Does stated happiness affects preferences for urban green spaces? An analysis of stated residential choices

Gengyang Tu

Ph.D. student, INRA, UMR 356 Laboratoire d'Economie Forestière, France

AgroParisTech, Laboratoire d'Economie Forestière, France

Address: Laboratoire d'Economie Forestière, 14 rue Girardet, 54000 Nancy, France

E-mail address: gengyang.tu@nancy.inra.fr

Jens Abildtrup

Researcher, INRA, UMR 356 Laboratoire d'Economie Forestière, France

AgroParisTech, Laboratoire d'Economie Forestière, France

Address: Laboratoire d'Economie Forestière, 14 rue Girardet, 54000 Nancy, France

E-mail address: jens.abildtrup@nancy.inra.fr

Abstract

This paper examines the influence of people's stated happiness on their preferences for urban green spaces on the basis of their residential choice. We applied a choice experiment (CE) that focuses on trade-offs between private housing characteristics and the environmental aspects of neighborhood. To estimate the impact of happiness on respondents' preferences for urban green spaces, the stated residential choice data is combined with self-reported happiness data. Accounting for the potential endogeneity of the stated happiness data, the results show that happiness have a positive impact on people's willingness to pay for living close to urban parks and forest.

Key words:

Discrete Choice Experiment; Integrated Choice and Latent Variable model; Housing attributes; Happiness; Consumer behavior;

1. Introduction

Psychological studies have provided strong support for the idea that positive emotions, such as happiness, may play an important role in people's decision-making process. For instance, when people are in a positive mood, they are more likely to engage in heuristic processing (Schwarz and Clore 1983), or to be optimistic about favorable events occurring (Wright and Bower 1992). Consumer behavior studies provide further evidence that being in a positive mood affects individuals' cognitive processing, which can influence the types of choices they make. Consumers with positive emotions tend to orient attention to abstract construal rather than focus on immediate and proximal concerns (Labroo and Patrick 2009), and to evaluate objects more favorably (Adaval 2003; Forgas and Ciarrochi 2001; Isen and Shalker1982; Meloy 2000). It is, for example, shown that consumers in a state of positive emotion are more likely to choose more variety across options (Kahn and Isen 1993), or prefer healthy foods over indulgent foods (Gardner et al., 2014).

In the environmental evaluation literature, a large number of studies prove that environmental elements, such as noise (Van Praag and Baarsma, 2005; Weinhold, 2013), flood (Luechinger and Raschky, 2009), air pollution(Ferreira et al., 2013a; Levinson, 2012; Welsch, 2002; 2006; 2007;) and environmental amenities (Brereton et al., 2008; Ferreira and Moro, 2010; 2013b; Smyth et al., 2008;), have an significant impact on people's stated happiness. In urban green spaces, But conversely, the impact of happiness on people's preferences for environmental attributes has so far received scant attention.

Discrete choice model (DCM) has been increasingly applied for the analysis of choice behaviors using experimental design data, such as residential location choice (Haefen and Phaneuf, 2008; Phaneuf et al., 2013, Liao, et al., 2015). Numerous studies have proposed alternative discrete choice models to represent a behaviorally more realistic choice process, e.g. accounting for the respondents' characteristics. Including such information has, among others, served to explain preference heterogeneity in the population (e.g. Yoo and Ready 2014). However, an important potential caveat is to include measures of the decision-makers' latent attitudes as explanatory variables of preferences. Incorporating responses to attitudinal questions as measures of underlying attitudes may lead to measurement error and endogeneity bias due to omitted variables (Ben-Akiva et al. 1999; Ashok, Dillon, and Yuan 2002; Ben-Akiva et al. 2002; Bolduc et al. 2005; Hess and Beharry-Borg 2012). An appropriate method to address this is applying the Integrated Choice and Latent Variable (ICLV) model. The ICLV model is a discrete choice model includes latent variables that capture attitudes and perceptions of the decision makers. The latent variable model is composed of a group of structural equations describing the latent variables as a function of observable exogenous variables, and a group of measurement equations, linking the latent variables to observable indicators.

This study investigates the influence of people's stated happiness on their preferences for urban green spaces on the basis of their stated residential choice. A survey which collects stated preference data from a choice experiment. To measure the effect of stated happiness on choice decision, an ICLV model was applied. The paper contributes to the understanding of the preference heterogeneity of the population, focusing on the impact of respondents stated happiness on choices between hypothetical residential locations.

2. Method

2.1. Discrete Choice experiment methodology

The DCE approach combines Lancasterian consumer theory (Lancaster, 1966), random utility theory (RUM, McFadden, 1974), experimental design theory and econometric analysis. Pioneered by Adamowicz et al. (1994), the CE has become a popular stated preference (SP) method for environmental valuation (Hanley, 2002; Abildrup et al., 2013). The central assumption of the CE method is that the utility derived from any option depends on the attributes/characteristics of the goods. Within a DCE, individual DCE questions are typically framed to imitate actual consumer purchasing situations where respondents are asked to choose between two or more alternatives. Resulting choices reveal an underlying (latent) utility function. Respondents' stated choices is then used to estimate the consumer's utility function. Numbers of studies explain the details on conducting a DCE and theoretical issues (Louviere et al., 2000; Hensher et al., 2005; Hess and Daly, 2014).

In this article, we chose to estimate preferences with a RUM model using SP data obtained from a CE to estimate people's preference for access to green spaces. More specifically, we focus on the trade-offs between private housing characteristics and the environmental attributes. In housing market studies, one challenge is the large number of potential attributes that have an impact on housing prices and the multicollinearity among these attributes may complicate estimations. Multicollinearity may be caused by the fact that households with the same preferences (and same socio-demographic characteristics) will choose the same location (Irwin, 2002).Using a CE, we are able to avoid multicollinearity among attributes since attribute levels are considered to be orthogonal in experimental designs (Earnhart, 2002). Applying a CE, we could also avoid the problem of omitted variable bias which may seriously undermine the model's ability to accurately estimate economic values (Bockstael and McConnell, 2006). For instance, unobservable neighborhood characteristics that matter to households are often expected to be correlated with the amenity of interest or other independent variables (Kuminoff et al., 2010). In our case, the attributes of interest, access to green spaces, are specified in an experimental design. Therefore, before the respondents make their choices between different housing alternatives, we ask them to only consider the attributes specified in the experiment while considering that all other attributes (e.g., crime rates) are the same as in their current housing situation.

2.2. Experimental design

Important decisions should be made at the design stage, which includes identifying relevant residential attributes and the attribute levels. Our study aim to focus on respondents' trade-offs between private housing characteristics and the environmental attributes of a neighborhood. The number of attributes is limited to five to focus respondents' attention on attributes of interest and to reduce the cognitive burden in making the choices. The experimental design in this study is based on the experiences from a previous study based on a face-to-face survey in Nancy carried out in 2013 (Tu et al., 2016).

A pivot-style experimental design is applied where the hypothetical alternatives are pivoted around the reference alternative. The reference alternative in our CE is the respondent's actual residence. During the interview, respondents are first asked to describe their current residence with respect to the selected attributes. They are then requested to choose between three residential options amongst which one is their actual house and the other two hypothetical alternatives are described in relation to the attributes of their current residence with some change of the attributes. The pivot-style experimental design makes the choice task more realistic and can provide greater specificity than the standard approach where the hypothetical alternatives are defined independently of the respondents' current situations (Hensher and Green, 2003; Hensher, 2004, 2006; Hensher and Rose, 2007; Train and Wilson, 2008). As the number of attributes in our experimental design is limited to five we exclude housing attributes es, e.g., public infrastructure, which may influence the choice of housing. To overcome this problem, the respondents were told that the hypothetical alternatives are exactly the same as their current housing, except with respect to the five attributes in our CE.

Table 1 gives an overview of the attributes chosen, and the levels distinguished within each attribute. For proximity to urban green spaces, nominal deviations from current distance were used and respondents were asked to imagine the forest or park being further from their house. The levels of distance were defined according to the urban planning GIS data of the city of Nancy, provided by the Urban Community of Nancy (Comunauté Urbaine de Grand Nancy).

The attribute "scenic view of green spaces" is used to estimate the value generated by aesthetic amenity. Based on (Tu et al., 2016) 65% of the housing in Nancy has view to urban green space. Since we applied the pivot-style design, different designs should be made for people having view and not having view. To account for differences in reference level, we generated a heterogeneous conjoint choice design where the statistical design differed between respondents with and without view (see e.g., Sándor and Wedel 2005, Rose et al., 2008). A heterogeneous conjoint choice designs was estimated. . During the survey, respondents first answered if they have a view of green spaces or not and based on answer to this question the web-site automatically switched to the corresponding version of the design.

The size of living space and price were chosen as CE attributes to observe people's trade-offs between private housing amenities and environmental amenities. The designed levels are proportions of the price and living size of the house actually purchased. The price changes were distributed about zero as the changes in size of living space and view could both be positive or negative relative to the current situation. As the distance to forest and parks could only be negative (increasing distances) we included more negative changes than positive changes.

Table 1 House attributes and their levels in the CE

Attribute	Level
Distance to peri-urban forest	Current 2 km further 4 km further
Distance to park	Current 500 m further 1000 m further

Scenic view of green spaces	With view No view
Size of living space (m2)	-10% Current +10%
Price/rent of house	-20% -15% -10% -5% current +5%

The CE presents three alternatives to a respondent. Each of them has the same five attributes. The five attributes, with their different levels, have 324 combinations using a full factorial design. It is not realistic to include all alternatives in a CE. We therefore used a B-efficient design (Sándor and Wedel, 2001) that only made it possible to estimate the main effects and the interaction between the two attributes of distance. This interaction term was included to investigate the substitution between parks and forests. The priors used for CE design are obtained from a previous study of 86 house owners in the city of Nancy (Tu et al., 2016). We constructed a design with 12 different choice sets where each choice set contains a "status quo" option which is the current residence. As mentioned above, a heterogeneous conjoint choice design is applied according to the dummy variable "view of green spaces". The the two versions of design were made simultaneously, applying NGENE software (ChoiceMetrics 2014). An example of a choice situation is described in Table 2. The question asked is: "Imagine that, at the time you did choose your current residence, the following two other alternatives existed. Assuming that all other characteristics stay the same, only these five attributes vary. Which residence would you have chosen among the three options?"

Table 2 Example of a choice situation

Attributes	Current house	Alternative 1	Alternative 2
Distance to forest	Current distance	2 km further	Current distance
Distance to park	Current distance	500 m further	1000 m further
Scenic view of green spaces	Current view	No view	With view
Size of the house	Current size	10% more	10% more
Price/rent of the house	Current price/rent	15% less	5% less
I prefer (choose only one please!) →	□	□	□

2.3. Survey and data description

Our study area is the urban agglomeration of the city of Nancy, which had 124,217 households in 2006, according to French National Institute of Statistics and Economic Studies (INSEE). In the agglomeration of Nancy, there is 5118 hectare of peri-urban forest which covers nearly 37% of its territory and there are 23 urban parks open to the public. These parks include spaces with solitaire trees but not forest cover and are very different from peri-urban forests.

Our web-based survey was administrated by the company “Made in Survey”, and was carried out in January, 2015. The questionnaire consisted of an introduction and four main sections. The first main section aimed to obtain information about the respondents’ recreational activities (the number of visits to forests around the city), while the second section asked about respondents’ actual primary residences characteristics (living spaces, housing prices and scenic views of green spaces) and personal information. A hyperlink to a map (Google Map) of Nancy was added to help the respondents to find the forest they lived close to and visited the most often around the city of Nancy. The third section the CE was implemented. Finally, respondents were asked to reveal their happiness level on a scale of one to ten.

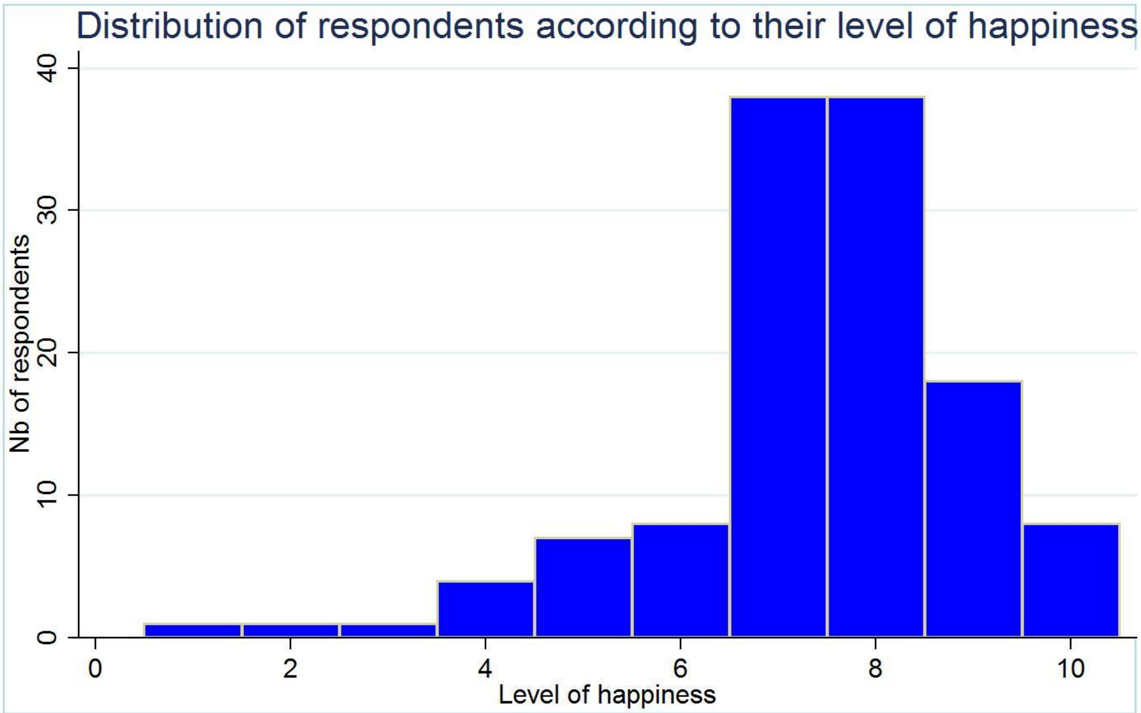
The respondents are all adults (+18 years old) who live in Nancy and its surrounding area, which is our study area. We questioned only one member per household. On average, the interviews lasted 15 minutes. A total of 129 house owners accepted to respond to our survey and 124 of the questionnaires were sufficiently complete to be used for our analysis. The variables used in the analysis are described in Table 3. Figure 1 shows the distribution of the response to the happiness question.

Table 3 Description of variables

Variable	Obs	Mean	Std. Dev.	Min	Max
DCE attributes					
Distance to forest	124	5.35	4.688	0	20
Distance to park	124	5.349	6.654	0	35
Living space of house m^2	124	118.544	49.065	21	400
Housing price €1000	124	157.469	77.888	35	500
View of green spaces(dummy)	124	58.1%			
Socio demographic variables					
Stated happiness level(1-10)	124	7.395	1.592	1	10
family satisfaction (1-10)	124	7.669	1.622	1	10
health (1-10)	124	8.073	1.673	2	10

Education level	124	2.718	1.130	0	4
Income 1000€/month	124	2.996	1.263	1	8
Private garden (dummy)	124	78.22%			

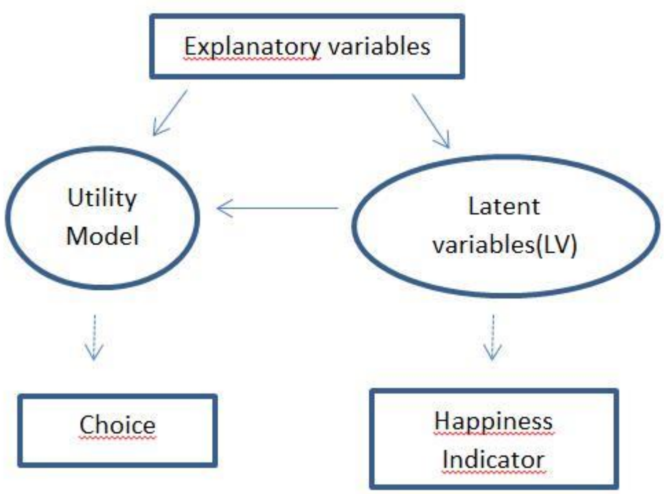
Figure 1.



3. Model specification: ICLV model

It has been argued that responses to attitudinal questions, such as stated happiness, cannot be incorporated into the choice model directly, since this may lead to measurement error and potential problems with endogeneity bias due to omitted variables (Ben-Akiva et al. 1999; Ashok, Dillon, and Yuan 2002; Ben-Akiva et al. 2002; Hess and Beharry-Borg 2012). In our case, the unobserved individual variables affecting their statement on happiness may very well also affect their choices across housing alternatives. The ICLV framework of this study is illustrated in Fig. 2. The ellipses represent unobservable variables, while the rectangles represent observable variables. Each of these sub-models comprises a structural component and a measurement component. Since the latent attitudes (i.e. latent variables) cannot be directly observed from stated choices, they should be identified through a set of attitudinal indicators. The latent variable model permits identifying latent constructs as a function of the indicators, and capture the causal relationships between exogenous explanatory variables and the latent variables. By simultaneously integrating discrete choice and latent variable models, the latent variables can be treated as explanatory variables in the utility functions of choice alternatives.

Figure. 2 The structure of ICLV model (adapted from Hess and Beharry-Borg 2012)



3.1 Structural equation of a latent variable

$$v_n = \mathrm{g}(r, \mathrm{z}_n) + \omega_n \qquad (1)$$

The latent variable "v_n" depends on a vector of social characteristics variables with a vector of estimated parameters r. The term ω_n is a random term, which we assume normal distributed $N(0, \sigma_n)$ across respondents. It is assumed that v_n can explain simultaneously the choice utility and happiness. The choice of explanatory variables is according to previous happiness studies (Levinson, 2012; Luechinger, 2009). We exclude some variables, such as "number of adults" and "number of children", because of the multicollinearity and endogeneity problems.

3.2 Measurement model for the happiness indicator

There are different perceptions and cognitions about happiness. Some studies assume happiness meaning the same thing to all individuals (Layard, 2005; Myers and Diener, 1995). Others argue that the meaning of happiness is different across individuals (Gilbert, 2006). In addition, studies find that there are different types of happiness according to cultures (Tsai et al., 2006) and age (Mogiler, et al., 2011). Another issue with stated happiness data is that they are bounded from below and from above. This implies that one can neither observe a decline in happiness if it was in the lowest category in the preceding period, nor an increase if it was in the highest category. A way of addressing this problem is by collapsing the information of happiness variables in two categories (high/low) and applying a binary choice model (Welsch and Ferreira, 2014). For these reason, we treat the stated happiness only as a general psychological feeling that may influence choices instead of considering utility as other happiness studies. And we separate the happiness data in to two categories. For this data set, a threshold of six produced the best model fit criterion. The measurement model is a binary logit model which describes the probability that happiness is more than 6 (Green, 2003):

$$I_n = \begin{cases} 1, & if\ happy > 6,\ \ with\ probability\ P_n \\ 0, & if\ happy \leq 6,\ \ with\ probability\ 1 - P_n \end{cases} \tag{2}$$

We assume that the latent variable v_n may explain the happiness indicator. With

$$P_n = \ e^{(\lambda * v_n + \tau)} * \left[1 + e^{(\lambda * v_n + \tau)}\right]^{-1} \tag{3}$$

The term λ is the estimated parameter of the latent variable and τ is an independently and identically distributed error term. Consequently, if there are N respondents, then the likelihood function is

$$L_{I_n}(\lambda | v_n) = \prod_{n=1}^{N} {P_n}^{I_n} (1 - P_n)^{1 - I_n}$$

3.3 Random utility model for the description of choice utilities

A mixed logit (ML) model is applied to account for the heterogeneity of preferences (Revelt and Train 1998). The ML model assumes that the preferences vary across respondents but not across choices for the same respondent. A panel specification allows for repeated choices for each individual. The ML model uses random parameters to account for individual heterogeneity in preferences (Hensher and Greene, 2003; Greene and Hensher, 2010). In our case, all attributes in the CE are specified as random parameters with normal distributions.

In a given sample with *N* respondents, each respondent *n* faces *T* choice situations which contain a choice set of *J* alternatives. The utility for respondent *n* choosing alternative *j* in the choice set in situation *t* is:

$$U_{njt} = \beta_{\mathrm{ASC}} * ASC_i + \beta_n * X_{njt} + \varepsilon_{njt}, \quad n = 1, \dots, N, \quad j = 1, \dots, J \quad t = 1, \dots, T \quad (3)$$

An Alternative Specific Constant (ASC) is a constant equal to one for the status quo alternative, and zero otherwise, in order to capture the systematic component of a potential status quo effect according to Scarpa et al. (2005). The term X_{njt} is a vector of observed five CE attributes of this study and β_n is a vector of individual-specific coefficients with a density function $f(\beta_n|\theta)$ where θ are the parameters of the distribution. In our study, we specified a random attribute follow a normal distribution. The unobserved error term ε_{njt} is assumed to be Gumbel-distributed.

In a conditional logit model, the probability of an individual *n* to choose alternative *i* conditional on knowing β_n can be expressed by:

$$P_n(i|\beta_n) = \frac{\exp(\beta_{\mathrm{ASC}} * ASC_i + \beta_n * X_{nit} + \varepsilon_{nit})}{\sum_{j=1}^{J} \exp\left(\beta_{\mathrm{ASC}} * ASC_j + \beta_n * X_{njt} + \varepsilon_{njt}\right)} \quad (4)$$

In the case of multiple choices for each respondent, the joint probability refers to the probability that the individual *n* make the sequence of *T* choices specified as $t = \{1, \dots, T\}$. Knowing the probability of each choice is presented by equation (2), the logit probability of the observed sequence of choices conditional on knowing β_n is given by:

$$P_n(i_{n1},\dots,i_{nT}|\beta_n)=\prod_{t=1}^{T}P_n(i_{nt}|\beta_n,X_{njt}) \tag{5}$$

where i_{nt} represents the alternative chosen by individual *n* in choice situation *t*. The unconditional logit probability that individual *n* makes the observed sequence of choice *j* is integrated over the distribution of β:

$$L_n(\theta)=\int P_n\big(i_{n1},\dots,i_{nT}|\beta,X_{njt}\big)f(\beta|\theta)d\beta \tag{6}$$

Now assume that respondents' stated happiness level have an impact on their choice. Rewriting equation (3) with respect to an ICLV model we specify our utility model as:

$$U_{njt}=\beta_{\text{ASC}}*ASC+\beta_n*X_{njt}+\mu*\big(X_{njt}*v_n\big)+\varepsilon_{njt},\ \ n=1,\dots,N;\quad j=1,\dots,J;\quad t=1,\dots,T \quad (7)$$

The error term ε_{njt} and the error term $\omega_{\ n}$ in the structural model of LV are independent. The term μ is a vector of interaction parameters between latent variable v_n and selected attributes. It is supposed to capture the interaction effect of preference and happiness. The joint log-likelihood function is composed of two components that include the probability of the observed choices in the choice task $t=1,\dots,T$ and the probability of stating a high level of happiness. The combined log likelihood is given by:

$$LL=\sum_{n=1}^{N}ln\int_{\omega}\int_{\beta}\big[P_n\big(j_{n1},\dots,j_{nT}|\beta,\mu,X_{njt},v_n\big)f(\beta|\theta)d\beta\,d\omega L_{I_n}(I|v_n,\tau)\big]f(v_n|z,r,\omega)d\omega$$

(8)

Both components are dependent on the specification of the latent variable v_n in equation (1) and were estimated simultaneously using PythonBiogeme (Bierlaire, 2003).

.

3.4 Well fare measurements

The WTP for attributes in preference space will be $-b_n/\alpha_n$. If we use the ML model, then both the price parameter α_n and attribute parameter b_n are random. As a result, the distribution of WTP which is a ratio of two random variables will be skewed and if the distribution of α_n can take the value 0 then this ration is undefined.

Train and Weeks (2005) suggested estimating the ML model in WTP space. Applying this approach, the WTP is directly estimated by reformulating the model in such a way that the WTP of attributes coefficients are obtained directly from the regression. Previous studies have shown that the WTP space models provide more reasonable estimated WTP values with distributions that have lower densities associated with extreme values (Train and Weeks, 2005), whereas other studies found that applying estimations in WTP space made their models fit the data less well (Sonnier et al., 2007; Train and Weeks, 2005). However, Scarpa et al. (2008) reported that the specification in WTP space had a better fit than the model in preference space in their empirical study.

Based on the equation (3), if we separate the price attribute from the vector of attributes, i.e., assume $\beta_n X_{njt} = \alpha_n p_{njt} + b_n X'_{njt}$, where p_{njt} denotes the price attribute, and X'_{njt} denotes a vector of other non-monetary attributes. The α_n is the random parameter for price and β'_n are individual random parameters of other non-monetary attributes. The utility for respondent *n* choosing alternative *j* in situation *t* is:

$U_{njt} = \beta_{\text{ASC}} * ASC_j + \alpha_n p_{njt} + b_n X'_{njt} + \varepsilon_{njt} \qquad n = 1, \dots, N, \quad j = 1, \dots, J \quad t = 1, \dots, T$ (9)

ε_{njt} is a random term that is Gumbel distributed whose variance is $Var(\varepsilon_{njt}) = k_n^2(\pi^2/6)$, where k_n is the scale parameter for the *n*th individual.

Dividing equation (9) by k_n does not change the household's behavior and gives us a new error term ϵ_{njt} which is IID extreme value distributed with a variance of ϵ_{njt} is $\pi^2/6$:

$$U_{njt} = \lambda_n p_{njt} + \beta'_{ASC} * ASC_j + c_n X_{njt} + \epsilon_{njt}, \tag{10}$$

where $\lambda_n = \alpha_n/k_n$, $c_n = b_n/k_n$, $\epsilon_{njt} = \varepsilon_{njt}/k_n$, and$\beta'_{ASC} = \beta_{ASC}/k_n$. Using the fact that the WTP for a given attribute is obtained through the ratio $\text{WTP}_n = c_n/\lambda_n = b_n/\alpha_n$, equation (10) can be rewritten as:

$$U_{njt} = \lambda_n [p_{njt} + \gamma_n X_{njt}] + \epsilon_{njt} \tag{11}$$

Apparently, equations (10) and (11) describe the behaviors of individuals in the same way. In the case of a model in willingness to pay space, this problem of unrealistic skewed distributions can be avoided by specifying directly the distribution of the WTP parameter γ_n since $\gamma_n = b_n/\alpha_n$. The model in willingness to pay space can be estimated using hierarchical Bayesian estimation or maximum simulated likelihood estimation

(Train 2003). In this study, the maximum simulated likelihood estimation is applied as in Thiene (2009).

The same procedure will be applied with equation (7).

4. Estimate results

The results are shown in table 4. Compare with the adjusted pseudo R-square of the mixed logit model (0.112), the latent variable mixed logit model has a higher pseudo R-square (0.354). It implies the ICLV model fits our data better than the mixed logit model. Therefore, we will only discuss from the ICLV model.The ASC is statistically significant at the 1% level. The positive parameter estimate for ASC captures a systematic status quo effect. It implies that if all other attributes are equal, respondents generally prefer to choose the status quo alternative, i.e., the houses they are actually living in. That is to say, respondents show an affinity for this alternative beyond what the specific attribute levels for this alternative relative to the other two alternatives would predict. The distance to parks strongly affects people's choice of a residential location. The random parameter of distance to park is significantly different from zero at the 5% level. The mean of the parameters are negative because people's utility decrease as the distance to urban green spaces increase. There results suggest that residents are willing to pay more for living 1 km closer to parks on average. The standard deviation parameter of distance to forest and distance to parks are significantly different from zero at the 1% level. This shows that people's preferences for living close to forest and parks are heterogeneous. The parameter of living space is significantly different from zero at the 1% level and has a positive impact on choice. Not surprisingly, the square of the variable "living space" has a significant effect at the 1% level and a negative sign. This implies that usually, respondents prefer larger living spaces and the marginal WTP for one extra square meter of living space will decrease when the living spaces increase. The mean parameter of the view of green spaces is significantly different from zero at the 1% level, with a positive sign showing the importance of a view in the individual's choice of residential location. It is also important to consider the significance of the standard deviation parameter which indicates the heterogeneity of preference on view of green spaces.

Table 4 Parameter estimates for the MNL, ML and LC model

	Mixed logit model			Latent variable mixed logit model		
	Coefficient	Robust Std err	p-value	Coefficient	Robust Std err	p-value
Mean of parameter						
ASC	1.62	0.316	0.00	1.70	0.205	0.00
house price	-0.0457	0.0171	0.01	-0.0880	0.0183	0.00
distance forest	-0.102	0.0377	0.01	-0.0720	0.0435	0.10
distance park	-0.187	0.155	0.23	-0.427	0.215	0.05
living space	0.0981	0.0238	0.00	0.101	0.0223	0.00
living space2	-0.000147	6.86e-05	0.03	-0.000149	6.34e-05	0.02
view	1.20	0.188	0.00	1.27	0.177	0.00
Standard deviation of parameter						
distance forest _sd	-0.290	0.0575	0.00	-0.329	0.0687	0.00
distance park _sd	-1.08	0.205	0.00	0.978	0.196	0.00
living space _sd	-0.0757	0.0158	0.00	-0.0793	0.0147	0.00
view _sd	1.39	0.247	0.00	1.63	0.260	0.00
Interaction terms of attribute and latent variable						
B_priceLV				0.0445	0.00822	0.00
B_disfLV				-0.00480	0.00272	0.08
B_dispLV				0.261	0.133	0.05
Structural equation of latent variable (LV)						
r_cons				-1.33	2.28	0.00
r_ln_avinc				-0.419	0.302	0.22

r_education		0.264	0.105	0.02
r_health		0.260	0.0643	0.00
r_unemployed		-0.695	0.376	0.00
Happiness indicator				
lambda		2.79	1.13	0.01
Number of observation	124	124		
Log-likelihood	-1212.348	-1220.527		
Pseudo R-square	0.120	0.354		
Pseudo R-square Ajusted	0.112	0.343		

The latent variable, LV, is both significant in happiness measurement model and choice utility model through the interaction terms. The coefficient of LV*distance to forest is negative. It suggests happier people anticipate more loss when they live further to forest. (See table 1. In the choice experiment, we propose them only to live further to forest/parks – not closer). The coefficient of LV*distance to parks is positive. It shows happier people anticipate less loss when they live further to parks. The coefficient of LV*price is positive. It indicates that happier people wants to pay more for house in general.

The scale parameter "lambda" in the happiness indicator function (see section 2.2.2) is significantly positive. So the "LV" function has a significant positive effect on stated happiness. The parameters in LV indicate people with higher education and better health condition are normally happier. The insignificance of income is common in happiness studies. For example, Tversky and Griffin (1990) find that although respondent prefer aposition with higher salary, her happiness only increases if she earns more than one's colleagues, even the salary is lower. A negative sign of "unemployment" indicates that being jobless can make people less happy.

The WTP for attributes are presented in Table 5. The marginal WTP for living space is €1170. Generally, respondents are willing to pay €763 for living one kilometer closer to forest. The respondents who have reported a higher level of happiness (">6") are willing to way €15.5 more for living one kilometer closer to forest than the respondents who have reported a lower level of happiness. Respondents are willing to pay 5250€ more to live 1 km closer to an urban park in general. The respondents with a high level of happiness are will pay €875 less for living 1 km closer to an urban park than the ones who have reported a lower level of happiness.

Table 5. Willingness to pay estimates in €1000 (standard errors in parentheses)

WTP parameters	Mean	Std. Dev.	Impact of Happiness
ASC	20.0		
	(4.35)		
distance forest	-0.763	-3.57	-0.0155
	(0.469)	(0.784)	(0.0205)
distance park	-5.25	-12.1	0.875
	(2.52)	(3.28)	(1.22)
living space	1.17	-0.927	
	(0.347)	(0.231)	
living space2	-0.00173		
	(0.000873)		
view	15.4	17.8	
	(3.41)	(3.94)	

5. Discussion and conclusion

Environmental attributes may affect people's happiness, but reversely, the effect of happiness on people's preference for environmental attributes has so far received scant attention. This is a pioneer study who investigates the impact of the feeling of happiness on people's preferences for urban green spaces based on their residential location choices. An ICLV model is applied to account for the endogeneity of happiness. The results of this study show that the level of happiness has an impact on respondent's preference for urban green spaces when they are making house purchasing decision. Furthermore, the results show the impacts of happiness on forests and parks are different. Happier people are less willing to live further to forest. But surprisingly, we find that happier people anticipate less well fare lost if they live further to parks. One possible explanation is happier people are more tolerant of the loss of urban artificial green space such as parks. But they anticipate more loss face to natural landscape deterioration, such as living further to forest. Further estimation is needed for to explain this result.

The findings of this paper might have important policy implications. Understanding the link between happiness and urban green spaces can help design urban planning policies. To avoid population loss and attract new population, increasing the happiness level of unhappy people (happy<6) through building more urban parks is necessary. To improve the life satisfaction of a city in general, urban planners would better increase the forest cover rate or enhance forestry recreation.

The study confirms the results from the face-to-face survey carried out in 2013 with respect to preferences for urban green space(Tu et al., 2016). While this previous study confirmed that the respondents were able to understand the hypothetical residential choice situations presented for them, it is obvious that people's residential location choice could be strongly affected by other factors such as schools, hospitals, etc. in their real choices of residence. Therefore, additional information on respondents' neighborhood is needed if the objective is to predict choice of residential location. It is also difficult to assess whether happiness has an impact on decision with long-lasting effects as residential location choice. This will be an interesting topic for the future research.

References

Abildtrup, J., Garcia, S., Olsen, B.S., Stenger, A., 2013. Spatial preference heterogeneity in forest recreation. Ecological Economics 92, 67-77.

Adamowicz, W., Louviere, J., Williams, M., 1994. Combining stated and stated preference methods for valuing environmental amenities. Journal of Environmental Economics and Management 26, 271–292.

Adaval, Rashmi (2003), “How Good Gets Better and Bad Gets Worse: Understanding the Impact of Affect on Evaluations of Known Brands,” Journal of Consumer Research, 30 (December), 352–67.

Ashok, K., Dillon, W. R., & Yuan, S. (2002). Extending discrete choice models to incorporate attitudinal and other latent variables. Journal of Marketing Research, 39(1), 31-46.

Ben-Akiva, M., McFadden, D., Gärling, T., Gopinath, D., Walker, J., Bolduc, D., ... & Rao, V. (1999). Extended framework for modeling choice behavior. Marketing letters, 10(3), 187-203.

Ben-Akiva, M., McFadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., ... & Munizaga, M. A. (2002). Hybrid choice models: progress and challenges. Marketing Letters, 13(3), 163-175.

Bierlaire, M.(2003). BIOGEME: A free package for the estimation of discretechoice models, in:Chevroulet, T., Sevestre, A. (Eds.), Proc.3rd Swiss Transportation ResearchConf., March19–21, 2003, Monte-Verita, Ascona, Switzerland.

Brander, L. M., and Koetse, M. J., 2011. The value of urban open space: meta-analyses of contingent valuation and hedonic pricing results. Journal of environmental management 92(10), 2763–73.

Brereton, F., Clinch, J.P., Ferreira, S. (2008), Happiness, Geography and the Environment, Ecological Economics 65: 386-396.

Cavailhès, J., Brossard, T., Foltête, J.C., Hilal, M., Joly, D., Tourneaux, F.P., Tritz, C., Wavresky, P., 2010. GIS-based hedonic pricing of landscape. Environmental and Resource Economics 44(4), 571–590.

Del Saz Salazar, S., and García Menéndez, L., 2007. Estimating the non-market benefits of an urban park: Does proximity matter? Land Use Policy 24(1), 296–305.

Ferreira, S., Akay, A., Brereton, F., Cuñado, J., Martinsson, P., Moro, M., Ningal, T.F. (2013a), Life Satisfaction and Air Quality in Europe: Ecological Economics 88: 1-10.

Ferreira, S., Moro, M . (2013b), Income and Preferences for the Environment: Evidence from Subjective Well-Being Data, Environment and Planning A 45: 650-667.

Ferreira, S., Moro, M. (2010), On the Use of Subjective Well-Being Data for Environmental Valuation, Environmental and Resource Economics 46: 249-273.

Fishbach, Ayelet, and Aparna A. Labroo (2007), "Be Better or Be Merry: How Mood Affects Self-Control," Journal of Personality and Social Psychology, 93 (2), 158–73.

Forgas, Joseph P., and Joseph Ciarrochi (2001), "On Being Happy and Possessive: The Interactive Effects of Mood and Personality on Consumer Judgments," Psychology and Marketing, 18 (March), 239–60.

Gardner, M. P., Wansink, B., Kim, J., & Park, S. B. (2014). Better moods for better eating? How mood influences food choice. *J Consumer Psychol*, *24*, 320-335.
Gilboa I, Schmeidler D, Wakker P., 2002. Utility in case-based decision theory. Journal of Economic Theory 105(2), 483–502.

Greene, W.H., Hensher, D.A., 2010. Does scale heterogeneity across individuals matter? An empirical assessment of alternative logit models. Transportation 37(3), 413–428.

Greene, WH., 2003. *Econometric analysis*. Pearson Education India.
Hand, M.S., Thacher, J.A., McCollum, D.W., Berrens, R.P., 2008. Intra-regional amenities, wages, and home prices: the role of forests in the southwest. Land Economics 84(4), 635–651

Hanley, N., Wright, R.E., Koop, G., 2002. Modelling recreation demand using choice experiments: climbing in Scotland. Environmental and Resource Economics 22 (3), 449–466.

Hensher DA, Rose JM, Greene WH. 2005. Applied choice Analysis:A Primer. Cambridge University Press: Cambridge.

Hensher, D., 2004. Accounting for stated choice design dimensionality in willingness to pay for travel time savings. Transportation Research Part B:Methodological 38, 425–446.

Hensher, D., 2006. How do respondents process stated choice experiments? Attribute consideration under varying information load. Journal of Applied Econometrics 21(6), 861–878

Hensher, D., Greene, W., 2003. Mixed logit models: state of practice. Transportation 30, 133–176.

Hensher, D., Rose, J., 2007. Development of commuter and non-commuter mode choice models for the assessment of new public transport infrastructure projects: a case study. Transportation Research Part A: Policy and Practice 41, 428–443

Hess, S., & Beharry-Borg, N. (2012). Accounting for latent attitudes in willingness-to-pay studies: the case of coastal water quality improvements in Tobago. Environmental and Resource Economics, 52(1), 109-131.

Hess, S., & Daly, A. (Eds.). (2014). *Handbook of choice modelling*. Edward Elgar Publishing.

Hoshino T, Kuriyama K (2010) Measuring benefits of neighborhood park amenities: application and comparison of spatial hedonic approaches. Environment and Resource Economics 45(3):429–444

Irwin, E.G., 2002. The Effects of Open Space on Residential Property Values. Land Economics, 78(4), 465–480.

Isen, Alice M., and Thomas E. Shalker (1982), "The Effect of Feeling State on Evaluation of Positive, Neutral, and Negative Stimuli: When You 'Accentuate the Positive,' Do You 'Eliminate the Negative'?" Social Psychology Quarterly, 45 (1), 58–63.

Kahn, Barbara E., and Alice M. Isen (1993), "The Influence of Positive Affect on Variety-Seeking Behavior among Safe, Enjoyable Products," Journal of Consumer Research, 20 (September), 257–70.

Kahnemann, D., Tversky, A., 1979. Prospect theory: an analysis of decisions under risk. Econometrica 47(2), 263–291.

Klaiber, H. A., and Phaneuf, D. J., 2010. Valuing Open Space in a Residential Sorting Model of the Twin Cities. Journal of Enviroment Economics and Management 60 (2), 57–77.

Kuminoff, N. V., Parmeter, C. F., and Pope, J. C., 2010. Which hedonic models can we trust to recover the marginal willingness to pay for environmental amenities? Journal of Environmental Economics and Management, 60(3), 1–16.

Labroo, Aparna A., and Vanessa M. Patrick (2009), "Providing a Moment of Respite: Why a Positive Mood Helps Seeing the Big Picture," Journal of Consumer Research, 35 (5), 800– 809.

Levinson, A. (2012), Valuing Public Goods Using Happiness Data: The Case of Air Quality, Journal of Public Economics 96: 869-880.

Liao, Felix Haifeng, Steven Farber, and Reid Ewing. "Compact development and preference heterogeneity in residential location choice behaviour: A latent class analysis." Urban Studies 52.2 (2015): 314-337.

Louviere J, Hensher DA, Swait JD. 2000. Stated Choice Methods: Analysis and Application. Cambridge University Press: Cambridge.

Luechinger, S. (2009), Valuing Air Quality Using the Life Satisfaction Approach, Economic Journal 119: 482-515.

Mansfield, C., Pattanayak, S. K., Mcdow, W., Mcdonald, R., and Halpin, P., 2005. Shades of Green: Measuring the value of urban forests in the housing market. Journal of Forest Economics, 11(3), 177–199.

Mcfadden, D., 1974, Conditional logit analysis of quantitative choice behavior. In Frontiers in Econometrics, ed. P. Zarembka, New York: Academic Press, 105–142.

Meloy, Margaret G. (2000), “Mood-Driven Distortion of Product Information,” Journal of Consumer Research, 27 (December), 345–59.

Oishi, Shigehiro, Ed Diener, and Richard Lucas (2007), “The Optimal Level of Well-Being: Can People Be Too Happy?” Perspectives on Psychological Science, 2 (4), 346–60.

Phaneuf, D.J., Taylor, L.O., and Braden, J.B., 2013. Combining Revealed and Stated
Poudyal, N.C., Hodges, D.G., and Merrett, C.D., 2009. A hedonic analysis of the demand for and benefits of urban recreation parks. Land Use Policy 26(4), 975–983.

Preference Data to Estimate Preferences for Residential Amenities: A GMM Approach. Land Economics 89(1), 30-52.
Revelt, D., and K. Train. 1998. Mixed logit with repeated choices: Households' choices of appliance efficiency level. Review of Economics and Statistics 80, 647-657.

Rose, J. M., Bliemer, M. C., Hensher, D. A., & Collins, A. T. (2008). Designing efficient stated choice experiments in the presence of reference alternatives. Transportation Research Part B: Methodological, 42(4), 395-406.

Sander, H. A., and Polasky, S., 2009. The value of views and open space: Estimates from a hedonic pricing model for Ramsey County, Minnesota, USA. Land Use Policy 26(3), 837–845.

Sándor, Z., and M. Wedel (2001) Designing Conjoint Choice Experiments Using Managers’ Prior Beliefs. Journal of Marketing Research 38, 430-444.

Sándor, Z., and M. Wedel (2005) Heterogeneous conjoint choice designs. Journal of Marketing Research 42, 210-218.

Scarpa, R., Ferrini, S., Willis, K., 2005. Performance of error component models for status-quo effects in choice experiments. In: Scarpa, R., Alberini, A. (Eds.), Applications of Simulation Methods in Environmental and Resource Economics. The economics of non-market goods and resource. vol. 6. Springer, Dordrecht, The Netherlands, 247–273.

Schwarz, Norbert, and Gerald L. Clore (1983), “Mood, Misattribution, and Judgments of Well-Being: Informative and Directive Functions of Affective States,” Journal of Personality and Social Psychology, 45 (3), 512–23.

Smyth, R., Mishra, V., Qian, X. (2008), The Environment and Well-Being in Urban China, Ecological Economics 68: 547-555.

Starmer, C., 2000. Developments in non-expected utility theory: the hunt for a descriptive theory of choice under risk. Journal of Economic Literature 38, 332–382.

Termansen, M., Zandersen, M., Mcclean, C., 2008. Spatial substitution patterns in forest recreation. Regional Science and Urban Economics 38 (1), 81–97.

Thorsnes, P., 2002. The Value of a Suburban Forest Preserve: Estimates from Sales of Vacant Residential Building Lots. Land Economics, 78(3), 426–441.

Train K. E., 2003. Discrete Choice Methods with Simulation. Cambridge: Cambridge University Press.

Train, K.E. and Wilson, W.W., 2008. Estimation on stated-preference experiments constructed from stated-preference choices, Transportation Research Part B: Methodological 42(3), Pages 191–203.

Troy, A., and Wilson, M., 2006. Mapping ecosystem services: practical challenges and opportunities in linking GIS and value transfer. Ecological Economics 60 (2), 435–449.

Tu, G., Abildtrup, J., Garcia, S., 2016. Preferences for urban green spaces and peri-urban forests: An analysis of stated residential choices, Landscape and Urban Planning, (148), 120-131.

Tversky, A., & Griffin, D.W. (1990). Endowment and contrast in judgments of wellbeing. In F. Strack, M. Argyle, & N. Schwarz (Eds.), Subjective well-being (pp. 101–118). New York: Pergamon.

Tyrvainen, L., Miettinen, A. 2000. Property Prices and Urban Forest Amenities. Journal of Environmental Economics and Management 39(2), 205–223.

Urban, J., Maca, V. (2013), Linking Traffic Noise, Noise Annoyance and Life Satisfaction: A Case Study, International Journal of Environmental Research and Public Health 10: 1895-1915.

Van Praag, B., Baarsma, B. (2005), Using Happiness Surveys to Value Intangibles: The Case of Airport Noise, Economic Journal 52: 111-125.

Van Praag, B., Baarsma, B. (2005), Using Happiness Surveys to Value Intangibles: The Case of Airport Noise, Economic Journal 52: 111-125.

Von Haefen, Roger H., and Daniel J. Phaneuf. "Identifying demand parameters in the presence of unobservables: a combined revealed and stated preference approach." *Journal of Environmental Economics and Management* 56.1 (2008): 19-32.

Weinhold, D. (2013), The Happiness-Reducing Costs of Noise Pollution, Journal of Regional Science 53: 292-303.

Welsch, H. (2002), Preferences over Prosperity and Pollution: Environmental Valuation Based on Happiness Surveys, Kyklos 55: 473-494.

Welsch, H. (2006), Environment and Happiness: Valuation of Air Pollution Using Life Satisfaction Data, Ecological Economics 58: 801-813.

Welsch, H. (2007), Environmental Welfare Analysis: A Life Satisfaction Approach, Ecological Economics 62: 544-551.

Welsch, H., & Ferreira, S. (2014). Environment, Well-Being, and Experienced Preference (Vol. 367, No. 14). Oldenburg Discussion Papers in Economics.

Wright, W. F., & Bower, G. H. (1992). Mood effects on subjective probability assessment. Organizational behavior and human decision processes, 52(2), 276-291.