subsidy for garden maintenance costs positively affects the demand for three of the most expensive elements, namely a drywall, native shrubs and perennial beds (Table 4, column 6). It should be noted that maintenance costs were not spelled out directly in the survey.

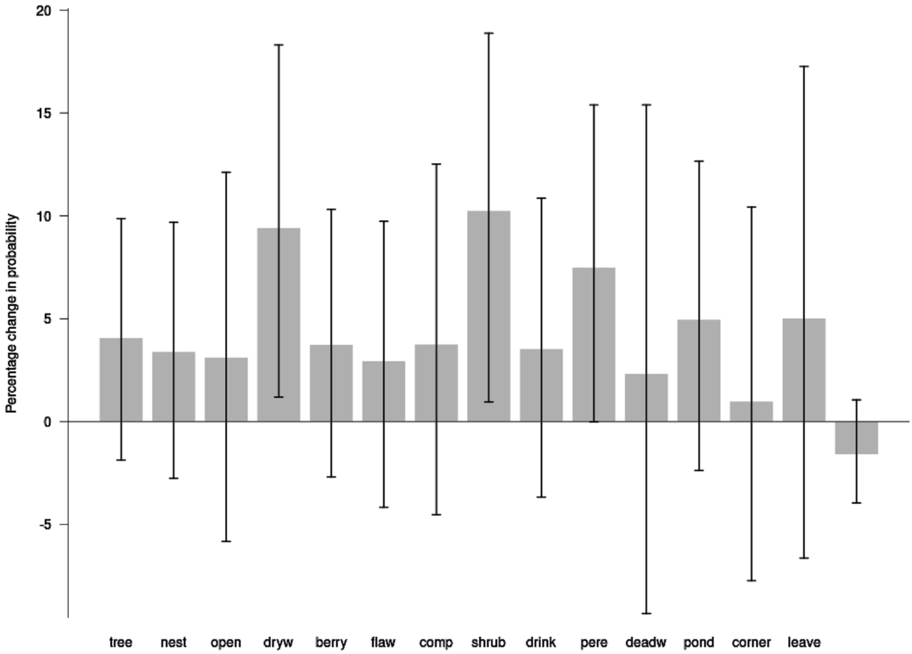

Fig. 5 Percentage changes of choice probabilities of garden elements (and the empty basket) after introducing an exemplary 30 percent subsidy of maintenance costs

However, we can only speculate whether this is the reason for the partial lack of effectiveness of this instrument.

The instrument which drives demand for the largest set of elements on offer is the rebate on new garden elements. This influences choice probabilities through two channels: (1) the significant effect of price (Table 4, column 2) and (2) a signalling effect of providing a rebate on the purchase price estimated through the effect of *money_new* (column 7). Here it should be noted that changes in individual, element-specific prices have a more limited effect as evidenced by the significant but very small own-price elasticities of demand for the elements. If prices are reduced in concert, however, the impact on choice probabilities is larger for the medium- and high-price elements.

Both socio-demographics as well as garden characteristics impact choice probabilities of many garden elements. As a socio-demographic variable, age has a mixed effect on choice probabilities. While larger, more expensive and longer-lived elements are less likely to be chosen the older the garden owner, smaller elements are more likely to be selected by older owners. Regarding the garden characteristics, the size of the garden (*size_garden*) has mixed effects. While respondents with larger gardens are more likely to add space-consuming or fixed elements, such as trees, a drywall or a pond, they are less likely to choose more transient elements like a flower lawn or a wild corner. The share of lawn shows equally mixed effects on choice probabilities. At the same time, these respondent and garden characteristics unambiguously explain class membership, i.e. the likelihood of a respondent to return an empty basket throughout the experiment.

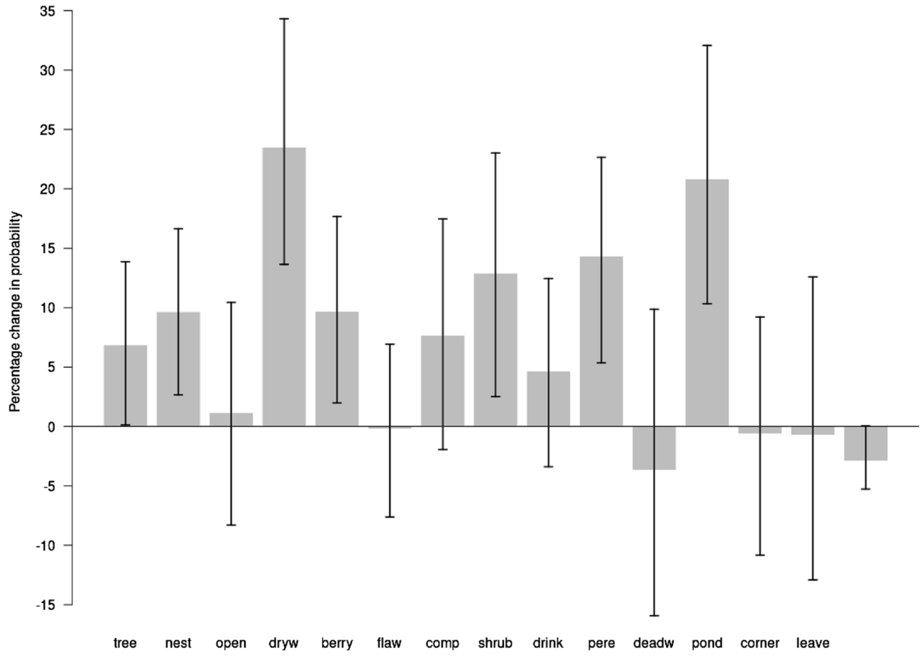

Fig. 6 Percentage changes of choice probabilities of garden elements (and the empty basket) after introducing an exemplary 30 percent subsidy of installation costs

On a methodological level, this study showcases the use of the BBCE to evaluate the effectiveness of environmental management policies in the face of private implementation costs. The fact that all possible elements can be presented in one choice task and that multiple elements can be selected is only practically possible when employing this basket-based approach. Whilst a standard discrete choice experiment could elicit the same information in theory, it is likely that the basket-based format is also cognitively easier for respondents as they can select their ideal combination of elements at given prices. In a standard choice setting, respondents would have to compare two (or more) combinations of elements none of which they really like. The estimation of the cross-utility effects shows that detecting such demand relationships would be almost impossible if the elements were portrayed as mutually exclusive alternatives in a traditional discrete choice experiment setting. The mostly significant cross-utility effects between elements illustrate the usefulness of the BBCE. As a caveat, however, it needs pointing out that the complementary relationships detected in the analysis apply exclusively to new elements added to the garden. Potential demand effects of elements already existing in a particular garden on those being added were not modelled (except from the effect of an element on the selection of another unit of itself, as captured by the variable *already in garden*). In other words, the analysis did not, for instance, examine if the probability of selecting a tree is affected by the fact that the garden already has a pond. It is generally possible to estimate such effects, but this would require (1) a large number of additional parameters (practically another gamma matrix), and (2) an option to remove existing elements from respondents' gardens in the choice task. Neither of these aspects were possible in the present study and we leave their investigation for future research. The first point above suggests another, general challenge of the BBCE. The econometric model requires the estimation of a large number of parameters. This increases the necessary sample sizes for modelling and also puts constraints on the number and types of variables to be included in the model.

Beyond that, the application of the BBCE as presented above introduces two new features that augment earlier applications of this approach (Caputo and Lusk 2022; Neill and Lahne 2022; Kilders et al. 2024; Ma et al. 2024; Neill and Britton 2024). Both of these features reflect challenges of the BBCE in environmental economics and may be relevant to applications in fields such as food or product choice where (i) the effectiveness of public policies in influencing behaviour is of interest and (ii) the experiment may contain durable goods in certain applications. First, an experimental design is used to set context variables for each choice via differing combinations of policy instruments. This layer is added to examine whether such policy instruments affect the demand for garden elements in the face of private purchase costs. In the specifications reported above, the effects of these policy instruments are modelled as potential shifts of the baseline utility of the garden elements on offer. Generally, it is also possible to interact these context variables with, for instance, the price parameter to study if cost sensitivity (or other effects on utility) are affected by the policy instruments. Second, the model is augmented by a latent class structure to accommodate the relatively high proportion of respondents who, in all their choices, select the no-purchase option. To adequately model the probabilities of such a series of basket-based choice responses at the individual level, the LC model distinguishes between respondents exhibiting such a choice pattern and those who select at least one element in at least one basket-based choice, i.e. those respondents that can be considered “in the market”. For instance, both the naïve and the LC model estimate that, on average, 16 percent of all respondents in the sample will purchase a tree. However, the LC model explicitly distinguishes between those who never buy anything (i.e. those “not in the market”) and those who do so at least once. Among the latter group 25 percent will purchase a tree. Since some characteristics of those respondents in the market are known, policy-makers and marketers can customise any offerings better towards that group of clients. Comparison of model fit reveals that this model augmentation is indeed necessary in the present application to adequately represent choice probabilities in the data. While it may be possible to accommodate the effect of respondents serially choosing an empty or full basket by including in the utility function an indicator which is common across all non-empty/non-full baskets, such a modelling strategy could not examine the heterogeneity of this type of response behaviour (which, in the LC model, is captured by the class membership function). In fact, the LC model structure may besuperior to the basic BBCE model in cases where there is a substantial proportion of respondents with a specific information processing strategy, such as serial choice of full or empty baskets, non-attendance of specific elements or elimination or selection of elements by aspects. It should also be pointed out that a substantial share of respondents who never want to add any element to their garden is a credible result given the assumption that many (or most) gardens are already configured according to their owners’ preferences.

An essential output of the study is the prediction of the type and the number of new elements that will be added to gardens in Germany as a result of a certain mix of instruments. Scenarios can be used to evaluate what combination of policy instruments will have which effects at the national level. The results indicate that instruments offering financial support have a positive effect on the installation probability of certain garden elements. Compared to the business as usual rate of installation, i.e., the rate of installation that could be expected without policy instruments, higher levels of financial support lead to higher choice probabilities. Even if these probabilities do not increase very much, this would still result in a much larger number of elements in the gardens on larger spatial scales, i.e., the landscape or national level. For biodiversity conservation, this is good news, as it is not required that all elements are present in all gardens. For the formation of green infrastructure networks via domestic gardens it is sufficient if some gardens offer specific elements and could function as stepping stones.

The empirical results have a number of implications for policy. First, the result that information provision by means of free consultations and helplines does not shift demand whereas only financial incentives do is sobering news for local councils which often have very tight budgets. While there may be some level of intrinsic motivation of garden owners to install biodiversity promoting elements, raising the adoption rate above that level will require financial incentives. These findings, however, should not be interpreted to imply that free consultation is irrelevant for garden owners at all times. It might be important, for instance, when garden owners consider changing their entire garden management or design. Second, the BBCE is based on the assumption that the level of biodiversity in a garden is correlated with the number of different elements present (Young et al. 2019; Felgentreff et al. 2025). However, not all garden elements may have the same effect on biodiversity. While an economic study such as the present one does not intend to provide any insights into the relative value of the elements for biodiversity conservation, it showcases the BBCE as a useful tool to model the effect of price and the policy instruments on each of them independently. Third, while the study only included respondents with access to a garden on their respective residential property, the results can, to some extent, also be transferred to other types of gardens which are privately managed, such as allotment gardens. Although such garden colonies tend to have stricter rules on the design and use of the individual gardens, they are still essentially managed by the individual owner (or tenant), so many questions about the installation of garden elements have the demand characteristics examined in this study.

A number of additional points regarding this study and suggestions for extensions can be made. In applications where some or all the elements offered in the experimental design may already be present in the respondent's home, a possible extension of the model is to estimate possible substitution or complementary relationships between *existing* and new items. The specification presented above only accommodates such relationships between new elements. However, it is conceivable that the probability of installing a, say, flowering lawn in the garden depends on another specific element being present, say, perennial bed.

Another extension is to allow for the choice of multiple units of a specific element. The BBCE as used here prompted respondents to only select a certain element or not. Neill and Lahne (2022) propose an extension of the BBCE in which respondents can also choose quantities of the goods on offer. The resulting data can then be analysed using an alternative model accommodating discrete-continuous choice (Bhat 2005, 2008). Finally, we see potential applications of the BBCE in other contexts of environmental and agricultural economics. This could include the estimation of recreation demand where the composite likelihood model as presented above would be able to deal with multiple destination visits. Another potential application in agricultural economics or environmental management could involve managers or landowners, such as farmers or forest managers, selecting and implementing various measures from a range of management practices. This modelling framework could be applied in a revealed preference context for ex-post policy evaluation or in a stated preference context for ex-ante policy evaluation to assess the likely uptake of different management options. Such insights could significantly aid in the design of these policies. If the number of combinations of these practices is sufficiently large, the econometric model presented here would be ideally suited to analyse the resulting choice probabilities. It would also help explain the characteristics and potential reasons for opting out of the policy entirely.

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Data Availability The questionnaire and survey data which this study is based on are available from the corresponding author on request.

Declarations

Competing Interests The authors declare that they have no competing interests.

References

Bel K, Fok D, Paap R (2018) Parameter estimation in multivariate logit models with many binary choices. Econom Rev 37(5):534–550

Ben-Akiva ME, Lerman SR (1985) Discrete choice analysis: theory and application to travel demand, vol 9. MIT Press

Bertram C, Meyerhoff J, Rehdanz K, Wüstemann H (2017) Differences in the recreational value of urban parks between weekdays and weekends: a discrete choice analysis. Landsc Urban Plan 159:5–14

Besag J (1974) Spatial interaction and the statistical analysis of lattice systems. J R Stat Soc B Methodol 36(2):192–225

Bhat CR (2005) A multiple discrete-continuous extreme value model: formulation and application to discretionary time-use decisions. Transp Res B Methodol 39(8):679–707

Bhat CR (2008) The multiple discrete-continuous extreme value (MDCEV) model: role of utility function parameters, identification considerations, and model extensions. Transp Res B Methodol 42(3):274–303

Cameron R (2023) Do we need to see gardens in a new light? Recommendations for policy and practice to improve the ecosystem services derived from domestic gardens. Urban For Urban Green 80:127820

Cameron RWF, Blanuša T, Taylor JE, Salisbury A, Halstead AJ, Henricot B, Thompson K (2012) The domestic garden - its contribution to urban green infrastructure. Urban For Urban Green 11:129–137

Caputo V, Lusk JL (2022) The basket-based choice experiment: a method for food demand policy analysis. Food Policy 109:102252

Coisnon T, Roussilière D, Rousselière S (2019) Information on biodiversity and environmental behaviors: a European study of individual and institutional drivers to adopt sustainable garden practices. Soc Sci Res 84:102323

Delahay RJ, Sherman D, Soyalan B, B, Gaston KJ (2023) Biodiversity in residential gardens: a review of the evidence base. Biodivers Conserv 32:4155–4179

Dewaelheyns V, Kerselaers E, Rogge E (2016) A toolbox for garden governance. Land Use Policy 51:191–205

Ellis EE, Wilkinson TL (2021) Moth assemblages within urban domestic gardens respond positively to habitat complexity, but only at a scale that extends beyond the garden boundary. Urban Ecosyst 24:469–479

Felgentreff ES, Jakubka D, Knapp S, Bernhardt-Römermann M (2025) The garden biodiversity index: a self-assessment tool for evaluating biodiversity in private gardens. Landsc Urban Plan 263:105449

Fogel NS, Zwarun L, Schrock CD, Camilo GR (2023) A survey of American residential garden conservation programs. J Urban Ecol 9:juad017

García-Antúnez O, Lindgaard J, Lampinen J, Olafsson AS (2023) Gardening for wildlife: a mixed-methods exploration of the factors underlying engagement in wildlife-friendly gardening. People Nat pan 3.10450

Goddard MA, Dougill AJ, Benton T (2010) Scaling up from gardens: biodiversity conservation in urban environments. Trends Ecol Evol 25:90–98

Goddard MA, Dougill AJ, Benton T (2013) Why garden for wildlife? Social and ecological drivers, motivations and barriers for biodiversity management in residential landscapes. Ecol Econ 86:258–273

Goddard MKA, Ikin, Lerman SB (2017) Ecological and social factors determining the diversity of birds in residential yards and gardens. In: Murgui E, Hedblom M (eds) Ecology and conservation of birds in urban environments. Springer International Publishing, Cham, pp 371–397

Hailu A, Adamowicz WL, Boxall PC (2000) Complements, substitutes, budget constraints and valuation. Application of a multi-program environmental valuation method. Environ Res Econ 16:51–68

Hoehn JP, Loomis JB (1994) Substitution effects in the valuation of mulitple environmental programs. J Environ Econ Manage 25:56–75

Jaeger SR, Rose JM (2008) Stated choice experimentation, contextual influences and food choice: a case study. Food Qual Prefer 19:539–564

Kerr KCR, Harricharan AK (2021) Assessing the impact of complimentary wildflower seed packets as an outreach tool for promoting pollinator conservation at a zoo. Appl Environ Educ Commun 20:92–106

Kilders V, Caputo V, Lusk JL (2024) Consumer preferences for food away from home: dine in versus delivery. Am J Agric Econ 106(2):496–525

Kwak K, Duvvuri SD, Russell GJ (2015) An analysis of assortment choice in grocery retailing. J Retail 91(1):19–33

Lange F, Hermans Z, Koster JD, Smismans R (2022) Promoting pro-environmental gardening practices: field experimental evidence for the effectiveness of biospheric appeals. Urban For Urban Green 70:127544

Ma X, Gallardo RK, Canales E, Iorizzo M (2024) Quality-related descriptors to increase fresh blueberries purchase-evidence from a basket-based choice experiment. J Agric Appl Econ Assoc. https://doi.org/10.1002/jaa2.118

Neill CL, Britton LL (2024) Are all meats substitutes? A basket-and-expenditure based approach. Agribusiness. https://doi.org/10.1002/agr.21963

Neill CL, Lahne J (2022) Matching reality: a basket and expenditure based choice experiment with sensory preferences. J Choice Model 44:100369

Parsons G, Leggett CG, Herriges J, Boyle K, Bockstael N, Chen Z (2021) A site-portfolio model for multiple-destination recreation trips: valuing trips to national parks in the Southwestern United States. J Assoc Environ Resour Econ 8(1):1–25

R Core Team (2023) R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Richards TJ, Hamilton SF, Yonezawa K (2018) Retail market power in a shopping basket model of supermarket competition. J Retail 94(3):328–342

Shaw AE, Miller KK (2016) Preaching to the converted? Designing wildlife gardening programs to engage the unengaged. Appl Environ Educ Commun 15:214–224

Song I, Chintagunta PK (2006) Measuring cross-category price effects with aggregate store data. Manage Sci 52(10):1594–1609

van Heezik Y, Freeman C, Davidson K, Lewis B (2020) Uptake and engagement of activities to promote native species in privategardens. Environ Manag 66(1):42–55

Wheeler MM, Neill C, Groffman PM, Avolio M, Bettez N, Cavender-Bares J, Chowdhury RR, Lindsay Darling JMG, Hall SJ, Heffernan JB, Hobbie SE, Larson KL, Morse JL, Nelson KC, Ogden LA, O'Neil-Dunne J, Pataki DE, Polsky C, Steele M, Trammell TLE (2017) Continental-scale homogenization of residential lawn plant communities. Landsc Urban Plan 165:54–63

Young C, Frey D, Moretti M, Bauer N (2019) Research note: garden-owner reported habitat heterogeneity predicts plant species richness in urban gardens. Landsc Urban Plan 185:222–227