Do emotions matter? Coherent preferences under anchoring and emotional effects

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ABSTRACT

Emotions can affect individuals’ preferences and economic behavior. In this paper we consider the relationship between emotions and anchoring effects in non-market valuation. The findings show that although anchoring effects are relevant, elicited preferences are coherent, in the sense that they are sensitive to changes in the dimension of the good. Additionally, it is found that the relationship between emotional intensity and the level of anchoring is U-shaped, with anchoring declining as emotional intensity rises until a minimum is reached. Thus, preferences can be substantially less affected by anchoring effects if emotional intensity deviates from extreme values. Finally, it is found that the degree of sensitivity to scope is influenced by the level of emotional load involve in the valuation task.

1. Introduction

A relevant issue in Economics is to provide a reliable answer to the question of how individuals do make choices. The traditional model is based on the assumption that individuals have stable and well-defined preferences, and their choices are driven by consistent optimization (Sen, 1982). The idea is that if agents are motivated enough (normally through monetary incentives) they are going to do the best for themselves, that is, maximize their utility function. The failure of this motivational requisite (or incentive compatibility) is the most widespread explanation for the observed deviations between real and predicted behavior with the traditional economic model.1

This general framework constitutes a simple, intuitive and powerful way to explain a wide range of economic behavior. However, “while this model of individual behavior dominates...
contemporary economic analysis there is a long history among economists of questioning its behavioral validity and seeking alternatives” (McFadden, 1999). Some of the most relevant “anomalies” have been found in terms of its deviations from the transitivity assumption (Allais, 1953), monotonicity (Kahneman et al., 1982) and procedural invariance (Tversky and Kahneman, 1986; Arrow, 1982).

This paper considers the role of human emotions in the procedural invariance observed in what has been termed “the anchoring effect”. Our empirical evidence focuses on the relationships between emotions and anchoring effects in the context of the valuation of non-market goods utilizing the double-bounded dichotomous choice (DBDC) contingent valuation method. The main tested hypotheses are the following: i) the role of human emotional intensity on welfare estimates; ii) the independence of the cognitive (i.e. anchoring) and the emotional dimensions; and iii) the sensitivity to scope when both the emotional and the cognitive dimensions are present.

In general, anchoring effects are the most relevant and well documented behavioral responses in eliciting judgments of willingness to pay for public goods with the DBDC method (Green et al., 1998; Kahneman and Knetsch, 1992). This method was proposed as a potentially advantageous technique over the single bounded dichotomous choice (SBDC) method, because of the larger amount of information requested from the individual. Thus, the technique represents a good example of how an undesirable cognitive dimension (i.e. anchoring effects) may outweigh the desirable economic and statistical advantages of a methodology (Carson et al., 2001; McFadden and Leonard, 1993; Bateman et al., 2001; DeShazo, 2002; Whitehead, 2002; Burton et al., 2003).

From a theoretical standpoint, anchoring effects can be conceived as the “pervasive judgment biases in which decision makers are systematically influenced by random and uninformative random points” (Chapman and Johnson, 1999). Since widespread anchors can have an influence on human preferences and values, this would question the assumptions of unique and stable preferences. Without these assumptions, there can be significant doubts about the ability of standard preference elicitation techniques, such as DBDC, to capture human preferences (Slovic, 2000).

Anchoring effects have been found in a wide array of other contexts. They are also a main component of theories explaining several other “anomalies” of the economic model of consumer choice, such as the preference reversals and the WTP/WTA discrepancy. Tversky and Kahneman (1974) argue that anchoring effects can be explained because of a cognitive heuristic by which decision makers first focus on the anchor and then make a series of dynamic adjustments toward their final estimate. Because these adjustments are insufficiently developed, the final answer is biased toward the anchor.

Although Tversky and Kahneman’s work has had a tremendous influence on economics and psychology, providing a better understanding of how individuals make choices, it seems that it has partially obstructed the inclusion of emotional aspects’ into the economic model. Economists have been aware of the role of emotions in individual’s behavior since early works (Smith, 1759; Commons, 1934). However, until recently little attention has been paid to the role of the emotional dimension in individual economic behavior (some exceptions are Frank, 1988; Kauffman, 1999; Slovic et al., 2002; and Gifford, 2002, among others). Several arguments have been used to explain this phenomenon. For instance, Loewenstein (2000) pointed out that emotions have been perceived as transient and unimportant, and therefore too unpredictable and complex to be included in a formal model. Although many economists would agree that emotions have a significant influence on behavior, most would leave them out either because they have nothing to do with rational decision making or because they only produce noise around some average behavior (which is the one predicted by the neoclassical model).

A common characteristic of most economic models that incorporate emotions is the implicit assumption that the cognitive and the emotional dimensions are independent. This assumption has been a constant source of controversy in research on emotions (Hilgard, 1980; Zajonc, 1980), which has been revitalized in recent years as the “cognition–emotion debate” (Lazarus, 1984 and Leventhal and Scherer, 1987). More recently, a new literature has emerged that considers choices as a result of a dual-process (Hsee and Rottenstreich, 2004; Kahneman and Frederick, 2002; Chaiken and Trope, 1999; Sioman, 1996), resulting from a combination of a deliberative and an affective dimension. Hsee and Rottenstreich (2004) propose the terms “valuation by calculations” and “valuation by feelings” to refer to these two dimensions. These authors argue that under the valuation by calculations system, changes in scope have a relatively constant influence on value throughout the entire range, while under the valuation by feelings system, the value is highly sensitive for a change from 0 to some positive value, but is largely insensitive to further variations of scope.

The plan of the paper is as follows. In the next section we present the details of the experimental design that provided us with the source data for the study of the relationships between the emotional and cognitive dimensions in the contingent valuation method. Section 3 outlines the econometric model utilized to estimate the anchoring effects in the DBDC model.

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2 Hanemann et al. (1991) demonstrated that it raises the level of statistical efficiency of parameter estimates and welfare measures.

3 For instance, in the assessment of the willingness to pay for public goods with bidding games and other elicitation methods, the pricing and rating of gambles, the risk assessment, the estimation of probabilities, social judgments, knowledge questions, and the predictions of future performance.

4 For a detailed review of anchoring effects see for instance Chapman and Johnson (1999) or Ariely et al. (2003).

5 Emotions have been also termed in the literature as “affect” (Slovic et al., 2002), “visceral factors” (Loewenstein, 2000) or “passions” (Frank, 1988).

6 There is a long tradition of research in other decision sciences (e.g. psychology, sociology and neurosciences) suggesting that emotions may play a significant role in several aspects involved in the decision-making processes. For instance, emotions may affect memory (Heuer and Reisberg, 1990), perceptions (Zajonc, 1980; Lerner and Keltner, 2001), creativity (Isen et al., 1985), problem solving abilities (Isen et al., 1987), motivated cognition (Camerer and Lovallo, 1999; Dovidio et al., 1995), purchase intentions (Brown et al., 1998), variety seeking (Kahn and Isen, 1993) and performance (Damasio, 1994).
Section 4 discusses the results regarding the hypotheses of the relationships between the emotional load facing the individual in the valuation task and the degrees of anchoring and scope effects, as well as the relationships between anchoring and scope effects. Finally, Section 5 summarizes the main findings of the paper and sets up some of the implications for further research.

2. Experimental design

2.1. The good to be valued

The application focused on the valuation of the rehabilitation of a network of walking paths in the island of Gran Canaria, Spain. The network is an ancient infrastructure which was used in previous centuries for communications between villages. In recent times, these paths have been abandoned and new roads have been built using modern techniques, at times replacing the old paths. The ancient path structure was mainly used for walking, although it also could allow carriage and animals transit in many parts of the network. The extension of the network is about 1000 km. In the last years rehabilitation work has been accomplished on 300 km using European funds.

The rehabilitated network is currently used by the local population and also by some tourists and visitors for hiking and walking. Due to its rural origin, most paths go through natural areas and allow users to enjoy nature and magnificent landscapes. The primary objective of the study was to determine how much would be the benefits for the resident population of the island to be obtained from the expansion of the rehabilitated network. The old abandoned paths are practically impenetrable, thus the expansion of the services of the network requires rebuilding more routes. All the construction techniques have been done following the old traditions and involving the original materials, and were supposed to continue to be so for the expansion of the network.\(^7\)

2.2. The computer-based questionnaire

Using the taxonomy proposed by Harrison and List (2004) our study is defined as an *artefactual field experiment*. The data collection was conducted in 2002 to the resident population of Gran Canaria. The questionnaire was administered via personal interviews at the subject's home. The interviews were conducted by professional interviewers of a survey firm, previously trained by the authors to standardize survey environment and subject attention. The interviews were supported by a computer-based questionnaire implemented on personal laptops computers. The computer-based survey instrument, while holds most of the desirable characteristics of lab experiments (e.g. control of the environment), has several advantages over the alternatives: it can reduce sample selection bias commonly observed in lab experiments, reduce interviewer bias effects, allow the consideration of additional covariates, and potentially permit improvements in the statistical design.\(^8\)

2.3. The design

A sample of households was randomly screened from the census population of Gran Canaria published by the Canary Islands Statistical Institute (ISTAC). The interviewers participated actively in several training sessions on the specifics of the questionnaire. They did work also for the pre-test surveys, providing comments and suggestions for improving the final questionnaire. Up to three focus groups of 5–10 subjects and three pre-tests of 20–30 subjects were needed in order to reach the final version of the survey instrument. In the process of successive revision of the pre-test questionnaires we considered critical issues such as the payment vehicle, the good to be valued and the information content of the market design. The number of valid interviews was 574, with a response rate of approximately 84%.

The survey instrument implemented the constructed market aimed at valuing in monetary terms the benefits that the population would enjoy from the expansion of the network. The questionnaire was structured in three main parts. The first part asked questions about the relative importance of a range of objectives of public policy in general, and recorded information on the various recreational activities that the subject made in leisure time. These questions preceded the presentation of the elements of the market scenario and were intended to introduce the subject to the valuation context. The second section presented the valuation scenario and asked the subject’s willingness to pay for the proposed policy. The policy proposal was presented by a descriptive paragraph, and by means of an interactive map on the computer, showing simulated pictures and drawings. The final section obtained information on socioeconomic variables such as employment status, education level, income level, family size, and year of birth.

Key elements of the scenario are the payment vehicle, the elicitation method and the provision rule. The elicitation method was the double-bounded dichotomous choice based on a bid design of alternative prices that were randomly distributed across the sample. Each individual in the sample randomly received one of the several initial prices. The bid vector was designed utilizing Cooper's (1993) methods for a predetermined number of bids and based on the information provided by an open ended pre-test question. A second follow-up bid vector was defined by the next successive price in the initial bid vector with an upper and a lower limit equally spanned. If the individual answered ‘yes’ to the first price, this price was increased; if the answer to the first price was negative then the price were lowered. The final elicitation tree is presented in Fig. 1.

\(^7\) For more up to date information regarding conservation of walking paths in Gran Canaria you can visit: http://www.grancanaria.com/patronato_turismo/1860.0.html.

\(^8\) As it was noted by a reviewer, in contexts in which the use of computers is restricted to some portion of the population (normally younger and more educated people), the use of computer-based questionnaires may invoke some selection bias. In this study, this potential issue was tested by employing information obtained in pilot surveys and focus groups. This analysis found no selection bias effect.
The payment vehicle was a contribution to a special fund for the specific purpose of carrying out the expansion of the walking paths network. In order to enhance the incentive compatibility of the payment vehicle we tested alternative provision rules in the initial stages of the study (i.e. focus groups, in-depth surveys and pilot surveys). The most satisfactory option was to follow a wording structure similar to the one proposed in Rondeau et al. (1999) and Poe et al. (2002). This

![DBDC structure diagram]

Fig. 1 – DBDC structure.
consists of a provision point mechanism (PPM) with money back guarantee (MBG) and a proportional rebate of excess contributions (PR). Subjects were told that the public good is provided only if the sum of contributions equals or exceeds its cost (the provision point). If contributions fall short of costs, they are completely refunded (the money back guarantee), whereas if they exceed costs, the excess is returned to each contributor proportionally to the share of their individual contribution in the total amount contributed (the proportional rebate). In addition, the chosen payment vehicle was perceived as feasible from a policy perspective, since some local facilities are commonly financed by special contributions.

2.4. Sensitivity to scope

The proposed expansion of the network of ancient walking paths is designed with the aim of increasing the leisure options of the objective population and potential visitors to the island of Gran Canaria. The accomplishment of the project involves costs which are expected to increase linearly with the size of the network. Thus, an interesting question from a policy perspective is how preferences would change across different projects. This would allow us to test for the coherency of the preferences as the subject evaluates expansions of different scales which could raise different benefits. Three alternative projects were presented to the subjects in split samples, and varied only in the number of kilometers of the proposed expansion, above the currently rehabilitated 300 km, i.e. 30, 100 and 300 km. All these projects were feasible in the island according to experts and would serve for the purposes of increasing the amount of services provided by the network. Subjects were presented with the three alternatives and randomly asked to value only one of the proposed projects, conditional on the relative benefits that the other two alternatives would provide them.

2.5. The measure of the emotions intensity: the EIS-R scale

Since emotions are omnipresent in everyday life and play an important role in several scientific theories, a particular challenge is agreeing upon a concrete definition of this phenomenon, including its conceptualisation and operationalisation. A large part of the disagreement between different theories can be subscribed to different definitions of what constitutes an emotion. There is a distinction between emotions, moods and emotional disorders (Ben-Ze’ev, 2000). In particular, we are interested in emotion intensity, because it is argued to be an important predictor of mood experience, and therefore, of individual decision making. Affect or emotion intensity, as used here, can be defined as the “stable individual differences in the strength with which individuals experience their emotions” (Larsen and Diener, 1987).

There are several scales available that may be used to measure emotion intensity. In this paper we adopt a reduced version of the Emotional Intensity Scale (EIS) first proposed by Braaten and Bachorowski (1993). The main drawback of standard emotion scales is that they often combine frequency and intensity of emotions in the same scale. The EIS overcomes this problem by measuring only intensity of emotions. In addition to this, “the EIS is adequately developed and shows evidence for reliability and validity” (Bachorowski and Braaten, 1994). Therefore, we use a reduced version of EIS (EIS-R) proposed by Geuens and Pelsmacker (2002). The main advantage of EIS-R is that “it provides a more practical instrument for studies investigating the relationship of the EIS to cognitive, affective, or behavioral, at the same time that minimize maturation and fatigue effects in respondents”.11

3. The double-bounded dichotomous choice model

Consider the first stage in an elicitation process involving a yes/no question to pay a bid price ($B_i^1$) for an increase in the services provided by an environmental good from $q_0$ to $q_1$. Let $e_i$ be the expenditure function for individual $i$, that is, the inverse of the indirect utility function with respect to income. Under the typical assumption of consumer rationality, the answers would be yes if $e_i(q_1^i,V^i) + B_i^1 - e_i(q_0^i,V^i)$ and no otherwise, where $V^i$ is some fixed level of utility. The expenditure difference could be seen as the individual’s willingness to pay (WTP) for the offered services, that is, $WTP_i^1 = e_i(q_1^i,V^i) - e_i(q_0^i,V^i)$. Therefore, the observed answer $y_{i1}$ to the first bid price $B_i^1$ takes the value of one or zero if WTP$_i^1$ is higher or lower than the bid price, respectively.

Traditional CV models assume that the expenditure function is not fully observed by the researcher. Thus, the latent variable WTP can be viewed as a function of two components, a deterministic $\mu$ and a random component $\epsilon$. In general, we can assume a linear WTP function (Cameron, 1988), that is, $WTP_i^1 = \mu_i + \epsilon_i$, where $\mu_i$ and $\epsilon_i$ are, respectively, the mean and the standard deviation of WTP$_i$, and $\epsilon_i$ is a random error term.

The double-bounded dichotomous choice format (DBDC) consists of the inclusion of a second binary question. This method was first proposed by Carson (1985) and Hanemann (1985). The second bid offered ($B_i^2$) is assumed to be higher than ($B_i^1$) if individual $i$ answers positively to the first price and vice-versa. Let us assume that WTP from the first question is the true WTP (see for example, Herriges and Shogren, 1996 or Whitehead, 2002). Following the general setting developed in Araña and León (2007) for repeated elicitation formats (which includes DBDC), we consider here a simultaneous equation

\[ \begin{align*}
\hat{y}_{i1} & = \Pr \left( WTP_i^1 < B_i^1 \right) \\
\hat{y}_{i2} & = \Pr \left( WTP_i^1 < B_i^1 \right) \\
\end{align*} \]

- 9 In the context of controlled experiments and treating subjects in groups, Rondeau et al. (1999) found out that this payment mechanism can closely approximate demand revelation. This evidence was supported in the context of our experiment for the results of a split sample comparison between alternative payment vehicles in the pre-tests studies.

- 10 In the context of stated preference methods, there is an extensive literature that includes attitudinal scales and scales operationalising WTP as behavioural intention that reflects variables from social-psychology. Some examples are Brouwer et al. (1999), Heberlein et al. (2005), or Fischer and Hanley (2007).

- 11 Definition of EIS-R is presented in Appendix B. Results of the PCA and validity and reliability of the scale are available by the authors upon request.

- 12 Alternatively, the model can be specified directly in terms of the indirect utility function (Hanemann, 1984). McConnell (1990) shows how Cameron’s model may be seen as the dual of the Hanemann’s.
model with anchoring effects that allows us to consider the interdependencies between the stages in the elicitation process. That is, 

\[ \text{WTP}_i^1 = \mu_i^1 + \epsilon_i^1 \]

\[ \text{WTP}_i^2 = \mu_i^2 + \eta_i \beta_i^1 + \epsilon_i^2 \] with \( \eta_i \) being equal to \([0, 1]\) \( \forall i = 1, 2, \ldots n \)

where \( \mu_i^k \) are the linear predictors associated with \( k = 1 \) regression parameter vectors \( \beta_k \) and covariate vectors \( x_i^k \), \( \epsilon_i^k \) is the intercept term, and \( \eta_i \) captures the potential existence of an anchor effect of the first bid on WTP of individual \( i \) (Herriges and Shogren, 1996). The linear predictors are linked to the probability of a positive response by a bivariate normal cumulative distribution (BVN) called the link function. Simultaneity between responses is captured by the lower triangle component of \( \Sigma \) (e.g. \( \alpha_{ij} \)). This is a model of simultaneous equations with limited dependent variables (SLDV), which reduces to a general triangular system (Zellner, 1971) for complete data sets.

3.1. Inconsistency in elicited preferences between answers

The main advantage of DBDC over SBDC is that the former provides more information on individual’s preferences. Hanemann et al. (1991) showed that it leads to more efficient welfare estimates. This additional information may potentially allow the researcher to conduct studies at a lower cost (smaller sample sizes) while holding the precision of the WTP estimates constant (same variance). However, the DBDC has been questioned because of the empirical support to the argument that the distribution of WTP is incoherent between both steps (e.g. Green et al., 1998; Cameron and Quiggin, 1994). In other words, the mean or median WTP estimated using responses to the first valuation question differs empirically from the one estimated using the responses to the second question.

The presence of potential behavioral responses to the follow-up question has been argued in non-market valuation as the primary explanation of the incoherence between DBDC and SBDC (Alberini, 1995; Carson et al., 2001; Burton et al., 2003; DeShazo, 2002; Bateman et al., 2001). Innovative efforts to model econometrically some of the reactions to the second bid offered can be found in Cameron and Quiggin (1994), Herriges and Shogren (1996), Alberini et al. (1997), Whitehead (2002), Flachaire and Holland (2006) and Araña and León (2007). The arguments commonly raised for explaining these behavioral responses include anchoring effects, strategic behavior, yea-saying, nea-saying, uncertainty cost, weighted average, bargaining, guilty/indignation and quality/quantity shift, among others. For simplicity, in this paper we focus on the anchoring effects, which can be seen as a general cognitive heuristic implicitly linked to other behavioral responses.

3.2. Anchoring effects

An empirical result of the DBDC is the fact that, in follow-up question the distribution function of WTP could be influenced by precedent stage, implying some type of anchoring effect or behavioral process (e.g. Herriges and Shogren, 1996; Aadland and Caplan, 2004). In a general setting, Tversky and Kahneman’s (1974) describe the anchoring effect as “the process in which people make estimates by starting from an initial value that is adjusted to yield a final answer.”

Following previous models of DBDC (Herriges and Shogren, 1996; Whitehead, 2002), our model collects the influence of the starting bid amount on WTP in the term \( \eta_i \beta_i \). Parameter \( \eta_i \) measures the importance of the anchor effect of the first bid on WTP at an individual level. Thus, the anchoring effect hypothesis may be tested for each individual of the sample by considering these two alternatives: \( H_0: \eta_i = 0 \); and \( H_1: \eta_i \neq 0 \).

3.3. The econometric model

In order to estimate the model, we utilize a Bayes approach (Chib, 1992; Albert and Chib, 1993), similar to the one applied by Araña and León (2005). This approach has basically three main advantages over standard maximum likelihood estimation: i) it allows for more flexibility and unobserved heterogeneity in the model through the random parameters specification; ii) it allows for an easy and efficient comparison between models through the use of the Bayes Factor; iv) it relies on an exact theory of probability even with small samples, leading to more accurate results in this context. The detailed description of the econometric model and the components of the Bayesian approach are explained in detailed in the Appendix A.

4. Results

The estimation of the simultaneous equation model outlined in the previous section is particularly intended to raise further evidence on the anchoring effects produced by the first bid prices offered in the double-bounded dichotomous choice model. Although this model centers on anchoring effects, the data collected in our field experiment also allows us to investigate i) the potential relationships between anchoring effects and the emotional state of the individual, and ii) the potential relationships between anchoring effects and the scope of the environmental good to be valued, as represented

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13 Alternatively, it would allow us to increase the precision of the estimates (lower variance) holding sample size constant.

14 The inconsistency between first and second responses leads to the rejection of the maintained assumption of the restricted double bounded model (Hanemann et al. 1991) that the mean and variances are constant across both bounds, and that the correlation coefficient between the standard errors is equal to one, which essentially means that WTP1=WTP2. The rejection of this hypothesis implies a reduction in the efficiency gains of the double bounded elicitation procedure.

15 The number of bounds can be increased successively in the elicitation process, leading to what has been denominated the triple bounded dichotomous choice model (Langford et al. 1996). Cooper and Hanemann (1985) and Scarpa and Bateman (2000) showed that the efficiency gains are likely to diminish when the number of binary steps in the elicitation process is increased.

16 In order to test the sensitivity of the results to the econometric approach, maximum likelihood estimations of a bivariate probit model have been carried out. The results show no significant differences in terms of the hypotheses proposed in this study. The sensitivity analysis results, data set and the GAUSS program codes for the Bayesian estimation are available from the authors upon request.
by the number of kilometers to be rehabilitated in the policy program presented in the market construct.

Table 1 shows the estimation results for the simultaneous equation model for two alternative assumptions. Under the naïve assumption, we omit the bid price from the first response equation model for two alternative assumptions. Under the naïve and anchored individual (posterior standard deviations in parentheses)

Table 1 – Estimation results of Bayesian bivariate models for a naïve and anchored individual (posterior standard deviations in parentheses)

<table>
<thead>
<tr>
<th></th>
<th>Naïve model</th>
<th>Anchored model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta_1$</td>
<td>$\beta_2$</td>
</tr>
<tr>
<td>Intercept</td>
<td>18.9460</td>
<td>0.7664</td>
</tr>
<tr>
<td></td>
<td>(4.5615)</td>
<td>(3.6249)</td>
</tr>
<tr>
<td>EIS</td>
<td>12.9748</td>
<td>15.0844</td>
</tr>
<tr>
<td></td>
<td>(0.8970)</td>
<td>(0.6515)</td>
</tr>
<tr>
<td>Age</td>
<td>–0.2461</td>
<td>–0.2005</td>
</tr>
<tr>
<td></td>
<td>(0.0463)</td>
<td>(0.0353)</td>
</tr>
<tr>
<td>Log (KIL)</td>
<td>5.1005</td>
<td>7.1897</td>
</tr>
<tr>
<td></td>
<td>(1.7401)</td>
<td>(1.3784)</td>
</tr>
<tr>
<td>EDU</td>
<td>0.4274</td>
<td>0.5997</td>
</tr>
<tr>
<td></td>
<td>(0.1714)</td>
<td>(0.1259)</td>
</tr>
<tr>
<td>INC</td>
<td>0.0062</td>
<td>0.0030</td>
</tr>
<tr>
<td></td>
<td>(0.0018)</td>
<td>(0.0014)</td>
</tr>
<tr>
<td>BID 1</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0379)</td>
</tr>
<tr>
<td>$\alpha_{1}$</td>
<td>13.0619</td>
<td>(0.5807)</td>
</tr>
<tr>
<td>$\alpha_{2}$</td>
<td>11.0802</td>
<td>(0.6310)</td>
</tr>
<tr>
<td>$\alpha_{21}$</td>
<td>70.4236</td>
<td>(9.2962)</td>
</tr>
<tr>
<td>Mean WTP</td>
<td>19.18</td>
<td>[18.43, 19.98]</td>
</tr>
<tr>
<td>Marginal likelihood</td>
<td>–1113.97</td>
<td>–1057.26</td>
</tr>
</tbody>
</table>

logarithmic: when the number of kilometers of the walking paths network was increased, mean WTP also increased, but at a decreasing rate. Thus, the scope effect or the absence of sensitivity to the dimensions of the good to be valued can be rejected for this particular application.

2. The emotional state of the individual played a significant role on the elicited values of the environmental good in question. This relationship was positive, i.e. the higher the emotional state the large becomes WTP.

Even though these variables are important for explaining WTP at an aggregate level, they can be also related to the degree of anchoring which is likely to be found in the elicitation mechanism of the DBDC model. Thus, let us consider the relationships between the anchoring effects and i) the scope effect, and ii) the state of emotional load facing the individual.

4.1. Scope and anchoring effects

In order to ascertain whether scope effects are also present for the various anchoring bids utilized in the experiment, Table 2 reports the mean WTP for the subsamples of the lowest and highest bids utilized in the first dichotomous choice question. It can be seen that the size of the walking paths network has a similar influence on WTP across the lowest and highest bids offered to the individuals. This result is similar to the one found by Ariely et al. (2003) in what these authors called “coherent arbitrariness”. That is, although preferences are likely to be influenced by initial anchors or bids, they can be coherent in economic terms for the different dimensions of the good to be valued.18

However, the scope effect giving support to the coherence of preferences under anchoring, could be dependent on the emotional status of the individual facing the task of valuing different dimension of a given good. Thus, this potential relationship would raise the need to consider the role of emotions in both the anchoring and scope effects.

4.2. Emotional load and anchoring effects

The extent of the anchoring effects can be also influenced by the emotional status of the individual. In general, this hypothesis implies that the cognitive aspects of the valuation task, i.e. the commonly found recurrence to some anchor in order to base a valuation response, can be influenced by the emotional aspects involved. As can be seen in Table 3, the parameter of the anchoring effect $\eta_i$ is related with the level of emotional load posed by the individual in the valuation task.

The relationship between the anchor parameter $\eta_i$ and the EIS is depicted in Fig. 2. Low and high values of EIS correspond with significantly high levels of anchoring. This relationship is

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17 After testing for the validity and reliability of the EIS, the PCA reported that a model with only one factor provide the most satisfactory solution (e.g. reported Cronbach’s alpha was 0.92).

18 Ariely et al. (2003) found coherent preferences within individuals, i.e. by asking an individual about various dimensions of a given good. Since we used split samples for the sizes of the walking path network, our results can be interpreted as supporting coherent preferences at an aggregate level, rather than at an individual one, i.e. at a social welfare function rather than at individual utility functions.
not linear but U-shaped. The degree of anchoring declines as emotional intensity increases, reaching a minimum for an average value of EIS. At this point, anchoring effects are not significantly different from zero at the 99% level. Thus, even though anchoring effects are significant across the sample, those subjects with average EIS are not influenced by the first bid in the valuation process.

These results can be related to the evidence that purports a U-shaped relationship between human performance and emotional intensity (Ashcraft and Faust, 1994; Idzikowski and Baddeley, 1983). The “Yerkes–Dodson law” (Yerkes and Dodson, 1908) states that performance requires an intermediate level of emotional intensity (Leibenstein, 1987; Kauffman, 1999). When emotional intensity is too low there is insufficient attention and mental arousal, and short-term memory is blocked (Kahneman, 1973). When emotional intensity is too high thinking becomes disorganized, and there is difficulty to rationally evaluate the benefits and costs of alternatives (Eysenck, 1982; Yates, 1990; Lazarus, 1991; Oatley, 1992).

### 4.3. Emotional load and scope effect

The emotional state of the individual can also have an influence on his ability to perform according to coherent preferences, i.e. successfully passing the scope test. This hypothesis can be appreciated by looking at the relationships between the EIS and the size of the walking paths to be rehabilitated in the policy proposal. Table 4 shows the mean WTP for the different levels of the walking paths network according to three groups of individuals as bunched by their level of emotional state (low, average, and high). Fig. 3 depicts the general relationships between the mean WTP and the variable KIL for the three types of emotional profiles considered.

It can be seen that WTP is less sensitive for initial changes in scope (from 0 to 30 km) when the emotional scale is low. This sensitivity rises as the emotional scale increases, from 15.20 € to 31.21 €. In addition, for further increases in the size of the walking paths (beyond 30 km) WTP remains invariant for the groups of high and low emotional scales. Thus, the scope test is failed for subjects with extreme emotional scales (low and high). These subjects also posed a large degree of anchoring effects. However, the group of individuals with average emotional state showed a steeper valuation function in relation to scope (i.e. to the level of km). Thus, only those subjects with an average emotional state are likely to behave according to coherent preferences with no anchoring effect.

These results can be seen as giving some support to the hypothesis claimed by Hsee and Rottenstreich (2004) that under “valuation by feelings” preferences tend to be very sensitive to changes in the initial values of the good and very insensitive to changes for higher values; and under “valuation by calculations” preferences are less influenced by changes in initial values, and more sensitive to further values.

### Table 2 – Mean WTP (€) for different sizes of the network by starting bids (standard deviation in parenthesis)

<table>
<thead>
<tr>
<th>Size of the walking path</th>
<th>Starting bid</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>30 km</td>
</tr>
<tr>
<td>Lowest (6.01 €)</td>
<td>14.88 (2.38)</td>
</tr>
<tr>
<td>Total sample</td>
<td>19.94 (2.44)</td>
</tr>
<tr>
<td>Highest (48.04 €)</td>
<td>21.94 (3.69)</td>
</tr>
</tbody>
</table>

### Table 3 – Anchoring effects parameter by EIS levels

<table>
<thead>
<tr>
<th>EIS</th>
<th>Anchoring effect (η)</th>
<th>Confidence interval (99%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low EIS</td>
<td>0.42 (0.10)</td>
<td>[0.16, 0.67]</td>
</tr>
<tr>
<td>Avg EIS</td>
<td>0.15 (0.07)</td>
<td>[−0.01, 0.30]</td>
</tr>
<tr>
<td>High EIS</td>
<td>0.43 (0.11)</td>
<td>[0.17, 0.68]</td>
</tr>
</tbody>
</table>

### Table 4 – Mean WTP (€) of the size of the network by EIS levels (standard deviation in parenthesis)

<table>
<thead>
<tr>
<th>EIS</th>
<th>30 km</th>
<th>100 km</th>
<th>300 km</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low EIS</td>
<td>15.29 (1.99)</td>
<td>16.64 (2.55)</td>
<td>16.87 (2.18)</td>
</tr>
<tr>
<td>Avg EIS</td>
<td>19.83 (3.73)</td>
<td>25.80 (2.46)</td>
<td>28.29 (4.07)</td>
</tr>
<tr>
<td>High EIS</td>
<td>31.21 (5.97)</td>
<td>38.77 (2.01)</td>
<td>37.68 (4.72)</td>
</tr>
</tbody>
</table>

See Li (1998) for details.
relevant empirical effect that influences the elicitation of the value of non-market goods using DBDC.

However, in our empirical application we found that preferences were sensitive to the scope of the good, suggesting that the embedding effect was not relevant in this context, since the subject reacted significantly to the different dimensions of the good to be valued. Further, the sensitivity of WTP to the scope of the good was also found for the various levels of the anchor given by the first bid price; in other words, the “coherent” relationship between WTP and the dimension of the good was not affected by the bid price offered in the first binary question.

Thus, we can conclude that anchoring effects do not seem to have a relevant influence on the individual’s ability to discern among different dimensions of a non-market good in a valuation scenario. A useful implication might be that relative WTP could be successfully elicited. Nevertheless, anchoring effects are still present in our application and raise serious concerns about the underlying nature of human values and the capability of preference elicitation techniques to capture them. If individual choices are influenced by external anchors, it can be questioned how can preferences be defined and how can elicitation techniques be able to seize them. As pointed out by Ariely et al. (2003), “even if there are no clear violations of the transitivity axiom, the researcher cannot ascertain whether elicited choices reveal a set of unique and well-defined preferences”. In other words, preferences might still be affected by the bid price offered in the first binary question. The results show that anchoring effects decline as emotional intensity increases, reaching a minimum for an average value of EIS. After this point, anchoring effects are again significant. The major implication of these findings is that individuals tend to improve their ability for the non-market valuation task when their emotional intensity is moderate.

On the other hand, the omission of EIS in the valuation function could bias non-market valuation results. The correlation between cognitive and emotional intensity implies that some index of the latter needs to be considered in the systematic part of the utility or expenditure functions. To our knowledge, previous work has generally assumed independence between the cognitive and emotional dimensions. The common incorporation of unexplained emotional conditions as part of the stochastic term introduces correlation between the systematic and the stochastic parts, leading to biased results.

Some researchers have claimed that the finding of insensitivity to scope in some applications is a clear evidence of the inability of stated preference methods to capture preferences for public goods (Kahneman et al., 1999; Diamond and Hausman, 1994). Our results suggest that the degree of sensitivity to scope can be also related to the emotional load involved in the valuation task. This might prompt a need for further evidence on the role of emotions in the valuation of private and public or environmental goods.

Our results concur with the notion that there might be a trade-off between the emotional and cognitive dimensions in non-market valuation tasks. That is, some degree of emotional intensity might help reduce the cognitive load and enhance performance in human decision making. Nevertheless, it should be acknowledged that this relationship is complex because of the multivariate factors that can influence individual’s emotions and the cognitive aspects involved in the survey instrument. Further research should explore the relationships of other emotional and cognitive factors that might play a role in the decision making task and the formation of individual’s preferences.

Appendix A. Estimation of the Bayesian model for DBDC

In this appendix we illustrate the application of the model outlined in Section 3 for the double-bounded dichotomous choice data. For simplicity, let us decompose the joint bivariate normal distribution for \( (\alpha_i^1, \alpha_i^2) \) into the product of the marginal distributions of \( \alpha_i^1 \) and the conditional distribution \( \alpha_i^2 | \alpha_i^1 \), that is,

\[
WTP_i^1 = x_i^1 \beta_1 + \epsilon_i^1 \quad (A1.1)
\]

\[
WTP_i^2 = x_i^2 \beta_2 + B_i^1 \eta_{21} + \epsilon_i^2 \theta_{21} + \nu_i \quad (A1.2)
\]

where \( \epsilon_i^1 = WTP_i^1 - x_i^1 \beta_1, \quad \epsilon_i^2 = \sigma_i^2 - \sigma_{21}^2, \) and \( \nu_i \sim N(0, \sigma_i^2), \) \( \epsilon_i^1 \sim N(0,1) \) are independents. Thus, the set of unknown parameters is \( \theta = (\alpha, \sigma_{21}, \sigma_2^2) \), where \( \alpha = (\alpha_{01}, \beta_1, \beta_2) \). The following independent priors are assumed:

\[
f(\alpha) \sim MVN(\alpha_0, \psi_0^{-1})
\]

\[
f(\sigma_{21}) \sim N(\sigma_0, \sigma_0^{-1})
\]

\[
f(\sigma_2^2) \sim IG\left(\frac{\sigma_0^2}{2}\right)
\]

where MVN and N are a multivariate and univariate normal distribution respectively, and IG is the inverted gamma distribution. Since we have no prior information on model parameters, very non-informative diffuse priors are assumed by considering \( \alpha_0 = \sigma_0 = \sigma_0 = 0 \), and large values for the parameters collecting the variance \( (\psi_0, \psi_0) \). Therefore, the joint posterior distribution takes the following form,

\[
\pi\left(WTP_i^1, WTP_i^2, \sigma_{12}, \sigma_i^2, \beta_1, \beta_2, \gamma^1, \gamma^2 \right) = \prod_{i=1}^{n} \left\{ \left( \frac{1}{p_{21}^0} \right)^{1-\gamma} \left( \frac{1}{p_{21}^1} \right)^{\gamma} \left( \frac{1}{p_{21}^2} \right)^{1-\gamma} \left( \frac{1}{p_{21}^3} \right)^{\gamma} \left( \frac{1}{p_{21}^4} \right)^{1-\gamma} \right\} \times f(\alpha) f(\sigma_{21}) f(\sigma_2^2)
\]

(A1.6)
where \( p_i^m \), \( p_j^m \), \( p^o_i \), \( p^o_j \) are the probabilities of individual \( i \) responds \( \text{no/no}, \text{yes/yes}, \text{no/yes} \) and \( \text{yes/no} \) respectively, and \( Y^i = (y_1^i, \ldots, y_d^i) \), \( Y^j = (y_1^j, \ldots, y_d^j) \), \( WTP^j = (WTP^1, \ldots, WTP^j) \). Since the dependent variables follow normal distributions the posterior conditional distributions are as follows:

\[
\begin{align*}
    f \left( WTP^i_j | Y^i, WTP^2, \theta \right) &= \begin{cases} 
        \phi \left( WTP^i_j | (\mu_{12}, \sigma_{12}) \right) |(0, B_0) | & \text{if } y_1^i = 1 \\
        \phi \left( WTP^i_j | (\mu_{12}, \sigma_{12}) \right) |(B_0, \infty) | & \text{if } y_1^i = 0 
    \end{cases} \\
\end{align*}
\]

(A1.7)

\[
\begin{align*}
    f \left( WTP^2_j | Y^i, WTP^1, \theta \right) &= \begin{cases} 
        \phi \left( WTP^2_j | (\mu_{21}, \sigma_{21}) \right) |(0, B_1) | & \text{if } y_2^j = 1 \\
        \phi \left( WTP^2_j | (\mu_{21}, \sigma_{21}) \right) |(B_1, \infty) | & \text{if } y_2^j = 0 
    \end{cases} \\
\end{align*}
\]

(A1.8)

\[
\begin{align*}
    f \left( x | Y^1, Y^2, WTP^1, WTP^2, \sigma_{21}, \sigma^2 \right) &= \text{MVN} \left( \frac{1}{\sigma_x^2}, \frac{1}{\sigma_y^2} \right) \\
\end{align*}
\]

(A1.9)

\[
\begin{align*}
    f \left( \sigma_{21} | Y^1, Y^2, WTP^1, WTP^2, \sigma^2 \right) &= \text{IG} \left( \frac{\alpha_1}{2}, \frac{\alpha_1}{2} \right) \\
\end{align*}
\]

(A1.10)

\[
\begin{align*}
    f \left( \sigma^2 | Y^1, Y^2, WTP^1, WTP^2, \sigma^2 \right) &= \text{IG} \left( \frac{\alpha_2}{2}, \frac{\alpha_2}{2} \right) \\
\end{align*}
\]

(A1.11)

where \( \phi(\cdot) \) is the truncated normal distribution in interval \([a,b]\). If \( y^i = (y_1^i, \ldots, y_d^i) \), the Gibbs sampling works by iteratively replacing the initial value on the conditional distributions, and Eqs. (A1.7)–(A1.11) complete the MCMC algorithm. The algorithm is repeated \( t \) times, leading to the final values \( (WTP^1, WTP^2, \ldots, \mu_i^0, \mu_j^0, \sigma_i^0, \sigma_j^0) \) obtained from the joint distribution \( (WTP^1, WTP^2, x, \sigma_{21}, \sigma^2) | Y^1, Y^2 \). This sequence of \( t \) algorithms is conducted over \( H \) times, leading to \( H \) values for each parameter of the posterior distribution. These series of simulated values are utilised to generate the posterior moments for the parameters after discarding the first \( d \) values.

### Appendix B. The Reduced Emotion Intensity Scale (EIS-R)

Imagine yourself in the following situations and then choose the answer that best describes how you usually feel.

1. Someone compliments me. I feel:
   1. It has little effect on me
   2. Slightly pleased
   3. Pleased
   4. Very pleased
   5. Ecstatic—on top of the world
2. I am happy. I feel:
   1. It has little effect on me
   2. Slightly happy
   3. Happy
   4. Extremely happy
   5. Euphoric—so happy I could burst
3. Someone I am very attracted to asks me out for coffee. I feel:
   1. Ecstatic—on top of the world
   2. Very thrilled
   3. Thrilled
   4. Mildly thrilled
   5. It has little effect on me
4. I am at a fun party. I feel:
   1. It has little effect on me
   2. A little light-hearted
   3. Lively
   4. Very lively
   5. So lively that I almost feel like a new person
5. Something wonderful happens to me. I feel:
   1. Extremely joyful-exuberant
   2. Extremely glad
   3. Glad
   4. A little glad
   5. It has little effect on me
6. I have accomplished something valuable. I feel:
   1. It has little effect on me
   2. A little satisfied
   3. Satisfied
   4. Very satisfied
   5. So satisfied it’s as if my entire life was worthwhile
7. A person with whom I am involved prepares me a candlelight dinner. I feel:
   1. It has little effect on me
   2. Slightly romantic
   3. Romantic
   4. Very romantic
   5. So passionate nothing else matters
8. I am involved in a romantic relationship. I feel:
   1. So consumed with passion I can think of nothing else
   2. Very passionate
   3. Passionate
   4. Mildly passionate
   5. It has little effect on me
9. Someone surprises me with a gift. I feel:
   1. It has little effect on me
   2. A little grateful
   3. Grateful
   4. Very grateful
   5. So grateful I want to run out and buy them a gift in return
10. Something frustrates me. I feel:
   1. It has little effect on me
   2. A little frustrated
   3. Frustrated
   4. Very frustrated
   5. So tense and frustrated that my muscles knot up
11. I say or do something I should not have done. I feel:
   1. It has little effect on me
   2. A twinge of guilt
   3. Guilty
   4. Very guilty
   5. Extremely guilty
12. Someone criticizes me. I feel:
   1. It has little effect on me
   2. I am a bit taken aback
   3. Upset
   4. Very upset
   5. So extremely upset I could burst
13. I have an embarrassing experience. I feel:
   1. It has little effect on me
   2. A little ill at ease
   3. Embarrassed
   4. Very embarrassed
   5. So embarrassed I want to die
14. Someone knows I am rude to me. I feel:
   1. So incredibly hurt I could cry
   2. Very hurt
   3. Hurt
   4. A little hurt
   5. It has little effect on me
15. I see a sad movie. I feel:
   1. So extremely sad that I feel like weeping
   2. Very sad
   3. Sad
4. A little sad  
5. It has little effect on me 
16. I am involved in a situation in which I must do well, such as an important exam or job interview. I feel:  
1. It has little effect on me  
2. Slightly anxious  
3. Anxious  
4. Very anxious  
5. So extremely anxious I can think of nothing else 
17. I am in an argument. I feel:  
1. It has little effect on me  
2. Mildly angry  
3. Angry  
4. Very angry  
5. Extremely angry

REFERENCES


