THE DYNAMICS OF PREFERENCE ELICITATION AFTER AN ENVIRONMENTAL DISASTER: STABILITY AND EMOTIONAL LOAD*

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Abstract

Non-market valuation techniques are commonly applied with the aim of inferring the preferences of individuals for restoration policies after an environmental shock or a disaster caused to environmental assets. A crucial issue in this task is to determine what would be the appropriate lapse of time from which the valuation techniques should be applied, taking into account the potential for obtaining biased result in the moments just after the shock (Arrow et al. 1993). In this paper we investigate this issue by considering the role of the emotional load in explaining the dynamic patterns of willingness to pay. The data is modeled with a flexible mixture distribution approach that allows us to observe the dynamic behavior of heterogeneous groups of individuals. The results show that willingness to pay for a restoration policy tends to stabilize when the emotional load is also stable. The main implication is that the attitudinal investigation of the emotional state of the objective population could provide satisfactory information for determining the time frame for carrying out more costly non-market valuation studies.

Keywords: Contingent valuation, Emotions, Heterogeneity, Preference elicitation, Stability, Temporal effects, Willingness to pay.

1. Introduction

Environmental disasters can be caused either by natural or human forces. They normally have important impacts on the welfare of human societies, and substantial resources are commonly devoted to promptly counteract their effects. Non-market valuation techniques are useful to measure either the costs caused by environmental disasters, or the benefits that society would experience with a restoration policy. A seminal example of the use of this approach to evaluate environmental impacts was one conducted after the accident of the Exxon Valdez oil tank in the coast of Alaska in 1989 (e.g. Carson *et al*. 1992). A critical question that has not been thoroughly investigated in the literature is what would be the appropriate time lapse for conducting the valuation of the total damage to society after an environmental shock has occurred.

The question of the appropriate time lapse was earlier posed by the NOAA panel of Arrow *et al*. (1993) in their seminal review of the contingent valuation method following the Exxon Valdez oil impacts. Referring to the contingent valuation method, these authors conclude that "the survey must be conducted at a time sufficiently distant from the date of the environmental insult that respondents regard the scenario of complete restoration as plausible". In respect of the question of which time lapse would be appropriate, the same authors decided upon the moment at which preferences were stable, since "a clear and substantial time trend in the responses would cast doubt on the 'reliability' of the finding". Further, in what can be seen as a somewhat odd recommendation, the panel report suggests that "time dependent measurement noise should be reduced by averaging across independently drawn samples taken at different points in time."

Previous literature has focused on comparing the same survey instrument addressed to the same sample at two points in time. This literature is confluent among test-retest and split sample tests that CV results are stable over time[1]. For instance, Kealy et al. (1990), Loomis (1990) and Stevens et al. (1994) found that there were no changes across time. Split-halves reliability tests can also be conducted if different samples are used at two points in time. Reliable results were found, among others, in Reiling et al. (1990), Teils et al. (1995), Carson et al. (1997) and Whitehead and Hoban (1999). Nevertheless, as recently claimed by some authors (Vatn, 2004; Spash, 2006; Corrigan et al., 2008; Dietz et al. 2009), test-retest studies have not generally addressed the issue of the dynamic evolution of willing to pay values after an emotional shock caused by an environmental disaster.

The importance of using models that allow for the accommodation of preference dynamics in non-market valuation has been acknowledged in the literature (Vatn, 2004; Spash, 2006; Corrigan et al, 2008). In this paper we investigate the dynamic relationships between the emotional shock caused by an environmental disaster and its corresponding environmental value. The critical issue is what would be the common pattern of the dynamic evolution of the elicited values, and if this pattern can be explained by psychological variables such as the state of the emotional load. The

[1] Test-retest studies compare the same survey instrument addressed to the same sample at two points in time. In order to avoid recall bias, it is common to vary the valuation question or to span the time lag.

fact that the emotional state can influence human behavior has been widely reported by other authors (e.g. Frank, 1988; Lazarus, 1991; Kauffman, 1999; Loewenstein, 2000). In the case of environmental impacts, there is also evidence that they can produce noticeable impacts on human emotions. Thus, by investigating the emotional response to environmental impacts, its relationships with individual behavior can be ascertained in dynamic non-market valuation.

Furthermore, if there is some relationship between the emotional reaction and the overall dynamics of environmental values following some major shock or disaster, then this information can be utilized to provide a useful guide as to the appropriate moment of time for conducting valuation studies. It is well known that well conducted non-market valuation studies using stated preference methods involve substantial amount of resources and are more expensive than simpler attitudinal surveys that can be conducted through telephone. Thus, there might be a case for invoking the use of surveys investigating the emotional state of the relevant population before any valuation related to the environmental impact is finally accomplished. Relatively cheaper and less time demanding survey options like omnibus surveys (e.g. Gallup polls) have been proven to successfully elicit general public attitudes and emotional loads (Blinder and Holtz-Eakin, 1984; Fong, 2001).

On the other hand, although economists have been aware of the role of emotions in an individual's behavior since early works (Smith, 1759; Comoms, 1934), until recently little attention has been paid to the role of the emotional dimension in individual economic behavior (see, for instance, Frank, 1988; Kaufman, 1999; Slovic et al, 2002; and Gifford, 2002, Peters et al, 2003, Araña and León, 2008, Araña, León and

Hanemann 2008). There is also 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 in general, and in explaining human beings' reactions after environmental disasters. For instance, emotions may affect memory (Heuer and Reisberg, 1990), perceptions (Zajonc, 1980; Lerner et al., 2001), purchase intentions (Brown et al., 1998), motivated cognition (Camerer and Lovallo, 1999; Dovidio et al., 1995), performance (Damasio, 1994) and problem solving abilities (Isen et al., 1987).

The rest of the paper is organized as follows. The next section describes the specifics of the application and data collection. Section 3 presents the flexible econometric model employed in order to test the proposed hypothesis while accommodating for heterogeneity in human responses to environmental disasters. Section 4 provides the results of the experiments, and finally section 5 sums up and concludes the study.

2. Application and data sources

The application is concerned with an important environmental damage caused by the tropical storm Delta in the Canary Islands in 2005. The Canary Islands benefit from a mild subtropical weather that has been traditionally absent from extreme events such as hurricanes, strong storms or lasting peak heats. But following the worldwide pattern of increasing extreme weather events, there has been in recent years some repetitive phenomenon of strong storms. This was the case in November 2005, when the Delta storm passed through the Canary Islands causing major disruptions and devastation in public infrastructures and agricultural crops.

An important impact of this weather episode was the damage caused to a natural monument popularly called “Dedo de Dios (God’s finger)”. This was an impressive rock standing on the sea about 50 meters off the northern coast of the island of Gran Canaria. This rock has been given its name because it seemed to represent the sculpture of a big finger pointing up to the sky. The total altitude of the rock was about 150 meters, out of which 70 meters were the finger and the rest formed the base, simulating a hand palm. This was a natural monument that used to stand as one of the symbols of Gran Canaria, and was inserted in all tourist leaflets showing places of interest in the island. As a consequence of the strength of the winds blowing with the Delta storm, the part of the finger fell down, and dispersed onto the sea base.

The fall of the finger was reported as a major catastrophe in the local news following the Delta storm, and was widely discussed by the population and politicians. Special teams of experts were assembled in order to provide possible solutions to this damage, which involve the restoration by re-composition of the fallen parts, or by rebuilding it up using other materials. Even though the solution was somewhat difficult, technical opinion suggested that there was a possibility of restoring the finger part, but at a somewhat important economic cost.

A contingent valuation study was conducted with the aim of valuing the potential benefits of the rehabilitation policy. The study was split in four samples taken in four different points in time following the damage, in order to study the dynamics of the elicited values of an important environmental impact. The questionnaire was essentially the same in the four points of time with the aim of facilitating their comparative results. The first sample was taken two months after the damage, the second sample four months after, the third sample six months after, and the fourth sample thirteen months after.

The final survey was preceded by two pre-tests and two focus groups conducted with subjects randomly taken from the population of Gran Canaria. The pre-survey work allowed us to improve the final questionnaire, by identifying the information that the individuals could handle about the restoration possibility and the credibility of this proposal. The presentation of the good to be valued was framed as a proposal for a restoration policy consisting of the rehabilitation of the natural monument. The information package presented to the individuals contained pictures depicting the monument before and after the disaster, as well as wording descriptions of its historical formation. After a first set of questions about the subject's opinion on the importance of the natural heritage and general public policies, the information package proceeded as follows:

> "The natural and cultural heritage can be affected because of the pass of time, and because of the action of rain, wind and erosion. For instance, as a result of the recent Delta storm in the Canary Islands, there was a fall of the God's finger".

The subject was then asked if she had heard about the God's finger fall, and through which communication medium. Then the subject was given a set of pictures[2] and maps, with the following description:

> "The God's finger is one of the most representative natural monuments of Gran Canaria. It has been formed long time ago as a consequence of volcanic activity in the northern coast of the island (please, locate in the map). It was in the past also known as the Broken Rock. As a consequence of the Delta storm, the superior part of the Rock fell down by twenty meters, as illustrated in this picture."

[2] See sample of comparative pictures printed on this article.

The valuation question followed the preceding information set on the God's Finger impact. The payment vehicle was defined as a contribution to a special fund created only for the specific purpose of rehabilitation. As a decision rule, it was stated that the policy proposal would only be undertaken if the majority of the population would vote for its implementation. The willingness to pay question was preceded by a statement invoking income limitation and the consideration of other potential expenses on environmental and other public and market goods. The elicitation method was a dichotomous choice format involving a yes/no question to a bid price taken from a bid vector of five prices. This vector was designed using the optimal design method of Cooper (1993) for a predetermined number of bids and based on the information of an open ended pre-test survey. The valuation question reads as follows:

> In this study we would like to know about how much you would value the possible reconstruction of the God's finger to its original state. The reconstruction would be realized by artists and specialized technicians, so that it will be restored to a state identical to the one before the storm. To this aim, authorities will create a public trust fund to which every individual in society will pay an amount of money. The money will be correctly utilized with the only purpose of restoring the God's finger to its original state. The reconstruction will be carried out only if the majority of individuals in society agreed to pay the specified amount and therefore vote for the restoration. If the decision is undertaken, every adult individual in society will have to pay the agreed amount. Considering that your income is limited and that you might wish to expend your money on other personal necessities or other public measures, would you be willing to pay x € for the restoration of the God's Finger to its original state?

This question was followed by a set of debriefing questions to ascertain the reasons behind the subject's vote in favor or against the restoration policy at the price offered. In addition, some other qualitative questions about the subject's opinion of alternative policy options (e.g. restoration, no restoration, taking the pieces to a museum) were also asked using Likert scales.

Following the valuation section in the questionnaire, the emotional state was investigated with the aid of an Izard's *Differential Emotion Scale* (*DES*), adapted to the Spanish culture and language by Echebarría and Páez (1989). More concisely, respondents were asked, "To what extent did you feel [each different emotion]" when thinking about the fall of the monument as a consequence of the Delta storm. The emotions measured were enjoyment, sadness, disgust, guilt, anger, contempt, fear/anxiety, shame/shyness, and pride. The subject responded to this question emotion by emotion on 7-point Likert scales. The responses to these specific emotions were treated with factorial analysis in order to reach a summary index of emotional state of the subject when recalling the fall of the God's finger caused by the Delta storm.

The utilization of DES rating scales to measure specific emotions has a long tradition in emotion research and has been shown to successfully capture individuals' feelings in a wide range of domains (Larsen and Fredrickson, 1999; Peters et al, 2003, among others). Specifically, the adapted version of DES utilized here has been previously employed to estimate the impact of Madrid bombings on personal emotions (Conejero and Echebarría, (2007). It is also important to note that, although feelings are ideally measured right after they are produced, specific emotion rating scales can be expected to elicit meaningful self-reported feelings following considerable time spans (Larsen and Fredrickson, 1999). Moreover, positive emotions can be coded with negative emotions to generate an overall ranking of emotional intensity load that has been previously validated in other studies (Peters et al, 2003).

The final successive samples were taken randomly from the adult population of Gran Canaria, just following the Delta storm episode in 2005. The total number of observations was 1600, which was split in samples of 400 for each of the moments of time. The response rates were between 85-87% for all samples. The surveys were conducted in person by professional interviewers contracted by a survey research company. Interviewers received specific training sessions on the survey objectives and procedures, to make sure that the interviews were properly conducted.

3. Heterogeneous response modeling

An individual's response to environmental shock could vary according to her emotional state and personal characteristics. Thus, it might be convenient to consider the evolution of the heterogeneity across the surveyed population. To this aim, we consider in this section the application of a heterogeneous response model for dichotomous choice, based on the consideration of a smoothly mixing regression model (SMR), developed by Geweke and Keane (2007). The SMR model is an extension of the Bayesian mixture of normal model (Geweke and Keane, 1999), previously applied to CV data in a study by Araña and Leon (2005).

Although both models are flexible enough to accommodate a wide variety of WTP distributions even when considering a small number of components of the mixture (Geweke and Keane, 2007, Fig. 1. Page 256), SMR has the advantage of allowing researchers to explicitly include covariates in the estimation of the conditional probabilities for each component of the mixture (Geweke, 2007). Therefore, SMR allows us to test for the impact of emotions on WTP indirectly through its inclusion in the conditional probability equations rather than in the WTP valuation function.

According to the dichotomous choice format (Hanemann, 1984), the subject is offered a bid price (B_j) for a proposed restoration policy that increases environmental quality

q. The observed answer $\{y_i\}$ to bid price $\{B_i\}$ takes the value one if WTP_i is higher than the bid price, and zero otherwise. We can assume that the latent variable WTP is a function of two components, a deterministic μ and a random component ξ (Cameron, 1988). In general, we can write $\mathrm{WTP_i} = \mathrm{WTP_i}\,(\mu_i, \xi_i)$, where μ is the mean of WTP and ξ_i is a random error term, which is assumed normally distributed, with zero mean and σ standard error. Assuming independent answers and fixed covariates, the probability of a positive answer to bid price B_i is

$$\Pr\mathrm{ob}(y_i = 1) = \Pr\mathrm{ob}\left[\mathrm{WTP_i}\,(\mu_i, \xi_i) > \mathrm{B_i}\right] = F_\xi\left[\mathrm{WTP}^{-1}_{\mathrm{i}|\xi}(\mathrm{B_i}, \mu_i)\right] \qquad (1)$$

where $\mu_i = x_i^{'}\beta$ is the linear predictor associated with a k x 1 regression parameter vector β and a covariate vector x_i, including q, and $\mathrm{WTP}^{-1}_{\mathrm{i}|\xi}$ is the inverse of the willingness to pay function with respect to ξ_i. The linear predictor is linked to the probability of a positive response by a known cumulative distribution function $\{F_\xi\}$ or link function. The error distribution can be specified as some parametric form, and the model can be estimated by maximum likelihood (Hanemann and Kanninen, 1999).

However, this simple specification does not allow researchers to consider different groups of individuals across the sample following different distributions. Thus, the assumption of a common distribution can be overcome by considering that the stochastic terms adopt the following form:

$$\xi_i = e_{i1}(\alpha_1 + \eta_1\sigma_1) + e_{i2}(\alpha_2 + \eta_2\sigma_2) + \ldots + e_{ik}(\alpha_k + \eta_k\sigma_k) \qquad (2)$$

where α_j and σ_j $(\forall j=1,2,\ldots,k)$ represent the mean and the standard deviation of each of the normal forms in the mixture[3], and $\alpha' = (\alpha_1,...,\alpha_k) \in R^k$; $\sigma' = (\sigma_1,...,\sigma_k) \in R_+^k$ and $\eta_i | X \sim$ N(0, 1). Note that the definition of the random vectors $e' = (e_1,...,e_k)$ can be done in two different ways, which leads either to the mixture of normals or to the SMR models[4] (Fruhwirth-Schnatter and Kaufmann, 2008; and Geweke and Keane, 2007).

An a priori non-informative approach is to assume that the vectors *e*' are i.i.d. with a multinomial probability distribution of parameters

$$\pi_j = \text{Prob}(e_{ij} = 1) \quad (\text{j} = 1,...,\text{k}) \tag{3}$$

This specification leads to the mixture of normals model proposed by Geweke and Keane (1999). Alternatively, the group membership's probability can be defined to depend on certain covariates. Although there is a large set of alternatives to define π_j, it has been shown that a simplified multinomial probit model estimated through Bayesian MCMC works well for many applications in econometrics (Geweke and Keane, 2007, pag. 257). To simplify the MCMC simulation, we express the mixture model in terms of latent variables as in Diebolt and Robert (1994), Escobar and West (1995), and Geweke and Keane (2007). Therefore, the probability that each individual *i* belongs to each one of the classes *j* (π_j), can be rewritten as

$$\pi_j = j \quad iff \;\; \tilde{w}_{ij} \geq \tilde{w}_{il} \quad (\forall j \neq l, j = 1,...,k) \tag{4}$$

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[3] where $\sum_{j=1}^{k} \pi_j = 1$

[4] The mixture of normals model introduces flexibility in the distribution assumption and eliminates the normality assumption, and therefore approaches a semi-parametric model. Heckman and Singer (1984) and Zubov (1995) show that any distribution can be approximated arbitrarily well by increasing the number of mixtures *k* in the model.

where $\tilde{w}_{ij}$ represents the latent states corresponding to individual i and class j, which are dependent on a group of specific covariates z_{ij}, that is,

$$\tilde{w}_{ij} = \Gamma z_{ij} + \zeta_{ij} \tag{5}$$

where ζ_{ij}~ N(0, I_k), and Γ is the regression parameter vector[5]. SMR is an appropriate model for our experiment in the impact of the emotional load on the dynamics of non-market valuation for two reasons. First, it accommodates a flexible distribution for WTP avoiding potential problems with restricted assumptions like unimodality and conditional heteroscedasticity (Geweke and Keane, 2007). Second, by including the emotional load index into the vector of covariates z_{ij}, researchers can test for the relationship between the stability of WTP and the stability of emotions indirectly, thereby avoiding the potential endogeneity problems caused by the emotional load index.

Without further restrictions, the model is clearly unidentified in the sense that more than one set of values of the parameters imply the same p(y|**X**). In particular, to prevent interchanging the components of the mixture, some labelling restrictions are needed. Here we impose i) $\alpha_1 > \alpha_2 >... > \alpha_m$. The additional restrictions are the following[6]: ii) rank (**X**)=k and $a'\mathbf{X}' \neq (1,\ldots,1)$ for any k x 1 vector a; (ii) $p_j > 0$ $\forall j$; (iii) the support of $x_i^{'}\beta$ is a set of positive Lebesgue measure; (v) $\sigma_j = 1$ for some j.

[5] For identification reasons only J-1 parameter vectors are specified.

[6] It is important to note that by incorporating a multinomial probit model to define state probabilities, well known identification issues from this model also need to be addressed. Geweke and Keane (2007) show that the scale problem can be overcome by employing a fixed variance matrix, and that the identification question of the posterior distribution would be resolved by using any proper distribution for Γ. See Geweke and Keane (2007) for specific details about the specification and the inference of the functions of interest, and Geweke

Maximum likelihood estimators (MLE) of the parameters can be obtained by accordingly optimizing the maximum likelihood function using some non-linear method. However, sampling distributions of MLE cannot be derived in a closed form so that estimator properties rely almost exclusively on asymptotic or large sample situations. In particular, any model requires extremely large (as much as 1000 observations per parameter) samples to ensure the adequacy of asymptotic approximates (McCulloch and Rossi (1994)). In addition, asymptotic properties of ML estimators do not need to be maintained with small and finite samples (Amemiya, 1985, Huber, 1981). Anderson and Richardson (1979) and Griffiths, Hill and Pope (1987) found out relevant biases with numerical simulations of probit and logit models with small samples, while Copas (1988) utilize Taylor series expansions to define the bias obtained for a logit model with small samples.

In these cases a Bayesian approach could be utlized. Bayesian methods, as developed by Chib (1992) and Albert and Chib (1993), adhere to the likelihood principle and are conducted using formal rules of probability theory. This means that under mild conditions Bayes estimators are consistent, asymptotically efficient and admissible in small samples. As a practical matter, Bayesian inference is free from the use of asymptotic approximations and delivers exact, finite sample inference (Rossi and Allenby (2002)). An additional advantage of a Bayesian estimation approach lays in the fact that, since the number of clusters is unknown a priori, the attempt to estimate the parameters of an empty cluster leads to a violation of the regularity conditions for maximum likelihood estimation. Therefore, “standard asymptotic theory fails to provide correct asymptotic confidence intervals for the underlying parameters, whilst

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(2007) for an in-depth discussion about identification and interpretation issues in the mixture of normals and SMR models, and how to overcome them.

the a posteriori distribution still allows the parameter uncertainty to be gauged correctly even for non-regular estimation problems" (Aßmann and Boysen-Hogrefe, 2011). Definitions of the prior distributions, the conditional posterior analysis and the estimation algorithm can be found in Appendix 1.

Since we have no prior information on model parameters for the Bayesian models, we assume very non-informative diffuse priors with a large variance. The starting values for Gibbs sampling were taken from ML estimation, although the results were quite robust to changes in these parameters. The posterior results were generated by running the Markov chains for a burn-in period of 10000 draws and then retaining every 10th draw of the next 150000 draws. Convergence checks, as in Raftery and Lewis (1992) and Geweke (1992), did not indicate any problems, and this was checked by visual inspection of trace plots and re-running the samplers many times from different starting values.

5. Results and discussion

Normality testing

Before applying the flexible modeling approach of a mixture distribution it is convenient to test whether a rigid model such as Probit is appropriate for the binary choice data obtained in a CV experiment. Here we applied a specification test (H-H) for the distributional assumption of the error term of the Probit model proposed by Horowitz and Hardle (1994). Appendix 2 presents a detailed explanation of the methodology, and how it can be adapted for the parameterization of a latent variable (i.e. WTP) model. The H-H test allows us to determine whether there is a need to utilize a more flexible modeling approach to the empirical data in order to avoid the misspecification errors of rigid parametric structures such as Probit.

The H-H test statistics was computed for different values of *h*, in order to compare the sensitivity of the results to the choice of this parameter. The variance was estimated by (A.5) and the weighting function u(*v*) was assumed to take the unitary value inside the confidence interval and zero in other cases (Proença, 1993). The limits of the intervals were taken as the 10^{th} and 90^{th} percentiles, although the results were not sensitive to changes in these limits.

Table 1 presents the results of the test statistics for different values of *h* and their *p*-values for the different moments of time in which the experiment was carried out. For all the samples, it is observed that the Probit model is not rejected for low values of *h*. However, for values of *h* above 0.55 the test leads to the rejection of this rigid specification at the 5 percent level, suggesting that there is a need to consider a more flexible approach to model the empirical data. The left tail of the estimated distribution is always fatter for any value of *h* than the non-parametric approach. Thus, the Probit model particularly fails to represent those subjects on the tails of the distribution. A more flexible approach might be able to model more precisely these extreme responses to the WTP question, establishing different classes of individual positions with respect to the proposed policy[7].

[7] The Probit model was also compared with the SMR model utilizing the marginal likelihood estimates, showing that the SMR model was preferred according to Jeffreys' scale (Jeffreys, 1961). In addition, the estimation of both models with covariates showed that the Probit model overestimates the impact of most covariates on WTP. One key reason is that the SMR allows for a differentiation between mean and variance effects between groups of individuals, partially accommodating for scale heterogeneity (Louviere, 2006; Islam et al, 2007; Flynn et al, 2010) .

Stability of WTP

The NOAA panel report (Arrow *et al.* 1993), and widespread common sense among contingent valuation practitioners, concur with the hypothesis that preferences are not stable right after an environmental shock and that it is necessary to wait some time for the appropriate study to be conducted. In our results we find empirical support for this hypothesis, since the WTP distribution does not show stability right after the event has taken place.

Table 2 shows the proportions of individuals answering “yes” to each bid price in each observed point of time after the fall of the God’s finger. The chi-squared test statistics for the paired contingency tables across successive points of times proves that the sample proportions of responses to the bid prices were significantly different from the first to the second (M1 and M2), and from the second to the third (M2 and M3), but they were not significantly different from the third to the fourth point in time (M3 and M4). These results indicate that the WTP distribution might change before the first six months after the environmental disaster, and might become stable thereafter.

The mean WTP estimated with the SMR model for each point in time, and their corresponding credible intervals, are shown in Table 3. The number of mixtures in the error component of the SMR was three for the first sample (M1) and four for the three successive samples in time (M2, M3, M4). These numbers were determined by evaluating the marginal likelihood for each potential number of mixtures, and selecting the one with the largest marginal likelihood for each sample[8].

The results in Table 3 support the hypothesis of non-stable WTP right after the environmental shock. There is a sharp decline (40%) of the average value for a restoration policy from the first two months to the fourth month after the events. From the fourth until the sixth month after the event the decline is more moderate, of approximately 25%. From the sixth month, the average value approaches an average value between 12 and 13 €. Thus, it can be concluded that the mean WTP declines as the lapse of time increases, with a tendency to stabilize six months after the event.

According to the NOAA panel recommendations, contingent valuation studies should be carried out only when preferences are stable, resulting in stable WTP values, i.e. showing no significant temporal trends. The implication is that in the case of the application of this paper, i.e. the policy consisting of the restoration of the fallen part of the God's finger natural monument, only the results six months after the environmental impact satisfy the stability condition, and therefore any valuation study should be conducted beyond this time frame. This would guarantee the reliability of the results, provided other aspects for sound CV research were also taken into consideration.

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[8] The marginal likelihoods in the simulation study were calculated by a Bridge sampling approach based on M = 2000 draws from the posterior distribution and L = 1000 draws from the importance density.

However, adequate time lapse after an environmental shock could vary according to the type and magnitude of the event, its relevant population and the special circumstances in which it took place. In addition, not all practical applications can be designed with a formal test of the stability effects, due to the high costs that this practice would involve. Thus, the critical issue this paper investigates is what would be an appropriate and more efficient proxy for determining the adequate time lapse for a valuation study to be carried out. The answer to this question can be found by carefully studying the potential psychological reactions of individuals to the consequences of environmental shocks.

To the extent that psychological aspects influence human behavior, we can expect that the state of emotional load caused by the environmental shock would have an influence on an individual's valuation in stated preference experiments. In order to investigate this hypothesis we first look at the results for the emotional reactions to the fall of the natural monument following the Delta storm. Factor analysis revealed that the responses to the specific emotion questions could be incorporated into a single principal component, thus providing evidence that the individual emotion questions measured a common underlying concept[9].

Table 3 presents the results of the average emotional intensity scale for each point of time after the event. It can be seen that the emotional load is significantly higher in the first two months of the environmental shock than thereafter. The emotional load

[9] The resulting overall emotional intensity scale (EIS) had an internal consistency reliability (Cronbach's alpha) between 0.82 and 0.84 in the study population, for the subsamples of the different moments of time after the Gods' Finger fall.

decreases by about a third between the second month and the fourth month after the event. The final reduction reaches two thirds in the sixth months, stabilizing at this level (around 2) for successive periods of time.

Thus, the results indicate that time stability of the emotional effects after the environmental shock can be related to the stability of WTP (Figure 1). This finding supports the hypothesis that the initial overshoot of WTP might be caused by the emotional impact that the environmental disaster causes into human beings. The implication is that the investigation of the emotional state of the individuals can be a useful proxy for the investigation of the stability of WTP.

Heterogeneity

However, even though the environmental impact affects human emotions and WTP in a similar pattern, there might be some heterogeneous responses across individuals that might explain the direction of the trends after an environmental shock. Some individuals could feel their emotions strongly while others could respond more calmly or rather indifferently.

From a conceptual standpoint, these ideas can be modeled by hypothesizing that an individual's behavior might be explained by a mixture of utility functions of the form:

$$u(c|r) \equiv m(c) + n(c|e) \qquad (6),$$

where m(c) stands for "consumption utility" and n(c|e) represents the impact of emotions on individual utility, i.e. the portion of the environmental policy valuation that depends on the state of the emotional load of the individual. The implication is that the error term of the utility function would incorporate the impacts of the emotional load on the valuation of the environmental restoration policy, thereby leading to a source of heterogeneity across the sample of individuals.

Thus, while the consumption portion of overall utility [m(c)] is unique and stable, and so does the emotional part of utility $n(c|e_0)$ for a given emotional load (e_0), as far as the emotional load changes over time, so does overall utility. Moreover, we hypothesize that a cause for changing the emotional load is a catastrophic event. Thus, observed responses to state preference experiments will not result in the elicitation of a structured and stable preference function as far as the level of emotional load is not stable.

Therefore, it might be interesting to investigate the sources of heterogeneous responses across individuals utilizing the SMR model with covariates. Let us first consider how the evolution of WTP after the fall of the God's finger is related with the heterogeneity across the sample. As it can be seen in Table 5 and Figure 2, the SMR model raises four distinguished groups that evolve by changing their probability mass across time, i.e. their representation in the sample population. The first group starts from a large value of 45 € in the second month after the event and declines until a mean WTP value of 25 €. The participation of this group in the sample declines from 51% until about 30% in the stability period. The second group starts with a value off 31 € in the second month and declines to about 11 € in the stationary period. Its participation rises from 25% to 43% after one year of the event.

The third group of WTP values does not appear significant in the first two months after the event. They appear only in the second sample, i.e. only four moths after the environmental shock. They grow in relative importance until reaching a significant 14% of the sample one year after the event.

The final group includes those subjects who are not willing to pay any amount of money for the restoration policy. This group strongly declines its share from 23% of the sample to about 12% in the stability period. Some of these people decided to pay for the environmental policy proposal after the first two months of the event, joining the other groups with positive WTP values.

These results clearly indicate that there are shift share effects across the groups of individuals identified by the mixture model across time. Some individuals in the population of interest might reduce their WTP after reconsideration of the environmental policy as the time lapse from the event increases. Other individuals starting from low values for WTP would raise their bid after reconsideration. The overall implication is that we find mixed dynamic behavioral responses across individuals when the environmental policy proposal is considered under more settled emotional states.

The consideration of covariates in the SMR model allows us to explain the sources of heterogeneity across the sample. Table 6 presents the results of the estimated impacts of the covariates in the SMR model for each of the points of time after the fall of the God's finger. These are structural parameters that impact WTP for all latent classes in the model, i.e. x_i in equation (1) above[10]. Table 7 presents the impact of significant covariates on the probability that each individual belongs to each specific class in the SMR model i.e. covariates z_{ij} in equation (5) above. The significant covariates were gender (i.e. binary variable which takes value 1 if respondent is female and 0 otherwise), years of education, community attachment[11] and net annual household income. Covariates have been standardized to have zero mean and unit variance, for interpretation purposes and to suitably scale the values of the associated slope parameters.

The coefficients associated with demographic variables in all moments of time considered in this paper are consistent with expected results based on economic theory predictions and previously reported valuation studies. Table 6 shows that individuals that are more willing to pay for the restoration policy are likely to be females, have undertaken several years of formal education, and present high levels of community attachment. More precisely, for moment M1 females are willing to pay on

[10] Although a large list of covariates was considered in the analysis, we included in the final model only those for which the marginal posteriors associated with the estimated coefficients place nearly all mass over positive values, which means that the probability that they have an impact on WTP is higher than 0.95.

[11] In order to consider both affective and cognitive dimensions of community attachments, this construct was measured by using two questions similar to those used by other studies (Cowell and Green 1994; Goudy 1977, 1990; Kasarda and Janowitz 1974; Theodori and Luloff 2000, Theodori, 2001). The first question was "Suppose that for some reason you had to move away from this community. How sorry or pleased would you be to leave the region?" Response categories included (1) very pleased to leave; (2) some-what pleased to leave; (3) it would not make a difference one way or the other; (4) somewhat sorry to leave; and (5) very sorry to leave. The second question was "How interested are you in knowing what goes on in your community?" Response categories included (1) very disinterested; (2) somewhat disinterested; (3) neither interested nor disinterested; (4) somewhat interested; and (5) very interested. The factor analysis for these two questions reported a 0.79 Cronbach' alpha.

average 7.29 € more than males. Also, a one-standard deviation increase in years of education (4 years), annual household income (30.000 €), and community attachment (i.e. 0.3 points in the scale) presents an expected increase in WTP of 1.37, 9.27 and 5.71 € respectively.

Considering the evolution of the WTP valuation function across the four moments of time after the event (i.e. M1, M2, M3 and M4), Table 6 shows the impact of socioeconomic variables for each moment of time, whereby variation in the time after the environmental impact indicates different levels of emotional load. Although gender was significant under high emotional load (M1) it becomes non significant when emotions are stable (M3 and M4). There is no change in the role of community attachment across the four moments of time, however income and education become statistically and economically more significant in explaining WTP when emotions are stable (M3 and M4)[12]. Thus, the impacts of socioeconomic variables on WTP become stable when emotions are also stable, i.e in moments M3 and M4 after the environmental impact.

Table 7 presents the probabilistic characterization of individuals assigned to different latent classes or segments. The emotional impact scale (EIS) has a significant impact on the allocation of the individuals to the different classes. This can be interpreted as supporting the notion that emotions are a main source of heterogeneity in the observed WTP data. Moreover, the impact of EIS on the probability that an individual belongs to latent segments 1 and 2 (that is, those with higher mean WTP) is positive

[12] The larger relevance of socioeconomic variables in explaining economic behavior under moderate or low emotional loads has been a recurrent finding in the literature on emotions and human decision making (for instance, see Damasio, 1994; Lowenstein, 2000; Gifford, 2002).

and large, while the impact is negative for the probability to belong to segments 3 and 4 (low WTP). Therefore, these results are consistent with the hypothesis that high (low) EIS implies a larger number of individuals classified in high (low) WTP latent segments, which will result in higher (lower) overall estimated WTP.

The latter result, combined with the fact that the proportion of individuals in latent segment 4 (WTP=0) is reduced for successive points of time after the environmental shock, can explain the observed change in the WTP distribution and its stabilization after 4 months. This evidence is somewhat similar to the one obtained by Peters et al (2003). These authors observed that first time buyers found different numerical cues (i.e. WTP=0) to be more salient (i.e. anchoring effects) than more experienced buyers. The supporting argument is that this result might be a consequence of anchoring their first reactions to some reference point (WTP=0 in our case) when the subject faces the evaluation of unfamiliar events, and then "use her affective feelings as information to adjust away from the initial reference point" (Peters et al, 2003, pag 326).

Also, as predicted by the 'outrage model' (Kahneman et al., 1998), Table 7 shows that the probability that an individual belongs to the latent group 4 (i.e. WTP=0) becomes smaller as the emotional load triggered by the catastrophic event grows. Therefore, if the affective feelings elicited are strong, the anchor, the adjustment, and ultimately the WTP value should be much higher (Kahneman et al., 1998; Peters et al, 2003). Consequently, if the non-market valuation experiment is carried out too close to the moment in which the catastrophic event takes place, WTP would be much higher and unstable than when the valuation experiment is implemented when emotions are stable.

6. Conclusions

Environmental valuation methods provide useful tools for appraising the economic impacts caused by sudden environmental damages. This type of impacts can cause emotional effects on the population of interest and therefore affect the values elicited by non-market valuation methods. Since human behavior is largely influenced by emotional state there is a wider case for investigating the relationships between emotions and values in non-market valuation methods. In this paper we have studied the dynamics of values following an environmental damage caused by the extreme weather event of an intense tropical storm. The objective is to examine the expected relationships between the stability of WTP and the stability of the emotional load caused by the environmental impact of the storm on the natural monument of the God's finger. To answer this research question, the evolution of environmental values elicited with the CV method is studied in parallel with the emotional impact caused by the damage on the survey population.

The WTP data are analyzed utilizing a mixture of normal regressions approach that allows us to study the potential heterogeneity across the reactions of individuals to the environmental impact, while accounting for the potential endogeneity of the emotional load factor in explaining WTP. The results show that mean WTP just after the environmental shock overshoots its stable level, which is reached six months after the event. The estimation of structural valuation functions for WTP for each of the successive observed points after the event showed that socioeconomic variables such as income and education become more significant and have a larger impact on WTP at moments of time when emotions become stable and emotional loads are lower.

Therefore, the stability of the WTP valuation function was reached only when the emotional load caused by the fall of the God's finger was also stable. In addition, the emotional load played a significant role in explaining the heterogeneous responses of individuals in different classes of WTP values. That is, the emotional load had a negative impact on the probability that individuals were classified on a segment with low WTP, while it had a positive impact for individuals within high WTP classes. The determinants of response heterogeneity across the sample of respondents were found to be quite robust over time, which can be attributed to both socioeconomic variables and the impact of the emotional load.

Thus, our results lead us to conclude that when the emotional impact index becomes stable there is also stability for the WTP values. The implication is that the study of the appropriate moment for conducting valuation studies after an environmental shock should take into consideration the stability of the emotional load in order to ascertain the stability of economic values. Further research should be conducted on the study of the role that emotional reactions play in the formation of economic values of individuals in society, and how emotions can be incorporated into economic models of human behavior.

Appendix 1. Definition of the model and estimation strategy

We follow Geweke and Keane (2007)) parameterization, since it does facilitates the expression of prior distributions and also leads to a MCMC posterior simulator with good mixing properties. Let us consider four groups of unobservables in the model for the WTP equation: *i) the variance parameters* σ_j *(*$\forall j=1,2,\ldots,k$*); ii) the coefficient vector* β*; iii) the mean parameters* α_j *(*$\forall j=1,2,\ldots,k$*)*. And for equations (4) and (5): *iv) the coefficient vector* Γ; *v) the state probabilities* π_j; *vi) the latent states* $\tilde{w}_{ij}$

Prior Distributions

The prior distributions are defined as follows:

$$\beta \sim N\left(\underline{\beta},\ \underline{H_\beta^{-1}}\right)$$

$$\alpha \sim N\left(\underline{\alpha}, \underline{H_\alpha^{-1}}\right)$$

$$\underline{s_j^2}/\sigma_j \sim \chi^2\left(\underline{v_j}\right)$$

$$p(1/\sigma) = \prod_{j=1}^{k} \frac{1}{\left[2^{\underline{v}_j/2}\Gamma\left(\underline{v}_j/2\right)\right]} \left(\underline{s}_j^2\right)^{\underline{v}_j/2} \frac{1}{\sigma_j^{(\underline{v}_j-2)/2}} \exp\left(-0.5\,\underline{s_j^2}/\sigma_j\right)$$

$$\Gamma \sim N\left(\underline{\Gamma}, \underline{H_\Gamma^{-1}}\right)$$

where $\alpha = (\alpha_1,\ldots,\alpha_k)$ and $\underline{H_\alpha}$ is an k x k matrix. The last two matrixes are positive defined. The posterior distribution is derived by using the permutation-augmented Gibbs sampling algorithm, similar to Frühwirth-Schnatter et al (2004). As it is noticed by Geweke (2007), this sampler is preferred over random permutation sampler (Geweke and Keane, 2007) in our case because it imposes balanced labeling. This algorithm involves sampling from the full conditional posterior distributions when they are known in a feasible form. Thus, even though WTP = (WTP_1, WTP_2, ..., WTP_n)' is not observed, it is possible its simulation from available information. Thus, given Y = (y_1, y_2, ..., y_n)' and $\theta = (\beta, \alpha, \sigma, \Gamma)$, the posterior distribution following data augmentation $\pi(\theta|Y,WTP)$ and the conditional density of the latent variable $f(WTP_i|Y,\theta)$ are known in a manageable form.

Taking the starting value for θ, based on ols regressions, i.e. $\theta^{(0)} = (\beta^{(0)}, \alpha^{(0)}, \sigma^{(0)}, \Gamma^{(0)})$, the Gibbs sampling algorithm obtains iterated samples from each of the posterior conditional distributions. The algorithm is carried on *t* times leading to the simulated vector $(WTP^{(t)}, \beta^{(t)}, \alpha^{(t)}, \sigma^{(t)}, \Gamma^{(t)})$ obtained from the joint distribution $(WTP, \beta, \alpha, \sigma, \Gamma)|Y$. These series of algorithms of size *t* are repeated over H times, leading to H values for each parameter which are simulated from the posterior distribution, i.e. $[WTP_h^{(t)}, \beta_h^{(t)}, \alpha_h^{(t)}, \sigma_h^{(t)}, \Gamma_h^{(t)})]^H_{h=1}$. Individuals were assigned to groups based on the decision rule presented in (4) based on the estimated score of the latent variables for each individual and group. The moments of interest are obtained from these simulated values[13].

Following Frühwirth-Schnatter (2001) recommendations, we look at marginal density plots and two dimensions scatter plots of posterior simulations of group specific parameters to learn about the geometry of the posterior graph, to finally choose restrictions that guarantee unique labeling and test whether or not label switching may be an issue for our specific application. Also, different starting values were considered and final results were insensitive to them. Based on this analysis and the inspection of graphs for all posterior values, the chain shows to hold good convergence properties and no label switching issues raised.

[13] It is worth to note that simulating from full conditional distributions when high correlations between paramaters are present is not efficient, in the sense that the resulting sampler will be slowly mixing. However, after considering alternative blocking alternatives presented in Frühwirth-Schnatter et al. (2004), and observing no significantly impact on final results, for the sake of simplicity we present results obtained by sampling from the full conditionals. All the analysis were based on extensions of the open source codes provided by Sylvia Frühwirth-Schnatter in the MATLAB package BAYESF 2.0 freely available at: http://www.ifas.jku.at/e2571/e2626/e2632/index_ger.html

Appendix 2. An extended H-H Test for Normality

As it has been discussed in the text, before applying the flexible modeling approach of a mixture distribution it is convenient to test whether a rigid model such as probit is appropriate for the binary choice data obtained in a CV experiment. Horowitz and Hardle (1994) propose a specification test (H-H) for the distributional assumption of the error term of the probit model. In this appendix we adapt this test to the parameterization of a latent variable WTP model.

The test is based on the difference between the parametric fit of the model $\Phi\left(X'\beta\right)$ and the non-parametric regression of *Y* over $X'\hat{\beta}$. If the link function is correctly specified then this difference should be due only to sampling errors. The statistics under the null hypothesis is as follows:

$$T_n = \sqrt{h}\sum_{i=1}^{n} u(X_i'\hat{\beta})\left[Y_i - \Phi(X_i'\hat{\beta})\right]\left[\tilde{F}_i(X_i'\hat{\beta}) - \Phi(X_i'\hat{\beta})\right] \quad (5)$$

which is asymptotically normal with zero mean and variance σ_T^2. The value of *h* determines the bandwidth of the confidence interval in the kernel regression. u(.) is a weighted function which gives smaller relevance to extreme observations, and $\tilde{F}_i(.)$ is a kernel regression on the data with order r ≥ 2. Parameter β is estimated under the null assumption using ML for the probit model. $\tilde{F}_i(.)$ should have the properties of being asymptotically unbiased and uncorrelated with Y_i. The first property is obtained by using Bierrens (A.6) correction. The second follows by eliminating observation *i* from the computation of the kernel regression or *"leave-one-out"* estimation. The asymptotic variance σ_T^2 is replaced by the consistent estimator. We utilize a quartic kernel, which satisfies the requirements for Horowitz[14] proposition 1 to hold:

$$K(v) = \frac{15}{16}(1 - v^2)^2 I(|v| \leq 1) \tag{6}$$

where I is the indicator function. This estimator is asymptotically unbiased. Thus there is no trade-off between asymptotic bias and variance as is commonly the case with standard techniques of determining the bandwidth. Proença (1993) used Monte Carlo simulation to show that the test can be influenced by the choice of h with finite samples. These results suggest that under-smoothing could leads to the rejection of H_0. Thus, it is convenient to utilize large values of the bandwidth in order to improve the potency of the test.

[14] See for instance, Martins (2001) for a formal proof.

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Table 1. Horowitz and Härdle (H-H) test results for the different moments of time.

		h = 0.3	*h = 0.5*	*h = 0.55*	*h = 0.6*	*h = 0.7*	*H = 1*
Moment 1	Statistic	1.797	-0.677	-0.940	-1.579	-2.795	-5.933
	(p-value)	(0.931)	(0.254)	(0.132)	(0.048)	(0.004)	(0.000)
Moment 2	Statistic	1.657	-0.659	-1.12	-1.468	-2.644	-5.479
	(p-value)	(0.918)	(0.243)	(0.181)	(0.041)	(0.005)	(0.000)
Moment 3	Statistic	1.897	-0.604	-1.045	-1.503	-2.587	-6.351
	(p-value)	(0.985)	(0.183)	(0.115)	(0.046)	(0.003)	(0.000)
Moment 4	Statistic	1.804	-0.662	-1.096	-1.761	-2.906	-5.780
	(p-value)	(0.923)	(0.234)	(0.124)	(0.039)	(0.002)	(0.000)

Table 2. Paired contingency table test results.

Bids (€)	M1	M2	M3	M4
5	0.78	0.71	0.66	0.68
15	0.57	0.56	0.52	0.54
30	0.56	0.53	0.49	0.48
60	0.42	0.37	0.34	0.34
120	0.19	0.09	0.06	0.07
Contingency test chi-square	-	5.217*	3.738*	0.951

* Significant at the 95% level

Table 3. Mean WTP for each temporal study

	Moment 1 (2 months)	Moment 2 (4 months)	Moment 3 (6 months)	Moment 4 (13 months)
E (WTP)	27.48 [23.93, 30.61]	16.72 [14.83, 18.61]	12.79 [11.97, 13.713]	12.97 [11.03, 14.93]

Table 4. Emotions measurement and evolution after the catastrophic event (Scale 1-7)

	Moment 1 (2 months)	Moment 2 (4 months)	Moment 3 (6 months)	Moment 4 (13 months)
Emotional Intensity	6.49 [5.34, 7.64]	4.26 [3.24, 5.28]	2.37 [1.43, 3.31]	2.15 [1.29, 3.44]

Table 5. WTP valuation functions for each moment of time (standard error in parentheses)

Variables		M1	M2	M3	M4
Latent segment 1	Mean WTP	45.57 [37.38, 53.52]	27.05 [21.99, 32.41]	24.79 [20.12, 29.35]	25.18 [21.13, 30.06]
	p	0.53	0.41	0.28	0.31
Latent segment 2	Mean WTP	31.12 [17.24, 45.98]	15.92 [8.83, 23.11]	11.92 [7.68, 16.27]	10.68 [6.27, 15.84]
	p	0.24	0.33	0.47	0.43
Latent segment 3	Mean WTP	-	5.02 [2.23, 8.15]	6.15 [3.70, 8.69]	7.51 [4.72, 10.35]
	p	-	0.08	0.11	0.14
Latent segment 4	Mean WTP	0	0	0	0
	p	0.23	0.18	0.14	0.12
Total population	Mean WTP	27.48 [23.93, 30.61]	16.72 [14.83, 18.61]	12.79 [11.97, 13.713]	12.97 [11.03, 14.93]

Table 6. Posterior Means and 95 % probability High Density Interval of the impact of demographics on WTP for the SMR model during M1, M2, M3 and M4.

	M1		M2		M3		M4	
Covariates	**E(•|y)**	**95 % HDI**	**E(•|y)**	**95 % HDI**	**E(•|y)**	**95 % HDI**	**E(•|y)**	**95 % HDI**
Constant	25.135	[11.842, 38.564]	11.338	[2.287, 20.465]	9.426	[1.894, 17.022]	9.837	[2.993, 16.739]
Gender	7.249	[0.030, 14.542]	4.210	[0.871, 7.583]	2.837	[-0.995, 6.695]	2.694	[-0.260, 5.671]
Years of Education	1.373	[0.573, 2.180]	3.926	[3.204, 4.655]	4.173	[3.567, 4.784]	4.059	[3.393, 4.731]
Community Attachment	5.715	[1.584, 9.887]	5.679	[3.178, 8.205]	5.927	[3.780, 8.193]	5.931	[3.741, 8.089]
Income	9.274	[5.157, 13.433]	10.32	[6.959, 13.714]	11.912	[8.829, 15.026]	11.729	[9.164, 14.320]

Table 7. Probabilistic characterization of latent segments

		M1		M2		M3		M4	
	Covariates	***E(•|y)***	**95 % HDI**	***E(•|y)***	**95 % HDI**	***E(•|y)***	**95 % HDI**	***E(•|y)***	**95 % HDI**
Latent Segment 1 Prob (s,=1)	Constant	-1.156	(-3.691, 1.379)	-1.133	(-3.770, 1.504)	-1.144	(-3.730, 1.441)	-1.132	(-3.769, 1.503)
	Gender	0.424	(-0.340, 1.188)	0.420	(-0.352, 1.192)	0.407	(-0.395, 1.209)	0.419	(-0.352, 1.191)
	Education	-0.287	(-0.575, 0.001)	-0.278	(-0.587, 0.030)	-0.298	(-0.589, -0.007)	-0.278	(-0.587, 0.030)
	EIS	**0.782**	**(0.290, 1.273)**	**0.798**	**(0.321, 1.275)**	**0.735**	**(0.248, 1.221)**	**0.797**	**(0.320, 1.274)**
	Income	0.091	(0.051, 0.130)	0.090	(0.051, 0.129)	0.093	(0.054, 0.132)	0.090	(0.051, 0.128)
	Attachment	0.356	(0.203, 0.508)	0.363	(0.204, 0.522)	0.345	(0.189, 0.500)	0.363	(0.204, 0.521)
Latent Segment 2 Prob (s,=2)	Constant	-1.925	(-4.139, 0.289)	-1.810	(-3.935, 0.316)	-1.809	(-3.934, 0.315)	-1.809	(-3.934, 0.315)
	Gender	0.130	(-0.498, 0.758)	0.129	(-0.481, 0.738)	0.128	(-0.480, 0.737)	0.128	(-0.480, 0.738)
	Education	-0.052	(-0.348, 0.244)	-0.053	(-0.347, 0.241)	-0.053	(-0.346, 0.240)	-0.053	(-0.346, 0.240)
	EIS	**0.643**	**(-0.017, 1.303)**	**0.624**	**(-0.011, 1.258)**	**0.623**	**(-0.010, 1.258)**	**0.623**	**(-0.010, 1.258)**
	Income	0.005	(-0.078, 0.088)	0.005	(-0.082, 0.092)	0.005	(-0.081, 0.092)	0.005	(-0.081, 0.092)
	Attachment	0.130	(0.090, 0.169)	0.131	(0.094, 0.169)	0.131	(0.093, 0.168)	0.131	(0.093, 0.168)
Latent Segment 3 Prob (s,=3)	Constant	2.558	(0.132, 4.983)	2.507	(0.154, 4.860)	2.404	(0.075, 4.733)	2.506	(0.154, 4.859)
	Gender	0.195	(-0.472, 0.862)	0.187	(-0.474, 0.848)	0.193	(-0.454, 0.840)	0.187	(-0.473, 0.848)
	Education	0.363	(0.039, 0.686)	0.356	(0.026, 0.685)	0.370	(0.050, 0.690)	0.355	(0.026, 0.685)
	EIS	**-1.248**	**(-1.943, -0.552)**	**-1.211**	**(-1.885, -0.536)**	**-1.210**	**(-1.878, -0.543)**	**-1.210**	**(-1.885, -0.536)**
	Income	0.093	(0.006, 0.179)	0.092	(0.002, 0.182)	0.097	(0.007, 0.188)	0.092	(0.001, 0.182)
	Attachment	0.021	(0.019, 0.022)	0.020	(0.018, 0.022)	0.021	(0.019, 0.023)	0.020	(0.018, 0.022)
Latent Segment 4 Prob (s,=4)	Constant	-3.237	(-5.884, -0.586)	-3.205	(-5.908, -0.501)	-3.172	(-5.742, -0.601)	-3.204	(-5.907, -0.501)
	Gender	-0.175	(-0.955, 0.605)	-0.168	(-0.988, 0.652)	-0.168	(-0.987, 0.651)	-0.168	(-0.987, 0.651)
	Education	0.421	(0.052, 0.79)	0.438	(0.065, 0.811)	0.412	(0.039, 0.785)	0.437	(0.065, 0.810)
	EIS	**-0.212**	**(-0.379, -0.044)**	**-0.199**	**(-0.365, -0.034)**	**-0.205**	**(-0.371, -0.040)**	**-0.199**	**(-0.364, -0.033)**
	Income	0.102	(0.010, 0.193)	0.105	(0.015, 0.195)	0.100	(0.010, 0.190)	0.105	(0.015, 0.195)
	Attachment	-0.021	(-0.033, -0.030)	-0.031	(-0.033, -0.029)	-0.030	(-0.032, -0.028)	-0.031	(-0.033, -0.029)

Note: ("***E(•|y)***" represents the posterior means, and "95% HDI" the posterior high density intervals for a 95 % of probability).

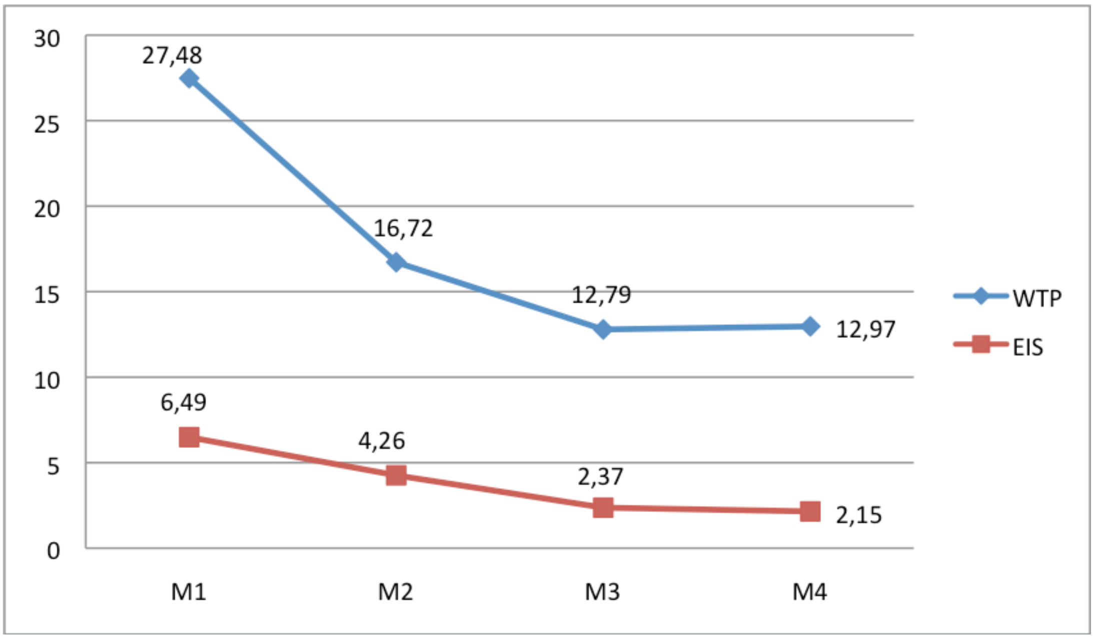

Figure 1. Dynamics of elicited E(WTP) and Emotional scale after the Delta Storm.

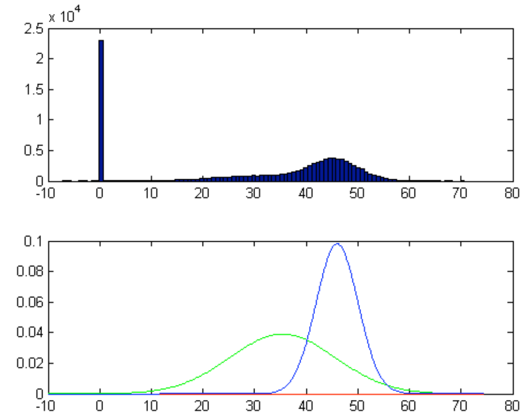

Figure 2a. Empirical and Estimated WTP in M1 (two months after)

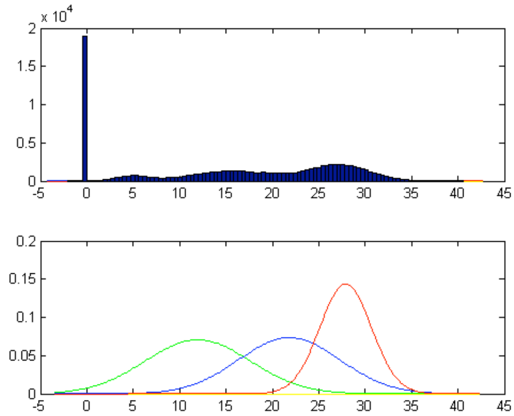

Figure 2b. Empirical and Estimated WTP in M2 (four months after)

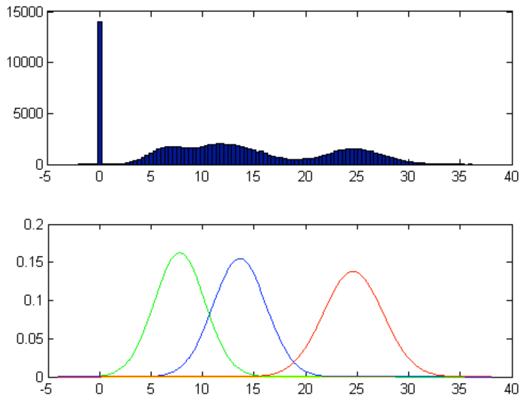

Figure 2c. Empirical and Estimated WTP in M3 (six months after)

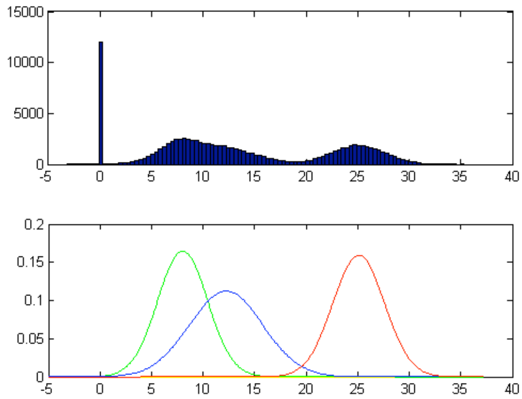

Figure 2d. Empirical and Estimated WTP in M4 (twelve months after)

Figure 2. Empirical and Estimated WTP distributions after the catastrophic event (x-axis represent WTP in euros and y-axis represents the probability associated with each WTP value).

(Attached file)

Figure 3. God finger before and after the Delta Storm