Does exclusion of protest zeros and warm-glow bidders cause selection bias in Contingent Valuation? An empirical case study in a Natura 2000 wetland area.

Abstract
A great issue of concern in valuation studies is whether respondents provide trustworthy and reliable answers conditional on the perceived information. Respondent may report either a higher than the true Willingness-To-Pay (WTP) due to warm glow or embedding effects or zero WTP which is lower than the true WTP due to protest behavior. We conduct a contingent valuation study to estimate the WTP for conserving a Natura 2000 wetland area in Greece. We find that 54% of the positive bidders exert warm glow motivations while 29% of all responses can be classified as protest zero bids. We employ three different models to test for the potential impacts of how these positive warm glow and protest zero bidders are treated. We first exclude the warm glow cases, secondly we include them, and, finally, we correct for selection bias by using the Full Information Maximum Likelihood method for grouped data model. Our findings show that removal of warm glow positive bidders does not distort the WTP estimate in any significant way. However, using the same approach for protest zero bidders, we find strong evidence of selection bias associated with removal of protest zero responses. Specifically, WTP estimates obtained after removal of protest responses are found to be biased downwards and the aggregated welfare measures would be significantly underestimated in our case. These results suggest that there could be serious consequences associated with the common approach of removing protest zero bidders in CVM.

Keywords: contingent valuation, selection bias, grouped data model

1. Introduction

The Contingent Valuation Method (CVM) is an often used method in economic valuation studies concerning non-marketed environmental goods. However, CVM has certain limitations and has received a significant amount of criticism from the scientific community. Venkatachalam (2004) provides a review of CVM where he refers to two major strands of criticism: Validity and reliability (Smith, 1993; Freeman, 1993; NOAA, 1993; Venkatachalam, 2004). The question that is being raised concerns to which degree CVM is able to measure the true economic value attached to the good under consideration (Freeman, 1993) and to which extent the variance of the value estimates is due to randomness (Mitchell and Carson, 1989). Within these two overall strands of criticisms, a range of various effects, errors, biases and issues have been mentioned in the literature; see e.g. Bateman et al. (2002) and Venkatachalam (2004) for an overview. In this paper we focus on two of these, namely warm glow effects and protest zero bidding in CVM.

The performance and validity of CVM surveys depend on whether respondents provide trustworthy and reliable answers conditional on the perceived information. There are cases where respondents report a willingness to pay (WTP) amount that may either exceed or be less than the true one. Respondents may deviate from the true value mainly for three reasons (Boyle, 2003). One reason could be a lack of comprehension of the study questions and information provided. Another explanation could be that respondents behave strategically. In this case they either free-ride or over pledge (Venkatachalam, 2004) or protest (Meyerhoff and Liebe, 2006) in an attempt to influence the provision of the good and/or the level of payment (Bateman et al., 2002). Thirdly, it is also possible that people object to some component of CVM simply 'refusing to play the game' that economists want them to (Mitchell and Carson, 1989, p. 166). Apart from the cognitive denial or hesitation of people to express their true value there may also be moral reasons that affect trustworthiness of WTP responses. Respondents may derive moral satisfaction by the act of giving *per se*, a behavioral effect also known as 'warm glow' (Nunes and Schokkaert, 2003). It has been suggested that such warm glow effects could explain the often observed scope or embedding problem, i.e. when the WTP value for one good does not differ significantly from the WTP for a more inclusive good even though economic theory and the basic assumption of non-satiation would suggest a higher WTP for a more inclusive good[1] (Harrison, 1992; Nunes and Schokkaert, 2003). Kahneman and Knetsch (1992) suggested that if the embedding phenomenon occurs, then the good, as a whole, is assigned a lower value than if it is evaluated as part of a more more inclusive good. It may be argued that if warm glow motivations are underlying a stated WTP, then the WTP represents a general donation to a charity, i.e. to do something good regardless of the described change in the good, rather than the individualistic preference-based value associated with the described change. Since the CVM framework relies on the latter, results are likely to be biased if the former is the actual respondent behavior. On the other hand, it could be argued that that it should not matter whether the individual's preferences arise from self interest or moral judgment (Arrow, 1951) and hence warm glow may be a tolerable fact for CVM (Nunes and Schokkaert, 2003). This in congruency might explain why it is not common to check for warm-glow motivations in responses in CVM applications, much less is there agreement on how to treat such responses if found. Nonetheless the need for more research on investigating and handling warm-glow cases was also emerged by

[1] Though, this would of course not be expected if the marginal utility of the additions in the more inclusive good is zero. In this case the WTPs would not differ, but this would be due to decreasing marginal utility rather than embedding.

former studies (Nunes and Onofri, 2004). It seems more common in the CVM literature to check for protest zero responses, and, when found, remove such responses from the dataset (e.g. Morrison et al., 2000).

Former studies on these issues have focused mainly on identifying them and explaining the determinants of protest zero or warm glow behavior rather than providing methodological solutions, i.e. how to treat such responses and the potentially accompanying biases. Whether to include or exclude those cases is a difficult question to answer. Keeping them in the dataset could potentially bias WTP estimates. However, excluding them would entail excluding a potentially non-random part of the sample. This might introduce sample-selection issues which could also lead to biased WTP estimates if the socio-demographic profiles and/or preference structures of excluded respondents systematically differ from the profile of respondents remaining in the sample. While the former has been explored by others, the latter has received surprisingly little attention in the literature. With this paper we aim to contribute to this gap in the literature by testing for selection bias associated with removal of protest zero and warm glow motivated bids in an empirical CVM survey considering a Natura 2000 wetland area in Greece. Furthermore, we show how to account for such selection bias in the WTP estimations.

The paper is organized as follows. First, we provide a brief overview of the literature on protest zero bids and warm glow. Section 3 presents the empirical dataset and the econometric approach used in the analysis which is provided along with some discussions in section 4. Finally, section 5 concludes on the results.

2. Methodological challenges

2.1 Protest zero bidders

It is quite common in CVM surveys to screen for and exclude protest zero[2] bidders from analysis since the stated zero WTP does potentially[3] not reflect the respondents genuine preference for the specified change in the good. If protests are included in the analysis then, firstly, mean WTP would most likely be biased downwards and, secondly, by wrongly assuming that the protest zeroes and the non-protest bids originate from a common unique preference structure, i.e. the latent demand curve, estimates of valuation function coefficients would also most likely be biased, though it is not possible to say *a priori* in which direction (Strazzera et al., 2003). The direction of the bias is unknown since protesters may genuinely assign a lower or higher than average value to the good (Halstead et al., 1992). Protesters refuse to pay not necessarily because they are indifferent to the public good being valued but due to their frustration referring to certain aspects of the survey. Thus, protest zero bidding respondents might actually have a positive value for the good in question but this value is not elicited in the survey. As including protest bids in the analysis may obviously question the validity and reliability of the results of the analysis, a similarly obvious and logical solution might be to simply exclude the protest bids from the analysis. However, this may not necessarily be a good solution. The reason is that

[2] Respondents who reveal positive WTP values may also hold protest beliefs (Jorgensen and Syme, 2000; Meyerhoff and Liebe, 2008). Here we have, however, chosen the more common approach of focusing on protest behavior in the zero bids (Morrison et al. 2000), even though this implicitly entails the assumption that respondents stating positive WTP are not susceptible to protesting.

[3] Of course the respondent may in fact have a genuine zero preference for the specified change in the good, but as the protest zero bid is not in accordance with the basic axiomatic assumptions underpinning the theoretical framework, it is impossible to know whether this is the case.

censoring of protest observations it is potentially the same as if a part of the sample is excluded non-randomly. This could cause sample-selection[4] bias which would produce biased parameters of model estimates simply because the sample would no longer represent the target population (Strazzera, et al., 2003). It is likely that protesters would state genuinely positive WTP bids under different circumstances, and as noted by Halsted et al. (1992) protesters may have a lower or higher than average WTP for the described change in the good. For example, if the genuine WTP in a group of protesters is on average significantly lower than the average WTP in the non-protesting group of the sampled respondents, then excluding the protesters from analysis would lead to overestimation of WTP for the target population and accordingly flawed policy advice. A noteworthy contribution to the literature in this respect is Jorgensen et al., (1999) and Jorgensen and Syme (2000, p.264) who discussed the common practice of censoring protest responses. They concluded that even though protest beliefs 'are unproblematic from the standpoint of attitude theory' researchers should make higher effort so as to interpret protest behavior properly. By deleting cases, as the usual practice commands it might lead to suspicion towards CVM validity.

As mentioned above, there is a need to examine whether characteristics of the protests systematically differ from the other observations. The literature provides some evidence of the profile of protest respondents. Meyerhoff and Liebe (2006) found that protest beliefs are negatively related to socio demographic characteristics, i.e. age and disposable income as well as to social norms and concern towards environmental problems. They also found that collective action for solving environmental problems enhance protesting. Later they have also concluded that survey characteristics such as the elicitation format, the payment vehicle, the survey method, and the geographical origin are determinants of protest behavior (Meyerhoff and Liebe, 2010). Mørkbak et al. (2012) have also shown that a range of socio demographic characteristics have predictive power on the probability of obtaining protest bids. Garcia-Llorente et al. (2011) found that the possibility of receiving protest responses is related to the particular public good for which payment is required, to respondents' socio demographic characteristics, pro-environmental attitudes, and stakeholder typology. They found that female respondents that have great interest in visiting the area under question were less likely to protest while locals showed the highest protest rate. Dziegielewska and Mendelsohn (2007) revealed that age, income, education and place of living are significant determinants of protest behavior. Overall, the literature clearly suggests that those who protest are generally not a random sample of the initial sample. Since socio demographic characteristics as well as respondent attitudes and behavior is commonly used as explanatory variables in the WTP function in CVM, this would suggest that the sample-selection bias could indeed be a serious problem when removing protesters. The relatively small strand of literature focusing on protest reduction entreaties to reduce the number of protest bids would seem to confirm that the mean WTP of protesters and non-protesters might indeed differ (Bonnichsen and Ladenburg, 2009; Atkinson et al., 2012).

[4] When mentioning selection we refer to sample selection provided that it is the analyst's decision to exclude non-randomly cases of the effective sample. However in case of protesting it is individuals that select themselves into the group of protesters by stating a zero bid and refusing to participate and thus it could also be regarded as self-selection.

2.2 Warm glow motivation

There are a number of studies that examine the existence of the embedding effect in CVM. Empirical results are mixed. Some studies conclude that CVM is exposed to embedding effects (Kahneman and Knestch, 1992; Desvousges et al., 1993) though receive a lot of criticism by some others (Smith, 1992; Harrison, 1992; Venkatachalam, 2004). Nunes and Schokkaert (2003, pp. 243) argue that the embedding effect does not necessarily imply contradictory behavior but it 'can be explained by the existence of a stable and measurable warm glow component in individual preferences'. In other words respondents may derive moral satisfaction by the act of giving *per se*, to some extent regardless of the proposed change in the good at stake. Thus, it may resemble a charitable donation which does not reflect the desired trade-off between on the one hand the described change in the good and on the other hand money, i.e. consumption of other goods. Hackl and Pruckner (2005) find no indication of the warm glow phenomenon in a health-related CVM study while Nunes and Schokkaert (2003) find a vigorous influence of warm glow effect on WTP measures for protecting the nature and propose a methodological approach accounting for the warm glow effect. Nunes and Onofri (2004) show that a number of socio demographic, attitudinal and behavioral characteristics significantly determine the probability of being a warm glow bidder, and they furthermore find evidence that warm glow bidders on average state higher WTP than others.

To our knowledge, the number of studies that suggest methodological answers for dealing with positive warm glow bidders is limited. Warm glow bidders respond positively and hence, econometrically, we face no irregularities as opposed to zero bidders' cases. Nevertheless, warm glow bidders do not report real economic preferences (Kahneman and Knetsch, 1992) and by including them in the analysis we might get unreliable WTP estimates and consequently a less solid and justifiable input to cost-benefit analysis and/or decision making. On the other hand, exclusion of such observations may introduce sample-selection bias if a non-random part of the initial sample is removed since it is not given that warm glow bidders comprise a random part of the sample. The findings of Nunes and Schokkaert (2003), Nunes and Onofri (2004) and Nunes et al. (2009) would suggest that warm glow bidders are not likely to be a random subsample of the initial sample, and, furthermore, they are likely to have different WTP values. Hence, even though the problem of identifying and accounting for warm glow seems to have been of less interest in literature, it would seem equally relevant and applicable as is the case for protest zero bidders. Whether or not they should be included or excluded from analysis is however not clear-cut and may be left open to the policy maker (Nunes and Onofri, 2004; Nunes et al., 2009).

3. Data and methods

3.1 Case study area

The Divari Pilou lagoon (Gialova) and Island of Sfactiria, is designated as a Natura 2000 area (GR255004) since 19/07/1996 and is located in the southwestern part of Peloponnesus, Greece. It extends across more than 3,500 ha of land, situated 12 km from the semi-rural area of Pylos and almost 48.5 km from the capital city of Messinia prefecture, Kalamata. The area is particularly characterized by the presence of 13 species of which two are designated as priority species. More specifically, the sea tortoise, *Caretta caretta*, which is one of the priority species of the Directive 92/43 EEC (Annex II), spends the reproductive season in the area. Of the remaining taxa, one of the most important is the Meditarranean Chameleon, *Chamaeleo*

chamaeleon. This lizard has a limited distribution in Europe, while in Greece is considered as threatened, included in the category "Rare". It is noteworthy that the site is the only place in the Greek mainland where the small chameleon population presently lives. The lagoon is also vital from an ornithological point of view, since a lot of migratory bird species are wintering there. Having such a rich avifauna, the area has also been classified as an EC Important Bird Area.

According to the latest *Environmental Impact Statement* (EIS) (D.C.M., 2007), the area is presently negatively influenced by a number of human activities which constantly deteriorate its preservation status. The five most crucial threats to the area according the EIS estimation seem to be: The direct threats to fauna and flora species, the fragmentation of biotopes, the use of agrochemicals/pesticides, the transport infrastructure and the nuisance caused by productive activities. Hence, human activities relevant to aquaculture, agriculture, and tourism (present leisure activities and tourism sector development) appear to be the most significant deteriorating factors.

3.2 Data collection

A written questionnaire was distributed to respondents between July, August and September of 2009. Respondents were chosen partly randomly and partly through a personal network (i.e snow-ball sampling), using convenience sampling in combination with a stratified sampling approach. Only responses from people that had prior knowledge of the area were collected. The target population was identified so as on site, off-site users as well as non-users to be taken into consideration. Sampling of users was almost straightforward given that the good to be valued was geographically well-defined. Regarding the population holding non-use values, the sampling was based on the notion that it is more correct to sample the non-user population by geographical location (Bateman et. al., 2002) and thus sampling was defined according to the population's distance from the good to be valued. The sample consisted of visitors (both foreign visitors and Greek visitors that reside outside Messinia prefecture), local residents that reside in the urban area approximately 48 km away from the area of interest and local residents who reside in rural areas almost 10 km away. Printed questionnaires were distributed to the targeted population. Participants were asked to fill in the questionnaire by themselves and then forward it back to the interviewer. The designated time frame was left open, ranging from a few hours to a few days depending on participant's availability.

The effective sample comprised of 334 respondents and in particular of 91 visitors, 91 rural and 152 urban residents. Table 1 presents the socio-demographic makeup of the sample. Half of the respondents were females, of middle age (40-60 years of age) and married. Due to the higher percentage of older respondents, only 40% of them stated that they had under age children while almost 70% lived in households consisting of 2 to 4 individuals. One out of two respondents had academic education and 45% was engaged in the public sector. Almost the same percentage was divided between private employees and entrepreneurs. About 12% of respondents didn't reveal their monthly income while out of those who did reveal it 30% and 20% fell into income categories €1.000-€1.400 and €1.400-€1.800 respectively.

Table 1
Socio-demographic characteristics of the sample.

	Mean	Std.Dev.
Visitors	0.27	0.45
Gender (Male)	0.45	0.49
Age	47.08	12.73
Marital status (Married)	0.71	0.58
Have children (under 18)	0.39	0.49
Education (University degree or higher)	0.63	0.48
Size of household	2.65	1.21
Personal net monthly income (1=lower than 1000€, 2=1000-1400€, 3=1400-3000€, 4=more than 3000€)	2.30	0.92

3.3 Questionnaire

3.3. 1 Hypothetical scenario

Prior to stating their WTP, respondents were asked to read the hypothetical scenario description thoroughly. The scenario described to respondents how the area of interest is currently suffering from a series of environmental problems, a lot of which are caused by increased tourism. The most recent EIS (D.C.M., 2007) provides a detailed analysis regarding the anticipated environmental problems caused by the development of the tourist sector and more specifically by a great project that has already been partially completed. This project concerns four new holiday resorts located in four different parts of the greater area, three of which are considerably close to the buffer zones of the area designated as a Natura 2000 site. It is projected that the number of tourists will rise significantly and that infrastructure facilities should improved so as to accommodate an expected 9,000 additional tourist visits per year (D.C.M., 2007). Furthermore, the hypothetical scenario described the preservation measures needed in order to avoid/ameliorate the environmental problems and the associated funding requirements. Respondents were asked to imagine that the cost of these preservation measures should be covered through a monetary yearly contribution provided by all visitors and local residents for the next five years.

3.3.2 Valuation question and payment vehicle

The payment vehicle was defined as a water tax for the local residents (in rural and in the urban centre as well) and as an entrance fee for the visitors (foreign and Greek). Monetary values were elicited through an ordered set of threshold values, i.e. a payment card. The payment card applied in the present study consisted of 15 different WTP levels: 0, 1, 2, 5, 8, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100 € or more. Before respondents made any decision regarding their maximum WTP amount, they were also given a "cheap talk" statement (Cummings and Taylor, 1999; List, 2001) and a budget constraint reminder (as proposed by Arrow et. al., 1993) in order to reduce potential hypothetical bias.

3.3.3 Follow up questions

Follow-up questions were necessary so as to identify invalid answers, i.e. answers that do not really reflect people's welfare change from the good to be valued (Bateman et al., 2002). In order to identify warm glow motivations, respondents were asked their most important reason for stating a positive WTP. Based on Jones et al., (2008) Toglidou et al., (2006) and Baral et al., (2008),, five possible reasons were available to respondents in a closed question format. Two out of the five reasons were directly linked to the area's values while the remaining three reasons

were interpreted to express warm glow effect. The next set of debriefing questions was aiming at distinguishing between valid-zero and protest-zero bids. The valid zero WTP bids reflect that respondents do simply not value the described change in the public good being offered (Strazzera et al., 2003) while protest-zero bids rather reflect the respondents' desire to protest against some aspect of the valuation process, stating a zero value even though they actually value the good (Jorgensen and Syme, 2000). In other words, such a zero bid is not derived from the respondent's preferences and does not reveal the assumed tradeoff relation between the described change in the environmental good and other consumption options. The reasons provided as answer options in this follow-up question were developed with inspiration from Jones et al., (2008) Toglidou et al., (2006) and Baral et al., (2008). The reasons for stating a positive WTP as well as the reasons for stating a zero WTP are summarized in table 2. A respondent was classified as protester or warm-glow bidder if he/she had chosen at least one of the reasons indicated to be related to protesting or warm-glow behavior, respectively, as indicated in the table.

Table 2
Warm glow and protest-zero bidders classification.

Respondent has a positive WTP:	**Is the reason related to warm-glow behavior?**
1. So as to preserve natural enviroment	Yes
2. So as to individually contribute to the area's preservation	Yes
3. Because the area is beautiful and unique	No
4. So as to maintain the quality of area's amenities for future generations	No
5. Because I can afford it	Yes
Respondent has a zero WTP because:	**Is the reason related to protest behavior?**
1. Others should pay	Yes
2. I cannot afford it	No
3. I don't have faith in the authority that will undertake to manage the preservation measures	Yes
4. I don't agree to pay an entrance fee/a water tax fee	Yes
5. I don't regard the environmental consequences on the area as important ones and thus preservation measures are not needed	No
6. I don't care	No

3.4 Econometric specification

3.4.1 Grouped data model

WTP responses were elicited using a payment card and thus the accurate level of the maximum WTP amount was not directly observable. Monetary values were censored within the amount intervals presented in the payment card. According to Cameron and Huppert (1989), an OLS procedure where interval midpoints are applied as proxies for the maximum WTP would lead to biased estimates of the parameters since "OLS systematically overstates the information in the data" (Cameron and Huppert,1989, pp.239). Alternatively they suggest the use of the Maximum Likelihood (ML) interval estimation method for a Grouped data model, which is considered a variant of the censored regression model. In this model, the dependent variable is coded as Y=1, 2, 3…..J according to the selected amount of latent variable Y^*

$Y = 1$ if $0 \leq Y^* < 1$
2 if $1 \leq Y^* < 2$
3 if $2 \leq Y^* < 5$
.
.
J if $Y^* \geq 100$

The observed dependent variable is $Y=j$ if $t_{j-1} \leq Y^* < t_j$, $j=1,\ldots J$, $t_0=-\infty$, $t_J=+\infty$. This simply means that the respondent's 'true' WTP (the latent variable Y^*) is between the specified amount chosen and the next amount on the payment card. In addition, a *lognormal distribution* for the WTP responses was suggested by Cameron and Huppert, (1989). The lognormal distribution is a useful first approximation since it is consistent with two conditions: first, implicit values will be non-negative[5] and second, as previous studies of Cameron and James (1986, 1987) have concluded, the distribution of valuations will be skewed due to the significant number of zero responses.

Referring back to the latent variable Y_i^* that represents the true valuation for each observation i, Y_i^* will lie between the lower t_{li} and the upper t_{ui} threshold of the specified interval. Likewise, the $\log Y_i^*$ will also lie between the log t_{li} and the log t_{ui}. For reasons of simplicity, we assume a following log-linear WTP functional form:

$$\log Y_i^* = x_i'\beta + \varepsilon_i \quad (1),$$

where x_i' is a vector of explanatory exogenous variables, β the associated vector of parameters and ε_i the random error term. If ε_i is distributed normally with mean 0 and standard deviation σ, that is $\varepsilon_i \sim N(0,\sigma^2)$ then the probability that a respondent will choose the WTP amount Y_i^* is

$$\Pr(Y_i^* \subseteq (t_{li}, t_{ui}) = \Pr((\log t_{li} - x_i'\beta)/\sigma < z_i < (\log t_{ui} - x_i'\beta)/\sigma) \quad (2)$$

where z_i is the standard normal random variable. Equation (2) can be rewritten as

$$\Pr(Y_i^*) = \Phi\left(\frac{\log t_{ui} - x_i'\beta}{\sigma}\right) - \Phi\left(\frac{\log t_{li} - x_i'\beta}{\sigma}\right) \quad (3)$$

where $\Phi(\cdot)$ is the cumulative density function of the standard normal distribution. For n observations, the total probability that respondents will have chosen the WTP amount recorded in the survey is interpreted as the *likelihood function* which is defined by the unknown parameters β and σ and is computed as the product of the likelihood contribution for each respondent. In order to obtain the optimum estimates of the unknown parameters β and σ, the log of the likelihood function has to be maximized. The *log-likelihood function* is

$$\log L = \sum_{i=1}^{n} \log\left[\Phi(\eta \log t_{ui} - x_i'\gamma) - \Phi(\eta \log t_{li} - x_i'\gamma)\right] \quad (4)$$

where $\eta=1/\sigma$ and $\gamma=\beta/\sigma$. The ML estimation technique is applied, providing a set of parameters β and σ that best fit the data (Bateman et. al., 2002). Further details regarding the ML formulas for

[5] We assume that WTP responses cannot take negative values meaning that no individual can be made worse off due to the hypothetical change.

the gradients and the Hessian matrix can be found in the Cameron and Huppert (1989) study as well as in Greene (2002, chapter 21).

Once the values of β and σ parameters have been estimated, the next step is to estimate the conditional mean of log$Y$* which will be $x_i'\beta$ for any given vector of x variables. However, the mean of the untransformed dependent variable Y* will be $E(Y^*) = \exp(x_i'\beta + \sigma^2/2)$ (Cameron and Huppert, 1989) where σ is an unbiased estimate of the true population error variance. Furthermore, the estimate of the median is given by the $\exp(x_i'\beta)$ implying that the median measure can be more robust compared to the mean, and hence can better depict the central tendency of the latent variable Y*. Mean estimate seems to be more sensitive to the error variance σ. However, both welfare measures can be used to compute the average mean and median WTP measure of the sample as well as to elicit aggregate estimates corresponding to the population of interest.

3.4.1 Grouped data for selectivity model

While some respondents are willing to reveal a true WTP reflecting their actual utility-based welfare change, others may hesitate to do so either due to warm glow effects or protest behavior. If affected by warm glow, respondents will most likely respond positively to the valuation question but the stated positive WTP will most probably be higher than their true WTP. In the latter case respondents will most likely react in a negative way, stating a zero WTP, but again, this zero WTP statement does not necessarily reflect their true WTP. The factors that affect the decision of a respondent to reveal his/her WTP differ from those that affect the valuation question. Hence, it may be argued that respondents face a 2-step decision process. The first step is to decide whether they will provide a true response, i.e. whether they want to "play the game" as requested, and if so, then the second step is to actually state their maximum WTP amount.

Let Y_i* denote the true maximum WTP amount stated in the second stage, and D_i is a dichotomous variable that takes the value 1 if the individual in the first step decides to reveal his/her true WTP, and 0 if not. D_i* represents the latent dependent variable of the participation equation that describes the first stage decision. Hence

$$Y_i^* = x_i'\beta + \varepsilon_i,\ \varepsilon_i \sim N[0,\sigma^2],\ i=1,\ldots N \quad (5)$$

$$D_i = \begin{cases} 1 \text{ if } D_i^* = z_i'\alpha + u_i > 0 \\ 0 \text{ otherwise} \end{cases} \text{for } i = 1,\ldots, m, \text{ where } m \le N \quad (6)$$

It is suggested that explanatory variable vectors x and z in equations (5) and (6) should be differentiated so as to avoid multicollinearity problems (Greene, 2006). There are two ways to estimate this two-stage model: Either the Heckman's 2-step method or the *Full Information Maximum Likelihood* (FIML) method. Although Heckman procedure is simpler than FIML, it will not be employed in the present analysis since it applies only to cases with a continuous dependent variable (as in open-ended value elicitation questions).

Since the values of the dependent variable Y_i are censored within the payment card intervals, a Grouped data model that is extended to accommodate the potential self-selection inherent in the

first stage of the decision process is applied. The model follows the same structure as the one presented above with the only difference that the valuation function in equation (5) will be log-transformed as in equation (1). Hence, the dependent variable will be the $\log Y_i^*$ that lies between the log of the lower and the upper threshold of the chosen interval. The log likelihood function to be maximized will thus be:

$$\log L = \sum_{D_i=0} \log[1 - \Phi(z'\alpha_i)] + \sum_{D_i=1, Y^*=J} \log[\Phi_2(z'\alpha_i, (\ln t_{ui} - x_i'\beta)/\sigma, -\rho) + \Phi_2(z'\alpha_i, (\ln t_{li} - x_i'\beta)/\sigma), -\rho] \quad (7)$$

where Φ_2 is the bivariate normal cumulative density function and ρ is the correlation between the two decision stages, testing for potentially biased WTP estimates caused by sample self-selection in the first stage. If $\rho<0$, the mean WTP would be underestimated. The opposite would stand in case that $\rho>0$. However if $\rho=0$, the two decision stages are independent and, hence, parameters can be estimated separately.

3.4.2 Model specifications

A binary logit model was employed so as to identify the factors that affect the probability of individuals' to *not* exhibit warm-glow behavior. The dependent variable takes the value 1 if there is no indication of warm glow in the respondent's WTP statement, and zero otherwise. Similar to warm glow behavior model, a binary model is used to identify factors affecting the propensity to *not* state a protest zero. The dependent variable takes the value 1 if the respondent states a positive WTP amount and zero if respondent states a zero bid for reasons classified as protest behavior (Table 2).

Accounting for warm-glow bidders, we examine three different model specifications: First by simply excluding warm-glow bidders – an approach which might be considered a reasonable approach when respondents are not providing a valid WTP statement. Secondly. we include the warm glow bidders without any special treatment. Third and finally, we include the warm glow bidders but only in the model setup described in equation (7) where potential sample self-selection biases are taken into account. We follow the same approach for the analysis of protest zero bidders. True zero responses are excluded from the analysis with no possible risk of selectivity bias since they represent an insignificant number of cases. Estimation of the parameters of the Grouped data model was performed using LIMDEP (NLOGIT 3.0) software package.

4. Results

4.1 Descriptive analysis

In 110 out of 311 returned questionnaires, a zero WTP was stated. Of these, only 19 could be classified as genuine zeros while the remaining 91 could be classified as protest zero bids. On the other hand, 201, i.e. 64.3%, of the returned questionnaires indicated positive WTP, though almost half of these (54.08%) were stated by individuals who, according to follow up questions, were warm glow thinkers to some extent. Table 3 shows the description of all explanatory variables that were used in model specifications presented in the following sections. Summary statistics are presented for each sub sample category, i.e. positive, warm glow and zero protest responses respectively. For some of the variables examined here, warm glow bidders' and

protesters' socio-demographic profiles differed from those of the remaining valid bidders[6]. This may indicate the potential introduction of a selection bias if these cases are simply removed from the analyzed sample.

Table 3
Summary of explanatory variables.

	Description	**ALL (N=311)**	**Valid positive responses (N=201)**	**'Warm glow' positive responses (N=109)**	**Protest zero bids (N=91)**
			Mean (std.dev)		
Independent variables					
WTP	Scale (payment card intervals). Willingness to pay	15.84 (22.42)	24.51 (23.78)	25.66 (24.58)	-
NWGL_BEH	Binary. If respondent is WTP as a non warm glow thinker then 1 else 0	0,46(0,34)	-	-	-
NPRO_BEH	Binary. If respondent is WTP and not to protest then 1 else 0	0,68(0.47)	-	-	-
Dependent variables					
FV_GV	Binary. If visitor then 1 else 0	0.26(0.44)	0.26(0.44)	0.30(0.46)	0.23(0.42)
GENDER	Binary. If male then 1 else 0	0.46(0.5)	0.46(0.50)	0.35(0.48)	0.49(0.50)
PYVISIT	Binary. If past visits is more than 2 times then 1 else 0	0.53(0.50)	0.50(0.50)	0.46(0.50)	0.60(0.49)
PRVIS_NR	Binary. If present visits is not on regular basis then 1 else 0	0.25(0.43)	0.26(0.44)	0.28(0.45)	0.26(0.44)
PSVIS_OY	Binary. If present visits is once a year then 1 else 0	0.47(0.50)	0.43(0.49)	0.42(0.49)	0.50(0.50)
AGE_YU	Binary. If age is less than 30 years then 1 else 0	0.22(0.41)	0.20(0.40)	0.25(0.43)	0.21(0.41)
AGE_ME	Binary. If age is 30 to 40 years then 1 else 0	0.23(0.42)	0.26(0.44)	0.24(0.43)	0.16(0.36)
EDU	Binary. If education is university degree or higher, then 1 else 0	0.64(0.48)	0.69(0.47)	0.65(0.48)	0.59(0.49)
INCOME_G	Scale. If personal net income <1000€=1, 1000-1400€=2, 1400-3000=3,	2.34(0.90)	2.32(0.89)	2.17(0.89)	2.51(0.92)

[6] We deliberately do not provide t-test statistics, since they will obviously not be significant due to the relatively low number of respondents. Nevertheless we see some tendencies in the mean values that might suggest differences.

	>3000€=4				
SIZEH	Scale. No of individuals	2.63(1.22)	2.68(1.22)	2.61(1.25)	2.46(1.16)
CHILDR	Binary. If presence of children (<18 years) then 1 else 0	0.39(0.49)	0.40(0.49)	0.32(0.47)	0.37(0.49)
E_IN	Scale. Environmental consciousness index[a], 1=5-15, 2=15-20, 3=20-25	1.87(0.69)	1.89(0.66)	2.15(0.69)	1.75(0.66)
AWAREPR	Binary. If respondent is aware of the environmental problems observed in the area then 1 else zero.	0.64(0.48)	0.69(0.46)	0.67(0.47)	0.53(0.50)
ATT_1	Binary. If respondent agrees that he/she would place natural and cultural heritage above his/her living standard then 1 else zero.	0.67(0.47)	0.76(0.43)	0.73(0.44)	0.53(0.50)
CL_2	Binary. If cluster 2[b] then 1 else 0	0.64(0.48)	0.64(0.48)	0.71(0.45)	-

[a] Respondents were asked to identify the frequency of five activities that relate to environmental behavior: (1) purchase of organic products, (2) provision with publications concerning environmental issues, (3) purchase of environmental friendly products (4) visit of web pages concerning environmental issues (5) recycling. An environmental index ranging from 5 (never) to 25 (always) was calculated using the Likert scores (1 to 5) adding up for the mentioned activities. The index aimed to capture the overall environmental behavior.

[b] Cluster 2 is formed by responders that have rated non-use values at a higher level. The variable is based on the outcome derived from a two-step cluster analysis that was employed to reveal natural grouping of respondents in regards to the significance they place in use and non-use values. Two clusters were identified, cluster 1 and cluster 2 that account for 36% and 64% respectively. **Cluster 2** respondents prioritized non use values higher, that is existence and wildlife existence values while **Cluster 1** respondents provided lower mean score for use values, namely actual and altruistic. Ranking of option and bequest values did not differ significantly between the two clusters.

4.2 Warm glow behavior

Table 4 reports the parameter estimates for the best fitting specification of the binary model examining warm glow behavior. Though the overall fit of the model is not impressive, increases in the "past year visits", "presence of children" and "environmental consciousness index" were found to significantly affect the propensity to exert warm glow thinking when stating a positive WTP. Specifically, respondents who were relatively more frequent visitors and respondents with children were less likely to express warm glow thinking. Furthermore respondents who were rated relatively high on the environmental consciousness index were more prone to warm-glow thoughts.

4.3 Protesting behavior

The simple binary model regarding a protest zero statement provided a fairly good fit to the data, correctly predicting 77% of the cases (Table 4). Socio-economic characteristic, i.e. age, income and education as well as attitudinal factors were found to significantly affect protesting behavior. Respondents of middle age as opposed to older ones and of higher education are found to have significantly lower probability of protesting. Nonetheless, the model reveals a positive relationship between income and protesting behavior which is in contrast to results in some former studies (e.g Meyerhoff and Liebe, 2006; Dziegielewska and Mendelsohn, 2007). Respondents who prioritize higher natural and cultural heritage and who are aware of

environmental problems observed in the area are less likely to protest against paying for the area's preservation. The latter is in line with findings in Meyerhoff and Liebe (2006). Interestingly, individuals who have visited the area more often have a higher tendency to protest. This could indicate that as people get more acquainted with the area, they become less willing to accept the monetary tradeoff suggested. In other words, the increased personal experience with the area which would otherwise indicate a relatively strong preference for the area might induce more lexicographical preferences and non-compensatory behavior that could translate into an increase in protest zero responses.

Table 4
Binary logit model results for warm-glow and protest bidders' profile (weighted by type of respondent[1]).

Dependent variable	**NWGL_BEH= 1 (positive responses)**		**NPRO_BEH=1 (all responses)**	
	Coef.	Std.error	Coef.	Std. error
ONE	0.380	1.122	1,972**	1,018
FV_GV	-	-	0,333	0,403
PYVISIT	0.829**	0.400	-1,266***	0,441
PRVIS_NR	-	-	-0,450	0,557
PRVIS_OY	-	-	-0,582	0,451
GENDER	-0.061	0.390	-	-
CHILDR	1.017**	0.431	-	-
E_IN	-0.621**	0.312	-	-
AGE_YU	0.328	0.626	-0,572	0,577
AGE_ME	0.354	0.464	2,289***	0,705
AWAREPR	-	-	1,083**	0,446
INCOME_G	0.067	0.245	-0,986***	0,264
EDU	-	-	1,020**	0,448
CL_2	-0.253	0.422	-	-
ATT_1	-	-	1,171***	0,405
N	131			198
Chi-square	16,80			57,96
Prob.	0,032			0,000
Pseudo-R^2	0,09			0,25
Correctly predicted	70,99			77,27

[1] Local respondents were oversampled, three times more than visitor respondents.
*** 1% significance level, ** 5% significance level, * 10% significance level

4.4 Grouped data model accounting for warm glow bidders; Correcting for selectivity bias.
Turning to the modeling of WTP, table 5 reveals that when warm glow bidders are simply excluded from the sample (model 1), two explanatory variables show a statistically significant bearing on WTP: education and household size. All other things being equal, respondents with relatively high levels of education state a significantly lower WTP for preserving the area than respondents with lower levels of education. The negative coefficient estimate for the size of household suggests that respondents living in relatively large households are willing to pay less than those living in smaller households. This could reflect the household budget constraint. The signs of all other coefficient estimates are as expected, though not statistically significant at conventional levels. This limited predictive power of the model is maybe not surprising considering the rather modest number of observations left after deletion of warm glow bidders.

By instead keeping the warm-glow bidders in the analysis, model 2 shows increased model fit, and more covariates are significant. Foreign and Greek visitors are willing to pay less compared to the local residents. This is most likely either due the effect of the different payment vehicles used in the survey (entrance fee for the visitors vs. water tax fee for the locals) or due to a larger

number of potential substitute sites that visitors may consider. The level of income is significant and, as economic theory would prescribe, WTP increases with increasing income. Importance of non-use values (variable CL_2) appears to be also a significant contributor to WTP. Thus, people who prioritized non-use values of the area at a relatively higher level were WTP more, *ceteris paribus*. A negative impact of increased education on WTP is found, as in model 1. It might be that well-educated people tend to act strategically and bid lower for free-riding reasons as suggested by Hackl and Pruckner (2005). The dummy variable WGL_BEH[7] was introduced so as to control for the effect that warm glow behavior could have on WTP. Somewhat surprisingly, this variable is far from statistically significant implying that WTP is apparently not, as we would have expected, inflated as a result of warm glow thinking.

Correcting for selectivity bias in model 3 returns almost the same output as model 1. The insignificance of the correlation parameter ρ suggests that removal of warm-glow bidders in our empirical case does not distort the WTP estimate – as also suggested by the insignificance of the warm glow behavior variable (WGL_BEH) in model 2.

Table 5
Grouped data model performance when including, excluding and correcting for selectivity bias for warm-glow bidders (weighted by type of respondent[1]).

	Model 1: Selection. Warm-glow bidders' cases are excluded.		**Model 2: No selection. Warm glow bidders' cases are included.**		**Model 3: No selection. Corrected for selectivity**	
Dependent =WTP	**Coef.**	**Std.error**	**Coef.**	**Std.error**	**Coef.**	**Std.error**
ONE	3.181***	0.779	1.913***	0.540	3.069	1.188
FV_GV	0.073	0.229	-0.410**	0.179	0.053	0.411
PYVISIT	0.156	0.213	0.207	0.179	0.223	0.403
AGE_YU	-0.348	0.373	-0.033	0.262	-0.356	0.630
AGE_ME	-0.348	0.258	-0.069	0.204	-0.307	0.314
EDU	-0.688**	0.284	-0.389*	0.211	-0.699**	0.343
SIZEH	-0.318***	0.097	-0.126*	0.072	-0.318**	0.141
INCOME_G	0.222	0.153	0.432***	0.109	0.225	0.213
E_IN	0.229	0.201	0.214	0.136	0.180	0.317
CL_2	0.348	0.235	0.493**	0.179	0.356	0.289
WGL_BEH			-0.027	0.173		
Selection equation NWGL_BEH= 1						
ONE					0.179	0.659
PYVISIT					0.559**	0.265
CHILDR					0.635**	0.272
GENDER					-0.005	0.266
E_IN					-0.349*	0.210
AGE_YU					0.092	0.410
AGE_ME					0.233	0.319
INCOME_G					0.013	0.159
CL_2					-0.153	0.259
Sigma	0.823	0.076	0.899	0.059	0.849	0.135
Rho					0.259	0.877
N	68		130		129	
LogL	-139,63		-283.001		-202,08	
AIC	4.430		4.539		3.459	

[7] WGL_BEH is defined as a binary variable that takes value 1 if respondent is a warm-glow bidder and zero otherwise.

[1] Local respondents were oversampled accounting for approximately three times as much as visitor respondents.
*** 1% significance level, ** 5% significance level, * 10% significance level

4.5 Grouped data model accounting for protesters; Correcting for selectivity bias.

The results of model 1 in table 6 are almost identical to the ones derived from model 2 in table 5 where all positive bidders, including warm glow bidders, were examined, though model 2 in table 5 provides less structural explanations for WTP. However, this could be expected given the large share of zero bids from protesting respondents. As model 1 and model 2 reveals, WTP is positively related to the environmental consciousness index. Looking closely at model 1 and 2 we observed that excluding cases from the sample would result in changing not only the predictive ability of variables but also their directional impact on WTP, positive or negative.

The selection equation in model 3 is in line with the logit model presented in table 4. The correlation parameter ρ is statistically significant and also high ($\hat{\rho} = -0.782$) indicating a strong selection bias associated with the typical approach of removal of protest zero responses. Since the correlation is negative, estimates obtained after removal of protest zero responses are biased downwards and the aggregate welfare measures would be significantly underestimated if based on model 1. It seems that protest respondents represent individuals that on average would be willing to pay a higher amount for the area's preservation than those who provide valid statements to the valuation question. Considering the selection equation, the model reveals that respondents of higher income classes, older respondents, less educated respondents, those who have visited the area more than two times in the past, and those who were less aware of the area's problems and with less strong environmental attitude were significantly more likely to protest. Model 3 indicates that the WTP statements depend significantly on the frequency of visits, educational level, income class and type of respondent. Specifically, locals, frequent users of the area, less educated and wealthier respondents are willing to pay more. The argumentation behind the relationship between these covariates and WTP corresponds to that described for model 2 in the former section.

Table 6
Grouped data model when including, excluding and correcting for selectivity bias for protesters (weighted by type of respondent).

	Model 1: Selection. Protesters' cases are excluded		**Model 2: No selection. Protesters' cases are included**		**Model 3: No selection. Corrected for selectivity**	
Dependent =WTP	Coef.	Std.error	Coef.	Std.error	Coef.	Std.error
ONE	1,670***	0,505	1,171	0,965	1.989***	0,500
FV_GV	-0,327*	0,174	0,088	0,328	-0,471**	0,210
PYVISIT	0,327**	0,169	-0,286	0,324	0,396*	0,218
AGE_YU	0,259	0,254	-0.494	0,481	0.345	0,291
AGE_ME	-0,019	0,201	0,788**	0,405	-0.262	0,219
E_IN	0,267**	0,128	0,608**	0,241	0.188	0,166
EDU	-0,335*	0,206	0,119	0,378	-0,428*	0,248
SIZEH	-0,095	0,071	-0,052	0,135	-0,096	0,124
INCOME_G	0,501***	0,108	-0,233	0,201	0,630***	0,124
Selection equation NPRO_BEH=1						
ONE					0,973	0,709
FV_GV					0,239	0,275
PYVISIT					-0,626**	0,266

PRVIS_NR					-0,147	0,339
PRVIS_OY					-0,215	0,298
ATT_1					0,626**	0,243
AWAREPR					0,495**	0,252
AGE_YU					-0,323	0,364
AGE_ME					1,059**	0,337
EDU					0,494*	0,251
INCOME_G					-0,498***	0,156
Sigma	0,930	0.059	2,097	0.138	1,005	0.123
Rho					-0,782***	0.156
N	143		205		186	
LogL	-312.32		-489,29		-372,22	
AIC	4.508		4.871		4.239	

Note: Variable CL_2 which corresponds to the cluster of respondents that value higher non use values is excluded from the analysis. Only positive bidders were asked to value area's use and non use values. Since we wanted to compare the performance of present model and of the one where protesters are included, *CL_2* variable had to be excluded.
*** 1% significance level, ** 5% significance level, * 10% significance level

4.6 Willingness to Pay estimates

Table 7 presents a summary of the simple and the parametric mean and median WTP. According to the simple nonparametric WTP distribution in the full sample, respondents are willing to pay on average €16 per year for preservation of the area, though the median WTP is only about half of that, indicating that the distribution is right-skewed. However, if only positive responses are taken into consideration, the mean WTP increases to €25 per year. This is not surprising since 110 zero bids are essentially left out. Almost the same mean WTP is obtained when looking only at the warm glow responses, corresponding to the findings in table 7. While the econometric models accounting for warm glow bidders estimate a slightly higher mean WTP than suggested by the non-parametric mean, again we find no marked impact of correcting for selectivity bias related to warm glow bidders. The median values may be considered preferable or at least more conservative welfare measures that better represent the central tendency of the WTP distribution especially with the apparent right-skew. Simple and parametric median values were almost the same (€20 and €19 respectively), when considering the sub-sample of individuals that hold positive values for the good in question.

Interestingly, the estimated welfare measures are considerably higher if protest zero bidders are included and selectivity bias accounted for in the analysis. The mean value estimated for all respondents (protests zero bidders as well as valid bids) when accounting for selectivity bias, is equal to €47 per year. Hence, the selectivity bias manifests itself as the difference between the mean WTP estimated from the model correcting for selectivity bias (model 3) and the mean WTP estimated under the typical approach where protest responses are simply excluded, implicitly assuming that ρ=0 (model 1). Hence, our results suggest that mean WTP may be underestimated by as much as 37% – and 33% for the median WTP – due to selectivity bias when excluding protest zero bids from the analysis.

Table 7
Summary of results.

Willingness to Pay (WTP)		
Descriptive	Mean (std.dev)	Median

Sample all (N=311)	15.84 (22.42)	8.00
Positive responses (No cases=201)	24.51 (23.78)	20.00
Warm- glow bidders (No cases=109)	25.66 (24.58)	20.00
Econometric models	Mean estimate.	Median estimate.
Grouped data model estimates: Accounting for warm glow bidders		
Model 1	26.66	18.99
Model 2	27.99	18.66
Model 3	24.27	16.93
Grouped data model estimates: Accounting for protesters		
Model 1	29.31	19.00
Model 2	53.06	5.89
Model 3	46.74	28.22

Note: In model 2, the mean estimate is almost double the sample mean, which is justified by the high error variance in the model. The median on the other hand, although being a more robust estimate, is biased downwards as a result of the large number of zero protest cases included in the sample.

5. Conclusions

We employ a CV survey to estimate the WTP for the implementation of a CMP in a Natura 2000 wetland area, in Greece. Results suggest that 54% of the positive bidders are individuals who could be considered as warm glow thinkers while 29% of all responses can be classified as protests zero bids. It may be that certain aspects of study design such as the scenario description, the sampling procedure, the presentation of the survey questions affect warm glow behavior (Venkatachalam, 2004). Convenience sampling and self-administered questionnaires in particular can be prone to unreliable results (Hanemann, 1994). A meta-study by Meyerhoff and Liebe (2010) revealed that geographical origin significantly affects protest behaviour and former studies originated from Greece have shown a high rate of protest responses (e.g Jones et al., 2008; Oglethorpe et al., 2000) with the most common explanation being that the government ought to pay. Hence, recommendations elicited by the aforementioned past studies were confirmed in our survey, where convenience sampling and geographical origin lead to significant rates of warm glow and protest bidders.

Based on binary logit models, we find that increasing visit rate as well as parenthood negatively impacts the propensity to exhibit warm glow thinking while increasing environmental consciousness shows a positive impact. Similarly, we find that older, less educated and higher income respondents that also have visited the area frequently are more likely to state a protest zero bid than others.

Regarding the treatment of positive warm glow bidders, we find no evidence that WTP was inflated or deflated as a result of including these responses. The model correcting for selection bias also suggests that selection bias is not present and removal of warm glow bidders does not distort the WTP estimate. Models of WTP accounting for protest zero bids show more interesting results. Comparing the two models, i.e. the one excluding and the other including the protest zero bids, we find that excluding these observations from the analysis – which is common practice in empirical CVM applications – would result in changing not only the predictive ability of variables but also their directional impact on WTP, positive or negative. The model correcting for selection bias reveals a significant correlation parameter between the selection and valuation

equation, indicating a strong selection bias associated with removal of protest responses. Since the correlation parameter is negative, WTP estimates obtained after removal of protest zero responses is biased downwards and the aggregated welfare measures would be underestimated. Our results suggest that the mean WTP may be underestimated by as much as 37% – and 33% for the median WTP – due to selectivity bias when excluding protest zero bids from the analysis in our empirical case.

Conclusively, we have no way of assessing what the actual WTP would be in our case, since this is a purely hypothetical setup, and, furthermore, we refrain from generalizing our results since they are based on a single empirical case study. Notwithstanding this, our results suggest that there could be serious consequences associated with the common approach of removing protest bidders, and we urge fellow researchers to conduct similar explorations to investigate this issue further.

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