The Role of Emotions on Tourists' Willingness to Pay for the Alpine Landscape: a Latent Class Approach

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Abstract: Previous research suggests that landscape preferences vary systematically among people. While various sources of heterogeneity have been considered in landscape preference literature, the role of emotions on willingness to pay for landscape features has never been examined.

This paper presents results of a choice experiment carried out for eliciting tourists' willingness to pay for Alpine landscapes. The emotional state of respondents was used to model heterogeneity in a latent class approach.
The study area is a valley in the Italian Alps, characterized by a strong importance of the primary sector and a low number of tourists. For this reason, an effective landscape management could attract new visitors, providing additional income for the local inhabitants.
Results indicate that respondents prefer a variegated and multi-faced landscape, with a mix of tree species, several agricultural crops and open areas with grazing animals and that incidental emotions play a role in the construction of landscape preferences and influence willingness to pays.

Keywords: willingness to pay for landscape, incidental emotions, discrete choice experiment, latent class model, best-worst scaling, mountain landscape

Introduction

Mountain European landscapes are currently the result of a dynamic interaction between natural and cultural aspects, that have occurred over the past centuries to adapt the spatial structure of the landscape to changing society's needs and demands (Antrop, 2005). In particular in the last century, mountain landscapes in Europe have been affected by changes due to socio-economic drivers such as depopulation, abandonment of traditional human activities and marginalisation of agro-pastoral systems (Fyhri, Jacobsen, & Tømmervik, 2009; Vos & Meekes, 1999). In the Alpine area, for many centuries landscape has been shaped by deforestation, in order to obtain timber, fuelwood for domestic use and open spaces for livestock breeding (Viazzo, 1989). In the last decades, the Alpine landscape was characterised by a natural reforestation of grasslands and meadows due to the gradual abandonment of primary-sector related activities. Forest and grassland management, together with the intensification and mechanization of the agricultural sector, contributed to

substantial changes in land use and in landscape aesthetics. The common perception about the Alpine area changes from being considered a productive area to be seen as an area with a high aesthetic and recreational value.
Landscape beauty is an important ecosystem service that can be classified within the sphere of cultural services (MEA, 2005), that is, non-material benefits derived from nature affecting people's physical and mental states. Preferences towards an aesthetically pleasing environment are well-documented in the literature (De Groot, Wilson, & Boumans, 2002; Scarpa, Notaro, Raffaelli, & Louviere, 2011) but seldom taken into account in traditional land management, aiming at maximising agricultural and forestry production but not considering non-market benefits (Daily et al., 2009; Grêt-Regamey, Walz,&Bebi, 2008; De Groot, Wilson & Boumans 2002). In this framework, investigating people´s preferences for landscape attributes might be useful to include the views of natural resource users in management. In particular, it is widely acknowledged that landscape features can play a major role in determining tourism attractiveness.
In this study, we applied a Discrete Choice Experiment (DCE) in order to evaluate tourists' preferences and Willingness to PAY (WTP) for physical features of the mountain landscape. As changes of farming practices have an influence on the aesthetic of a landscape in view of the public, we evaluate the impact of forest trees composition, agricultural land use and grassland management on perceived scenic beauty by tourists.
So far, empirical research evaluating landscape preferences in the Alpine area with stated preference methods are very limited. Arnberger and Eder (2011) used a DCE to explore the effects of crop production and meadows changes in Upper Austria, but a monetary evaluation was not provided. Notaro and Paletto (2011) evaluated forest and alpine pasture environmental services in a case study in the Italian Alps using the Contingent Valuation method. Scarpa et al. (2011), employing a DCE, estimated the WTP for external benefits of Alpine grazing commons in North Italy.
Given that previous studies suggest that landscape preferences are affected by personal emotional state (e.g. Arnberger & Eder, 2011; Van Zanten, Verburg, Koetse, & Van Beukering, 2014), in this contribution we also explore the effect of incidental emotions on preferences and WTPs. This topic is relevant because, if different emotions lead to different WTPs, the estimation of environmental benefits might be biased. This is an important issue in environmental policy, because misspecified WTP might, for example, lead to wrong computations in Cost-Benefit analysis (Hanley et al., 2016); thus, leading natural resource planners and managers to make environmental decisions that do not satisfactorily represent public goals and preferences.
Only a few papers in the DCE literature have explored the effect of emotions on human choices and values (Arana & León, 2009; Araña, León, & Hanemann, 2008; Hanley et al., 2016).
To the best of our knowledge, our study is the first that employs incidental emotions to characterize classes of respondents in a latent class model (LCM), which we utilise to estimate tourists' landscape preferences and WTPs. Another novelty of our study is that we quantify forest, grassland and agricultural attributes in an Alpine area, with respect to the relative contribution of each attribute to landscape value expressed in monetary terms.

The role of emotions in decision-making and their measurement

In psychological theory emotion is any mental experience with high intensity and a high degree of pleasure or displeasure (Cabanac, 2002). Emotions have four components: physiological responses, such as an increase in heartbeat; facial expressions, such as flocking; behavioural responses, such as 'attacking or escaping' and experiential components, as being fearful (Bradley & Lang, 2000).

The literature in behavioural science and psychology highlighted the role of emotions in decision-making, in the context of actual choices and behaviours. In particular incidental emotions, such as anger, fear, surprise, disgust, joy or sadness, may occur while individuals make a decision and influence high-level cognitive processes, altering how people make choices (Blanchette & Richards, 2010) but they are unrelated to the decision at hand (Rick & Loewenstein, 2007).

Several theories explain these findings. Positive and negative emotions bring different ways of processing information. Positive emotions carry more on an heuristic processing and negative emotion on a systematic processing (Blanchette & Richards, 2010; Bodenhausen, Gabriel, & Lineberger, 2000). According to the theory of affect priming (Forgas, 1995), mood may affect judgements and decisions because people in good moods remember and attend more positive things, whereas people in bad moods remember and attend more negative things. Additionally, the theory of mood protection states that happy people are motivated to maintain their positive feelings (Isen, Nygren, & Ashby, 1988), while experimental work suggests that sadness motivates people to change their circumstances (e.g. Lerner, Small, & Loewenstein, 2004). Overall, the evidence is that the information used in decision-making changes with mood and people likely take different decisions in different moods.

To measure emotions, four major categories of response systems are available in the literature: physiological, brain activity, behavioural and self-reported measurements (Mauss & Robinson, 2009). Physiological measures, including heartbeat, pressure, breathing, body temperature and pupil diameter, are registered with specific instruments while brain activity are measured with electroencephalogram and magnetic resonance imaging. Behavioural measures are facial expressions, tone of voice and posture of the body, which can be detected through direct observation of respondents, or more recently with the help of computer programmes (Cohn & Kanade, 2007). Finally, self-assessment measures allow capturing emotions by asking questions to respondents. 'Self-reports of emotion are likely to be more valid to the extent that they relate to currently experienced emotions' (Mauss & Robinson, 2009, p. 213).

Incidental emotions in choice experiments

'The psychological evidence suggests a strong likelihood that incidental emotions will influence an individual's stated preferences for environmental goods, even though they do not affect the payoffs from choice alternatives. If this was the case, there may be a fundamental threat to conventional economic models' (Hanley et al., 2016, p. 3).

As a matter of fact recent research on choice experiments has shown that respondents might not answer valuation questions according to the basic principles of consumer theory. In particular, their decision rules might depart from the pure compensatory heuristics—or random utility maximisation (Simon, 1955)—due to some aspects of the context (Hensher, 2006; Swait et al., 2002). An individual's emotional state is a relevant element of the context and has a role in the selection of the decision rule influencing the valuation process (Arana & León, 2009).

However, a limited number of DCEs deal with the impact of incidental emotions on respondents' choices over environmental goods. Hanley et al. (2016) in a laboratory setting inducing emotions to students asked to make choices on beach recreation. They find no statistically significant effects of changes in the emotional state on estimated preference parameters and WTPs. However, the authors recognise that the particular hypothetical nature of that stated preference exercise could have influenced the results of the study. Arana and León (2009) in a laboratory experiment in which emotional states of sadness and disgust are manipulated, show that these specific emotions play a heterogeneous role in the choice of the

linear compensatory rule, which implies the consideration of all attributes, over the non-compensatory alternatives. They find that sadness involves a larger propensity to use a compensatory rule and a larger WTP for all attributes that ameliorate the environmental impacts of a stone mining facility in Las Palmas (Canary Islands). Using the same case study, they have investigated in the field the role of emotions on the strategy selection on DCE, observing that extreme bounds of emotional intensity and negative emotions increase the probability of using a non-linear compensatory rule in the decision process.
These studies suggest that incidental emotions might play a significant role in explaining individual decisions in choice experiments that value environmental goods and emotional engagement may explains part of preference heterogeneity.

Materials and methods

Study area

Landscape preferences were evaluated for an area called 'Terza Sponda', which is situated in the lower part of the Non Valley (Northeast of the Italian Alps—province of Trento). The study area covers 46 km2 at an altitude between 660 m a.s.l. and 800 m a.s.l. and counts approximately 3,600 inhabitants.
The valley is included in the typical Alpine context characterised by forests, grasslands and agricultural fields. In the study area apple orchards represent the dominant agricultural landscape (about 20% of land area), while forests cover around 70%. Grassland areas are limited and mainly managed for the hay production (meadows).
The primary sector is quite important for the local economy. In particular, most of the local inhabitants rely on apple cultivation as their main source of income. On the other hand, tourism is not an important activity for the valley unlike the rest of the province of Trento. The tourism in Non Valley is mainly in the summer season including activities such as walking, hiking, picnicking and enjoying landscape. In this context, a well-preserved surrounding may attract additional tourists. It is recognised that rural tourism plays a key role in the local development (Arnberger & Eder, 2011). It follows the importance of managing landscape beauty effectively.

Survey design and administration

We conducted a DCE to evaluate tourists' aesthetic preferences and WTPs for an Alpine landscape. The study was designed to investigate whether incidental emotions may explain part of the individuals' preference heterogeneity.
The DCE is a stated preference method, in which respondents make choices over goods or policies, defined in terms of attributes and levels in hypothetical scenarios (Henser, Rose, & Greene, 2005). The inclusion of a cost attribute allows WTP for any change in each attribute to be calculated. Each hypothetical scenario consists in a number of alternatives and an 'opt-out' alternative, which usually is the current state, called the status quo. DCE has been widely applied in transport economics, health and marketing and is increasingly being employed in the environmental literature (Adamowicz, Glenk, & Meyerhoff, 2014), in particular for valuing land use alternatives (Campbell, Hutchinson, & Scarpa, 2009; Rambonilaza & Dachary-Bernard, 2007; Scarpa, Gilbride, Campbell, & Hensher, 2009).
Based on the information derived from the literature and experts' opinions, attributes and levels were designed to be as policy relevant as possible. Landscape attributes and levels considered were forest tree species composition, agricultural land use and grassland use (see Table 1).

Table 1. Attributes and levels considered in the DCE

Attributes	Levels
Forests	1. 90% Scots pine – 10% Norway spruce (SQ) 2. 70% Scots pine - 30% Norway spruce (FOR CONIFERS) 3. 60% Scots pine – 30% Norway spruce – 10% European beech (FOR MIXED)
Agricultural land use	1. 100% apple orchards with protective nets (SQ) 2. 100% apple orchards without protective nets (AGR APPLE) 3. Mixed crops (AGR MIXED)
Grassland use	1. 3% of the land surface covered by grasslands (SQ) 2. 15% of the land surface covered by grasslands (MEADOWS) 3. 15% of the land surface covered by grasslands and presence of livestock (PASTURES)
Extra cost per overnight stay per person	1. 0 (SQ) 2. 0.50 3. 1.50 4. 3.00

All these attributes were specified on three different levels, the first of which corresponded to the current situation, that is, the status quo (SQ), whereas the remaining two represent hypothesised changes.

The status quo in 'Terza Sponda' is a situation in which forests are almost all composed by Scots pine (90% of the total forest area), pure or mixed with Norway spruce, with a sporadic presence of European beech. Agricultural fields are almost all employed for apple cultivation and they are very often covered by protective nets to shelter apples from weather hazards (like heavy rain and hail). Grassland areas cover only 3% of the land surface and no grazing livestock. Starting from this situation, we hypothesised two alternative scenarios for each landscape attribute. Regarding forests, the proposed forest management was focused towards two main options: (1) an evolution of the conifer forests, bringing an enhancement of the Norway spruce up to 30% and (2) conifer- broadleaved mixed forests of 60% of Scots pine, 30% Norway spruce and 10% of European beech. Additional levels for the agricultural lands were: (1) a situation in which apple orchards are still the only crop but orchards are not covered by protective nets and (2) a mixing of apple orchards (widely under nets) and vineyards, cherry trees, berries and apricots (all ancient cultivations in the valley). Finally, the proposed evolution of grasslands foresaw an increasing extension from the current 3% of the land area up to 15%, with or without grazing activities. These attribute levels were effects-coded, while the cost was entered as a continuous variable.

The cost associated with each choice card was a tourist tax, proportional to the number of night overstays. A tourist tax was in use in the area in the past and, at the time of the survey, there was a political discussion on the reintroduction of such a tax for financing destination marketing and other tourism-related activities. The tourist tax has been introduced in November 2015. In our case study, the tourist tax had the objective to cover the costs of an effective landscape management based on users′ preferences. In particular, such cost was justified by the need of establishing a system of compensation for farmers who accepted to change land use management.

We adopted the Best-Worst approach (Louviere & Islam, 2008) and asked the respondents to make two choices for each choice task. Specific guidance was provided in terms of how the ranking should be generated. To avoid rank order effect half of the sample was told to choose first the best-preferred alternative from the three alternatives, and then the worst preferred alternative from the remaining two alternatives, and the second half first the worst and then the best. The main advantage of using best-worst DCEs is that it allows getting more data on respondent's preferences than the 'pick one' traditional DCE, with only a little increase in the cognitive effort (Marley & Louviere, 2005), enhancing the informative value of small samples (Scarpa et al., 2011). The Best-Worst approach was particularly useful in our case study as we could rely only on a limited number of tourists to interview because, as already mentioned, the area is not a typical destination for tourism.

A question was designed to collect information on emotional states. Using the approach of self-reported emotions, we asked respondents to self-assess their emotional state. We proposed both positive (be happy, amused, relaxed, satisfied), and negative emotions (be unhappy, tired, worried, disappointed, bored), plus a neutral one (be surprised). The self-reports were measured on a pick one basis. This piece of information was then used to create a new variable (EMOT1) that was effects-coded, using the neutral emotion as reference level (coded as zero), while positive emotions were coded as 1 and negative emotions coded as −1.

A pilot study was conducted in June 2013 to fine-tune the questionnaire and check attributes and levels. For the pilot and the final survey, we generated an Optimal Orthogonal Choice Design. The design was 100% efficient for estimating main effects and conditional logit model, under the null hypothesis of no information about the parameters, and other assumptions in Street and Burgess (2007) for designs optimal on the differences of attribute levels (Rose & Bliemer, 2009). The experimental design was prepared in NGene software (ChoiceMetrics, 2012).

Figure 1 shows an example of choice task included in the questionnaire.

Figure 1. Example of choice task included in the questionnaire

	alt1	**alt2**	**alt3**
Forests	90%-100% Scots pine	70% Scots pine + 30% Norway spruce	90%-100% Scots pine
Agricultural fields	Only apple orchards with nets	Only apple orchards without nets	Only apple orchards with nets
Grasslands	15% of the land area with grazing animals	3% of the land area	3% of the land area
Night overstay tax	3.00	0.50	0
Preferred solution			
Least preferred solution			

* Original questionnaire was all written in Italian, the present choice task has been translated by the authors.

Face-to-face surveys were administered during summer 2013 by two trained interviewers in different areas of 'Terza Sponda'. Tourists from outside the province of Trento composed the target population. Interviewers randomly invited people to take part in the survey. Once the interview was completed, the next person encountered was asked to participate in the study. To capture all types of tourists, interviews were conducted on both weekdays and weekends, and from morning through evening. The survey was completed by 90 individuals (87% response rate), which answered to 12 choice cards bringing to 2160 completed choice observations.

Econometric analysis of choice data

A latent class choice model has been applied to account for possible heterogeneity of tourists in landscape preferences, with the aim to segment respondents based on their emotions. This

analysis can give us a clear idea of the effect of incidental emotion on preferences and WTPs. These models have recently been applied in landscape valuation in different contexts (Arnberger & Eder, 2011; Eder & Arnberger, 2016; Garrod, Ruto, Willis, & Powe, 2012; Morey, Thiene, De Salvo, & Signorello, 2008).
A LCM can be considered a mixed logit, which addresses the issue of heterogeneity assuming a discrete mixing distribution for the parameters, with individual parameters clustered in classes (Greene & Hensher, 2003).
The unconditional probability of individual i choosing alternative j is a weighted average of all the parameter estimates βk for each class c:

$$P_{ij} = \sum_{c=1}^{C} P_c P_{j|c} \tag{1}$$

Where Pc is the probability of belonging to the class c and Pjjc is the probability of choosing j conditional on membership in class c and takes the form:

$$P_{ij|c} = \frac{e^{\beta'_{ik|c} x_{ikj}}}{\sum_{n=1}^{N} e^{\beta'_{ik|c} x_{ikn}}} \tag{2}$$

It is possible to condition the probability of belonging to a class on covariates, normally using socio-economic variables as covariates. The novelty of our approach is that we employ the individual emotional state to characterise the classes. The hypothesis is that variations of incidental emotions partially explain observed heterogeneity in preferences.
The model for Pc takes the following form:

$$P_c = \frac{e^{\gamma'_c z_l}}{\sum_{c=1}^{C} e^{\gamma'_c z_l}} \tag{3}$$

Where Z includes covariates and γ includes coefficients specific to the class c.
The use of best-worst approach requires the redefinition of the formula for the conditional probability. In our best-worst format respondents are asked to state their most (best) and least (worst) preferred alternatives in a set of three alternatives J, say j1, j2 and j3 in each of the 12 choice task t. We assume that each respondent choose his/her most preferred alternative j in each of J-1 sequential choice tasks (that is, j1 as first best and j2 as second best), each containing one alternative less than the previous choice task.
The probability of occurrence of each ranking option for each participant i in each class c is obtained as follows:

$$P_{ij|c}\left[ranking\left(j_1, j_2, j_3\right)\right] = \frac{e^{\beta'_{ik|c,t,j_1}}}{\sum_{j=j_1,j_2,j_3} e^{\beta'_{ik|c,t,j}}} \frac{e^{\beta'_{ik|c,t,j_2}}}{\sum_{j=j_2,j_3} e^{\beta'_{ik|c,t,j}}} \tag{4}$$

As the best-worst approach allows us to retain two choice observations from each single choice task t, we estimate our models by using the ‘exploded’ parametric mixed logit model (Luce & Suppes, 1965; Scarpa et al., 2011). In order to illustrate the effect of emotions, we estimate three LC models without emotions (one, two and three classes), then the best resulting model is also evaluated including emotions in the class allocation function. We also include socio-economic variables in a second model in order to understand the effect of

personal characteristics on class allocation. In a second step we show how WTP is affected when emotional states of respondents are taken into account.
We estimate WTPs for each attribute calculating the ratio of the attribute coefficient to the price coefficient, with a negative sign, for each class; the Krinsky-Robb procedure was used to estimate non-symmetric confidence intervals (Krinsky & Robb, 1986). We use a Wald test to test for statistically significant differences in parameters amongst classes. The LCM has been estimated using Limdep Nlogit (version 4.0) (Greene, 2009).

Results and discussions
Amongst respondents, women constituted 63% of the sample, while men accounted for the remaining 37%. Concerning educational levels, most of the respondents achieved a high school education and an additional 30% obtained a university degree. The average age was 44 years old. Table 2 compares characteristics of survey respondents with tourists in Trentino, available from local statistics (PAT, 2014). Although comparisons are not easy, because some classifications are different, these statistics suggests that our collected sample is reasonably representative of regional tourists.
Age, number of family members, mode of vacation (alone, with family, in a couple or with friends) and naturalistic motivation for the vacation are very similar. Regional arrival of respondents is also in line with local statistics (with a large portion of respondents coming from Lombardy, then from Veneto and Emilia-Romagna).

Table 2 - Profile comparison of survey respondents with summer tourist population in Trentino

	Tourists in Trentino	Survey respondents
Age (mean)	48.8	44.1
Family members	3.8	3.7
On vacation:		
Alone	7.7%	6.7%
Family	36.4%	34.4%
Couple or friends	56.4%	58.9%
Vacation for:		
naturalistic motivation	61.5%	63.3%
cultural motivation	8.2%	15.6%

Results of the econometric models are reported in Table 3, containing summary statistics of models with one, two and three classes. The one class model is the standard MNL model. In the LC framework the number of classes is arbitrary; thus, the first task is to choose the most suitable model. Adding classes allows better addressing of preference heterogeneity but, at the same time, it increases the number of estimated parameters and model complexity. For this reason, there is a vast consensus in the literature that a smaller number of classes should be preferred (Mariel, Meyerhoff, & Hess, 2015).
The goodness of fit of the models is evaluated by means of the conventional indicators, such as loglikelihood function, AIC and BIC. It can be seen from Table 3 that the simple MNL model has a considerably lower log-likelihood than the two and three classes models, meaning that more than one class should be chosen to obtain a higher quality of the model. Thus, preference heterogeneity seems to matter. This result was expected and it is confirmed by most of the CE applications. In choosing between two and three classes, goodness of fit indicators suggest that a 2-class model should be preferred. This model shows in fact the lower level of both AIC and BIC. Results of the two class models are shown in Table 4. We

present two models with emotions. In the first one only emotions are included in the class allocation function, while in the second we include also socio-economics variables.
Estimate parameters for attribute levels do not change significantly. For simplicity, we then investigate the model without socio-economic variables to calculate class probabilities conditional on emotions.
We first describe the model without emotions, representing our baseline. Looking at the estimated parameters, it can be easily seen that classes are quite different both for signs and for magnitude.

Table 3. Summary results of LC models (1, 2 and 3 classes)

	1 class	**2 classes**	**3 classes**
LL	-1876.4	-1832.258	1825.275
AIC	1.74	1.71	1.72
BIC	1.77	1.75	1.78
R^2	0.200	0.227	0.230

Table 4: LC models with 2 classes

	M1 - Without emotions			**M2 - With emotions**			**M3 - With emotions and socio-economics**		
Parameter	**β**	**t-test**	**sign.**	**B**	**t-test**	**sign.**	**B**	**t-test**	**sign.**
FOR_CONIFERS|1	-0.094	-1.6	*	-0.097	-1.64		-0.093	-1.588	
FOR_MIXED|1	0.247	4.127	****	0.251	4.18	****	0.249	4.164	****
AGR_APPLE|1	0.014	0.235		0.017	0.28		0.017	0.276	
AGR_MIXED|1	0.314	5.356	****	0.313	5.34	****	0.307	5.25	****
MEADOWS|1	0.051	0.877		0.05	0.84		0.054	0.922	
PASTURES|1	0.176	3.047	***	0.179	3.09	****	0.174	3.001	****
SQ|1	-1.562	-5.38	****	-1.55	-5.35	****	-1.554	-5.313	****
COST|1	-0.128	-3.242	***	-0.127	-3.24	****	-0.128	-3.24	****
FOR_CONIFERS|2	-0.333	-4.3	****	-0.293	-3.85	****	-0.352	-4.545	****
FOR_MIXED|2	-0.505	-6.002	****	-0.542	-6.47	****	-0.495	-5.934	****
AGR_APPLE|2	-2.595	-15.566	****	-2.592	-15.86	****	-2.516	-15.882	****
AGR_MIXED|2	0.549	6.172	****	0.571	6.48	****	0.579	6.625	****
MEADOWS|2	-0.862	-10.418	****	-0.81	-9.97	****	-0.884	-10.658	****
PASTURES|2	0.311	3.813	****	0.261	3.23	****	0.331	4.087	****
SQ|2	-1.391	-5.712	****	-1.394	-5.85	****	-1.304	-5.518	****
COST|2	-2.090	-20.532	****	-2.051	-20.8	****	-2.033	-21.198	****
Constant				1.507	9.74	****	1.775	2.667	****
EMOT|1				-0.286	-2.34	***	-0.370	-2.72	***
GENDER							0.100	0.488	
AGE							-0.002	-0.274	

Coefficients for the cost attribute are negative in both cases, as expected, indicating that utility decreases with higher tourist taxes. The coefficient for FOR_CONIFERS is negative in both classes. This attribute is associated with the expansion of an additional coniferous type in forest and it is least preferred compared to the current situation. In the first class, FOR_CONIFERS is actually not statistically different from zero, indicating that tourists might be indifferent between the current situation and an additional coniferous species. The positive coefficient for FOR_MIXED seems to indicate a trend of preferences towards a larger variety of tree species, which is also confirmed in the literature about people's preferences about forest trees composition, not only in a framework of non-market valuation but also in other studies in the field of social sciences (Grilli, Jonkisz, Ciolli, & Lesinski, 2016; Paletto, Giacovelli, Grilli, Balest, & De Meo, 2014). For example, Gundersen and Frivold (2008) reviewed 53 studies carried out in Scandinavian countries and found many studies in which people´s preferences are towards mixed forests. Similarly, Giergiczny, Czajkowski, Żylicz, and Angelstam (2015) implemented a CE for studying attitudes of forest users towards forest structure, finding preferences towards irregular canopies and forest patterns with many tree species. On the other hand, FOR_MIXED is negative in the second class. This is a clear source of heterogeneity; some tourists are attracted by a higher variety of tree species, while others are not willing to change the present forest landscape. Differences may be found also in the attitudes towards protective nets in apple orchards. In the first class, AGR_APPLE is positive but not statistically significant, suggesting that respondents in this class are indifferent towards protective nets. In the second class AGR_APPLE is negative and significant, meaning that members of that class do not increase their utility from a landscape without protective nets. Instead, the coefficient for AGR_MIXED is positive and statistically significant in both classes, indicating strong preferences for a variety of crops, rather than for apple monocultures. Apple orchards create a similar visual impact everywhere, while other crops may create a multi-coloured and variegated landscape, which may be preferred by visitors. For this reason, AGR_MIXED, being a motley solution, might be preferred with respect to apple orchards.

In addition to AGR_MIXED, another common feature between classes is the result obtained for PASTURES. This is the level associated with an increase of the grassland area and the presence of livestock. Members of both classes prefer seeing livestock, which is reasonable. Although not focused on economic valuations, a similar result in terms of preference was found by Arnberger and Eder (2011), who found that people prefer landscapes with the simultaneous presence of orchards and animal breeding. MEADOWS, which is the level associated with an increase in the grassland area without breeding animals, is positive but non-significant in the first class, while it turns negative in the second. A negative WTP for open areas without animals was also found by Dachary-Bernard and Rambonilaza (2012), while studying public preferences for land use alternatives in Parc naturel régional d'Armorique (France). This result suggests the idea that what matters for tourists is having the possibility to see livestock, rather than open areas without animals.

SQ is negative in both classes. This result was also expected and indicates people tend to prefer alternative management strategies compared to the current situation.

Moving to the model including incidental emotions, it is possible to see that coefficients are quite consistent because there are no changes in signs. The two classes seem to be quite different, suggesting the presence of preference heterogeneity. A pairwise Wald test on class parameters (Table 5) also confirmed that almost all the coefficients, with the exception of PASTURES and the SQ, are statistically different across classes.

The coefficient for the emotion variable (EMOT1) is negative and statistically significant. This means that people with stated negative emotions are more likely to belong to the first class, which is associated with higher levels of preferences and higher perceived disutility of the SQ. On the other hand, people with positive emotions are more likely to belong to the second class, showing lower preferences for landscape attributes.

Specifically, even concordant attributes between classes show very different WTP levels (see Table 6). For example, even though AGR_MIXED is positive for both classes, in the first one people are willing to pay 4.9 € per night overstay of their vacation for a variety of cultivations, while in the second-class only 0.56 €. WTP for a variety of crops is the highest amongst attributes in both classes. Similar differences may be found in PASTURES and FOR_MIXED. In general, it is possible to say that respondents in the first class exhibit a higher propensity to contribute to landscape changes than people in the second. Members of the second class are willing to contribute for landscape only for different crops and for livestock, while members of the first tend to prefer also other proposed alternatives, in particular a shift towards mixed tree species in the forest areas. This result is also confirmed by the WTP for the SQ, which is negative and significant for both classes but in the first one is particularly high (more than 24 € per night overstay).
Our results comply with those of Arana and León (2009) and indicate that negative emotions render people more prone to prefer higher environmental quality. Our results are also consistent with the theory of mood protection, stating that happy people are motivated to maintain their positive feelings (Isen et al.,1988), because happy respondents were less likely to choose a different than actual landscape. An alternative explanation could be that those people are generally more happy with the status quo and do not feel a need for change, or they do not care. Our results are coherent with previous experimental work that suggest that sadness motivates people to change their circumstances (e.g. Lerner et al., 2004), since sad respondents were more likely to choose alternative proposed landscapes.
Amongst individual characteristics that influenced class allocation, we found that gender and age did not play a significant role in class allocation. Conversely, individual income seems to explain class membership; people with higher income are more likely to belong to class number one, all else held equal. Education level is also an important variable and suggests that people with a higher education degree belong to class number two.
In general, class allocation function seems to be mostly affected by emotions rather than individual characteristics, as the coefficient is the highest in absolute terms.

Table 5. Wald test on parameters of the LC - 2 class model

Parameter	β	t-test	sign.
FOR_CONIFERS	0.197	2.00	**
FOR_MIXED	0.792	7.52	****
AGR_APPLE	2.608	14.81	****
AGR_MIXED	-0.258	-2.38	***
MEADOWS	0.859	8.31	****
PASTURES	-0.082	-0.81	
SQ	-0.156	-0.41	
COST	1.924	17.92	****
Wald stat	688.060		****

*,**,*** and **** indicate significance levels at 10%, 5%, 1% and 0.1%, respectively

Table 6. Krinsky-Robb Estimation for the WTP in the model including emotions (€ per night overstay)

	Class 1			Class 2		
Attribute	WTP	s.e.	sign.	WTP	s.e.	sign.
FOR_CONIFERS	-1.52	0.69		-0.28	0.03	****
FOR_MIXED	3.94	1.13	*	-0.52	0.04	****
AGR_APPLE	0.26	0.57		-2.52	0.05	****
AGR_MIXED	4.9	1.32	*	0.56	0.04	****
MEADOWS	0.78	0.58		-0.78	0.04	****
PASTURES	2.8	0.81	*	0.26	0.04	****
SQ	-24.34	5.73	**	-1.36	0.09	****

*,**,*** and **** indicate significance levels at 10%, 5%, 1% and 0.1%, respectively

Policy implications

As Hanley et al. (2016) point out, non-considering emotions may lead to biased information for policy-relevant decisions, for example, if such information is used in cost-benefit analysis (CBA). From a LC model, WTP may be used in a CBA calculating the total average of the sample, as a weighted average of attributes WTP and class probabilities:

$$WTP = WTP_{c1} x P_{c1} + WTP_{c2} x P_{c2}$$

Where WTPc1 and Pc1 are WTP and class probability for each attribute in class one, respectively, and WTPc2 and Pc2 are WTP and class probability for each attribute in class two. Estimated WTPs for each attribute, as well as class probabilities, are presented in Table 7. In the second model, class probabilities are conditional on EMOT1; they are, therefore, presented for each emotional status.

As expected, negative emotions lead to larger WTP estimates. It can be seen that the final WTP is much higher in the model including incidental emotions, because EMOT1 affects not only estimated parameters but also class probabilities, contributing to an increased difference in WTP estimates. Results of this contribution suggest that emotions play a role in the stated preferences of respondents, which is reflected in different WTP levels for the total sample. Not accounting for incidental emotions may lead to suboptimal decisions, caused by biased WTP estimations. In our case study, the non-consideration of the emotion would have led to an under-estimation of the tourist tax per night overstay. More research would be necessary to extrapolate results and draw exact conclusions; nevertheless, this work suggests that emotions should be considered in future studies to avoid incurring biased WTP estimates. Overall, it can be said that tourists interviewed in the 'Terza Sponda' show a positive WTP for several of the proposed landscape alternatives. In particular, people belonging to the first class seem to show a good level of acceptance to all the relevant attributes of the Alpine landscape. Positive and high WTP was found for forests with mixed tree species composition, variegated crops and pastures. The second class showed the presence of tourists with different preferences. In fact, many coefficients were negative, meaning that WTP is negative as well. In particular, alternative forest management seems to be not preferred, compared to the current situation. Given the opposite signs for the WTP levels between classes, the overall effect of a switch in tree species composition cannot be foreseen a priori. Despite the general more negative attitude, people are still willing to contribute for a diversification of crops and for pastures. Given these results, it can be said that alternative land uses solutions, foreseeing an increase in the agricultural field might be accepted with a high level of consensus from tourists. Conversely, tourists seem to be indifferent towards the use of protective nets against hail and other hazards for apple orchards. These results were not expected, because nets create a relevant visual impact and contribute to a sense of artificial landscape; they should be then less preferred compared to other solutions. A possible explanation might be that respondents are aware of the importance of agricultural outputs. Avoiding damage to agricultural yields is important not only for food-related issues but also for farmers, because a constant yearly production contributes to maintain solid market positions for farmers. For this reason, removing nets could represent a non-efficient alternative, because it implies damaging part of agricultural yield.

Table 7: Average WTP for the total sample (in €)

Attribute	**M1 - No emotions**	**M2 - including emotions**		
		Positive emot.	Neutral emot.	Negative emot.
FOR_CONIFERS	-0.62	-1.23	-1.30	-1.35
FOR_MIXED	1.50	2.91	3.14	3.32
AGR_APPLE	-0.16	-0.38	-0.24	-0.13
AGR_MIXED	2.01	3.90	4.12	4.29
MEADOWS	0.24	0.42	0.50	0.56
PASTURES	1.13	2.22	2.34	2.44
SQ	-9.92	-18.43	-19.71	-20.74
Prob. class 1	0.80	0.77	0.82	0.86
Prob. class 2	0.20	0.23	0.18	0.14

Conclusions

The present contribution attempted to address an important issue such as the economic valuation of tourist preferences for landscape patterns. For this purpose, a DCE application has been carried out by means of personal interviews. A latent class logit model has been used to account for preference heterogeneity across the sample, using incidental emotions and socio-demographics to estimate class membership probabilities. Emotions were proved to play an important role in the formation of preference heterogeneity. In particular, it was shown that negative emotions lead to a higher propensity to accept improvements in landscape quality, higher levels of WTP and higher perceived disutility of the SQ, confirming findings in behavioural and psychology literature.

The results from this study highlight that incidental emotions should be taken into account when valuing landscape preferences for their potential policy implications, since individual WTP estimates and preferences can depend on interviewees' emotions. The sphere of individual emotions require more research to effectively draw general conclusions, for this reason including emotions in future studies is recommended. Understanding how tourists perceive components of the scenic beauty of a destination is an important piece of information for decision makers, because they can understand what people prefer and plan new strategies accordingly. However not considering the influence of emotions may lead landscape planners and managers to fail in anticipating public responses to policies. In our study, tourists in both classes tend to be willing to pay for a variegated landscape, with several crops in agricultural fields and open areas with breeding animals. Since the province of Trento has recently introduced a tourist tax to finance promotional activities, this work indicates that at least part of that amount of money could be used for managing landscape differently. In particular, a switch in the landscape management towards an increasing mix of natural elements may represent a winning strategy for the 'Terza Sponda' for attracting new tourists giving rise to positive effects on the local development. Given that preferences elicited in this study are very often confirmed in the literature, such a solution could be effective not only in the 'Terza Sponda' but also in several other alpine contexts.

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