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**The Effects of Emotions on Stated Preferences for Environmental Change:
a re-examination**

Yilong Xu, Mikolaj Czajkowski, Nick Hanley, Leonhard Lades,
Charles N. Noussair and Steven Tucker

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Yilong Xu

Utrecht School of Economics
Utrecht University, The Netherlands
Email: y.xu3@uu.nl

Mikolaj Czajkowski

University of Warsaw
Faculty of Economic Sciences, Poland
Email: mc@uw.edu.pl

Nick Hanley

School of Biodiversity, One Health and Veterinary Medicine
University of Glasgow, Scotland
Email: Nicholas.Hanley@glasgow.ac.uk

Leonhard Lades

Economics, University of Stirling, Scotland
Email: l.k.lades@stir.ac.uk

Charles N. Noussair

Eller College of Management
University of Arizona, Tucson, AZ, USA
Email: cnoussair@arizona.edu

Corresponding Author

Steven Tucker

School of Accounting Finance and Economics
Te Raupapa – Waikato Management School
University of Waikato
Email: steven.tucker@waikato.ac.nz

Abstract

We consider how people's emotions affect their stated preferences and willingness to pay for changes in environmental quality, focusing on the effect of incidental emotions. We use videos to induce emotional states and test the replicability of the results reported in Hanley et al. (2016). Additionally, we employ a novel methodology - Face reading software - to verify whether the intended emotional states were successfully induced. We find that our treatments succeed in implementing the predicted emotional condition in terms of self-reported emotions, but had a variable effect on measured (estimated) emotional states. We replicate the result from Hanley et al. (2016): induced emotional state has no significant effect on stated preference estimates or on willingness to pay for an environmental quality change. Moreover, we confirm that, irrespective of the treatment assignment or emotional state - be it self-reported or measured - we observe no significant effect of emotion on preference estimates. We conclude that stated preference estimates for environmental change are unaffected by changes in incidental emotions. Our results suggest that preference estimates are robust to the emotional state of the responder.

JEL Classification

Q51, C09, Q57, D03

Keywords

Choice experiments
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1. Introduction

Stated preference studies, and in particular discrete choice experiments, are frequently used to measure the economic value of environmental public goods to inform cost benefit analyses and environmental policy making (Johnston et al., 2017). The design and analysis of most stated preference studies rely on traditional economic assumptions that suggest that participants in these studies make rational choices and have stable, consistent, and complete preferences (Hanley and Barbier, 2009; Hanley et al., 2016). Only if these assumptions hold do choices in stated preference studies inform us about the welfare-relevant decisions that maximize participants' utility (Weimer, 2016).

A growing number of studies suggest that stated preferences, as well as binding decisions, can be influenced by welfare-irrelevant factors, and that people's decisions are sometimes mistaken. Building on these studies, Lades et al. (2024) call for a new behavioral approach to cost-benefit analysis. For example, participants' personality traits correlate with environmental choices (Boyce et al., 2019), the framing of discrete choice experiments can influence how much participants are willing to pay (Faccioli and Glenk, 2022; Kragt and Bennett, 2012; Faccioli, Kuhfuss, and Czajkowski, 2019; Bergstrom, Stoll, and Randall, 1989; Boyle, 1989; Hoehn and Randall, 2002; Rolfe, Bennett, and Louviere, 2002; Kragt and Bennett, 2012), contextual factors defining the valuation settings influence decisions (Tinch, Colombo, and Hanley, 2015), whilst the presentation of information that characterizes a hypothetical market can affect WTP (Bateman et al., 2009; Matthews, Scarpa, and Marsh, 2017; Hassan, Olsen, and Thorsen, 2018).

Welfare theory suggests that people's willingness to pay should be influenced by welfare-relevant factors such as income or the price of substitutes. However, when changes in variables which are not part of the standard model of choice, such as the framing or context of choices, influence willingness to pay values, then both cost-benefit analysis as a means of making public policy decisions, and the use of stated preference values within such a cost-benefit analysis, are challenged. For example, the willingness to pay for an environmental good might be relatively high in one choice frame, so that a cost benefit analysis suggests the policy to be implemented. With an alternative frame, however, the outcome of the cost benefit analysis might have been very different. The welfare economists' analytical tools, such as the Kaldor-Hicks criterion, are not well-suited to deal with such context dependencies (Hanley et al., 2016).

We study the impacts of one specific contextual factor – incidental emotions – in the present paper. Insights from behavioral science and psychology suggest that incidental emotions, such as happiness or sadness, can influence people’s choices but do not have a connection to the expected payoffs from the decision at hand (Lerner et al., 2004; Lerner et al., 2015; Loewenstein, 2010; Blanchette & Richards, 2010). While influencing behavior, incidental emotions do not have a direct effect on our material well-being and standard economic theory dictates, therefore, that they should not affect our decisions. Indeed, economists have long ignored the effects of emotions on decision-making despite prominent calls for more research (e.g., Damasio, 1994; Elster, 1998; Frank, 1988; Loewenstein, 2000; Lerner, Li, Valdesolo, & Kassam, 2015). However, this situation is changing, and Dukes et al. (2021) even suggest that behavioral research has now entered an “era of affectivism” in which the effects of emotions on cognition and behavior are core to the analysis.

A number of studies have analyzed the effect of incidental emotions on choices in stated preference studies specifically. These studies typically induce emotions such as happiness or sadness by showing movie clips (e.g., Kirchsteiger et al., 2006; Ifcher and Zarghamee, 2011; Oswald et al., 2015), pictures (Notaro and Grilli, 2022), or by asking participants to recollect a sad or happy event in their life (e.g., Strack et al., 1985; Myers and Tingley, 2016), and then follow up with the decision task (Lyubomirsky, King, and Diener, 2005). For example, Araña and León (2008) show that intense emotions can increase anchoring effects in contingent valuation studies. Araña and León (2009) use film clips to induce disgust and sadness in participants and find that these influences emotions influence stated preferences as measured in a discrete choice experiment. Sad participants were more likely to act as predicted by random utility maximization than others. Hanley et al. (2016) used video clips to make participants feel happy or sad, and found that emotional state had no effects on participants’ willingness to pay for beach quality enhancement in New Zealand. Notaro et al. (2019) find tourists’ preferences and willingness to pay for management of Alpine landscapes were influenced by their self-reported emotional state in a latent class model using choice experiment data. Notaro and Grilli (2022) find that lower levels of induced fear (through a re-assuring picture) lead to increased willingness to pay for wolf conservation relative to showing people a more “worrying” image. Overall, these studies imply that incidental emotions might have an influence on the values that stated preference researchers estimate and communicate to policy makers.

There is more evidence for the effect of incidental emotions on decisions in other contexts. Examples include the effects of experimentally manipulated emotions on time

preferences (Lerner, Li and Weber, 2013; Ifcher and Zarghamee, 2011), risk preferences (Wright and Bower, 1992; Johnson and Tversky, 1983; Nygren et al., 1996; Lerner and Keltner, 2001; Loewenstein et al., 2001), overconfidence (Ifcher and Zarghamee, 2014), gambling (Stanton et al., 2014), moral judgments (Drouvelis and Powdthavee, 2015), productivity (Oswald, Proto, and Sgroi, 2015), and pro-environmental behavior (Lange and Dewitte, 2020). There is also a large related literature on pro-social behaviour (Drouvelis and Grosskopf, 2016). Results in some areas are not conclusive: inducing emotions did not change generosity or prosocial behaviors in all studies (e.g., Lane, 2017; Fiala and Noussair, 2017, Ibanez et al., 2017, Kirchsteiger, Rigotti, Rustichini, 2006, Tan, Forgas, 2010; Kandrack and Lundberg, 2014; Drouvelis and Grosskopf, 2016; Kessler et al., 2022).

An important limitation of many of these studies is that the emotional state the participants were in when making their choices was self-reported. For most studies, no objective data are available on whether the emotion induction (the experimental treatment, for example) was successful. A related limitation is that the emotional state in these studies is often measured after, but not during, the choice process. For instance, Araña and León (2009) first ask subjects to watch film clips, write down how they felt about the clips, and then do the main experiment. Only after the main experiment did they ask respondents to reflect on their emotions when watching the films. Even though a survey might be rather short, it is quite possible that the emotional state may not entirely be as described by such self-assessments. People find it very difficult to predict or recall emotional states (Wilson and Gilbert, 2003) and the imposed emotional state may have changed as the participant progressed through the survey due to (a) simply the passage of time, and/or (b) the effects of participating in the survey itself. Indeed, emotions can change over time from the beginning to the end of a decision-making process (Lerner et al., 2005; Notaro and Grilli, 2022). Kugler et al. (2020) argue that taking a survey regarding one's emotional state makes one's state more negative.

To overcome these limitations, the present paper re-tests the results found in one of the earliest stated preference studies that tested for the effects of incidental emotions (Hanley et al., 2016), using an identical experimental procedure with a new sample of participants, but with additional measures of respondents' emotional states based on Facereader technology. The aim of our paper is to re-test published results and to extend them with improved measures of emotions. Re-testing (or replicating) experimental results is a valuable exercise in the context of the so-called "replication crisis" in economics and psychology (Maniadis et al., 2017, Maxwell et al., 2015). To extend the previous results, we estimated people's objective

emotional states over time as the experiment proceeded, in addition to collecting data on self-reported emotional status, as per Hanley et al. (2016). To do this, we videotaped participants (with their consent) and analyzed the videotapes with Facereader software designed to track emotional states, as explained below. This approach provides continuous estimates of happiness, surprise, disgust, sadness, fear, neutrality and overall emotional valence. Therefore, we can estimate the initial emotional state induced by the movie clip, as well as the emotional state at the exact time when participants complete the stated preference choice tasks – to the extent that emotional condition is reflected by facial expressions.

Summarizing results, we find that showing participants happy movie clips makes them happier as measured using both Facereader and self-reports. However, the sad movie clips had a negative effect only on participants' self-reported happiness and not on the Facereader measures. We find that none of the treatments had a statistically significant effect for participants' economic choices in terms of their preference parameters. Moreover, neither 'sad' nor 'happy' emotions observed on participants' faces while they were making choices seemed to have a significant impact on their estimated preferences. The same result was found when, instead of observed emotions when choosing, we used the emotions observed while watching the film clips or at the end of the survey. The overall conclusion that emerges from our paper is thus a reassuring one in terms of the use of stated preference measures in cost-benefit analysis: incidental emotions have no significant effect on willingness-to-pay estimates. This strengthens the conclusion reached by Hanley et al. (2016), since it relates to people who are measured as being happy or sad, not just those who are treated into being happy or sad (and self-reported to be so).

2. Materials and Methods

The experiment was conducted at the Waikato Experimental Economics Laboratory at the University of Waikato, New Zealand between November 2018 and March 2019. A total of 298 participants participated in the study across 22 sessions. Participants were recruited university wide and managed using the Online Recruitment System for Economics Experiments (ORSEE).¹ Some participants may have participated in previous economics experiments, but none had prior experience with choice experiments, or the emotion inducement methods

¹ For a discussion of the ORSEE program, see Greiner (2004).

employed. Each participant only participated in a single session of the study, so that we used a between-subject design. The experiment was computerized using the z-Tree software package.² All interaction and decision-making of participants took place via a computer within privacy barriers. Therefore, stimuli outside the experimental design were minimized. The time required to complete the experiment varied across participants. However, each session concluded when the last person finished their tasks to avoid distraction. Participants were asked to wait quietly until the experimenter announced the conclusion of the session, upon which all participants simultaneously left the laboratory. On average, each session lasted approximately 45 minutes including the instructional period and participant payments. Participants were paid 20 NZD for their participation.

Identically to Hanley et al. (2016), our design consisted of three treatment conditions based upon the target emotional state induced: Happy, Sad and Neutral. In order to induce the emotional state, the participants watched a series of short movie clips, which were approximately 6-7 minutes in length. We used these particular movie clips as they have been shown in previous research to effectively evoke the specific emotion (Rottenberg et al., 2007; Feinstein et al., 2010; Schaefer et al., 2010), and were the same movie clips used in Hanley et al. Details of the movie clips used are presented in Table 1.³

Table 1: Movie clips used in the experiment

Emotional State	Clip Title	Duration	Total Duration	Description
Happy	Ladder 49	1:18	6:14	Man finds out that his wife is pregnant
	Love Actually	2:21		Man proposes to a woman
	Love Actually	1:19		People meeting loved ones at an airport
	Indiana Jones	1:16		Children return home to parents
Neutral	Stock Market Report	1:30	5:53	Woman reports on the stock market
	Golf Grip Video	1:51		Man describes how to grip a golf club
	Abstract Painting	1:06		Woman describes acrylic painting techniques
	Antiques Auction	1:26		Man describes items sold at an antiques auction
Sad	The Champ	2:42	6:42	Child experiences his hero's death
	Born on the 4th of July	1:59		Man injured from war has returned home and is distraught
	Forest Gump	2:01		Man is at the graveside of his love

The main procedural difference between our study and Hanley et al. (2016) is the assessment of the participants emotional states. Hanley et al. relied solely upon self-reporting.

² See Fischbacher (2007) for a discussion of z-Tree.

³ The movie clips are available at <http://tinyurl.com/hnr3jnt>

More specifically, upon completion of the choice experiment, participants were asked to reflect upon their emotional state during the presentation of the movies. Participants were asked: “While I was watching the film I felt... 1 = sad (bad), 4 = neither happy nor sad (neither bad nor good), 7 = happy (good).” In our experiment, we also elicited self-reported emotional states via questions at the end of the choice tasks. The questions asked the participant to reflect back to their emotional state while watching the movies:

“Can you tell us how you felt like when watching the film clips?”

While I was watching the film I felt... 1 = sad, 4 = neither happy nor sad, 7 = happy.”

Moreover, we asked about the participants’ current emotional state:

“Finally, can you tell us how do you feel now?”

I feel... 1 = sad, 4 = neither happy nor sad, 7 = happy.”

These responses are our estimates of stated emotional condition. We also asked participants to indicate whether they felt bad/good, relaxed/tense, and not aroused/aroused but do not analyse answers to these questions here.

In addition to the elicitation of self-reported emotions, we videotaped the entire experiment and used the Noldus FaceReaderTM software to measure the conformity of six basic universal emotions (Ekman, 2007). The video is recorded at 30 frames per second and at each frame FaceReader reports the conformity of a subject’s facial expressions, on a scale of 0 to 1, to those associated with six basic emotions: happiness, sadness, anger, fear, disgust, and surprise. FaceReader can detect emotions as effectively as trained human observers (Kuderna-Iulian, Marcel, & Valeriu, 2009; Lewinski, den Uyl, & Butler, 2014; Terzis, Moridis, & Economides, 2010). It is capable of accurately classifying both intended and unintended emotions (Bijlstra & Dotsch, 2011; den Uyl & van Kuilenburg, 2005), but only captures observable changes in face movements. The synchronization of the stimuli in z-tree and the facial expression was established using the MuCap program (Doyle & Schindler, 2015). The average emotions are then calculated over a specified time interval of interest.

3. Stated Preference Choice Experiment

Embedded within the experimental design described above was a stated preference choice experiment, which replicated that used in Hanley et al. (2016). The choice experiment asked

participants to make choices over alternative beaches on the North Island of New Zealand which the participant could choose to visit on a future occasion. The beaches were described in terms of three environmental attributes and a travel cost (travel distance) from their home. The three environmental attributes were:

- water quality at the beach, described in terms of the impacts from variations in pollution loadings from human sewage and farmland run-off on faecal coliform counts and algal blooms;
- clarity of the water at the beach, described in terms of sediment levels in the water, mud deposited on beaches and the spread of mangroves preventing easy access to the water;
- fish populations in coastal waters, focussing on species relevant to local recreational use (e.g. snapper).

Each of these environmental attributes could take one of three possible levels, all described qualitatively. Travel distance was described in kilometres from home to a given beach location (one-way), of between 30 and 120 kms. Participants were told that improvements in any of the three environmental attributes could be achieved by changing catchment management practices, but that the default outcome would be a continued decline in quality. Using a Bayesian efficient design, we generated 12 choice cards per participant (see an example in Figure 1).

The procedures of each session were as follows: (1) As participants arrived at the laboratory, they were free to choose any computer terminal to use during the session. (2) At the start of the experiment, the experimenter provided a brief welcoming statement and emphasized the requirement of no interaction or communication allowed between participants throughout the experiment. (3) The experimental program was initiated simultaneously for everyone, and the camera was turned on. Participants were told that the camera was turning on and asked to wait for 15 seconds before the survey appeared. (4) The participants first answered basic demographic questions (e.g. area of study, where are they from, gender, date of birth and zip code) followed by a series of questions associated with New Zealand beaches (e.g. how often do you go to the beach, how far is the beach most visited and main activity at the beach). (5) After these initial questions, the movie clips were played. Each participant was provided a set of headphones to allow for individualized and private viewing. (6) Upon completion of the movie clips, participants were sequentially provided the choice experiment question cards. (7) Lastly, the participants were sequentially asked to self-evaluate their emotional state while

watching the movie clips and their current emotional state. (8) The camera was switched off and the experiment concluded once everyone had finished the survey questions. Participants that finished early were asked to wait quietly until the experimenter announced the experiment was completed for everyone. Participants were paid as they exited the laboratory (there was no link between the amount paid to each participant and their responses during the experiment: all participants were paid the same as a show-up fee).

Participants' stated emotions were elicited using a 7-point Likert scale. The intensity of our physiological measure of expressed emotions was indicated by Facereader on a scale from 0 to 1 using a proprietary algorithm. Participants' preferences for the three environmental attributes of beach quality and travel costs were estimated from their responses in the discrete choice experiment included in the survey.

Figure 1: Examples of choice cards

	Beach A	Beach B	Go to neither – I would not want to visit either of these beaches and would stay at home instead.
Water quality	Very good	Good	
Sediments	Medium	Low	
Fish populations	Increasing	Declining	
How far from where you live?	120 km	30 km	
I would choose:	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

	Beach A	Beach B	Go to neither – I would not want to visit either of these beaches and would stay at home instead.
Water quality	Good	Poor	
Sediments	Medium	High	
Fish populations	Declining	Increasing	
How far from where you live?	50 km	50 km	
I would choose:	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

4. Econometric Approach for Preference Estimation

Modelling participants' economic choices observed in our discrete choice experiment is based on random utility theory (McFadden, 1974). In this model, the utility of the individual i resulting from choosing alternative j in situation t can be expressed as:

$$U_{ijt} = \mathbf{X}_{ijt} \boldsymbol{\beta} + e_{ijt},$$

where \mathbf{X}_{ijt} is a vector of the observed attributes of the alternative j , with the corresponding vector of parameters, $\boldsymbol{\beta}$, and e_{ijt} is a random error component that represents unobserved portion of the utility.

The researcher does not observe e_{ijt} , however, they are able to assume its distribution, $f(e)$. Depending on this assumption, the model can be transformed into different classes of choice models. Assuming that the stochastic component e_{ijt} follows an independent and identically distributed extreme value (type I) distribution,⁴ it leads to the logit probability specification, used in simple conditional logistic regressions, with a probability of choosing alternative j from a set of J available alternatives given as:

$$P_{ijt}(\boldsymbol{\beta}) = \frac{\exp(\mathbf{X}_{ijt}\boldsymbol{\beta})}{\sum_{k=1}^J \exp(\mathbf{X}_{ikt}\boldsymbol{\beta})}.$$

An inconvenient assumption of this simple (multinomial logit, MNL) model is the independence and identical distribution of the error term for all of the alternatives and participants, as well as identical preferences of different participants – the same coefficients $\boldsymbol{\beta}$ in the utility function of all individuals. One way of relaxing this assumption – that is, allowing for some level of (unobserved) preference heterogeneity and, possibly, correlations between the alternatives and choice tasks – is to include consumer-specific parameters, $\boldsymbol{\beta}_i$, which leads to a Mixed Logit Model (MXL).

A commonly used approach is to make mixing distributions continuous. If individual parameters are assumed continuously distributed following a parametric distribution specified a priori by a modeler, $\boldsymbol{\beta}_i \sim f(\mathbf{b}, \boldsymbol{\Sigma})$, with mean \mathbf{b} and variance-covariance matrix $\boldsymbol{\Sigma}$, a random-parameters mixed logit model is formed (RP-MXL, McFadden and Train, 2000; Hensher and Greene, 2003).

Given our interest in how preferences are being influenced by the treatments, the observed emotions, and the stated emotions, the means of random parameters can further be

⁴ The density for this distribution is given by: $f(\varepsilon_{ij}) = e^{-\varepsilon_{ij}} e^{-e^{-\varepsilon_{ij}}}$, and the distribution is $F(\varepsilon_{ij}) = e^{-e^{-\varepsilon_{ij}}}$. The variance is constant and equal $\sigma = \pi^2/6$. Since the scale of utility is irrelevant for behavior, utility can be divided by σ without changing the results. Since the mean is not zero, in our estimation we take into account the differences between two elements with the same expected value. Thus, the distribution of the difference of two extreme values

$\varepsilon_{ijk}^* = \varepsilon_{ij} - \varepsilon_{ik}$ is logistic with cumulative distribution $F(e_*) = \frac{\exp(e_*)}{1 + \exp(e_*)}$.

modeled as functions of explanatory variables \mathbf{z} – dummy coded treatments or continuous indicators of respondents’ incidental emotions: $\beta_i \sim f(\mathbf{b} + \mathbf{z}_i\boldsymbol{\delta}, \boldsymbol{\Sigma})$, where $\boldsymbol{\delta}$ is a vector of estimated attribute-specific effects of the explanatory variables \mathbf{z} .

In a MXL, the probability of making a given vector of choices in a set of T situations is a weighted average of standard logit probabilities and can be written as:

$$P_i(\theta) = \int \left(\prod_t \sum_j I_{ijt} P_{ijt}(\boldsymbol{\beta}) \right) f(\boldsymbol{\beta}|\theta) d\boldsymbol{\beta},$$

where I_{ijt} equals 1 if individual has chosen alternative j , and it equals 0 otherwise. The utility function for participants is analogous to an MNL model, except for the fact that the vector of the parameters β_i can vary for different participants. Consequently, utility can be written as:

$U_{ijt} = \mathbf{X}_{ijt}\boldsymbol{\beta}_i + e_{ijt}$, where the density of vector β_i is given by function $f(\boldsymbol{\beta}|\theta)$ where θ are the parameters of the β distribution. The model is estimated using the maximum likelihood method for the utility function parameters, conditional on individuals’ observed choices and attribute levels associated with choice alternatives. Estimating the MXL model requires the use of simulation methods because the integral in (1) does not have a closed form. We can thus apply a simulation procedure in which β_r is drawn from $f(\boldsymbol{\beta}|\theta)$ and, for each β_r , the logit formula is calculated. The simulated probability is given by the average over R draws:

$$\hat{P}_i(\theta) = \frac{1}{R} \sum_{r=1}^R \left(\prod_t \sum_j I_{ijt} P_{ijt}(\boldsymbol{\beta}_r) \right).$$

$\hat{P}_i(\theta)$ is an unbiased estimator of $P_i(\theta)$ by construction. The simulated probabilities can then be used in a log-likelihood function (McFadden and Train, 2000). In the simulation, we used 10,000 scrambled Sobol draws (Czajkowski and Budziński, 2019). This allows us to generate estimates of the mean preference for each choice experiment attribute (indicating the relative importance to choices of each attribute averaged across the sample), as well as the standard deviation of estimated values around each mean, indicating the degree of preference heterogeneity for each attribute.

5. Results

In the following analysis, we examine the survey and physiological data from the experiment to determine whether the treatments, the observed emotions, and the stated emotions influence participants' economic decisions and their preference parameters. We estimated the utility function parameters using the following explanatory variables for the means of the random parameters:

- Model 1: Dummy variables for 'sad' and 'happy' treatments which allow us to compare the mean estimated utility function parameters across experimental treatments, with the neutral movie clips as the baseline.
- Model 2: Continuous measures (0 to 1) of participants' observed 'sad' and 'happy' emotions, as recorded by FaceReader software, which allows us to test whether the mean estimated utility function parameters are associated with *observed* 'happy' and 'sad' emotions.
- Model 3: A measure (on a scale of 1 to 7, normalized to a mean of zero and a standard deviation of one) of participants' self-reported emotional states, which allows us to test whether the mean estimated utility function parameters are associated with *self-reported* emotions.

The results are presented in Table 2.

Table 2. Stated Preferences for Beach Characteristics, including the Interactions of Mean Preferences with the Experimental Treatments, Observed, and Stated Emotions – Results of the RP-MXL Model

	Model 1 – Analysis of treatments			Model 2 – Analysis of observed emotions				Model 3 – Analysis of stated emotions			
	Mean in 'neutral treatment' (s.e.)	St. Dev. (s.e.)	Interactions of Mean		Mean assuming average observed 'sad' and 'happy' measures (s.e.)	St. Dev. (s.e.)	Interactions of Mean		Mean assuming average stated emotion (s.e.)	St. Dev. (s.e.)	Interaction of Mean 'sad- happy' (movie)
			'sad' treatment	'happy' treatment			'sad' (choice)	'happy' (choice)			
Status quo (alternative specific constant)	0.41 (0.31)	2.11*** (0.21)	-0.55 (0.43)	-0.59 (0.42)	-0.19 (0.25)	2.16*** (0.21)	-0.02 (2.43)	0.80 (0.87)	0.10 (0.35)	2.16*** (0.21)	-0.05 (0.10)
Water quality	1.52*** (0.15)	0.82*** (0.11)	-0.01 (0.20)	0.02 (0.19)	1.53*** (0.12)	0.83*** (0.12)	-0.70 (1.15)	0.27 (0.41)	1.45*** (0.15)	0.83*** (0.11)	0.03 (0.04)
Sediments	-1.05*** (0.15)	0.99*** (0.09)	0.23 (0.20)	0.10 (0.19)	-0.93*** (0.11)	1.02*** (0.10)	1.11 (1.13)	-0.20 (0.40)	-0.82*** (0.15)	1.01*** (0.10)	-0.04 (0.04)
Fish populations	0.20* (0.11)	0.55*** (0.08)	0.23 (0.15)	0.12 (0.14)	0.29*** (0.08)	0.58*** (0.09)	-0.89 (0.87)	0.25 (0.31)	0.35*** (0.12)	0.57*** (0.09)	-0.01 (0.03)
- Distance (100 km)	-1.06** (0.44)	1.29*** (0.20)	0.50 (0.43)	0.71 (0.46)	-0.79*** (0.29)	1.60*** (0.16)	-2.35 (4.28)	0.25 (0.70)	-0.93** (0.39)	1.48*** (0.20)	0.08 (0.08)
Model diagnostics											
LL at convergence	-2071.53			-2037.33				-2078.59			
LL at constant(s) only	-2609.41			-2564.66				-2609.41			
McFadden's pseudo-R ²	0.2061			0.2056				0.2034			
Ben-Akiva-Lerman's pseudo-R ²	0.4331			0.4329				0.4318			
AIC/ <i>n</i>	1.7630			1.7639				1.7648			
BIC/ <i>n</i>	1.8357			1.8376				1.8253			
<i>n</i> (observations)	2384			2344				2384			
<i>r</i> (participants)	298			293				298			
<i>k</i> (parameters)	30			30				25			

Notes: *, **, *** represent statistical significance at 0.1, 0.05 and 0.01 level, respectively. Standard errors in parentheses. For log-normally distributed parameters (-Distance) the mean and standard deviation of the underlying normal distribution are provided. The analysis of observed emotions is based on 5 fewer respondents for whom emotions were not correctly observed.

The estimated coefficients presented in Table 2 represent utility function parameters. They do not have direct interpretation, but their signs and relative magnitudes reflect the relative importance of beach characteristics and the influence of explanatory variables. Focusing first on general preferences for beach attributes in the neutral condition in Model 1, when holding observed emotions constant at their mean in Model 2, and when holding stated emotions constant at its mean in Model 3, we observe that participants show a strong preference for improved water quality and a somewhat weaker, though still significant, preference for better fish populations. Beaches with worse sediment issues or those located further away (incurring higher travel costs for participants) were less favored, as indicated by the negative and significant coefficients for these attributes. The estimated coefficients do not offer a direct interpretation, but their signs and magnitudes reflect their relative importance to participants' choices.⁵ As expected, we noted considerable preference heterogeneity, evidenced by relatively high and significant standard deviations for each environmental attribute.

Including interactions of the means of random parameters associated with specific attributes enables us to test whether treatment and/or incidental emotions influenced inferred preferences. Model 1 includes two dummy variables for the 'sad' and 'happy' treatments (compared to a 'neutral' reference). We find that none of the treatments significantly affected participants' economic choices in terms of their stated preference parameters.

Similarly, in Model 2, neither the 'sad' nor 'happy' emotions observed on participants' faces while making choices had a significant impact on their stated preferences. This outcome was consistent, whether we measured emotions during decision-making, while watching film clips, or at the end of the survey.⁶

Finally, in Model 3, we considered participants' stated emotions as interactions of the means of random parameters. Here too, we found no significant effects of participants' stated emotions on their economic choices. This result was the same whether the emotions were stated at the end of the survey or during the movie viewing.⁷

⁵ The ratios of the estimated coefficients represent marginal rates of substitution of different attributes – the rates at which participants were willing to trade one attribute for another, while keeping their utility level constant.

⁶ The results of the models presented here as well as all additional models mentioned are available in the online supplement to this paper, available at <http://czaj.org/research/supplementary-materials>.

⁷ The exact question asked to participants was “Finally, can you tell us how do you feel now?” and used the same 7-point Likert scale responses.

The consistent signal from all three models is thus that variations in incidental emotions have no significant impact on stated preferences for environmental attributes.

6. Discussion and Conclusions

The literature exploring the impact of emotions on Willingness-to-Pay and preferences is expanding, raising important questions about the reliability of Stated Preference (SP) measures in Cost-Benefit Analysis. Emotional influences on SP assessments could potentially undermine their validity for informing policy decisions, which traditionally rely on rational economic choices which do not depend on contextual factors deemed irrelevant to economic decision-making in the standard model. The influence of emotions on environmental choices is garnering increasing academic interest, particularly because it challenges traditional interpretations and applications of stated preference measures in cost-benefit analyses. Our paper replicates and extends the findings of Hanley et al. (2016). Consistent with this earlier research, the results confirm that participants prefer beaches with better water quality, more robust fish populations, fewer sediments, and lower travel costs. Importantly, similarly to the earlier study, we observed no impact of emotional conditions or emotion treatments on participants' stated preferences for changes in the environmental qualities of New Zealand beaches.

This paper can be viewed as a simple replication of the results reported in Hanley et al. (2016), in which we corroborate their finding that incidental emotions do not influence stated preferences or willingness to pay. However, our paper extends this earlier work, by additionally measuring participants' emotions by employing FaceReader technology to objectively measure emotions over time, rather than relying just on (i) which treatment participants were allocated to and (ii) their self-stated emotional condition. Facereader technology provided continuous, objective data on participants' emotions while watching the movie clips, during the discrete choice experiment, and at the conclusion of the experiment. We found that these objectively-measured emotions also had no discernible effect on stated preferences (Model 2), which aligns with the findings from self-reported emotions (Model 3), and the random allocation of participants to treatment condition (Model 1).

Despite these null results concerning the effects of emotion treatments on stated preferences—consistent with findings by Hanley et al. (2016)—it is worth noting that emotions induced by short video clips may not affect stated preferences for certain types of goods, such

as beach visits. Emotional states have been demonstrated to influence behavior in various other decision-making contexts, such as supporting wildlife conservation or protecting Alpine landscapes, as noted by Notaro et al. (2019; 2022). A possible explanation is that the nature of the choices in these other studies may inherently evoke stronger emotional responses compared to choices about beach quality. However, we currently lack empirical evidence to support this speculation in our study's context.

Looking forward, several paths appear promising for further research. Firstly, the intriguing relationship between treatment and objective emotional measures suggests a need for deeper investigation into how emotions are induced and measured in experimental settings. It may be beneficial to explore if different methods of emotion induction or varying contexts of decision-making might reveal more about the subtleties of emotional effects on economic choices for the environment. Second, expanding the scope of studies to include a broader range of environmental and personal factors could help in understanding the conditions under which emotions might influence economic decisions. Finally, employing longitudinal studies could provide insights into the persistence of emotional effects over time, offering a more dynamic understanding of how emotions impact stated preferences.

In conclusion, while our study supports the view that incidental emotions do not significantly sway stated preferences in environmental settings, the observed results suggest that the interplay between emotions and economic decisions is complex and merits further exploration. This ongoing research is crucial not only for theoretical enrichment but also for its practical implications in policy analysis.

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