‘Been there done that’: Disentangling option value effects from user heterogeneity when valuing natural resources with a use component.

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'Been there done that': Disentangling option value effects from user heterogeneity when valuing natural resources with a use component. †

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Abstract. Endogeneity bias arises in contingent valuation studies when the error term in the willingness to pay (WTP) equation is correlated with explanatory variables because observable and unobservable characteristics of the respondents affect both their WTP and the value of those variables. We correct for the endogeneity of variables that capture previous experience with the resource valued, humpback whales, and with the area of study. We consider several endogenous behavioral variables, so we apply a multivariate probit approach to jointly model them with WTP. In this case, correcting for endogeneity increases econometric efficiency and substantially corrects the bias affecting the estimated coefficients of the experience variables, by isolating the decreasing effect on option value caused by having experienced the resource. Stark differences are unveiled between the marginal effects on willingness to pay of experience of the resources in an alternative location versus experience in the location studied.

Keywords: contingent valuation, respondent experience, option values, multivariate probit, endogeneity, whales

JEL Codes: Q21, Q26, Q51, and Q57

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1. Introduction

Economic theory suggests that for a policy to be optimal it must balance benefits and costs at the margin, which, under general conditions, results in a maximization of net social benefits. When it comes to the conservation of natural resources and environmental amenities, it is more often than not the case that, while it is relatively easy to compute the cost of a policy, its benefits are difficult to monetize, since such policies often deal with goods and services without a market price. This is the case also of policies related to whale conservation.

According to economic theory, the total value of a resource includes several components, one of which is the so-called *existence value*. This is the value that individuals derive from the mere existence of a resource, even if they never plan to use it (Krutilla, 1967). Similarly, *option value* is the value that individuals place on having the option to enjoy a resource in the future, although they may not currently use it, while bequest values would refer to the value placed on the knowing that future generations will have the option to enjoy the resource. If these passive values are ignored or underestimated during the policy design process, the outcome of a policy will be sub-optimal. Since passive (or *non-use*) values cannot be estimated through market prices, researchers must resort to non-market valuation techniques that do not rely on observing market behavior, but instead use information obtained directly from stated preferences.

The most commonly used stated-preference method to estimate non-consumptive values is the Contingent Valuation Method. Contingent Valuation (CV) basically consists of directly asking individuals to state the value they place on a proposed policy involving a change in the quantity or quality of a certain resource (Freeman III, 1993; Cummings et al., 1986; Mitchell and Carson, 1989). One of the main concerns regarding CV studies is the accuracy of the CV estimates. Valuation accuracy is based on two concepts: reliability and validity. Validity implies that the CV estimate measures what it is theoretically supposed to measure and that it changes in a theoretically predicted way. Reliability refers to the stability of the measure over time and populations (Cameron and Englin, 1997; Whitehead et al., 1995). If the estimates are not both valid and reliable (i.e inaccurate), their use becomes questionable in designing the public policies.

In CV studies, willingness to pay (WTP) functions are estimated to identify the variables that affect WTP, which can help to test the theoretical validity of WTP measures when economic theory guides the empirical model. For example, it is in many instances assumed that WTP should be positively correlated with income; that more avid recreationists should be willing to pay more for an improvement in a recreational facility (Whitehead, 2005); or that those who know or have previously directly enjoyed an environmental asset are willing to pay more for its preservation.

In general, observed behavioral choices (visiting a recreational site, purchasing recreational equipment, visiting the area to be considered for preservation, etc.) are used as an independent variable in the WTP functions in many CV applications, since they can act as a proxy for underlying unobservable attitudes towards the environment.[1] In this study, we focus on the effect of behavioral choices that increase the respondent's level of experience of the resource valued. However, one problem associated with the use of these variables as independent variables is that they may actually be endogenously determined. Endogeneity occurs when the error term in the behavioral model is correlated with the error term in the WTP model.

This potential problem of the endogeneity of the experience binary variables in the main *WTP* equation could be regarded as a problem of *endogenous switching* (Miranda and Rabe-Hesketh, 2005). This problem affects the regression whenever the dependent variable of a model, in our case the binary variable *agree*, is a function of a binary regime switch, in our case the binary variables capturing previous experience with the resource. For example, studies on smoking and drinking behavior suggest that having a higher education degree may be an endogenous switch, since impatient individuals (an unobservable characteristic) are both more likely to smoke and drink and less likely to invest in human capital, and therefore less likely to have completed a degree (Miranda and Bratti, 2006).

Standard regression techniques result in biased and inconsistent estimators if there exist unobserved factors that affect the response in the main regression and are correlated with unobserved factors also affecting the switch processes (Heckman, 1978; Heckman, 1979). For example, in that case a naïve probit model relating whether an individual is willing to pay for conservation of a natural resource (a binary variable) to variables that describe whether the individual experienced that resource would yield estimates likely reflecting the combined effect of unobserved attitudes towards and/or norms about the resource and of the experience itself. These naïve probit estimates would, however, be biased, since they would attribute the net effect to the experience alone, likely masking the negative effect of a diminished option value. In fact, in some cases, although the unobserved characteristics had a positive effect on the *WTP* for the preservation of the resource, the net effect of the experience variable as such could well be negative, since the individual would now, having already experienced the resource, have a lower option value than those having yet to enjoy the experience of the resource.

This paper examines the issue of endogeneity bias in *CV* studies. This issue has not received much attention in the *CV* literature and only a few papers, reviewed in Section 2, have explored it. Moreover, the research to date has examined only the case of a single endogenous variable. The novelty of the present contribution is that we consider more than one behavioral variable and we apply a multivariate probit model to jointly estimate the *WTP* model and this set of multiple behavioral models. The focus of this paper is on the effect of correcting, in a dichotomous-choice *WTP* equation, for the endogeneity of explanatory variables that capture the respondent's previous experience with the good valued: humpback whales in Newfoundland and Labrador (NL). It is likely that a respondent's *WTP* to preserve the whales is correlated with that respondent's off-site use of the resource, the choice to visit Newfoundland and Labrador (a popular destination for whalewatchers) and, more importantly, to participate in whale watching (either in that province or elsewhere), so the endogeneity must be addressed. Our contribution has to do also with the specific effect that a reduced option value has in the correction of the signs of experience variables. We also pay special attention to the differences between having experienced a resource (whales in this case) at a given site and having experienced that same resource elsewhere.

The type of issue on which we focus in this paper has been addressed, with a similar methodology (even if most often restricted to the bivariate case) in other subfields of Economics, including Health Economics (Buchmueller et al., 2004; Benítez-Silva et al., 2004; Contoyannis and Jones, 2004; Balia and Jones, 2008; Sosa-Rubí et al., 2009), Law and Economics (Deadman and MacDonald, 2004), Labor

Economics (Pagani and Marenzi, 2008), Agricultural Economics (Dasgupta et al., 2007), Transportation Economics (Fosgerau and Bjørner, 2006), and Economics of Education (Greene, 1998; Fairlie, 2005). We believe, however, that the issue remains somewhat underexplored in the Environmental Economics literature and that the present paper is the first one to use multivariate analysis of order higher than two in a CV study to correct for the endogeneity of independent variables in the WTP equation. This is also the first study, to our knowledge, that considers separately the effect of correcting for the endogeneity of on-site user experience versus off-site user experience of the resource valued.

We use data from a nationwide phone survey of Canadians. The respondents were presented with a valuation scenario based on a policy consisting on subsidizing and enforcing the use of acoustic alarms in order to reduce the likelihood with which whales become entangled in fishing nets in the waters off Newfoundland and Labrador. The results indicate that jointly estimating the WTP equation and the behavioral models (that explain respondents' previous experience with the resource) using a multivariate probit model increases econometric efficiency and substantially corrects the endogeneity bias affecting the estimated coefficients of the experience variables, although the correction of mean WTP estimates is less substantial.

The paper is organized as follows. Section 2 presents a review of the literature dealing with endogeneity in CV. The dataset is described in Section 3. The empirical model is presented in Section 4. Section 5 discusses the results of the regression analysis, followed by conclusions and the suggestions for future research in Section 6.

2. Respondent experience and endogeneity in contingent valuation studies

The role of the familiarity of respondents with the valued resource, or their experience with it, and the information they have about it has gained a great deal of attention in *CV* studies. The research in this area has considered the effects on the size and validity of *WTP* responses of the quantity and quality of information about the resource (Whitehead et al., 1995; Ajzen et al., 1996; Blomquist and Whitehead, 1998; Hoehn and Randall, 2002), past experience with the resource, and knowledge about it (Whitehead et al., 1993; Boyle et al., 1993; Whitehead et al., 1995; Loomis and White, 1996; Brown et al., 1996; Champ et al., 1997; Cameron and Englin, 1997; Turpie, 2003; Kniivila, 2006; Tisdell et al., 2008). The absolute majority of articles report that experience and knowledge about the resource positively affect the validity and reliability of the estimates. In addition, Paradiso and Trisorio (2001) show that a direct knowledge of the good valued reduces the observed disparity between hypothetical and real *WTP*.

However, the experience and information variables in the *WTP* model are likely to be endogenous, since, as Cameron and Englin (1997) argue, respondents' experience with the resource valued can be endogenously determined by their past behavior. Cameron and Englin argue that users of a typical, not exotic, environmental good are self-selected, making it possible that respondents gained their experience with the good due to the same unobservable "reasons" as those that influenced their *WTP* for the resource. In that case, the estimation of the standard single equation *WTP* model leads to reduced econometric efficiency, since the error term in the *WTP* equation is correlated with the familiarity/experience variables, which biases the coefficient of these endogenous variables. Cameron and Englin consider the case of the valuation of improvements in trout habitats affected by the potential endogeneity of fishing experience and suggest the use of a simultaneous equations model to correct for possible endogeneity bias.

Alberini et al. (1997) use a two equation model to jointly estimate the *WTP* to avoid the episode of respiratory illness. The first equation models the *WTP* to avoid illness and the second one models the dichotomous variable describing the mitigating behavior (visiting a doctor).[2] The authors indicate that the error term of the second equation is likely correlated with the one in the *WTP* equation and suggested either estimating the equations separately (since the *doctor visit* variable did not enter the main *WTP* equation) or jointly as system of seemingly unrelated equations. They detected some correlation among the two errors. However, the joint estimation resulted in a non-significant increase in econometric efficiency.

Fosgerau and Bjorner (2006) use a simultaneous equation model to correct for endogeneity bias when estimating the *WTP* for noise reduction. The authors argue that the respondents' reported annoyance from road noise is potentially an endogenous variable. In the approach followed by Fosgerau and Bjorner an ordinal variable for *WTP* and a continuous one for annoyance are jointly modelled. Their results show that modelling annoyance as an endogenous variable significantly (up to 10%) reduced the standard errors of the expected marginal *WTP*.

Whitehead (2005) also mentions that it is often the case that researchers include potentially endogenous variables in the *WTP* model, which results in inconsistent estimates of the coefficients of the endogenous variables. As a way of obtaining consistent estimates, he discusses the instrumental variable approach and, as an alternative, the joint estimation of the behavioral and *WTP* models. In Whitehead

(2005) respondents were asked about their WTP for the improvement of the resource quality and the history of past visits to the resource, as well as about future visits after the enhancement in the quality of the resource. Both approaches lead to an increase in econometric efficiency and a significant correction on the welfare estimates. Accounting for the endogeneity of the change in visits in both independent and jointly estimated models of WTP and behavior yields an increase in the ratio of use value to total value. In his study of WTP for water quality improvements, Whitehead (2006) asked respondents about their perception of water quality. The author argues that the water quality perception variable was potentially endogenous, as it might be affected by the same unobserved characteristics (i.e taste) as the WTP for water quality improvement. In order to avoid the endogeneity bias, Whitehead (Whitehead, 2006) applied a bivarite probit model.

Similarly, Bohara et al. (2007) examined households' WTP for a curbside recycling program. They found that households who had previous experience with the recycling program through a pilot project were more likely to reduce the garbage container size and express a higher WTP for a curbside recycling program than non-participants in the pilot project. As in Whitehead (2006), the loss in econometric efficiency was avoided by the simultaneous estimation of two equations: one for the WTP for the curbside recycling program and another one for decision whether or not to reduce the container size, as the authors detected endogeneity behind these two decisions.

Garcia et al. (2007, 2008) in their recent study of WTP for forest biodiversity preservation in France used a similar approach. In particular, these authors argue that the value a respondent places on biodiversity preservation may vary depending on whether the respondent is a forest visitor or not. That is, the decision whether or not to participate in forest recreational activities might be correlated with the decision to pay to support forest biodiversity. Using a bivariate probit model, Garcia et al. (2008) showed the significant dependence between these two decisions. Hence, the application of a separate probit model would lead to a loss of econometric efficiency. The simultaneous bivariate probit formulation applied in Garcia et al. (2007), which resembles more our own analysis below than the one in Garcia et al. (2008), shows efficiency gains in the estimation procedure but a relatively small correction of the mean WTP estimate.

A recent study by Konishi and Adachi (2009) considers the endogeneity of averting behavior (self-protection against arsenic contamination) in a CV study of drinking water quality. They find that correcting for endogeneity results in a change in sign from positive to negative for the estimated effect of self-protection (the endogenous behavioral choice) on the WTP for public efforts to improve water quality.

Our study builds on this subset of the CV literature by considering the effect of correcting for the suspected endogeneity introduced by three experience variables. The use of a multivariate probit to deal with this issue is however, relatively innovative, since previous CV studies dealt, to our knowledge, with only one endogenous variable. Applications of the multivariate probit are also relatively few in the Economics literature in general, likely because they require high dimensional numerical- or simulation-based integration, and integration (or simulation) of the multivariate normal density over subsets of a Euclidean space is computationally burdensome (Huguenin et al., 2009). However, our main contribution is to consider separately, for the first time to our knowledge, the effect of correcting for the endogeneity of on-site versus off-site experience of use of the resource valued.

3. Data

The 29-question survey was administered in French and English by a professional survey research company and covered the ten Canadian provinces. The respondents were adult (over 19 years old) Canadian citizens, landed immigrants and those holding a student or work visa. The final response rate was about 23% and the final sample includes 614 usable observations, although some of these contained some missing values. The response rate is somewhat lower than what is usually obtained in similar phone surveys.

We suspect that those who decided to co-operate with the survey effort might have a higher level of knowledge about wildlife and higher *WTP* for wildlife preservation than an average Canadian. In fact, according to our data 37% of our respondents[3] participated in whale watching activities at some point in time, while 33% of respondents fish and 8% hunt. At the same time, according to the Survey on the Importance of Nature to Canadians conducted in 1996 (DuWors et al., 1999) 5% of Canadians hunted, 18% fished and 19% participated in wildlife viewing. We thus acknowledge that some sample selection bias may be affecting our study and, therefore, would recommend caution when extrapolating values of welfare measures obtained from our sample to the general population. This extrapolation is, in any event, not necessary for the purpose of showcasing the effect of accounting for endogeneity in some of the independent variables, which is the main focus of this paper.

The survey first included general questions about attitudes towards the environment, whale watching experiences, whale watching experience in NL, and travel to or affinity with this province. Then respondents heard about the whale entrapment problem in the waters off NL and were asked if they were aware of this issue. After that, a hypothetical whale conservation policy was briefly described. The conservation policy proposed was simple and plausible, based on imposing and subsidizing the use of acoustic alarms to prevent whales from becoming entangled in fishing gear. Respondents were then asked about their willingness to support the policy through a dichotomous-choice question. There were two versions of survey, one that used donations to environmental organization as the payment vehicle and another that suggested a tax increase instead. The following question was posed:

- Donation version: *Would you be willing to donate $[15, 30, 45, 60, 75 or 100, randomly assigned] per year for the next five years to support the program?*

- Tax version: *Would you be willing to support this program if the extra taxes your household had to pay were $[15, 30, 45, 60, 75 or 100, randomly assigned] per year for the next five years?*

In both cases, the possible answers were: "yes", "no", and "don't know". These answers were coded as the variable *agree* with the value one for a "yes" and the value zero for a "no" or a "don't know". If the answer was "no", the respondent was asked to provide the reasons behind that answer. Using the resulting answers to this debriefing question, protesters were identified and removed from the dataset. The final section of the survey included several socio-economic questions (age, income, education, etc.). Table 1 includes a description of the variables and Table 2 provides summary statistics.

[INSERT Table 1 about here]

[INSERT Table 2 about here]

Whether the answer to dichotomous-choice *WTP* question was "yes" or "no", respondents were asked to rank their confidence on that answer on a scale from 1 (*not sure at all*) to 10 (*very sure*). This variable was rescaled down into variable *sure*.

We constructed two sets of weights. The variable *sure* was used to construct the first set of weights, while the second set (WWW) is based on the age-gender distribution of respondents in each province. The product of *sure* and the weights based on the age-gender distribution ($WWWsure$) provided us with the sampling weights to be used in the regression analysis. The goal was to obtain not only a more representative but also a more reliable estimate of WTP, since the literature suggests that those who are more doubtful about their answers in CV studies tend to be behind most of the hypothetical bias in those studies (Champ et al., 1997; Champ and Bishop, 2001). We also expect to obtain a more precise estimate of WTP, since the weighting procedure should lead to more efficient estimates of WTP and an improvement in the goodness of fit of the overall regression model. Moreover, this procedure is expected to improve the representativeness of the results obtained from the analysis of the data in the sample.

As it often occurs in CV studies we faced some problems of item non-response in our dataset. Five variables presented missing values: income, age, age group,[4] education, and the number of people under 18 in a household. We decided to use multivariate imputation techniques to handle these missing values, rather than simply discarding the incomplete observations. In order to impute the missing values for the variables we followed the imputation approach developed by Royston (2004, 2005a, 2005b), based on a chained equations algorithm. As a result of the imputation, we obtained ten datasets that we could use for the further data analysis. Each dataset included 614 complete observations with small variations in the imputed values across datasets. For more commonly applied procedures, the *mim* command in STATA makes it possible to obtain a summarized result based on the combination of datasets. However, *mim* does not support multivariate probit analysis.[5] Therefore, we applied our analysis to one individual set of 614 observations. While there are slight variations in the results according to the choice of dataset, the conclusions do not change in qualitative terms depending on this choice.

4. Econometric Model

In this section we describe the econometric model we used to empirically analyze the responses to the survey and in particular to account for the likely link between WTP to protect whales and previous experience: having been to the province of Newfoundland and Labrador and participation in whalewatching. In estimating the WTP equation, addressed the potential endogeneity of these experience binary variables.

The causal relationships between participation in whalewatching and the answer to the payment question in our survey is complicated by the potential endogeneity. Those respondents who had experienced whalewatching at the time of the survey might be systematically more likely to agree to the payment question (that is, to be willing to pay for the protection of whales) due to unobserved characteristics of theirs. On the other hand, once someone experiences whalewatching they might feel their WTP reduced because now their option value is lower. Thus, the coefficient of the variables capturing whalewatching experience in the naïve WTP probit equation could well be biased, as it would overstate the positive impact of previous experience of the resource on the WTP for its preservation. In other words, a plain probit model would not allow us to discern whether previous experience with whales affected *WTP* and how. For this reason, the experience variables (*beentoNL*, *whalewatchedelse* and *whalewatchedNL*) were treated as potentially endogenous variables in our *WTP* model.

Two-step techniques may be biased when the variable concerned (in our case *agree)*, is discrete (O'Higgins, 1994). Therefore, we applied a full information approach when dealing with the issue of endogeneity in the estimation of the three equations involved.

We estimated a four-equation latent dependent-variable model. The model is based on the assumption that there are four underlying latent propensity variables *WTP**, *WH**, *WHNL**, and *BEEN**, which represent, respectively, (a) the propensity to agree to the payment question (thus the *WTP* for whale conservation), (b) the propensity to do whalewatching elsewhere, (c) the propensity to do whalewatching in NL, and d) the propensity to visit NL. These latent variables are in actuality not observable, but we have available information on the realized response to the payment question, and the three questions of previous experience.

The propensities *WTP**, *WH**, *WHNL**, and *BEEN** may be mapped to the corresponding three observable binary discrete variables *agree*, *whalewatchedelse, whalewatchedNL*, and *beentoNL*. More precisely, these binary variables are:

$$agree = \begin{cases} 1if\, WTP* > bid \\ 0if\, WTP* \leq bid \end{cases} \tag{1}$$

$$whalewatchedelse = \begin{cases} 1ifWH^* > 0 \\ 0ifWH^* \leq 0 \end{cases} \tag{2}$$

$$whalewatchedNL = \begin{cases} 1ifWHNL^* > 0 \\ 0ifWHNL^* \leq 0 \end{cases} \quad (3)$$

and

$$beentoNL = \begin{cases} 1ifBEEN^* > 0 \\ 0ifBEEN^* \leq 0 \end{cases} \quad (4)$$

In order to account for the endogeneity relationships described above, we estimated a multivariate probit model, which allows the unobservables in Equations 1, 2, 3, and 4 to be jointly distributed as a multivariate normal with free correlations. To be more precise, in the multivariate probit model the error terms in the four equations are jointly distributed with a multivariate normal distribution function, that is (ε_1, ε_2, ε_3, ε_4)~MVN (0, Σ) where Σ is the variance–covariance matrix taking values of 1 on the leading diagonal, while the off-diagonal elements are to be estimated. This matrix Σ is given by:

$$\Sigma = \begin{bmatrix} 1 \ \rho_{12} \ \rho_{13}\rho_{14} \\ \rho_{21} \ 1 \ \rho_{23}\rho_{24} \\ \rho_{31} \ \rho_{32} \ 1\rho_{34} \\ \rho_{41} \ \rho_{42}\rho_{43}1 \end{bmatrix} \quad (5)$$

where ρ_{ij} represents the correlation coefficient between ε_i and ε_j, with $i, j = 1, 2, 3, 4$ and $i{\neq}j$. By allowing the off-diagonal elements of Matrix Σ to differ from zero we account for the effect of unobserved characteristics that potentially influence at the same time two of the choices made by the respondent. This model takes then into account the likely possibility that some unobserved factors that influence a respondent's *WTP* also affect the likelihood to participate in activities that put the respondent in contact with the resource. We can test the hypothesis of correlation among these unobserved components of the four equations by considering the joint significance of the coefficients of correlation between their error terms.

Our multivariate probit model included a structural *WTP* equation (where the dependent variable was *agree*) and three reduced form equations for the three, potentially endogenous, experience binary variables: *whalewatchedelse, whalewatchedNL*, and *beentoNL*.[6] The focus of our analysis lied ultimately on the main *WTP* equation, including the estimation of the effects of previous experience on the estimated *WTP*. Therefore, we included some binary variables that captured respondent experience in the *WTP* equation. It is in this case advisable (Monfardini and Radice, 2008), although not required (Wilde, 2000), to use exclusion restrictions in the equations of the experience variables. Thus, we included some variables in the equations for *whalewatchedelse* and *whalewatchedNL* that we expected to affect *WH** and *WHNL** but not *WTP** after *beentoNL*, *whalewatchedelse* and *whalewatchedNL* have been controlled for. In this way, we captured the variation in *beentoNL*, *whalewatchedelse* and *whalewatchedNL* that was not correlated with the variation in *WTP**. This exogenous variation improves the estimation[7] of the relationship between *agree* and *beentoNL/ whalewatchedelse/whalewatchedNL*, while getting rid of the spurious correlation that the endogeneity introduces.

We experimented with different specifications of the secondary experience equations, but the differences were not qualitatively very different in terms of *WTP* or joint significance of the correlation coefficients among equations. However, Wilde (2000), exclusion restrictions are not needed for recursive multivariate probit models as long as there exist variations in covariates.

The variables that were assumed to explain choices related with experiencing whales but not directly affect her *WTP* were variables about the location and family composition of the respondent's household: *coastal, children* and *under18*. In order to evaluate the validity of these instruments, we tested the null hypothesis of their non-significance in the experience equations, a test which (as shown in Table 3) confirmed that they significantly affect experience choices, and then we tested the null hypothesis of their non-significance in the WTP equation. The results of this last test (not reported but available upon request) also confirm that it cannot be rejected that after controlling for the rest of variables in the model, the variables used to introduce exclusion restrictions have no effect on WTP.[8]

The four equations were simultaneously estimated using in STATA 9.2 (StataCorp, 2005) the command *mvprobit* (Cappellari and Jenkins, 2003), that employs the Geweke-Hajivassiliou-Keane (GHK) simulator to evaluate the M-dimensional normal integrals in the likelihood function.[9]

Since the procedure used involves simulation, one of the key choices the researcher must make is about the number of draws to consider. For moderate to large sample sizes, setting the number of draws (R) equal to an integer approximately equal to the square root of the sample size is considered appropriate (Cappellari and Jenkins, 2003).[10] Therefore, we used 25 draws in the multivariate probit.

In principle, the multivariate probit model boils down to its more familiar univariate and bivariate probit counterparts when the number of equations is one and two, respectively. The structure of the multivariate probit model is similar to that of a seemingly unrelated regression (SUR) model, except that the dependent variables are binary indicators. Also like in the case of SUR, the equations need not include exactly the same set of explanatory variables.

5. Results

Table 3 shows the results of the different probit regressions described above. The likelihood-ratio test of the null that the correlation coefficients among the four binary variables concerned is jointly equal to zero ($\rho_{ij} = 0$ for all $i \neq j$) suggests that the joint estimation of agree and the experience variables through *mvprobit* is preferred to the plain probit model.

[INSERT Table 3 about here]

The results of the individual *probit* regressions can be compared with those obtained from the *mvprobit* model that jointly estimates the four equations involved. The main *WTP* equation relates the binary variable *agree* to the *bid* value, a series of variables that describe the respondent's household. These variables include the experience variables which we suspected endogenously determined: *whalewatched*, *whalewatchedNL*, and *beentoNL*. Additionally, we included the variable *tax* in order to investigate the effect of the payment vehicle on the respondent *WTP*.

As expected, the estimate of the coefficient of *bid* is negative and highly significant in the *mvprobit* model, while only significant at the 5% level in the probit model that ignores the correlation between the experience decisions and the *WTP* decision. There appears to be a non-linear effect of age on *WTP*. The plain probit model suggests that the probability that *agree* takes the value of 1 rises with age until the age of about 35 and declines beyond that, perhaps reflecting that individual option values decrease with age. The *WTP* equation in the *mvprobit* model estimates the peak *WTP* at 38.4 years of age instead. Income has a positive and weakly significant effect, although the *mvprobit* yields a higher level of significance for this variable.

The estimated coefficient of the variable *education* changes sign between the plain probit and the *mvprobit*, under which it also becomes statistically significant. This variable is used to explain the choice of whalewatching outside NL and also the decision to visit this province, so once these decisions are modelled jointly, using *mvprobit,* with the *WTP* decision, the endogeneity bias affecting its estimate is expected to decrease. The variable *heard* has a positive but non-significant at conventional levels coefficient (p-value is 0.131) under *mvprobit*, and still only significant at 10% under the plain *probit.*

As expected, the positive and highly significant estimated coefficient on the variable *enviro* confirms that those respondents who reported to belong to an environmental organization such as *Greenpeace* appear significantly more likely to be willing to pay to support whale conservation.

As explained in Section 3, the survey followed a split-sample approach that would make it possible to investigate the potential for payment vehicle effects. Respondents in one of the subsamples were proposed a policy scenario that involved the use of a federally funded program that would, during five years, help prevent incidents of entanglement by subsidizing and enforcing the use of acoustic devices in fishing gear. These respondents were asked about their *WTP* taxes to support this program. The second version of the questionnaire included the description of a policy scenario based on the use of a program that would, also during five years, help prevent incidents of entanglement by subsidizing and enforcing the use of acoustic devices in fishing gear. However, in this second case the proposed program would be funded by voluntary contributions, so respondents were asked about their willingness to make voluntary donations to support the program. As shown in Table 3, those who received the *tax* version of the survey were significantly more likely to *agree* to the proposed *bid* value. This suggests that perhaps respondents incorporated in their calculations the potential for free-riding left by the donation format.

The variable *planatall* presents a positive and highly significant estimated coefficient in both models. This means that those who answered 'yes' or 'maybe' to the question "are you planning to go whalewatching within the next five years?" are more willing to pay to protect whales. This suggests that there may be a substantial proportion of the benefit derived from the conservation of whales that is related to an *option value*.

Residents in the provinces of Manitoba and Ontario appear to be significantly more likely to pay for whale conservation.

5.1. Correlation effects

The *mvprobit* model estimates include measures of correlation between the errors of each of the four equations involved. This helps us understand the direction of the bias involved in assuming that there is no endogeneity between the decisions to acquire experience and the decision about WTP for conservation.

The positive effect of *whalewatchedelse* on WTP was underestimated by the naïve probit model (first column of Table 3). The *mvprobit* model (last column of Table 3) shows a stronger and also significant effect for this variable and also a significant and negative correlation (ρ_{21}) between the errors of the main WTP equation (whose dependent variable is *agree*) and the *whalewatchedelse* equation. This suggests that there are unobserved characteristics of the respondents that, after controlling for the independent variables included in both equations, make them less likely to be willing to pay to support whale conservation if they have already been whalewatching somewhere other than NL, and *viceversa*. However, since they have not yet enjoyed watching the NL whales, even after controlling for *planatall* and *planswhalewatching,* there may remain some effects due to option values that, when properly isolated, result in a significantly positive sign for *whalewatchedelse*. That is, those who have already enjoyed whalewatching themselves in a region other than NL might feel they derive utility now from the preservation of whales in this particular province, suggesting that whales in different regions enter as complements the utility function of those who enjoy whalewatching. They have 'done that', but they have not 'been there'. The *mvprobit* model allows us to disentangle the (negative) effect of unobserved characteristics from the effect of whalewatching *elsewhere* itself on *WTP*, which is indeed positive. By lumping together the two effects, the naïve probit model underestimates the effect of *whalewatchedelse*, making it appear non-significant and actually very close in magnitude to the effect of *whalewatchedNL*.

When it comes to *whalewatchedNL*, which indicates who did whalewatching in NL, we show in Table 3 that, although its estimated coefficient is non-significant in both models at conventional levels of significance, under *mvprobit* the relevant p-value is only 0.132, while under *probit* it is 0.742. Moreover, we can see that its effect on *WTP* appears to be substantially overestimated by the plain probit model, where it takes a positive sign. The *mvprobit* model shows instead a negative effect for this variable and also, crucially, a significant and positive correlation (ρ_{31}) between the errors of the main *WTP* equation and the *whalewatchedNL* equation. This confirms the suspicion that there are unobserved characteristics of the respondents that, after controlling for the independent variables included in both equations, make them more likely to be willing to pay to support whale conservation of NL whales if they have already been whalewatching in the province studied, and *viceversa*. One could elucubrate that the reason for this effect is that, after controlling for the observable variables included in the equations, there may remain some positive effects on WTP of having enjoyed marine wildlife viewing in NL due to option values. That is, those who have already enjoyed whalewatching in NL might be happier to support conservation efforts in that area, while the effect of the whalewatching experience itself, in line with the results described above for *whalewatchedelse*, actually has a negative effect on WTP. Those for whom *whalewacthedNL* takes the value of one have both 'done that' (*whalewatched*) and 'been there' (they did it in NL), so now their option value is much lower, suggesting that whalewatching in NL in the future is just a substitute for whalewatching in NL in the past.

The *mvprobit* makes it possible again to disentangle the positive effects on WTP of unobserved characteristics of the whalewatchers from the net effect of whalewatching in NL, which is itself actually negative.[11] By lumping together the two effects, the naïve probit model was incorrectly allocating a positive net effect to the variable *whalewatchedNL,* rather than the correct negative one, and in this case was making it look the same as the effect of *whalewatchedelse*, which, as explained above, was actually significantly positive and much larger instead. This result is in line with the one obtained by Cameron and Englin (1997), who also observed that failing to correct for the endogeneity of years of fishing experience would result in a positive effect of experience on WTP, while the net effect, when endogeneity was corrected for, was negative. Similarly, Konishi and Adachi (2009) found that after correcting for endogeneity the estimated effect of private mitigating behavior on *WTP* for public mitigation of environmental risks associated with water pollution.

Finally, the fact that someone has been to the province to NL appears to have a positive and statistically significant effect on *WTP* for whale preservation in the province. Those who have 'been there' but not 'done that' yet, seem to be interested in keeping the option open. By lumping together the net effect of this variable with the effect of unobservable respondent characteristics that are positively correlated with *WTP* and negatively correlated with the likelihood of having been to NL, or *viceversa*, the naïve probit model generated a downward bias on the coefficient of variable *beentoNL*.

5.2. Mean willingness to pay

Using the STATA code developed by Jeanty (2007), we computed the mean *WTP*, corresponding confidence intervals as well as the achieved significance level, following Krinsky and Robb's (Krinsky and Robb, 1986; Krinsky and Robb, 1990) procedure to compute the 95% confidence interval. As Park et al. (Park et al., 1991) observe, the presence of confidence intervals for the mean *WTP* allow to directly compare the estimates of *WTP* across models and methods.[12]

[INSERT Table 4 about here]

Table 4 reports the estimated mean (which for this type of model is the same as the estimated median) *WTP* measure and the 95% confidence intervals calculated using the Krinsky-Robb method (using 10,000 iterations). The $77.67 obtained by the univariate probit model turn into $82.32 once the endogeneity of the experience variables is accounted for through the *mvprobit*.

Note that the *mvprobit* estimate is also more precise, partly because it is higher, \$82.32 versus \$77.67. The adjustment in mean/median WTP that results from accounting for the endogeneity of the experience variables is meaningful in this case, most of all when we consider that the relevant population would in principle extend to the adult Canadian population. To put this figure in perspective, we can extrapolate these results to the adult population of Canada – 23,939,993 people. Using the naïve probit mean WTP, the aggregate WTP would be lower by about \$113 mln (or \$26 mln using a conservative estimate, which takes into account the response rate of 23%), and if used in policy design could lead to a significant social loss.

6. Conclusions, limitations, and suggestions for further research

The present paper focused on the issue of endogeneity bias in contingent valuation studies. If one or more explanatory variables in the WTP equation are correlated with the error term, a bias occurs, since a set of observable and unobservable characteristics of the respondents simultaneously affect both their WTP and the value of the endogenous variables. While the issue of endogeneity bias has been discussed in other areas of Economics, such Health and Labour Economics, it has not gained much of attention in the Environmental Economics literature yet.

The literature that discusses the endogeneity in the context of CV studies is very scarce. Moreover, the existing CV research models no more than one endogenous variable and, therefore, applies bivariate analysis to correct for endogeneity. In the present paper we identified instead a number of potentially endogenous variables. In particular, we focused on the variables that capture the previous experience with the good valued and area of study, humpback whales in Newfoundland and Labrador in our case. We thus jointly model the answers to the *WTP* question and to the questions that measure respondents' previous experience. Our multivariate probit model includes a structural *WTP* equation and three reduced form equations for the three, potentially endogenous, experience binary variables.

One clear advantage of multivariate model is that it allows controlling for all independent variables in the behavioral and structural equations, thus separating the effects of unobserved characteristics from the effects of a particular behavioral variable on *WTP* decision. In contrast, the plain probit model "mixes up" the effects of an endogenous variable and unobserved characteristics on the *WTP* which results in the "obscuring" the effect of the behavioral variable on *WTP*. The comparison of the multivariate probit regression results and the ones obtained under naïve (plain) probit setup revealed that the coefficients of the behavioral variables in multivariate model become statistically significant and acquire signs to opposite to one another. These results show that careful modelling of the endogenous variables may lead to revealing the direction of the net effects of the behavioral variables on *WTP*. The joint estimation of behavioral equations and the *WTP* equations can detect if unobserved characteristics of the respondents affect the *WTP* for the resource as well as respondents' choices that lead to the contact and experience with the resource. Our multivariate probit regression results show an interrelationship between the answer to the *WTP* question and observed behavioral choices as well as the interrelationship between the choices. The correlation coefficients, obtained using our multivariate model appeared to be jointly statistically significant, while most of them are also individually significant. Overall we found that jointly estimating the WTP equation and the behavioral models increases econometric efficiency and substantially impacts the estimated coefficients of the experience variables by correcting the bias caused by their endogeneity.

In particular, we have shown that it is difficult to disentangle the net effects of experience of a resource on willingness to pay for its preservation when the potential endogeneity of the relevant experience variables if not accounted for. Additionally, we have shown that, in line with theoretical expectations, there can be substantial differences in terms of their effect on willingness to pay estimates between variables that identify experience of the resource in the site and experience of the same (or similar) resource in an alternative region. Having already experienced a resource in a given area decreases willingness to pay for its preservation in that same area, likely because of a reduction in option values, while having enjoyed access to the resource only elsewhere, increases it.

Correcting for endogeneity bias makes it possible to obtain estimates that can be more safely used in benefit transfer studies. Moreover, as the results demonstrate, modelling endogenous variables can also lead to changes in the welfare estimates. In particular we show that when behavioral variables are modeled as endogenous variables, the mean WTP obtained through Krinsky Robb procedure increases by about 6%.

As we mentioned previously, there are other variables such as membership in environmental organizations, future plans for whale watching, being hunter or fisherman that could be considered as potentially endogenous. The cost of modeling these additional variables as endogenous along with the variables discussed in the paper would be very high in terms of computational complexity. Further work will explore this issue, while the focus of the current paper lied on the experience variables and our results clearly demonstrated the endogeneity issue has to be addressed in the contingent valuation studies.

Notes

[1] Since these attitudes affect *WTP* and are usually correlated with other explanatory variables in the *WTP* model, leaving them out would cause omitted variable bias.

[2] One way to conceive our example that relates to this example would be to consider the lack of experience with whales as 'the illness' and the whalewatching trips as 'the mitigating behaviour'.

[3] This proportion happens to be remarkably close to its counterpart in Loomis and Larson (1994) study of the valuation of whales in California (35%).

[4] This variable is not described in Table 1, because it just captured information on the age interval of those few respondents who did not volunteer a point value for *age*. Its values were used, however, during the recursive imputation process of missing values of *age*.

[5] See Galati et al. (2008) for details.

[6] It could be argued that additional problems of endogeneity could be posed by variables such as *enviro*, or *planatall*. However, we focus here on the experience variables. Furthermore, considering additional dimensions of the multivariate probit would sunstantially increase the computational burden involved.

[7] Using the exclusion restrictions improves the validity of tests of exogeneity of the potentially endogenous explanatory binary variables (essentially, tests of whether the correlations of the errors of the probit models are zero) when the distributional assumptions are misspecified (Monfardini and Radice, 2008).

[8] Following Wilde (2000) and due to the dififculty of achieving meaningful convergence of the model when inserting exclusion restriction in that equation, we did not use any exclusion restrictions in the equation for *beentoNL*.

[9] For details about this simulator see Train (2003) or Greene (2003, 931-933) and references therein.

[10] And to make the estimates insensitive to the choice of seed.

[11] Although in our sample only significant at the 15% level.

[12] See Haab and McConnell (2002, 110-113) for more details on this procedure.

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Table I. Variable definitions

Variable	Description
age	age of respondent
agesq	squared age
agree [a]	whether the respondent is willing to pay the proposed *bid*
beentoNL [a]	whether respondent from outside NL has ever visited NL
bid	amount in dollars proposed as contribution to the conservation program: extra taxes or donation per year for five years
children [a]	whether respondent household includes members under 18
coastal [a]	coastal province
education [c]	highest level of education completed
enviro [a]	member of environmental organization
heard [a]	awareness about the whale entanglement problem
income [b]	income bracket
Manitoba [a]	respondent resides in Manitoba
Ontario [a]	respondent resides in Ontario
planatall [a]	respondent plans to go whalewatching or maybe go whalewatching within the next five years
planswhalew [a]	respondent plans to go whalewatching within the next five years
tax [a]	respondent received the tax version of the questionaire
under18	number of members of the household under 18
whalewatchedelse [a]	respondent whalewatched somewhere other than NL
whalewatchedNL [a]	respondent whalewatched in NL
WWWsure	weight constructed as product of sampling weight and degree of uncertainty in the response

a. Equals 1 if true and 0 otherwise.

b. Value of 1 corresponds to ”less than \$30,000”, value of 2 – ”between \$30,000 and \$50,000”, 3 –” between \$50,000 and \$70,000”, 4 - ” between \$70,000 and \$90,000”, 5 - ”between \$90,000 and \$110,000”, 6 - ” between \$110,000 and \$130,000”, 7 - ”over \$130,000”.

c. 1 = “less than high school”; 2 = “completed high school 3 = some community college / vocational/trade school/ CEGEP”; 4 = “completed community college / vocational/ trade school/ CEGEP”; 5 = “some university”; 6 = “university certificate or diploma below a bachelor’s degree”; 7 = “university degree”; 8 = ”university certificate or diploma above”.

Table II. Summary descriptives. N= 514 (protest responses excluded)

Variable	Mean	Std. Dev.	Min	Max
age	47.515	16.445	19	90
agesq	2527.570	1643.661	361	8100
agree	0.502	0.500	0	1
beentoNL	0.216	0.412	0	1
bid	53.405	27.993	15	100
children	0.372	0.484	0	1
coastal	0.210	0.408	0	1
education	4.261	2.305	1	8
enviro	0.119	0.324	0	1
heard	0.747	0.435	0	1
income	3.193	1.914	1	7
Manitoba	0.033	0.179	0	1
Ontario	0.412	0.493	0	1
planatall	0.549	0.498	0	1
planswhalew	0.202	0.402	0	1
tax	0.490	0.500	0	1
under18	0.691	1.069	0	5
whalewatchedelse	0.317	0.466	0	1
whalewatchedNL	0.064	0.245	0	1
WWWsure	0.689	0.415	0.030	3.056

Table III. Individual versus Multivariate Probit regressions. N=514 (100 protests excluded)

	probit	probit	probit	probit	mvprobit
agree					
bid	-0.0061**				-0.0053***
age	0.0352$^{\circledast}$				0.0307$^{\circledast}$
agesq	-0.0005**				-0.0004**
income	0.0739*				0.0666**
education	0.0041				-0.0684**
heard	0.2661*				0.1987$^{\circledast}$
enviro	0.8647***				0.7126***
tax	0.6025***				0.4824***
planatall	0.5959***				0.4112***
PROV8	1.0939***				0.9475***
PROV6	0.3275**				0.3415***
whalewatchedelse	0.1156				0.9810**
whalewatchedNL	0.1043				-0.5305$^{\circledast}$
beentoNL	0.1817				1.3448***
cons	-1.4635**				-1.2541**
whalewatchedelse					
under18		-0.1559***			-0.1944***
edu		0.0989***			0.1254***
planswhalewatching		0.5557***			0.5835***
coastal		0.3559**			0.5027***
cons		-1.0117***			-1.1649***
whalewatchedNL					
children			0.5084**		0.4344**
planswhalewatching			0.6123**		0.5317**
beentoNL			1.2486***		1.5879***
cons			-2.4222***		-2.4111***
beentoNL					
edu				0.1122***	0.1083***
age				0.0126***	0.0128***
cons				-1.9777***	-1.9812***
ρ_{21}					-0.5197**
ρ_{31}					0.5321***
ρ_{41}					-0.5778***
ρ_{32}					-0.7051***
ρ_{42}					-0.2276**
ρ_{43}					-0.1970
Log-likelihood	-201.413	-298.799	-63.529	-165.814	-614.667
Wald test χ^2	93.18***	42.18***	422.53***	16.50***	335.83***
Likelihood-ratio test that $\rho_{ij}=0$ for all $i \neq j$					$\chi^2(6)$=594.07***

$^{\circledast}$= significant at 15%; * = significant at 10%; ** = significant at 5%; *** = significant at 1%

Table IV. Mean (and median) willingness to pay estimates and Krinsky and Robb (10,000 draws) 95% confidence intervals for probit and mvprobit models

	probit	*mvprobit*
Mean/Median *WTP*	77.67	82.38
Lower Bound	50.56	51.68
Upper Bound	152.89	141.5
ASL*	0.0073	0.0047
CI/Mean	1.32	1.09

*ASL = Achieved significance level for testing H_0: WTP¡=0 vs. H_1: WTP¿0