Do Visual Representations Influence Survey Responses? Evidence from a Choice Experiment on Landscape Attributes of Green Infrastructure

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Abstract

Visual representations, such as photographs and images, commonly supplement verbal questions in stated preference surveys to better describe choice questions to research subjects, but the effects of those visual representations on survey responses are rarely explored. This paper uses a split-sample experiment to investigate how images influence people's choices in a choice experiment regarding the landscape attributes of green infrastructure, a new approach to stormwater management. The results suggest that images alone and text descriptions alone are equally effective at conveying visually salient landscape attributes. When respondents are presented with both images and text, they exhibit stronger preferences for landscape attributes with high visual salience than when presented with either images or text alone. Furthermore, respondents are less likely to ignore individual attributes in choice questions when both images and text are provided. However, the provision of images makes responses more random, i.e., respondents' preferences for attributes are less consistent across choice questions.

Keywords: Non-market valuation, Generalized mixed logit model, Cognitive overload, Landscape visualizations

Introduction

Visual representations such as photographs and computer-generated images have been widely used to illustrate choice questions and ensure respondents understand the scenarios in stated preference studies. However, we are not aware of any study that has explored whether the use of visual representations affects the results of stated preference methods compared to using other methods (e.g., text descriptions) of communicating the attributes that respondents are being asked to value. Surprisingly, this has been an open issue since when contingent valuation was still the most prominent approach to stated preference methods. In the Report of the NOAA Panel on Contingent Valuation (Arrow et al. 1993), it stated that "if CV surveys are to elicit useful information about willingness to pay, respondents must understand exactly what it is they are being asked to value (or vote upon) …" Despite this support for the use of visualizations to supplement verbal descriptions in stated preference surveys, the report warned that "this technique is a two-edged sword because the dramatic nature of a photograph may have much more emotional impact than the rest of the questionnaire." It also pointed out that not considering the impacts of using visualizations on survey responses is one shortcoming in the report of Carson et al. (1992) to the incident of Exxon Valdez oil spill.[1] Therefore, this paper uses a split-sample choice experiment to address a long-standing question: are people's choices influenced by visual representations?

The choice experiment in this paper is on valuing landscape attributes of green infrastructure. Green infrastructure (GI) is a cost-effective stormwater management approach that focuses on creating local-scale ecosystems to treat stormwater at the source, and serves as a substitute for or a complement to conventional stormwater management approaches. Given the benefits that GI generates for climate resiliency, habitat and wildlife, and human communities, it is being promoted to combat more severe environmental problems such as downstream water pollution and urban flooding caused by stormwater

[1] Some recent choice experiment research using visualizations include De Valck et al. (2014) on shared trail design, Elsasser and Hamilton (2010) on forest conversion programs, and Scarpa, Campbell and Hutchinson (2007) on landscape improvement schemes.

runoff (USEPA, 2016). When it comes to the adoption of new technologies that generate environmental benefits such as solar panels and wind farms, the appearance of such infrastructure is one of the principle determinants of public acceptance (del Carmen Torres-Sibille et al., 2009; Dimitropoulos and Kontoleon, 2009). The environmental benefits of decentralized stormwater management have been examined together with flood frequency reductions by Londoño Cadavid and Ando (2013). However, the understanding of what types of GI landscape design are preferred by citizens remains sparse (Tzoulas et al., 2007; Schäffler and Swilling, 2013). While fills this gap in the literature, this choice experiment is therefore suitable for addressing our primary research objective regarding the impacts of using visualization supplement verbal descriptions in informing people's choices.

Seeking answers to the principle research question requires (1) investigating people's preferences and values regarding the landscape attributes of GI and (2) exploring how visual representations influence the preferences captured by choice experiments. This paper designed a stated choice experiment with three alternative survey treatments. The three survey treatments provide different information to explain choice scenarios: the control uses both images and text descriptions to illustrate the choice scenarios, treatment one uses only text, and treatment two uses only images. The impacts of showing additional images or text can therefore be identified through paired comparisons between the control and treatments.

This paper assesses the impacts on people's responses to choice questions or the preferences they have revealed in choice experiments from two dimensions: those on their taste, i.e., the marginal utility of attributes, and those on the randomness of their choices,[2] which is measured by the variance of the error term in utility function (or scale parameter). Therefore, the data is analyzed using a generalized mixed logit model (GMXL) proposed by Fiebig et al. (2010),[3] which extends one of the current standard discrete choice models, the

[2] This dimension could be interpreted as the certainty of their choices, which refers to whether they believe that they have picked the preferred option (Kiani et al. 2014).

[3] The model is called the generalized multinomial logit model in the terminology of Fiebig et al. (2010), but we prefer the name GMXL suggested by Greene and Hensher (2010) because GMXL is a general form of the mixed logit.

mixed (or random parameter) logit model by accommodating the differences in the randomness of people's choices, i.e., scale heterogeneity. This model enables the measurement of choice randomness via the scale parameter in utility function.

The findings from the GMXL models suggest that choices are susceptible to the method used to convey choice scenarios and that providing more information makes people's responses to choice questions more random. To help understand the conduits of those impacts, this paper exploits the strategy proposed by Hess and Hensher (2010) to retrieve individual-specific information processing strategies for attributes in choice questions. The level of attention paid by respondents to attributes is inferred by the individual-specific parameters of their marginal utility. The results indicate that people pay more attention to attributes in choice questions when more information is provided, i.e., there is a lower prevalence of attribute non-attendance (ANA).[4]

This work contributes to the literature by investigating the impacts of using visualizations on respondents' choices and providing caveats for scholars when conducting stated preference research that includes visualizations. The findings indicate that the policy implications of research can be greatly influenced by the method of describing the survey questions. The article proceeds with a review of the use of visual representations and its potential impacts on people's choices. The econometric model is then discussed, followed by an overview of the survey design, data, and model specification. The empirical result section first provides the overall findings regarding preferences for the landscape attributes of GI, and then discloses the impacts of scenario visualization on people's taste and choice certainty. The analysis is complemented by a search for the channels of such impacts. The final section summarizes the findings and provides suggestions for future research.

[4] Attribute non-attendance refers to the situation in which respondents ignore some of the attributes in choice scenarios and evaluate the utility of each scenario without considering the ignored attributes (Scarpa et al., 2009). ANA is one of the most studied issues in the recent literature of choice experiments, and many studies have shown that not accounting for ANA can lead to serious problems in the estimation results (Carlsson, Kataria, and Lampi, 2010; Hess et al., 2013)

Visual Representations and People's Choice

Visual representations may be better at capturing resource conditions that would be difficult to describe using narrative methods (Manning and Freimund, 2004). Photo-based surveys have demonstrated their suitability as an instrument when evaluating landscape preferences (Barroso et al. 2012), and preferences solicited using photo-based off-site surveys are found to be highly consistent with those from on-site surveys (Hill and Daniel, 2007; Natori and Chenoweth, 2008). Although visual representation is preferable to text descriptions in many circumstances, visual representations could make consumers use less systematic cognitive processes when making choices (Townsend and Kahn, 2014).

The influence of different textual information's provision on people's responses to questions regarding their landscape preferences has been a popular research topic outside the discipline of economics, such as in environmental psychology and landscape planning. For example, both Hill and Daniel (2007) and van der Wal et al. (2014) found that respondents' expressed landscape preferences were malleable[5] depending on the additional information they were provided. However, the literature remains unclear as to how supplemental visual representations might change the patterns of responses to verbally-based surveys.

Showing images in addition to text descriptions enriches the information set, potentially enabling respondents to make more precise decisions with greater available information; nevertheless, a choice task with more sources of information is also a more complex choice task. More complicated choice questions are harder to answer, so people may make their decisions more randomly or exhibit less certainty in picking the option they really prefer. Information overload has long been recognized as a challenge that can lead to dysfunctional preferences and inconsistent choices (for a recent review, see Chernev, Böckenholt, and

[5] These studies use the term "preference" to infer concepts such as judgments on landscape scenic beauty and responses to questions soliciting their preferred landscape conditions, so people's "preferences" are certainly malleable in this context.

Goodman, 2015). In light of this line of research,[6] we explicitly model the impacts of using supplemental images on both people's taste and randomness in answering choice questions.

[6] Although not focusing on the impacts of using visual representations, two recent papers using stated choice experiments have found significant effects on the choice certainty when respondents are provided with different information (Czajkowski, Hanley, and LaRiviere, 2016; Lusk, Fields, and Prevatt, 2008). Both papers adopted the treatment of providing more complete and generally more positively framed information than that which was offered in their control, but their conclusions regarding the impact on respondent choice certainty are mixed.

Econometric Treatment

The conceptual framework of stated choice experiments is based on the random utility maximization model (Holmes and Adamowicz, 2003), in which people are assumed to assess the utility of each option (or alternative) in a given choice set using a function of the attributes attached, and choose the option that gives them the highest utility. Given this setting, in a simple multinomial logit model, the utility (U) of person i for choosing a certain option q in a choice scenario n can be expressed as

$$U_{iqn} = \beta A_{qn} + \varepsilon_{iqn} \tag{1}$$

where A_{qn} is a vector of the attributes of option q in scenario n, β is a vector of the taste parameters (i.e., the marginal utility of each attribute), and ε_{iqn} is an unobserved random component assumed to be independently and identically distributed following type I extreme value distribution.

In the choice modeling literature, preference heterogeneity across individuals is commonly modeled in terms of people's tastes and randomness when making choices, where the former focuses on the heterogeneity in β and the latter is reflected in the scale parameter. In essence, the scale parameter measures the variance in the error term for the random utility function (see Hensher, Louviere, and Swait, 1998 and Louviere et al., 1999 for detailed discussion). The higher (lower) the scale parameter in a respondent's utility function, the lower (higher) the variance in utility over choice options, so a respondent makes less (more) random choices from the perspective of random utility model. Relaxing the restrictive independence of irrelevant alternatives property in a multinomial logit model and allowing individual preference to be heterogeneous in terms of their taste and scale, the utility function of the generalized mixed logit model can be written as

$$U_{iqn} = [\sigma_{in}\beta + \gamma\Gamma\nu_i + (1-\gamma)\sigma_{in}\Gamma\nu_i]A_{qn} + \varepsilon_{iqn} \tag{2}$$

where σ_{in} is the individual- and scenario-specific scale parameter of person i, Γ stands for the lower triangle of the Cholesky matrix, ν_i is a vector of random variables with zero means and known variances representing the individual deviations from the population means of the taste parameters (β), and γ controls how the covariance matrix of the taste parameters are scaled. Note that if $\gamma = 1$ and σ_{in} is normalized to 1, the utility function above reduces to the form in the mixed logit model.

Equation 2 shows that σ_{in} and β always enter the utility function multiplicatively, so normalization on one of the two is necessary to identify the other. Since σ_{in} is a scaler, it is straightforward to normalize σ_{in} and constrain it to be positive since the scale should not change the signs of the taste parameters. A convenient method of achieving the requirement is to assume that σ_{in} follows a lognormal distribution with mean equal to one and variance equal to τ (Fiebig et al., 2010). That is

$$\sigma_{in} = \exp(\bar{\sigma} + \tau\varepsilon_{0in}) \tag{3}$$

where $\bar{\sigma} = -\tau^2/2$ for $\mathrm{E}(\sigma_{in}) = 1$, and $\varepsilon_{0in} \sim N(0,1)$.

How to identify the impacts of exogenous factors on taste is a prolonged interest in discrete choice modeling, and valid approaches are readily available, such as adding socio-demographic variables as the covariates of taste parameters (Revelt and Train, 1998). The current study applies an alternate approach and specifies the separate parameters for attributes in each survey treatment. The concept of investigating the differences in scale across individuals, choice scenarios, or survey treatments using the GMXL model was set out in Fiebig et al. (2010), and Czajkowski, Hanley, and LaRiviere (2016) have implemented the concept and extended the model by adding the ability to capture observed differences in the scale variance, τ. Following their formulation allows the scale parameter in equation 3 to be rewritten as

$$\sigma_{in} = \exp(\bar{\sigma} + \theta z_{in} + \exp(\lambda z_{in})\tau\varepsilon_{0in}) \tag{4}$$

where z_{in} is a vector of the covariates for the observed heterogeneity in scale mean and variance. In order to control for the observed changes in scale associated with the provision of different information across survey treatments, the focus in this paper of z_{in} is a set of dummy variables indicating which survey treatment a respondent takes.[7] Therefore, a positive θ shows that the average scale in the utility of samples in the alternative treatment is higher than that in the control, which indicates that respondents give less random answers to the choice questions in the treatment. A negative θ indicates that the deterministic component in the utility function decreases relative to the random component, so respondents' choices are made with more randomness or, from an econometric perspective, more noise. The impacts of different information provision on the degree of within-sample scale heterogeneity (i.e., the variance in scale) are revealed through λ, where a positive (negative) λ is associated with higher (lower) scale heterogeneity within each sample.

The parameter γ determines the degree of the scale parameter that affecting the covariance matrix of the taste parameters (see equation 2). One special case is where γ equals 1, which indicates that the covariance matrix is unaffected by the scale. This is the GMXL - Type I in the terminology of Fiebig et al. (2010). Alternatively, the GMXL - Type II is when γ equals 0, in which the covariances will be as equally scaled as the means. Empirically, γ can be estimated via a logistic transformation as between 0 and 1, or it can be constrained according to the study objectives or the researchers' belief.[8] Given the above specification, the conditional probability of a respondent i choosing option q out of all Q options in a choice scenario n can be represented as

$$P_{iqn} = \frac{\exp[(\sigma_{in}\beta + \gamma\Gamma v_i + (1-\gamma)\sigma_{in}\Gamma v_i)A_{qn}]}{\sum_{q'=1}^{Q}\exp[(\sigma_{in}\beta + \gamma\Gamma v_i + (1-\gamma)\sigma_{in}\Gamma v_i)A_{q'n}]}$$

[7] Although the current paper focuses on the observed scale differences attributable to the provision of information, the scale can also vary across individuals. Unobserved scale heterogeneity among individuals has long been recognized in the literature (Hensher, Louviere, and Swait, 1998).

[8] For example, Green and Hensher (2010), Hensher, Beck, and Rose (2011), and Czajkowski, Hanley, and LaRiviere (2015) all employed Type II GMXL, although none of them explicitly stated the reason for imposing such a constraint. One possible explanation is the numerical problem when using the logistic transformation for γ, as noted in Keane and Wasi (2013).

(5)

Hence, the simulated likelihood function, with R random draws on υ_i and ε_{0n}, for I respondents choosing a sequence of N choice scenarios with Q options in each scenario is

$$\mathcal{L} = \sum_{i=1}^{I} \frac{1}{R} \sum_{r=1}^{R} \prod_{n=1}^{N} \prod_{q=1}^{Q} (P_{iqn})^{c} \tag{6}$$

where $c = 1$ if respondent i chooses q in choice scenario n, and $c = 0$ otherwise.

The GMXL model is able to identify preferences with multimodal or heavy-tailed distributions of marginal utility, led by extreme behaviors such as near lexicographic preferences or highly random behavior at very low scale, and it thus outperforms the nested models[9] in terms of the model fit (Fiebig et al., 2010; Hess and Rose, 2012; Keane and Wasi, 2013).

In order to explore whether people pay more or less attention to attributes in choice questions when different information is provided, we apply the strategy proposed in Hess and Hess (2010). The analysis derives the posterior individual-specific coefficients following the "conditioning of individual tastes" strategy (Revelt and Train, 2000) to infer the level of attention respondents paid to attributes in choice questions. The individual-specific coefficients of marginal utility and its variance can be derived conditioning on the choices that a respondent makes for choice questions in choice experiments with multiple choice scenarios (i.e., repeated choice experiments). The individual-specific coefficients conditioning on the sequence of observed choices, c_{iN}, of respondent i for all N choice scenarios can be given by

[9] Some of the nested models are multinomial logit, scaled multinomial logit, and mixed logit models.

$$\beta_i = \sum_{r=1}^{R} \frac{P(c_{iN}|A_{qN}, \beta_r)}{\sum_{r=1}^{R} P(c_{iN}|A_{qN}, \beta_r)} \beta_r \tag{7}$$

where β_r is a draw from the estimated means and covariance matrix of marginal utility, and A_{qN} is a matrix comprising the attributes of all N scenarios. The details of this can be found in chapter 11 of Train (2009). Given the above, the individual-specific conditional variance of a particular element k, which measures the variability in β_i across all choice question,[10] can be written as

$$Var(\beta_i^k) = \sum_{r=1}^{R} \frac{P\left(c_{iN}\middle|A_{qn}, \beta_r\right)}{\sum_{r=1}^{R} P\left(c_{iN}\middle|A_{qn}, \beta_r\right)} (\beta_r^k)^2 - \left[\sum_{r=1}^{R} \frac{P\left(c_{iN}\middle|A_{qn}, \beta_r\right)}{\sum_{r=1}^{R} P\left(c_{iN}\middle|A_{qn}, \beta_r\right)} \beta_r^k\right]^2 \tag{8}$$

Hess and Hensher (2010) used this strategy to infer respondents' information processing strategies in choice experiments. They suggested that a respondent can be labeled as ignoring a certain attribute if the conditional mean of their taste parameter (elements in β_i) has very high uncertainty. They use the coefficients of variation for posterior individual-specific parameters to assess the uncertainty. That is to say, given the individual-specific mean of β_i, the higher the variation of β_i across choice questions, the less attention a respondent pay to the attributes. They also suggest a criterion – coefficient of variation greater than 2 for allocating respondents to the attribute non-attending group.

[10] The intuition of the individual variance of β_i is that a respondent can have different marginal utility for each attribute in each choice questions, because of effects such as learning or interactions with other attributes.

Survey Design and Data Description

The data used in this study came from a survey of citizen preferences for four landscape attributes of green infrastructure. The survey begins with questions about the places in which the respondents currently live and the characteristics that might guide choice of a new neighborhood. Before the choice questions, the survey provided respondents with background information about GI and the four landscape attributes being studied. Twelve choice questions were presented in randomized order to reduce the potential biases of ordering effect and respondent fatigue. The background context of the choice questions was asking respondents to imagine they had decided to move to a new home and were choosing where to live. Each choice question asked the respondents to choose between a pair of neighborhoods that have various landscape attributes associated with green infrastructure and cost. The survey offered three types of neighborhood with different housing densities from which respondents should choose, so the images describing the choice scenarios can better meet respondents' expectation when looking for a new neighborhood in which to live. The three types of neighborhood, from low to high housing density, are: detached houses on medium-size lots, detached houses on small-size lots, and townhouses and duplexes. Examples of the same choice scenario for three different housing densities are shown in Figures 1a, 1b, and 1c. The choice questions are followed by several debriefing questions regarding respondents' attitudes toward green spaces;[11] for instance, their potential concerns and general expectations.

The four landscape attributes – diversity in plant species, presence of water, percentage of green space mowed, and level of geometry (natural vs. designed appearance of plantings) - are some of the core elements in designing green infrastructure; their levels were identified through discussion with landscape architects. The levels of the four attributes are listed in Table 1. Diversity in plant species is used to represent commonly-discussed biodiversity in

[11] In current study, green spaces that constitute the visible aspects of green infrastructure are defined as unbuilt areas in a neighborhood with grass, shrubs, trees, or other vegetation and that are owned by a city, township, school district, neighborhood association, or utility company. It does not include lawns or vegetated areas on private properties.

environmental studies, because it is a dimension of biodiversity that can be near-perfectly controlled by landscape design and is easy for respondents to understand. Still, the survey does mention that green spaces with greater plant variety will tend to have more different types of birds, insects and other animals. The presence of water shows how long water will stay at the designed area after a rainstorm. “Always” indicates that there is always a pool of water (a retention basin) in the area. The level of “sometimes” is defined as water staying in the retention basin up to one day after the storm. “Never” means that water will run off immediately. The percentage of green space mowed is simply the percentage of public grassed-covered area that are mowed.[12] The level of geometry describes whether the edges of plantings are clearly defined and is a surrogate measure for the level of visible human intervention in shaping the landscape outcomes. “Formal” means that the plantings in a green space are placed in a neat pattern with well-defined edges. “Medium” shows that the edges are somewhat defined, while “informal” is when there are no apparent edges in planting, so the landscape has a naturalistic appearance. It is worth mentioning that no matter whether green spaces look highly “man-made” or display natural forms, they have been “designed” by landscape professionals. A cost attribute is included in the form of an additional annual home association fee.

This study develops three alternative survey treatments to measure the values of the four landscape amenities accompanied with GI to address the research interests. Hereafter, the three treatment versions are called: base, text-only, and image-only. The base version presents the choice scenarios with both images and text descriptions of the attributes. The image-only and text-only versions are designed identically to the base version, except for the presentation of the choice scenarios. The text-only version only includes only written depictions of each options attributes, and the image-only version only displays images to illustrate the landscape attributes of the options, while the cost attribute is still textually stated. The features of each version are summarized in Table 2.

An orthogonal fractional factorial main effect design was used to create a design with 12

[12] It is possible that people connect this attribute to the level of maintenance for the landscape.

choice sets using the SAS% ChoicEff macro.[13] Computer-rendered images were generated using terrain visualization software: Visual Nature Studio (VNS). The terrain of the neighborhood was exported to VNS from the Geographic Information System.[14] Rendered images from three different neighborhood view angles were composed into a single composite image, which is used in the survey to give the respondents an idea of the place as a whole.

The participants were recruited through the KnowledgePanel, a web-panel service provided by GfK Knowledge Networks.[15] In total, 499 valid samples were collected in March of 2016, with 159, 170, and 170 samples for the base, text-only, and image-only version, respectively.[16] The participants are possible home buyers who live in the suburban areas of the Chesapeake and Delaware Watersheds in the age range between 25 to 64 years old. The survey regions were filtered by population density at the zip code level to ensure that the survey setting was familiar and understandable for respondents. Only people who lived in a zip code with a population density of 500 - 5000 per square miles were targeted for recruitment. Detailed socio-demographic information of respondents, such as income, education, employment status, home ownership, and marital status, were provided through the KnowledgePanel database. A pretest with 131 panelists who lived in the same survey areas was conducted to identify the survey's potential flaws and ensure ultimate data quality.

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[13] A two-block design with 24 choice sets was also tested, and the simulation result did not show that this 24-choice design was superior to the 12-choice design. In addition, although a main effect design does not consider interactions between attributes, it is appropriate since there is no evidence that preferences for any pairs of attributes would likely be correlated.

[14] The mock-up neighborhood adopted the exact terrain of a neighborhood called "Butterfly Acres" in Lititz, PA.

[15] The households in KnowledgePanel were randomly chosen and the number of surveys in which they are allowed to participate is limited. In addition, KnowledgePanel provides computer and internet services for households without home internet access. These features allow KnowledgePanel to cover more than 95% of US households, and the sample representativeness is thus comparable to that using random digit dialing with cellphone samples. It can also provide detail demographic information

[16] After completing the fieldwork, 530 people completed the survey with a median completion time of 11 minutes. The samples were trimmed if a respondent completed the survey in less than five minutes or chose the same option across all choice questions to enhance the quality of the responses.

The socio-demographic information of samples for all three survey treatments are reported in Table 3. The chi-square tests for each socio-demographic variable in each sample cannot reject the null hypothesis that the distributions of the variables are not significantly different across the samples for each version. This indicates that the randomization was successful and no difference in the preferences should be attributed to the differences between the socio-demographic profiles of the samples in each version. Note that the proportion of female respondents is roughly double that of male respondents. As sample weights were provided by the KnowledgePanel and included in the estimation, this sampling bias should not change the results from those estimated using the entire targeted population. The socio-demographic variables used for generating the weights include gender, age, education, household income, and home ownership status.

Model Specification

Given the experimental design, for an individual i who takes survey treatment s, the deterministic components of the utility function for option q of scenario n can be written as

$$U_{isqn} = \sum_{s=1}^{S}(\beta_{1s}\text{MedSpc}_{sqn} + \beta_{2s}\text{HiSpc}_{sqn} + \beta_{3s}\text{SmWtr}_{sqn} + \beta_{4s}\text{AwWtr}_{sqn} + \beta_{5s}\text{Mow0}_{sqn} + \beta_{6s}\text{Mow30}_{sqn} + \beta_{7s}\text{Mow70}_{sqn} + \beta_{8s}\text{LowGeo}_{sqn} + \beta_{9s}\text{MedGeo}_{sqn}) + \beta_{C}\text{Cost}_{qn} + \varepsilon_{iqn}$$

Everything apart from the cost attribute in the models is dummy coded, where a "low" level of diversity in plant species (Spc), "never" presence of water (Wtr), "100%" area mowed (Mow), and "formal" level of geometry (Geo) are the basis for each attribute. See Table 1 for the names of the dummy coded variables. The above specification indicates that when samples from multiple versions are jointly used, the marginal utilities of the landscape attributes are separately estimated for each version. S indicates the number of treatments included in the model.

In recent studies using a mixed logit or GMXL model, it is common practice to assume that all parameters are randomly distributed and correlated (Green and Hensher, 2010; Hess and Hensher, 2010; Czajkowski, Hanley, LaRiviere, 2016). In addition, some studies assume a log-normal distribution for the cost (or price) parameter so that the parameter will have its theoretically correct sign and avoid the problem of infinite moments for the distributions of willingness-to-pay (Hensher, Rose, and Li, 2012). Given the relatively large number of parameters compared to the number of observations, this paper instead employs the assumptions of fixed cost parameter, all landscape attributes being normally distributed, and a restricted covariance matrix that only allows correlations between random parameters within each attribute and version (i.e., no correlation is allowed between different attributes. An illustration of the covariance matrix is shown in Table 4.[17]

[17] We examined the results using the assumption that all parameters were normally distributed and fully

In order to investigate the impacts of showing different information, samples from different versions are combined to estimate joint models. The first joint model combines the samples in the base and text-only versions, and examines the impacts of showing images in addition to text descriptions. The second joint model combines the samples in the base and image-only versions, and examines the impacts of including text descriptions. When the version dummy variables are included, the estimates of θ and λ in equation 4 reveal the impacts of different information on scale. Empirically, the value of γ would not drastically change the estimation results. In the case where $\sigma_{in} = 1$, γ indeed has no impact on the utility function. Therefore, the Type I GMXL models are estimated with $\gamma = 1$ to reduce unspecified correlations between the willingness-to-pay estimates.[18] Given the restricted covariance matrix structure in this paper, any scaling effect on the parameters will introduce correlations among them, even though researchers have no intention to do this (Train and Weeks, 2005). Note that given the current setting, σ_{in} reduces to σ_i, since no scale heterogeneity resulting from different scenarios is specified. All GMXL model estimations are executed using a Matlab package, Models for Discrete Choice Experiments (Czajkowski, 2016), using 500 Halton draws.

correlated. Most mean estimates for the WTP were not significantly different from those using the current setting.

[18] We ran the Type I, Type II GMXL and the GMXL model without constraints on γ. The results did not suggest any qualitative difference.

Empirical Results

This section starts by reporting the estimation results of the Type I GMXL models using samples from each version and the general patterns of citizen preferences for the landscape attributes of green infrastructure. The differences between results for each sample and thus the impacts on taste and scale parameters of scenario visualization are then presented. This section concludes with explanations for such impacts by exploiting the information regarding attribute non-attendance derived from posterior individual-specific parameters.

In this section of results, diversity in plant species is referred to as "diversity" with high, medium, and low levels; the presence of water is referred to as "water" with permanent, intermittent, and no; the percentage of green spaces mowed is referred to as "area mowed" with 100%, 70%, 30%, and 0% levels; and the level of geometry is referred to as "pattern of plantings" with formal, intermediate, and informal levels.

Preferences on the Landscape Attributes of Green Infrastructure

The results of the GMXL models using each of the three samples are presented in Table 5, and the corresponding willingness-to-pay (WTP) for the landscape attributes are shown in Table 6. High diversity is viewed as an amenity, although its estimate in the image-only version is of marginal significance. The WTPs for high diversity is spread across $20 to $66 in terms of the annual homeowner association fee. Respondents also showed a positive attitude towards medium diversity when described verbally. The finding that people are in favor of diversity is consistent with the majority of studies that look at the preferences for biodiversity (e.g., Birol, Karousakis, and Koundouri, 2006; Christie et al., 2006; Hanley, Wright, and Adamowicz, 1998). The significant estimates of permanent water across all three models indicate that people are greatly worried about whether the designed green spaces always have a pool of water, and the WTPs for avoiding such a design are $66 to $118. Even intermittent water, which drains within one day after a rainstorm, is unfavorable when illustrated using the images.

The preferences for area mowed show fairly different patterns across the three samples. People prefer medium levels of area mowed (30% and 70%) to the two extreme levels when the attribute is illustrated with both images and text descriptions. However, in the image-only samples, on average none of the level of area mowed is visually preferred to one another, while people have very heterogeneous preferences for each level. When images are absent, 0% area mowed is clearly viewed as a disamenity. This can be attributed to people's concerns such as the green spaces being not accessible or becoming overgrown. Some locations legislate against leaving areas to grow, as this is thought to symbolize a lack of care and municipalities believe that such areas harbor vermin – rats, snakes, and bad insects. Lastly, the pattern of plantings is generally viewed indifferently by the respondents.

The WTPs for landscape attributes vary greatly when respondents received different information. For example, when respondents were presented with both text and images, they were willing to pay three times more for more diversity and at least 78% more to avoid permanent water, than when presented with either only text or images. These results suggest that people's choices can be influenced by different information and pose a question for researchers: which set of WTPs should be used to inform policy? Overall, respondents consistently placed positive values on diversity and negative values on water, while the level of area mowed and whether the pattern of plantings was formal were of less concern. Considerable taste heterogeneity is identified through the significant standard deviation coefficients for all taste parameters except those of the pattern of plantings.

Impacts of Information Treatments on Taste Parameters

In the model results presented in Table 7a, the samples from the base and text-only versions are combined to estimate the GMXL model with the inclusion of covariates on scale parameters. The results shown in Table 7b are of the model estimated using samples from the base and image-only versions. The parameters of the landscape attributes from each version are estimated separately, but the cost parameter is set as equal across the two samples to achieve identification. The differences between the mean values of the coefficients and their asymptotic *t*-ratios are presented in Table 8.

The impacts of providing different information on people's tastes can be summarized as follows: when both images and text descriptions are used to describe choice scenarios, respondents exhibit significantly stronger preferences for diversity and water attributes, compared to those in the treatments where only either text or images were offered. When scenarios are shown with both images and text, the relative importance of diversity is at least three times greater than those when a sole type of information is shown (e.g., for high diversity, 1.4695 vs. 0.2872 and 1.9048 vs. 0.6060). This pattern is also observed in the WTPs reported in Table 6. A similar pattern is identified in preferences for water: the coefficients in the base version samples are of significantly greater magnitude than those in the other two samples.

In Table 7b, significant estimates for diversity and water in the image-only version samples prove that a landscape with high diversity is visually preferable, and water is also visually salient but viewed as a disamenity. Observing the similar WTPs (Table 6) and the coefficients of diversity and water in the text-only and image-only samples (Tables 7a and 7b), the values suggest that images are as effective as text descriptions at conveying these two landscape attributes with high visual salience. A noticeable impact of showing images on the preferences for area mowed is that the visual stimuli ease people's concerns for 0% area mowed in text-only samples, when both images and text depictions are offered. Lastly, the coefficients of pattern of plantings do not significantly differ across samples.

Though no formal tests were performed, the relative standard deviations measured by the coefficient of variation for the diversity and water attributes are generally greater in text-only and image-only versions than in the base version. This pattern suggests that respondents could better understand what the attributes and their levels exactly mean when shown a more complete information set, and they could thus make their decisions based on the information that the researchers intended to provide.

In summary, people's preferences regarding landscape attributes can be largely underestimated without proper information that describes the attributes, and both visual representations and verbal descriptions can help respondents better understand what they are being asked to value. Although why respondents expressed different preferences when provided different information is more of a landscape design issue and beyond the scope of the current paper, this paper suggests some caveats regarding the use of visual representations. First, respondent could have read more information from images than what the researchers intended to offer. For example, respondents might see the scenarios in this study are different in terms of whether the green spaces are well maintained and if the water area is accessible. [19] In addition, more unobserved attributes can be created by the interactions between landscape attributes (Dramstad et al., 2006). Lastly, images might not be able to adequately capture the dynamic aspects of attributes, such as how long the water stays in the current study. Fortunately, with extra care, these issues can be identified and addressed in the survey design and pretest processes.

Impacts of Information Treatments on Scale Parameters

In Tables 7a and 7b, the two positively significant estimates of θ indicate that the mean scale is lower when the respondents are provided with both images and text descriptions of choice scenarios. That is, on average, the base sample responses are more random than the responses in the text-only and image-only samples. This finding may be striking at first, but it may actually be more logical than the other way around.

Essentially, such an impact can be created by increasing the complexity of choice tasks. Extra images or text descriptions make the information set both more "complete" and more "diverse." We argue that completeness is a property that can facilitate the decision-making process, while diversity is a property requiring more cognitive processing. Therefore, the lower mean scale parameter when extra information is supplied can be considered as a result of the effect of higher information diversity outweighing the effect of higher information completeness. This study does not argue against the fact that some respondents can make

[19] These two attributes are associated with the aspect of engagement in the landscape. Humans by nature like environments that offer opportunities for meaningful engagement, so a landscape with no apparent sign of human activity was likely to be unfavorable (Kaplan and Kaplan, 1989; Zacharias, 2001).

decisions more easily when extra information is provided, but such consequences are less likely to happen in the current study. Images and text descriptions are very different psychological stimuli, and respondents who answer the base version are asked to process two types of stimulus for each choice question.

Why would complexity make choices more random? One explanation is that people might not be able to precisely evaluate the total utility of each option for each choice when the complexity of their choice task increases. This is the situation where people find making a choice difficult because they know too much and they finally just go with their gut.[20] Another explanation is that humans tend to use automatic processes in cognitive processing to process visual information, while automatic processes are less systematic than their counterpart, controlled processes, which are used to handle textual information. Townsend and Kahn (2014) found that providing visual depictions can make consumers less likely to pick their best option when the choice set is large.

Another rather different interpretation of this finding from a more economics perspective is that people behave more extremely when information is sparse or insufficient. This interpretation is in agreement with the argument in Fiebig et al. (2010), who suggested that people's behavior is less extreme when the choice tasks are more complex. In the context of the current study, when only text descriptions are provided, some "nature lovers" would make their choices solely based on the attribute of diversity (e.g., always go with the option with higher diversity) and ignore other attributes. That is, they have lexicographical behavior. When images were provided, they might realize that they also wanted to see water near the houses, which meant that they now needed to make a tradeoff. van der Wal et al. (2014) also found that the provision of new information of which people were not formerly aware could

[20] For example, someone is choosing a new place to live in from two candidate apartments that are similar in every way but a neighbor lives next door. If information about the neighbors is revealed then the decision would be easy, but the final decision will be made randomly otherwise. This is a case in which more information makes the decision less random, i.e. completeness is added with barely any additional diversity. Picking a college might not be too difficult for some high school graduate-to-be: reasonable tuition, good reputation, and great sport teams. However, when they are told how to assess whether the tuition is reasonable or what a good reputation really means, their decision can become harder because things are unlike what they thought in their naiveté. One distinction between these two cases is whether the new information is what a person wanted to know to make their choice before they received the information.

make people less likely to uphold extreme behavior in their landscape preferences. A similar story can be found between the image-only and base version samples. People might not realize that the images actually illustrate four landscape attributes, so their decisions were made based on the fewer characteristics that they have observe. Once the text descriptions are attached, they need more cognitive effort to consider more attributes and the exact levels, so the decision process is no longer that simple.

The significant τ in Table 7a indicates that the scale parameter is heterogenous across respondents. Although the τ in Table 7b is not significant, its magnitude is comparable to that in Table 7a. The insignificant estimates of λ in Tables 7a and 7b suggest that the variability in scale parameter is not affected when the respondents are provided with different information.

Among the two of the studies investigating the impact of information provision on the scale parameters, Czajkowski et al. (2016) found that giving a more complete information set regarding biodiversity conservation programs made respondents give more predictable choices (i.e., higher mean scale parameter). However, Lusk et al. (2008) found the opposite in their experiment when providing more information about the benefits of grass-fed beef. The treatment performed in the latter study was directly linked to a certain attribute (grass-fed or not), so the complexity of the choice tasks could be increased when the extra information was new to the respondents or when an attribute was previously ignored by some respondents in the case where the extra information was absent. This explanation is consistent with that proposed in the previous paragraph. However, the treatment carried out in Czajkowski et al. (2016) involved much more than just adding information about the attributes. The alternate version of their survey was rewritten according to the feedback of a group of stakeholders and intended to provide a more comprehensive context for respondents. The revised survey emphasized the positive impacts and consequences of the program in which they were interested in, so respondents' preferences could be somewhat guided in favor of biodiversity conservation. It should be no surprise that their conclusion regarding the impact of the scale is considerably different from those of the current paper and of Lusk et al. (2008).

Impacts of Information Treatments on Attribute Non-attendance (ANA)

The previous subsection indicates that respondents make more random choices when provided with both images and text, and we propose two main hypotheses for such an impact: (1) respondents need to evaluate the tradeoffs between more attributes, and (2) the information from both images and text is too much and thus leads to cognitive overload. Although it is unlikely that we can test the first hypothesis given the available data, it is possible to test whether respondents indeed received the extra information and take that into consideration. Therefore, this section examines if respondents paid more attention to (or were less likely to ignore) the attributes when provided extra information, using the strategy proposed by Hess and Hensher (2010). In essence, the results indicate that providing images alone can draw a similar level of attention to using text descriptions, and respondents do pay more attention to attributes when more information is offered. The latter finding suggests a potential information overload problem resulting from the provision of extra information.

The coefficients of variation (C.V.) for posterior individual-specific parameters of attributes are used to assess the level of attention, where a higher C.V. equates to a low level of attention. The individual-specific means and standard deviations that are conditional on the observed choices of each respondent are derived according to the three GMXL models with samples from each survey treatment, which generated the results in Table 5. The means and medians of the individual-specific C.V. and the percentage of respondents who did not pay attention to the level of diversity and water are reported in Table 9. A respondent is recognized as not attending a level for an attribute if the corresponding C.V. was greater than two. Although this value is determined rather arbitrarily (Hess and Hensher, 2010), it is considered reasonable. If given a C.V. that equals two, the probability of the mean being not significantly different from zero is approximately 30%. Still, the means and medians of the C.V. are presented as robustness checks for whether the numbers suggest consistent implications regarding the levels of attention paid.

The rates of not attending any specific level of attribute were lowest among the respondents who took the base version survey, except for that of not attending medium level of diversity. In particular, the rates of ANA for high diversity and permanent water in the base version samples were less than half of that for the text-only version samples. This suggests that people are twice as likely to ignore the diversity and water attributes when the choice questions are not described by images.[21] The means and medians of the individual-specific C.V.s for the base version samples were lowest among all three samples. These patterns consistently showed lowest uncertainty for the posterior distributions conditioned on the observed choices in the base version samples, and supported the claim that respondents paid more attention to attributes when extra information was provided. In addition, stronger preferences for diversity and water in the base version sample can be partly ascribed to the lower prevalence of ANA.

The ANA rates and the median C.V. for diversity and water in the image-only version sample were lower than in the text-only version sample. This implies that, to the majority of respondents, images alone can attract greater attention to diversity and water, the two attributes with high visual salience, than text descriptions. The provision of extra images, in addition to text, decreases the rates of ANA on the levels of diversity and water, and thus strengthens the preferences in the population level. Such impacts from the provision of images are attributable to the notion that photographs can increase people's curiosity and enhance the clarity of their stated preferences (Barroso et al., 2012).

The results suggest that people are better informed and pay more attention to each attribute when both types of media are provided to describe choice questions. However, perceiving too many attributes could overload respondents' cognitive processes and force them to choose more randomly across all scenarios. This explains the lower mean scale for the base version samples. It is worth mentioning that the results do not show the noticeable

[21] Note that focusing on the rates for high diversity and permanent water, whose parameters are statistically significant across all models, is comparatively more insightful than looking at the rates for other attribute levels. The employed approach tends to identify more respondents who ignore an attribute when the conditional mean of a posterior distribution is closer to zero. ANA rates can also largely change when different base levels for each attribute are used in dummy coding.

portion of respondents who did not attend to any attributes in the choice questions, i.e., entirely ignored the questions. No more than three respondents were identified as not attending to both the diversity and presence of water attribute in any of the three samples. Hence, the results reported in this section are likely demonstrative of the pattern regarding ANA, but not of "question non-attendance," which is one of the least desirable things to see in a choice experiment.

Finally, it is important to clarify the difference between preference uncertainty for a certain attribute, which can be measured in this subsection using the coefficient of variation, and randomness when making choices, which is measured by a scale parameter. The preference uncertainty for a certain attribute shows how well people know their value for an attribute. This study proposes that, people will be less likely to ignore attributes and better informed on the condition of the attributes when more information is provided, so the preference uncertainty for a certain attribute thus can be lower. However, the randomness of making choices across all choice scenarios can still be higher due to the greater information received as discussed in the previous subsection.

Conclusions

Employing visual representations to demonstrate choice scenarios in stated preference surveys is a long-standing practice, particularly when the research questions are associated with landscapes. However, the impacts of such practices on preference were largely unknown, despite the fact that the policy implications can be greatly influenced by the use of visualizations. This paper conducts a choice experiment with three survey treatments to fill the gap in the literature. The three survey treatments provided different information regarding the choice scenarios, where one treatment used both images and text descriptions to describe the choice scenarios, one only used text descriptions, and one only used images. The impacts on people's choices of showing images and text descriptions are identified by the paired comparisons between treatment results. The data is from a survey that looks at citizen preferences on salient landscape attributes of green infrastructure. The findings also enhance the understanding of such preferences and can be used as a guide for the GI designs.

The results suggest that images alone are as effective as text alone at conveying landscape attributes with high visual salience, such as variety of plant species and the presence of water. When respondents were presented with both text and images, they exhibited stronger preferences for those visually salient landscape attributes and were less likely to ignore those attributes than when presented with either only images or only text. Therefore, this paper argues that providing both images and text helps respondents better understand choice questions and more accurately state their preferences for given scenarios. Although people pay more attention to individual attributes in choice questions with the provision of visual representations, the extra visual stimuli also increase choice randomness (measured by a scale parameter), which is indicative that respondents are less certain whether they picked their preferred options for each choice question. This may be attributed to the cognitive overload caused by paying more attention to the questions.

In terms of the preferences for GI landscape attributes, the results show that people highly prefer richer variety in plant species, while having water present in green spaces is clearly unfavorable. Given the assumption that people can better understand planned landscape changes when using images and text together, the estimates for the taste parameters of the two attributes just mentioned, which have high visual salience, are significantly underestimated (in magnitude) when not illustrated with images or text. For example, when both images and text are offered, on average people are willing to pay three times more for higher plant varieties and at least 78% more to avoid water in green spaces, compared to those in the cases where only text or images are used to describe the choice questions. In addition to GI's hydrological benefits, homeowners' acceptance of GI also depends on whether they can understand and accept the potential landscape changes and associated environmental benefits that result from introducing GI to their neighborhoods. Therefore, it is necessary to provide both images and text descriptions in choice experiments to accurately capture the values that people place on visually salient attributes.

This paper concludes that including visual representations is preferable when using choice experiments to value landscape-related issues. In addition, accurate visualizations are essential to prevent biased results, given the findings that responses are susceptible to the method used to convey questions. Furthermore, researchers should be aware of the potential problem of providing excessive information and making people give exorbitantly random responses. It requires future research to investigate the optimal amount of information when describing landscape attributes in choice experiments, i.e., the amount of information that can help respondents best understand the questions without overwhelming them and making them answer questions randomly. Moreover, the determinants of making the choice questions easier or harder are worth exploring. In particular, studies have shown that people's experience and familiarity with a landscape are related to their corresponding preferences (Rogge, Nevens, and Gulinck, 2007; Scott et al., 2009). Incorporating experience and familiarity with a landscape and associated amenities into the analysis is a promising line for future research to complement the investigation of how different visual information can affect people's choices.

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Tables and Figures

Table 1. Landscape Attributes and Levels of Green Infrastructure

Attributes	Variety in Plant Species (Diversity)	Presence of Water (Water)	Percentage of Mowed Area (Area Mowed)	Level of Geometry (Pattern of Plantings)	Cost
Levels	High (HiSpc) Medium (MedSpc) Low*	Always (AwWtr) Sometimes (SmWtr) Never*	0% (Mow0) 30% (Mow30) 70% (Mow70) 100%*	Informal (LowGeo) Intermediate (MedGeo) Formal*	$110 to $0

*: Base levels

Table 2. Survey Treatments

Survey Version	Including Images in Choice Questions	Including Texts in Choice Questions
Base	Yes	Yes
Text-Only	No	Yes
Image-Only	Yes	No

Table 3. Socio-Demographic Profiles of Respondents by Survey Version

	Base (n = 159)	Text-only (n = 170)	Image-only (n = 170)
Mean Age	50.51	47.81	50.54
Female	63.52%	68.24%	65.88%
College Educated	57.86%	53.53%	60%
Live in Single Family Houses	69.81%	62.94%	66.47%

Table 4. Covariance Matrix Structure

	$Att1.1^a$	$Att1.2^a$	$Att2.1^a$	$Att2.2^a$	…	$Att1.1^b$	$Att1.2^b$	$Att2.1^b$	$Att2.2^b$	…	Cost
$Att1.1^a$	#	#									
$Att1.2^a$	#	#									
$Att2.1^a$			#	#							
$Att2.2^a$			#	#							
…					#						
$Att1.1^b$						#	#				
$Att1.2^b$						#	#				
$Att2.1^b$								#	#		
$Att2.2^b$								#	#		
…										#	
Cost											#

Note: Att t.l stands for the level l of attribute t, and

a: Base Version Samples

b: Text-only or Image-only Samples

#: Free parameters to be estimated

Table 5. Results of the GMXL Models for Each Single Version

		Base		Text-Only		Image-Only	
Attribute	Level	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
		Mean					
Diversity	Medium	1.3999***	0.2751	0.5417***	0.1846	0.1027	0.3390
	High	1.7415***	0.3570	0.8127***	0.2158	0.6462*	0.3514
Water	Sometimes	-0.7290***	0.1624	-0.1254	0.1681	-0.4553***	0.1104
	Always	-3.1396***	0.3617	-2.4801***	0.3429	-2.1697***	0.3699
Mowed	0%	0.3627	0.3499	-1.4790***	0.3578	-0.2273	0.3699
	30%	0.6117**	0.2527	0.2693	0.2643	0.0358	0.2612
	70%	0.9643***	0.2865	0.6080**	0.2492	-0.2981	0.3174
Geometry	Medium	-0.1403	0.1631	0.1801	0.1763	-0.3298*	0.1741
	High	0.1915	0.2509	-0.4227*	0.2499	-0.2986	0.1835
Cost		-0.0266***	0.0050	-0.0376***	0.0064	-0.0319***	0.0055
		Standard Deviations					
Diversity	Medium	1.6432***	0.2361	1.3119***	0.2492	2.4934***	0.2795
	High	2.4346***	0.3269	1.5469***	0.2203	2.2105***	0.2844
Water	Sometimes	1.1912***	0.2150	1.4400***	0.2151	0.5743***	0.1831
	Always	2.8573***	0.3523	2.7042***	0.2801	2.8129***	0.3231
Mowed	0%	1.7704***	0.3292	2.6765***	0.3468	0.6380	0.4762
	30%	1.1559***	0.3032	1.7347***	0.2876	0.7591*	0.4093
	70%	0.7815**	0.3502	1.0455***	0.3470	1.0382**	0.4379
Geometry	Medium	0.3281	0.2427	0.4398	0.2639	0.5538***	0.1880
	High	0.6642*	0.3400	1.2799***	0.2553	1.1019*	0.6235
τ		0.6870	0.5966	1.0387***	0.3552	1.1497**	0.5169
Log-Likelihood Ratio		-845.87		-1006.8		-999.19	
Observations		1908		2040		2040	
Parameters		26		26		26	

*, **, ***: Significant at the 10%, 5%, and 1% levels, respectively

Table 6. Willingness-to-pay for the Landscape Attributes of Green Infrastructure

		Base		Text-only		Image-only	
Attribute	Level	Mean	S.D.	Mean	S.D.	Mean	S.D.
Diversity	Medium	52.65*	61.80*	14.42*	34.93*	3.22	78.10*
	High	65.50*	91.57*	21.63*	41.18*	20.24	69.23*
Water	Sometimes	-27.42*	44.80*	-3.34	38.34*	-14.26*	17.99*
	Always	-118.09*	107.46*	-66.02*	71.99*	-67.96*	88.10*
Mowed	0%	13.64	66.59*	-39.37*	71.25*	-7.12	19.98
	30%	23.01*	43.48*	7.17	46.18*	1.12	23.77
	70%	36.27*	29.39*	16.19*	27.83*	-9.34	32.52*
Geometry	Medium	-5.28	12.34	4.80	11.71	-10.33	17.34*
	High	7.20	24.98	-11.25	34.07*	-9.35	34.51

*: Significant at the 5% level.

Table 7a. Results of the GMXL Model with the Base and Text-only Version Samples

		Base		Text-only	
Attribute	Level	Coeff.	S.E.	Coeff.	S.E.
		Mean		Mean	
Diversity	Medium	1.3069***	0.2533	0.3321**	0.1633
	High	1.4695***	0.3231	0.2872*	0.1489
Water	Sometimes	-0.6728***	0.1793	-0.1004	0.1001
	Always	-3.0862***	0.3319	-1.6584***	0.1749
Mowed	0%	0.2443	0.3634	-1.0908***	0.2854
	30%	0.5830**	0.2353	0.0881	0.1963
	70%	1.0127***	0.3452	0.2725	0.1770
Geometry	Medium	-0.0819	0.1703	0.1397	0.1144
	High	0.1173	0.3156	-0.2538**	0.1183
Cost		-0.0250***	0.0034	Equal across samples	
		S.D.		S.D.	
Diversity	Medium	1.7222***	0.2465	0.9115***	0.1608
	High	2.5421***	0.3171	1.0135***	0.1247
Water	Sometimes	1.1287***	0.2210	0.9736***	0.1427
	Always	2.4316***	0.3224	1.8128***	0.1877
Mowed	0%	1.6768***	0.3576	1.7778***	0.1988
	30%	1.3008***	0.3204	1.2342***	0.1569
	70%	0.9953**	0.4184	0.7581***	0.1755
Geometry	Medium	0.5122	0.3848	0.2732*	0.1444
	High	0.7296*	0.3989	0.7499***	0.1786
θ		0.3419***	0.1202		
τ		0.9990**	0.4729		
λ		-0.2740	0.6239		
Log-Likelihood Ratio		-1858.9			
Observations		3948			
Parameters		52			

*, **, ***: Significant at the 10%, 5%, and 1% levels, respectively

Table 7b. Results of the GMXL Model with the Base and Image-only Version Samples

		Base		Image-only	
Attribute	Level	Coeff.	S.E.	Coeff.	S.E.
		Mean		Mean	
Diversity	Medium	1.5228***	0.2961	0.1717	0.1673
	High	1.9048***	0.4127	0.6060***	0.1640
Water	Sometimes	-0.7569***	0.1847	-0.3902***	0.0846
	Always	-3.3878***	0.3352	-1.8633***	0.2298
Mowed	0%	0.3553	0.4075	-0.2606	0.2135
	30%	0.6395**	0.2601	-0.0054	0.1759
	70%	1.0190***	0.3220	-0.2811	0.1893
Geometry	Medium	-0.1279	0.1946	-0.2579**	0.1245
	High	0.1747	0.3385	-0.2682**	0.1357
Cost		-0.0276***	0.0029	Equal across samples	
		S.D.		S.D.	
Diversity	Medium	1.7226***	0.2736	1.9654***	0.1762
	High	2.7689***	0.3821	1.8411***	0.1910
Water	Sometimes	1.2752***	0.2200	0.6471***	0.1432
	Always	2.5475***	0.3275	2.5903***	0.2247
Mowed	0%	1.9796***	0.3157	0.2890*	0.1734
	30%	1.3418***	0.3372	0.5256***	0.2033
	70%	0.9208**	0.3876	0.7173***	0.2064
Geometry	Medium	0.3867	0.2660	0.6158***	0.1302
	High	0.7857*	0.4053	0.5222***	0.1892
θ		0.4751***	0.1428		
τ		0.8638	0.6606		
λ		0.2932	0.6700		
Log-Likelihood Ratio		-1812.5			
Observations		3948			
Parameters		52			

*, **, ***: Significant at the 10%, 5%, and 1% levels, respectively

Table 8. Differences of Mean Estimates between Treatments

		Base vs. Text-only		Base vs. Image-only	
Attribute	Level	Difference	t-ratio	Difference	t-ratio
Diversity	Medium	0.9747***	3.2338	1.3511***	3.9730
	High	1.1823***	3.3230	1.2988***	2.9245
Water	Sometimes	-0.5724***	2.7879	-0.3667*	1.8051
	Always	-1.4278***	3.8056	-1.5245***	3.7512
Mowed	0%	1.3351***	2.8891	0.6158	1.3386
	30%	0.4949	1.6149	0.6450**	2.0542
	70%	0.7402*	1.9080	1.3001***	3.4807
Geometry	Medium	-0.2217	1.0808	0.1299	0.5625
	High	0.3710	1.1010	0.4428	1.2142

*, **, ***: Significant at the 10%, 5%, and 1% levels, respectively

Table 9. Rates of Attribute Non-Attendance on Diversity of Plant Species and Presence of Water

	Percentage of ANA			Average Coefficient of Variation			Median Coefficient of Variation		
	Base	Text -only	Image -only	Base	Text -only	Image -only	Base	Text -only	Image-only
Diversity									
Medium	8.81	14.47	4.12	3.932	5.578	7.026	0.711	1.341	0.786
High	7.75	15.75	10.59	1.347	2.799	1.825	0.778	1.555	0.909
Water									
Sometimes	4.40	13.21	14.12	1.257	2.718	2.660	0.587	1.146	0.836
Always	3.14	6.29	9.41	1.510	1.698	3.102	0.441	0.675	0.589

Figure 1a. Example Choice Question with Low Housing Density

Neighborhood A		Neighborhood B	
Diversity in Species	Low	Diversity in Species	High
Standing Water	Never	Standing Water	Always
Percentage of Green Space Mowed	30%	Percentage of Green Space Mowed	70%
Annual Homeowner Association Fee	$100	Annual Homeowner Association Fee	$50
○		○	

Figure 1b. Example Choice Question with Medium Housing Density

			
Neighborhood A		Neighborhood B	
Diversity in Species	Low	Diversity in Species	High
Standing Water	Never	Standing Water	Always
Percentage of Green Space Mowed	30%	Percentage of Green Space Mowed	70%
Annual Homeowner Association Fee	$100	Annual Homeowner Association Fee	$50
○		○	

Figure 1c. Example Choice Question with High Housing Density

Neighborhood A		Neighborhood B	
Diversity in Species	Low	Diversity in Species	High
Standing Water	Never	Standing Water	Always
Percentage of Green Space Mowed	30%	Percentage of Green Space Mowed	70%
Annual Homeowner Association Fee	$100	Annual Homeowner Association Fee	$50
○		○	