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On scope effects in Contingent Valuation: does the statistical distributional assumption matter?

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Abstract

In this paper, we test for scope effects in Contingent Valuation applying different distributional assumptions for WTP, a non-parametric estimation and an estimation based on an open-ended format. Mean WTP is sensitive to the distributional assumption, but so is the scope effect. The non-parametric model, without conditions on the distribution, is the best able to identify scope effects. More sophisticated models, such as the spike model, and open-ended follow-up question give more information about individual WTP and are thus more powerful in revealing scope effects. For small sample size, a non-parametric analysis, a spike model or an open-ended format may therefore be better than the classical parametric dichotomous choice analysis to identify scope effects.

Keywords

Contingent valuation, scope effect, forest policy, ecosystem services, single-bounded-dichotomous-choice, Turnbull, Spike models

***JEL classification*:** D61 - H41 - O13 - Q23 - Q57

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On scope effects in Contingent Valuation: does the statistical distributional assumption matter?

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WORKING PAPER

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1 Introduction

The supposed insensitivity to scope in stated preferences methods and in particular in contingent valuation (CV) studies is a hot controversy in the literature. Economic theory, in particular the non-satiety and decreasing marginal benefit principles, predicts that a given increase in the provision of a good should be valued less than a larger increase in the provision of the same good. For example, if one asks the WTP for cleaning up a lake, it should be lower than the WTP for cleaning up five lakes. However, Kahneman and Knetsch (1992) find no significant impact of scope, thus provoking the defiance on CV from many environmental economics scholars. Indeed, if Kahneman and Knetsch (1992, p.1) is right in assuming that "contingent valuation responses reflect the willingness to pay for the moral satisfaction of contributing to public goods, not the economic value of these goods", then CV is fundamentally flawed and cannot be used in valuation studies. However, Carson and Mitchell (1993a) reviewed Kahneman and Knetsch (1992)'s study, as well as other CV studies, and observed that the median is always higher for the WTP related to the bigger scope. Also, several studies (e.g. Smith and Osborne, 1996; Bandara and Tisdell, 2005) indicate that a scope effect is present when correcting WTP for the difference in sub-samples characteristics and applying the appropriate significance test, even with inexpensive survey methods (Whitehead et al., 1998). However, studies that systematically analyze scope effects in the stated preferences literature are scarce (Berrens et al., 2000; Lew and Wallmo, 2011), which appeals ex-post meta-analyzes to test the impact of scope on WTP across studies (Hjerpe et al., 2015; Smith and Osborne, 1996; Ojea and Loureiro, 2011). The lack of routine scope tests may also incitate distrust for stated preferences methods (see Heberlein et al. 2005).

In this paper, we apply a CV survey to measure the existence of scope effects in the valution of forests functions in Switzerland. The results show that our sample is, on average, willing to pay more for Swiss (larger) forests than for the sole Geneva (smaller) forests. However, the significance level of this difference is largely affected by the statistical distributional assumption regarding willingness to pay (WTP). Indeed, parametric estimations from dichotomous choice elicitation format such as normal and log-normal fail to identify statistically significant scope effects; results are mixed with logistic-based distribution and depend on the nature of the test used; and finally non-parametric models, spike models and open-ended estimates robustly reveal significant scope effects. We argue that, if sensitivity of mean WTP estimates to distributional assumption is acknowledged, split-sample comparisons and identification of scope effects can also be affected. This difference is even more pronounced in small samples.

We introduce the CV method and our questionnaire in section 2. The empirical approach and descriptive statistics are provided in section 3. Section 4.1 presents the results from different parametric distributions for the dichotomous choice format and different tests for scope effects. Section 4.2 analyses the results from the Turnbull non-parametric estimation, while section 4.3 uses an open-ended follow-up question to provide WTP estimates. Section 5 discusses and concludes.

2 Survey design

The contingent valuation method (CVM) is an economic valuation technique, which elicits the individual willingness to pay for a change in environmental quality by proposing a hypothetical scenario. This approach is thus part of stated preferences approaches. Since the Exxon Valdez oil spill in Alaska in 1989 (Carson et al., 1992), the literature has rapidly grown, with variable confidence. For the sake of comparability and reliability, in 1993 the National Oceanic and Atmospheric Administration (NOAA) provided some guidelines (Arrow et al., 1993) that remain as a landmark in the field, but CVM is still affected by several biases, provoking distrust from many scholars. Hausman (2012), for example, makes a case against the use of CVM.

According to Hausman (2012, p. 2), the method suffers in particular from the *hypothetical bias:* "What people say is different from what they do". Knowing that the statement is only an hypothetical situation, one could be tempted to either please the interviewer and thus accept the proposition whatever it is (*yea-saying bias*) (Tourangeau et al., 2000) or, for strategic purposes, to minimize WTP to free-ride (*Samuelson's prediction*) (Carson, 2012). The literature developed approaches to address this issue *ex ante* (Loomis, 2011). In particular, *consequentiality* and *cheap talk* are two practical pieces of advice for the survey design. Consequentiality means that the respondent must think that her answer will be considered and turned into real policy. The advantage of consequentiality is generally acknowledged (Herriges et al., 2010), although not totally sufficient to provide reliable estimates. Cheap talk explicitly points out in the question that surveys are generally subject to this type of bias and notifies the respondent to be careful about her answer (Cummings and Taylor, 1999). Some scholars have successfully tried other ex ante approaches as Jacquemet et al. (2013), who asks respondents to provide a "*solemn oath*". Another approach to deal with this bias is *ex post.* Assuming that the hypothetical bias is due to uncertainty, Champ et al. (1997) ask the respondent her degree of certainty and correct the resulting estimates according to it.

The *payment vehicle* might also have an impact on elicitation of preferences (Ivehammar, 2009). This point is of particular importance in regions where corruption is prevalent, but differences may also be due to free-riding possibilities linked with the payment vehicle. (cf. Baranzini et al., 2010). To be consequential, the payment vehicle must thus be credible, reliable and preferably avoid free-riding issues.

A particular attention has to be paid to the elicitation approach, which can take three formats: *open-ended*, *payment card* or *dichotomous choice.* These formats imply an *efficiency* vs *incentive compatibility* trade-off: if the open-ended and payment card formats allow to compute more precise estimates, they do not respect the condition that a truthful response to the question represents an optimal strategy for the respondent (Carson and Groves, 2007, p. 184).

Also, it is claimed that the dichotomous choice format imposes a lighter cognitive burden than the payment card or open-ended format (Champ and Bishop, 2006). Nevertheless, the open-ended format has the advantage of not providing any reference amount and thus produce no anchoring effect. The NOAA panel (Arrow et al., 1993) suggests to use dichotomous choice, first presented by Bishop and Heberlein (1979), but some scholars have extended it with the Double-Bounded-Dichotomous-Choice (DBDC) approach, which increases the efficiency by providing tighter estimates intervals and thus reduces the survey costs. Nevertheless, as Carson and Groves (2007) mention, the second bid's acceptance rate also suffers from *starting-point bias* and is thus not incentive compatible. We refer to Meshreky et al. (2014) for a complete analysis of different design effects on WTP estimates.

To understand the perceptions towards Swiss forests, assess their value, and test the scope issue, we run a face-to-face survey in the streets of Geneva from January to March 2014. The construction of the questionnaire was cautiously preceded by pre-tests, focus-groups and qualitative surveys (See Baranzini et al., 2015). The survey is composed of five parts: (i) a general part, assessing the respondent's perception, knowledge and relationship with the forest, (ii) a part on the use of forests (iii) some questions controlling for environmental friendliness, (iv) a contingent valuation scenario with a single-bounded-dichotomous choice WTP elicitation question and follow-ups and (v) questions about the respondent's socioeconomic characteristics. For comparability and validity checks, some questions are similar to WaMos2 (Office Fédéral de l'Environnement, 2013a), a national survey launched by the Swiss Federal Office for Environment. The questionnaire is composed by 28 questions and lasts about 15 minutes.

We base the scenario for the contingent valuation on an actual Federal program, part of the Forest Policy 2020, as recommended in Arrow et al. (1993). To analyze the existence of a scope effect, we use the split-sample approach as in Berrens et al. (2000): To a sub-sample (the "Swiss sub-sample", CH) composed by 228 individuals randomly picked in the whole population we propose the following scenario:

> "A third of the Swiss territory is covered by forests that are home of a rich and varied ecosystem. For several decades, biodiversity (fauna, flora, ecosystems) strongly diminishes. According to some estimations, one third of indigenous species are endangered. To preserve and develop in a sustainable manner forest biodiversity, the Confederation plans to increase the protected forest surface. The goal is to protect in 2030 10% of total Swiss forest (about twice the current protected surface). Protection of new surface has three principal consequences:
>
> - Increased Swiss Confederation spending to cover the costs linked to the program
>
> - Decreased income for the forest industry
>
> - Limitation of access and of recreational activities

> The Swiss Confederation wishes to finance the increased spending for the creation of new reserves by a specific tax. The Swiss Confederation needs to know the population's opinion to direct its environmental policy and to assess how this measure could be implemented. You could be asked to concretely contribute to the program. Hence, it is important that your answer truly reflects your willingness to contribute to the creation of new forest reserves.
>
> So, would your household be ready to pay X CHF per year (about X/12 CHF per month), to support the creation of new forest reserves in Switzerland? Before giving your answer, please consider that your income is limited and that you could be asked to contribute to other issues."

We then administer to another sub-sample (the "Geneva sub-sample",GE) exactly the same question, but referring to Geneva forests only. To avoid *part-whole bias* (Mitchell and Carson, 2013), an issue that is related to scope and emerging when individuals believe the program will apply to a larger scale, we remind the Geneva sub-sample that the program will apply to Geneva forests only. It is worth noting that Geneva forests account for about 0.2% of total forest surface in Switzerland, so that the difference in scope between the two versions of the program is important. Geneva being part of Switzerland, we consider the two program versions to be perfectly embedded in the sense of Kahneman and Knetsch (1992). Geneva program is indeed geographically nested in the Swiss program.

We build the question as an advisory survey, the amount X being randomly assigned between CHF 10, 60, 100, 250, 500 and 1000 and specifying that the results would be used to implement the policy[1]. To reduce the *hypothetical bias*, we follow Loomis (2011)'s ex ante approach and insist on scenario's *consequentiality* (Carson and Groves, 2007) with a reminder that the respondent might concretely contribute to the program. We also follow Mitchell and Carson (2013) and Cummings and Taylor (1999) and add a *cheap talk* to make the respondent aware of the opportunity costs she faces.

The Single-Bounded-Dichotomous-Choice (SBDC) approach with follow-up questions format is recommended by the NOAA panel (Arrow et al., 1993) and by most recent studies (Carson and Groves, 2007; Garcia et al., 2007; **?**), because of its incentive compatibility and its ability to avoid non-response and outliers (Bateman et al., 2002). Furthermore, as Swiss people are often consulted for referenda, this type of question seems particularly appropriate in our context.

We use a Federal or Cantonal lump-sum tax as payment vehicle because of forests public good characteristics: as the benefits are non-rival, the appropriate payment vehicle must request contribution from everyone. The off-site survey also requires a payment vehicle that includes forests non-users. In a Geneva CVM survey on tropical forests, Baranzini et al. (2010) indeed show that a tax provides a higher WTP than a voluntary payment in a forest fund, the latter being subject to free-riding.

[1]On December 31st of 2014, 1CHF=1.20EUR=0.98USD

With the SBDC approach, a selection of tax amounts (bid vector) is randomly assigned to respondents. As Haab and McConnell (2002) mention, the selection of bids is of particular importance. A carefully selected bid vector can considerably improve efficiency of WTP estimates. However, the optimal bid vector can only be designed if the true WTP distribution is known. Of course, if true mean WTP is known, there is no reason to derive an optimal bid vector" (Haab and McConnell, 2002, p. 129). Our 6 bids were selected after an exhaustive literature review and a meta-analysis (Meshreky et al., 2014), also confirmed by a preliminary open-ended qualitative questionnaire discussed in focus groups. This bid design methodology is an acknowledged practice since Kanninen (1993).

The follow-up consists of an open-ended question asking maximum WTP for the program, following Garcia et al. (2007). We use this approach to compute an open-ended estimate of WTP, despite the incentive incompatibility issue associated with an open-ended question and the anchoring created by the proposed bid. We design a second follow-up question to distinguish protest bids (Jorgensen and Syme, 2000) from people that are off the market (Kriström, 1997). If the answer to the previous question is zero, then the respondent has to state the reason. We identify protesters if the reason for not contributing is unrelated to the value of forest[2]. Other reasons are considered "real zeros" and thus off the market.

3 Empirical approach and descriptive statistics

Based on the Random Utility model (RUM) (McFadden, 1973), equations 1 and 2 show that an individual i accepts to pay a given amount (Bid) for a change if her utility with the new situation, which implies paying the bid, is higher than the utility associated with status quo. Self-utility is known by the individual but it is unobserved to the researcher. We thus need to go through dichotomous choice to elicit WTP and add an error term e_i.

$$\Delta U_i = U_i(y_i - Bid_i, z^1) + e_i^1 - U_i(y_i, z^0) - e_i^0 \geq 0 \tag{1}$$

$$P(WTP_i - Bid_i \geq 0) = P(\Delta U_i \geq 0) \tag{2}$$

Where y_i is the individual's income, z^0, z^1 are status quo and the new situation respectively and WTP_i the individual willingness to pay. The probability of accepting the bid is hence:

$$P(Yes|x_i) = P(WTP_i - Bid_i \geq 0) = F(\Delta U_i) = 1 - G(\Delta U_i) \tag{3}$$

With F the probability cumulative density function and G the probability survival function.

[2] "I already pay enough taxes", "Forest is a public good, so it is not reasonable to ask me to pay for it" etc.

The individual's probability to answer "Yes" to the bid can be modeled by the bid itself Bid_i, a vector of explanatory variables x_i and a random component ϵ_i as in equation 4.

$$P(Yes|x_i, Bid_i) = \alpha + x_i\beta + \gamma Bid_i + \epsilon_i \tag{4}$$

Where α is a constant, γ the coefficient for the Bid_i and β for x_i. Before estimating the model, the choice of the distribution for ϵ or F still has to be made.

We test different models by including several additional explanatory variables. The model choice is based on the coefficients significance levels, information criteria (AIC, Pseudo-R^2, Likelihood-Ratio Index) and differences in split-samples characteristics.[3] Based on these criteria, the final model does not include variables such as information on forests, working in forests, gender, the distance from home to forests and opinion on whether one should limit the access in forests to protect the biodiversity, among many others. We observe no income effect on WTP, a result often found in the literature for SBDC (c.f. Schläpfer, 2006), but also explained by the fact that the low response rate for the income question drastically reduces the number of observations when including it.

The final matrix of explanatory variables is composed by the variables described in table 1. $Member$ is a binary variable taking the value 1 if the individual is member of or donates to an environment friendly association; $Freq$ is the annual frequency of visits in a forest; $Urban$ is a binary variable taking the value 1 if the individual lives in an urban area[4]; $Company$ is the number of persons that usually visit the forest with the individual; and $Nhouse$ the number of persons that compose the household.

Our final sample is composed by 419 independent observations from which the sub-sample GE has 191 and CH 228 observations. The proportion of *members* is similar in both sub-samples and approaches 16%. Individuals in the Geneva sub-sample visit forests in average more often than those in the Swiss sub-sample, but the difference is not statistically significant. The Geneva sub-sample is significantly more urban, as 80% of this sample lives in the city of Geneva or its neighborhood against 73% for the Swiss sub-sample. GE's average household is also composed by a statistically lower number of person (2.6) than in the Swiss sub-sample (3.0).

As table 2 shows, each bid has been proposed to 16 persons minimum. The acceptance rates, unsurprisingly, decrease with the bid amount in both sub-samples. Protest rates are stable across bids, with the exception of the relatively low protest rate of the CHF500 bid in CH and the CHF10 bid in GE. It is interesting, but not surprising, to observe that the mean of the follow-up question usually increases with the bid proposed for the Swiss program, reveal-

[3] Adding explanatory variables to the model should not change mean WTP as it is evaluated at covariates mean. However, it allows to control for heterogeneous characteristics of split-samples, which may, in our case, have a different effect on mean WTP.

[4] A municipality is considered as urban if it is part of Geneva's first crown as defined in Direction Générale des Transports (2014)

Table 1: Summary statistics of covariates for Swiss and Geneva sub-samples

	Variable	Mean	Std. Dev.	Min.	Max.	N
CH	Member	0.158	0.365	0	1	228
	Freq	21.772	36.597	0	156	228
	Urban	0.732	0.444	0	1	228
	Company	1.838	1.558	0	6	228
	Nhouse	2.996	1.349	1	6	227
GE	Member	0.164	0.371	0	1	189
	Freq	22.785	42.426	0	156	191
	Urban	0.801	0.400	0	1	191
	Company	1.696	1.649	0	6	191
	Nhouse	2.555	1.208	1	6	191

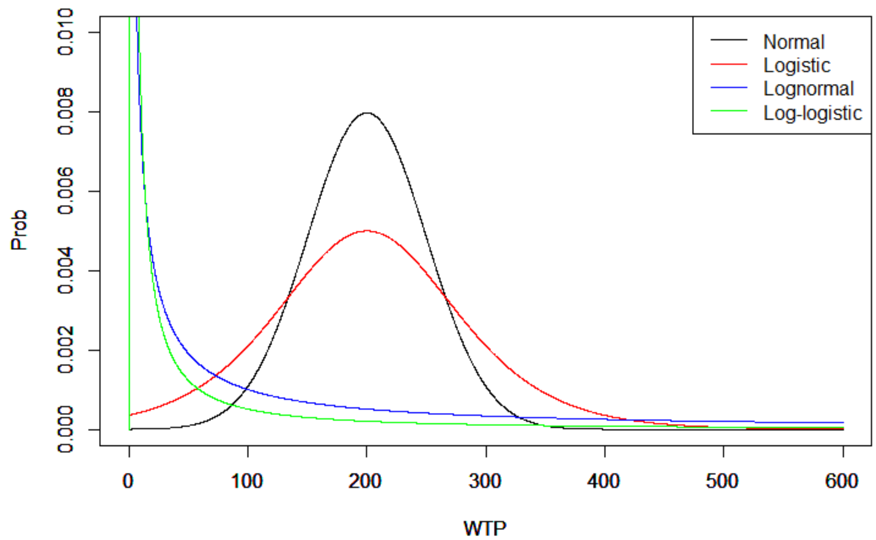
ing an anchoring effect. The possible anchoring effect is however less clear-cut for the Geneva program.

Table 2: Structure of answers to bids in Swiss (CH) and Geneva (GE) samples

		10	60	100	250	500	1000	Total
CH	Yes	26	22	18	12	6	6	90
	No	16	12	24	29	29	28	138
	(incl. protester)	(9)	(7)	(10)	(12)	(2)	(5)	(45)
	(incl. real zeros)	(7)	(4)	(8)	(9)	(11)	(10)	(49)
	N	42	34	42	41	35	34	228
	Acceptance rate	0.62	0.65	0.43	0.29	0.17	0.18	0.39
	Protest rate	0.21	0.21	0.24	0.29	0.06	0.15	0.20
	Follow-up mean[a]	23.44	54.07	87.81	124.48	171.67	303.10	126.84
	(Std.dev)	(34.60)	(27.63)	(110.85)	(115.22)	(226.11)	(386.98)	(212.07)
GE	Yes	34	25	19	3	3	1	85
	No	6	15	20	37	13	15	106
	(incl. protester)	(3)	(7)	(6)	(12)	(6)	(5)	(39)
	(incl. real zeros)	(3)	(7)	(9)	(8)	(2)	(1)	(30)
	N	40	40	39	40	16	16	191
	Acceptance rate	0.85	0.63	0.49	0.08	0.19	0.06	0.45
	Protest rate	0.08	0.18	0.15	0.30	0.38	0.31	0.29
	Follow-up (mean)[a]	46.24	40.50	60.40	84.68	203.00	141.82	79.30
	(Std.dev)	(54.87)	(34.10)	(54.88)	(83.02)	(216.75)	(136.59)	(101.90)

[a] Excluding protest answers

In the Swiss sub-sample, protesters are on average significantly older, they are less member of environmental associations, and live in a more urban environment than non-protesters. Interestingly, better information and more environmental friendliness imply a lower protest rate. We observe the same difference in the Geneva sub-sample for the age and urban environment, but the protester goes also more often in forest than non-protesters and is more often a male.



Note: Distributions are modeled with mean 200 and standard deviation 50

Figure 1: Theoretical WTP distributions

According to Halstead et al. (1992) protest bids should not be removed unless the sub-sample of protest bidders reveals the same characteristics as other respondents. This is apparently not the case here and dropping those observations may bias our estimates. However, considering them as real zeros would also create biases and there is no universally acknowledged method to deal with protest bids. In the following analysis we exclude protesters but, in terms of scope effects, results are similar when protesters are included.[5]

4 Results

4.1 Parametric estimation

With parametric modeling techniques, it is necessary to impose a distribution to F. Normal and logistic distributions have often been used because of their relative ease to handle[6]. However, as can be seen in figure 1, these distributions suffer from an important drawback because they are defined over $]-\infty:\infty[$, which includes the possibility of negative or infinite willingness to pay. As Bateman et al. (2002) mention, if an individual does not value the improvement in

[5]Results including protesters are available upon request.

[6]Indeed, it can easily been shown that $E[WTP] = \frac{\alpha+\bar{x}\beta}{\gamma}$ (see table 13)

the provision of the good, we expect a zero WTP. A negative WTP is acceptable only if the program can be considered as a deterioration (see Boman and Bostedt (1999) and the wolves example). In addition, an individual's WTP shall not be higher than her income and WTP should thus lie in the interval $[0 : y]$ in most cases. Other distributions can take care of these drawbacks: log-normal or log-logistic distribution, Weibull or, better, mixture models with a spike at 0 and truncated at income, as recommended in Bateman et al. (2002).

Since there is no consensus on the statistical distribution and since we are more interested in testing the scope effects, and its robustness across models, rather than in the value of WTP, we decide to run different parametric models (normal, logistic, log-normal, log-logistic) on our split-samples and apply different tests for scope effects. Coefficients of estimations of equation 4 resulting from Maximum Likelihood are shown in table 3. Probit and logit models correspond to a normal and logistic distribution respectively, log-normal and log-logistic distributions are, as usual, computed with probit and logit models respectively and applying the logarithm on the *Bid* variable.

We observe that the signs associated with the coefficients are always the same across models for each sub-sample. As expected, all remaining the same, the probability of accepting the bid significantly decreases with its amount in both sub-samples. The impact of the *Bid* variable is bigger for GE than for CH in all models, meaning that the acceptance rate decreases at a higher speed for the Geneva program. $Member$ and $Freq$ increase the probability of accepting the bid in both sub-samples, which is expected, although the coefficients are not statistically significant in the Geneva sub-sample. The coefficients associated with $Urban$, *Company* and $Nhouse$ have opposite signs in the sub-samples. In particular, living close to the city of Geneva increases the probability of a "Yes" for Geneva forests and decreases the probability of a "Yes" for Swiss forests. Geneva inhabitants can be more prone to enjoy the forests that are situated nearby. One explanation can be found in the type of travel to visit a forest. According to our survey, urban citizens walk more likely to forests than other citizens. Also, people living in the city own less frequently a car, making it more difficult to join a Swiss forest. We note also that coefficients from Geneva sub-sample are less significant due in part to the lower number of observations and to a lesser good fit. We keep the same explanatory variables for each sub-samples for comparison purposes, although they should have no impact on mean WTP and may not fit best.

Table 3: Results from the parametric estimations for the Swiss (CH) and Geneva (GE) sub-sample

	Probit		Logit		Log-normal		Log-logistic	
	CH	GE	CH	GE	CH	GE	CH	GE
Bid	-0.00197***	-0.00326**	-0.00352***	-0.0073**				
	(0.0004)	(0.0013)	(0.0008)	(0.0032)				
ln(Bid)					-0.451***	-0.672***	-0.767***	-1.238 ***
					(0.0788)	(0.126)	(0.142)	(0.271)
Member	0.776***	0.272	1.291***	0.511	0.650*	0.336	1.072**	0.554
	(0.276)	(0.283)	(0.485)	(0.486)	(0.277)	(0.304)	(0.510)	(0.528)
Freq	0.012**	0.003	0.022**	0.0044	0.012**	0.00184	0.0224***	0.0043
	(0.0047)	(0.0029)	(0.0092)	(0.0049)	(0.0044)	(0.00328)	(0.0071)	(0.0056)
Urban	-0.707***	0.070	-1.179***	0.215	-0.516*	0.164	-0.875**	0.365
	(0.241)	(0.283)	(0.423)	(0.488)	(0.243)	(0.309)	(0.442)	(0.535)
Company	-0.109	0.139**	-0.198	0.224**	-0.107	0.0967	-0.201	0.169
	(0.070)	(0.0620)	(0.123)	(0.104)	(0.0737)	(0.0661)	(0.125)	(0.113)
Nhouse	-0.163*	0.140	-0.280*	0.272	-0.191*	0.193	-0.330**	0.365*
	(0.088)	(0.098)	(0.159)	(0.186)	(0.0856)	(0.110)	(0.146)	(0.197)
Constant	1.410***	-0.051	2.390***	-0.084	2.999***	2.277***	5.130***	4.146***
	(0.403)	(0.389)	(0.725)	(0.669)	(0.557)	(0.592)	(1.053)	(1.164)
Observations	183	150	183	150	183	150	183	150
Pseudo R^2	0.288	0.222	0.293	0.240	0.303	0.314	0.305	0.323
AIC	194.5	174.5	193.3	170.8	190.8	155.4	190.3	153.7

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Coefficients from Maximum Likelihood Estimations, robust *Std. Err.* in parenthesis

Before testing for scope effect, it is first important to test if both sub-samples respond differently to the bid proposed and if coefficients are similar across sub-samples. We therefore run pooled models on top of models on split-samples and test for poolabilityusing the Likelihood Ratio test (LR) as in Berrens et al. (2000):

$$LR = -2[lnL_{Pooled} - (lnL_{CH} + lnL_{GE})] \sim \chi^2(7) \tag{5}$$

Where lnL_{Pooled} is the log-likelihood from the pooled model, lnL_{CH} the log-likelihood from the CH model, lnL_{GE} the log-likelihood from the GE model. The test statistic follows a Chi-square law with 7 degrees of freedom, the number of equality restrictions.

Table 4: LR Poolability tests

	Probit	Logit	Log-normal	Log-logistic
lnL_{CH}	-90.25	-89.65	-88.40	-88.15
lnL_{GE}	-80.26	-78.40	-70.72	-69.86
lnL_{Pooled}	-184.2	-182.9	-173.0	-172.4
LR	27.38	29.70	27.76	28.78

$\chi^2_{95\%}(7) = 14.067$
$\chi^2_{99\%}(7) = 18.475$

As shown in table 4, the null hypothesis of poolability is strongly rejected for all models indicating that sub-samples should not be pooled.

4.1.1 Estimates of Willingness to pay

As Poe et al. (1994) stress, if mean WTP does not reveal any scope effects, one should anyway check if statistical distributions are different. Indeed, two different distributions can have identical means. An analysis of mean, median and WTP distribution is therefore necessary to analyze scope effects. The computation of WTP central tendency (mean and median) depends on the distributional assumption (see table 13 in the appendix).

WTP resulting from parametric estimates are shown in table 5 and their distribution in figure 3. As expected, estimates are very sensitive to the distributional assumption and range from CHF300 to 1700 for the Swiss program and CHF190 to 500 for Geneva program. According to these approaches, we find that our sample is willing to pay in average more for the creation of new protected areas in Swiss forests than for the same program, but applied to Geneva forests only. However, using Z-tests, the difference is only statistically significant for the logit model.

The non-overlapping confidence interval method (Park et al., 1991) using Krinsky-Robb confidence intervals at 95% does not reveal any scope effect either since most of the intervals overlap in each models.

A complete combinatorial approach (CC), as proposed in Poe et al. (2005) aims at testing the difference between two distributions. This methodology requires Krinsky-Robb simulation technique. We simulate 1000 replication of WTP for both sub-samples and substract each possible combination of these WTP. The proportion of positive difference can be interpreted as a p-value for H0: $WTP_{CH} > WTP_{GE}$. This test rejects H0 with 90% confidence for the log-normal model. All other models do not reject H0, and the CC test concludes that no scope effects are observed.

4.1.2 Control for differences in samples characteristics

To check if differences in samples characteristics play a role in the determination of scope effects, we follow Carson and Mitchell (1993b) procedure and evaluate equation 4 for the Geneva program at CH covariates mean ($\bar{CH}$), to get an estimate of what the Swiss sub-sample would be willing to pay for the Geneva program. The results are shown in table 6 and display the same type of results as if we had not corrected for sample differences. No significant scope effects can be observed, but we can rule out the fact that samples characteristics have different effects in both sub-samples.

Table 5: WTP for the Swiss (CH) and Geneva (GE) forests from the parametric estimations

	Probit		Logit		Log-normal		Log-logistic[a]	
	CH	GE	CH	GE	CH	GE	CH	GE
Mean WTP	308.194***	215.06***	301.835***	185.29***	1691.974	334.96**	n.a.	500.81***
Std. Err.	(56.197)	(51.02)	(55.167)	(41.99)	(1485.073)	(154.49)	-	(83.22)
Krinsky-Robb CI[b]	[193; 447]	[154; 825]	[191; 447]	[132; 653]	[549; 80617]	[194; 3215]	-	[208; .]
Diff CH-GE	93.134		116.545**		1357.014		-	
Median WTP	Symmetric	Symmetric	Symmetric	Symmetric	144.400***	110.642***	145.867***	111.98***
Std. Err.	-	-	-	-	(35.12)	(20.07)	(36.310)	(18.61)
Krinsky-Robb CI[b]	-	-	-	-	[91; 249]	[83; 181]	[91; 255]	[87; 180]
Diff CH-GE	-		-		33.758		33.887	
Observations	183	150	183	150	183	150	183	150

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Std. Err. computed with the Delta Method in parenthesis, [a] Mean WTP is undefined for $\frac{1}{\gamma} > 1$ for the log-logistic , [b] CI at 95 %, computed with 1000 replications

Table 6: WTP for the Swiss (CH) and Geneva (GE) forests from the parametric estimations at the Swiss covariates mean

	Probit		Logit		Log-normal		Log-logistic[a]	
	CH	GE at $\bar{CH}$	CH	GE at $\bar{CH}$	CH	GE at $\bar{CH}$	CH	GE at $\bar{CH}$
Mean WTP	308.194***	246.200***	301.835***	209.855***	1691.974	393.042**	n.a.	182.043**
Std. Err.	(56.187)	(62.262)	(55.167)	(50.695)	(1485.073)	(190.509)	-	(44.675)
Krinsky-Robb CI[b]	[193; 447]	[154; 825]	[191; 447]	[132; 653]	[549; 80617]	[194; 3215]	-	[208; .]
Diff CH-GE	61.994		91.980		1298.932		-	
Median WTP	Symmetric	Symmetric	Symmetric	Symmetric	144.400***	129.825**	145.867***	131.353**
Std. Err.	-	-	-	-	(35.117)	(26.413)	(36.310)	(24.054)
Krinsky-Robb CI[b]	-	-	-	-		[83; 181]	[91; 255]	[87; 178]
Diff CH-GE	-		-		14.575		14.514	
Observations	183	150	183	150	183	150	183	150

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Std. Err. computed with the Delta Method in parenthesis, [a] Mean WTP is undefined for $\frac{1}{\gamma} > 1$ for the log-logistic , [b] CI at 95 %, computed with 1000 replications

4.2 Non-parametric estimates

We build an hypothetical survival function for discrete choice WTP data as in Bateman et al. (2002). This approach is also known as the Turnbull non-parametric estimator for binary data and has been developed in Kriström (1990). It has the advantage that thre is no need to assume any distribution for WTP. The estimated points of the survival function are calculated as

$$\hat{S}(Bid_j) = \frac{n_j}{N_j} \tag{6}$$

where Bid_j is the bid level $j = 1...6$, N_j is the number of persons whom the bid has been proposed to, n_j the number of persons who said "Yes" to this bid and $\hat{S}$ the estimated survival function.

A valid survival function has to be monotonously decreasing. As this is not the case for some bid levels, we correct for this issue using the *Pooled Adjacent Violators Algorithm (PAVA)* method, proposed by Robertson et al. (1988) and also called Turnbull Self Consistency Algorithm. This method pools the B_j with B_{j-1} if the acceptance rate for B_j is higher than for B_{j-1}.

As in Kriström (1990), we interpolate linearly between bids, but a step function is also applicable. We arbitrarily truncate our survival function at 1200, which is likely to underestimate the true WTP, because the last bid and the truncation point are close. Estimates of the survival function and the PAVA survival functions are illustrated in figure 2, which shows that the survival function for the Swiss sub-sample (black line) is usually higher than the Geneva sub-sample's survival function (dashed line). It is interesting to see that the survival functions are close at low bids and diverge only after a certain threshold.

To compare the survivor functions in figure 2 and test for differences, we use a non-parametric Kolmogorov-Smirnov test (KS) for measuring the distance between the two curves. This test does not reveal any significant difference between CH and GE distributions as a whole. However, a one-tailed KS-test concludes that the survival functions between the bids 250 and 1000 are significantly different at the 5% confidence level. In our bid design, since the bids are not equidistant , they may cause trouble with the KS test as all points of the estimated survival function have the same weight, while the highest bids have the strongest impact impact on WTP estimates. To correct for that issue, we interpolate $\hat{S}$ with 6 hypothetical equidistant bids and test again for significant difference in survival function. This procedure allows to reject the hypothesis of the same distribution for both sub-sample at the 95% confidence level, revealing that WTP distribution are, on average, higher for the Swiss program than for the Geneva program.

Using this approach, the median WTP for the Swiss sub-sample on the graph corresponds to the point where the function hits 0.5 on the Y axis, namely CHF 100 for both sub-samples. Mean WTP can be calculated as the area under the

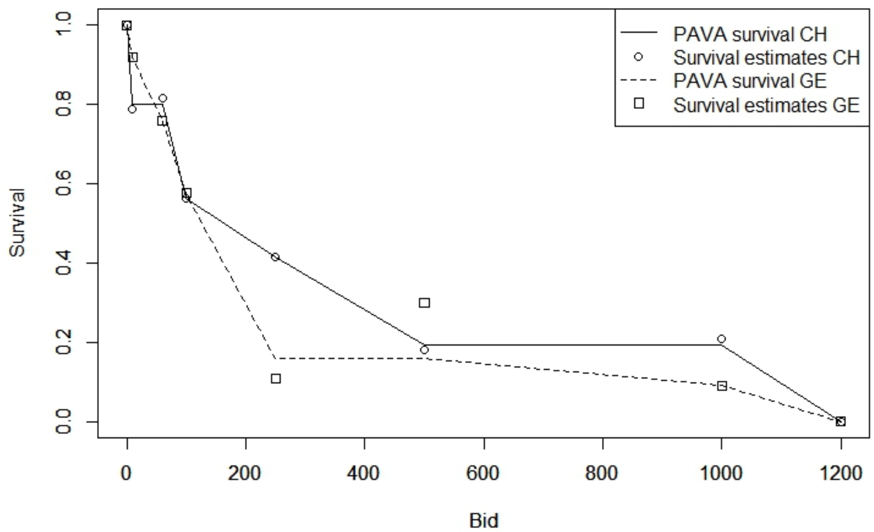


Figure 2: PAVA survival function of WTP

survival function according to:

$$W\bar{T}P = \sum_{j=1}^{6} \hat{S}(Bid_j)[Bid_j - Bid_{j-1}] \tag{7}$$

The estimated analytical variance of the population's WTP is then given by:

$$var(WTP) = \sum_{j=0}^{6} (Bid_j - W\bar{T}P)^2[\hat{S}(Bid_j) - \hat{S}(Bid_{j+1})] \tag{8}$$

and thus the standard error of the mean WTP is:

$$SE(W\bar{T}P) = \frac{\sqrt{var(WTP)}}{\sqrt{N}} \tag{9}$$

As table 7 shows, we observe that CH mean WTP is again larger than GE. Furthermore, a t-test, through the asymptotically normally distributed property, reveals that the Swiss mean WTP is significantly higher than Geneva WTP at the 95% confidence level. Hence, where parametric estimates fail to reveal scope effects by lack of efficiency, the Turnbull estimator manages to distinguish the difference.

Table 7: Non-parametric WTP estimates

	CH	GE
Mean WTP	345.880***	271.877***
Std. Err.	(27.378)	(24.351)
Diff CH-GE	74.003**	
Median WTP	163.043***	127.195***
Std. Err.	(28.214)	(23.399)
Diff CH-GE	35.848	
Observations	183	150

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3 An attempt to use the anchored open-ended follow-up

As mentioned earlier, our survey has a follow-up open-ended question to identify protest bids. However, these continuous answers also give information about WTP even in an anchored context. As our bids are the same in both sub-samples, there is no reason to believe that the anchoring effect would be different. Therefore, a simple analysis of weighted means can be run to test for scope effects. The weights are computed to keep the same proportion of each bids in both sub-samples, to ensure the same anchoring effect. As shown in table 8, we find again a larger mean WTP for the Swiss sub-sample. Applying a Welch test, the difference is significant at the 95% confidence level. More efficient estimates produced by the open-ended format are thus better able to reveal scope effects. One could argue that these estimates are subject to incentive incompatibility, but there is no reason to believe that its consequences would be different in two sub-samples from an identical population.

Table 8: Weighted average WTP from open-ended follow-up

	CH	GE
Mean WTP	126.841	97.375
Std. dev.	(212.067)	(48.830)
Diff CH-GE	29.466**	
Observations	182	119

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

If one is suspicious about the use of open-ended follow-up question as such, one can gather another information from these answers. Indeed, people that are off the market, and thus not willing to pay anything for the program, are less likely affected by the anchoring effect. The "real zero" information can thus be used to model WTP. Kriström (1997) proposes a spike model that split real-zeros and positive WTP in two groups. An asymmetric distribution can then be applied on the positive to get the conditional mean WTP. Coefficients from the

Table 9: Coefficients from the spike model for the Swiss (CH) and Geneva (GE) sub-samples

	CH	GE
$ln(Bid)$	-0.762***	-1.393***
	(0.126)	(0.274)
$Member$	0.272	-0.725*
	(0.341)	(0.390)
$Freq$	0.007	0.008
	(0.0048)	(0.0054)
$Urban$	-0.571*	0.413
	(0.301)	(0.500)
$Company$	-0.161	0.314***
	(0.099)	(0.114)
$Nhouse$	-0.160	-0.099
	(0.105)	(0.171)
Constant	5.428***	6.832***
	(0.812)	(1.284)
Observations	134	120
Pseudo R^2	0.396	0.566
AIC	116.4	78.38

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Coefficients from Maximum Likelihood Estimations
Robust *Std. Err.* in parenthesis

log-normal model applied on positive bidders are presented in table 9. Spike models also reject the null hypothesis for poolability given by the Likelihood ratio test ($LR = 22.4$).

We obtain the unconditional mean WTP by multiplying the conditional mean by the proportion of positive bidders (table 10). Results from the spike log-normal model again show a difference between CH and GE mean WTP. This difference is significant at 95% confidence level for the conditional mean and at 90% for the unconditional mean. By giving more information, the spike model with log-normal distribution on positive bidders thus identifies scope effects, even with a lower number of observations, contrary to the "plain" log-normal model. This proves that more sophisticated models are needed to better fit the real WTP distribution. Furthermore, the complete combinatorial approach rejects the hypothesis of same distribution at the 95% confidence level, which confirms the result for the means.

Table 10: WTP for the Swiss (CH) and Geneva (GE) forests from the spike model

	CH	GE
Cond. mean WTP	872.116**	272.314***
Std. Err.	(356.221)	(58.138)
Krinsky-Robb CI[b]	[443; 3998]	[206; 714]
Diff CH-GE	599.802**	
Uncond. mean WTP	638.599**	218.568***
Std. Err.	(260.839)	(46.663)
Diff CH-GE	420.031*	
Observations	134	120

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Std. Err. computed with the Delta Method

[b] 95%, computed with 1000 replications

5 Conclusion

We run a survey to assess the value of Swiss and Geneva forests through contingent valuation and test for scope effects applying various distributional assumptions for WTP, a non-parametric estimation and an estimation based on the open-ended format. While mean WTP is sensitive to the distributional assumption, we note that the non-parametric model, which has no a priori condition on the statistical distribution, is best able to identify scope effects. As summarized in table 11, more sophisticated models such as the spike model and open-ended follow-up question, by giving more information about individual WTP are also more powerful in revealing scope effects. For small sample size, a non-parametric analysis, a spike model or an open-ended format constitute therefore better options than the classical parametric dichotomous choice analysis for comparing two WTP estimations and identifying scope effects.

This general result may suffer from a number of limits related to our survey. First, the perfect embedding of the Geneva program in the Swiss program is an important assumption. Indeed, individuals may not believe that their money will be distributed the same way in Geneva and in Switzerland. Furthermore, differences in payment vehicles may have an effect on the WTP difference if individuals have a different perception between cantonal and federal taxes, which we do not control for. Use of absolute instead of relative changes could also have improved the understanding of the contingent question, which might have led to a more robust scope effect identification.

Since the NOAA panel guidelines, scope effects testing should be part of the standard validity tests for a contingent valuation survey. However, some studies do not successfully identify scope effect and argue that the method may be unreliable. We argue that one should not throw the baby with the water and systematically apply various tests, paying particular attention to test both for difference in point estimates such as mean and median, but also to differences in distribution.

According to the qualitative results of our survey (not reported here but available in Baranzini et al. (2014)), Swiss forests are also valued by the inhabitants of Geneva for their use. The canton of Geneva has no mountains, but 7% of our sample go most regularly in a forest that is situated in the mountains. 35% of them have also a preference for this type of forest, which shows that people living in Geneva also enjoy forests in other cantons. Therefore, Geneva inhabitants also value extra-cantonal forests for their use, which, in our opinion, justifies the centralized federal financing. The contingent valuation is less unanimous for revealing scope effects but the non-parametric method, the spike model and the open-ended format do confirm this hypothesis.

Table 11: Summary of results: failure (x) and success (✓) to reveal scope effects

Model	Mean	Distribution
Normal	x	x
Logistic	✓	x
Log-normal	x	✓
Log-logistic	-	x
Turnbull	✓	✓
Open-ended	✓	-
Spike	✓	✓

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Appendix

Table 12: Variables description

Variable	Description
Bid	Amount proposed to the respondent that varies randomly from 10, 60, 100, 250, 500 and 1000 CHF /year/household
$Member$	Binary variable taking the value 1 if the respondent is member of or donate to an environment friendly association.
$Freq$	Yearly frequency of Swiss forest visit, coded to a numerical variable from a multiple choice
$Urban$	Binary variable taking the value 1 if the respondent lives in Geneva city or a municipality of its first crown.
$Company$	Number of persons that usually go to the forest together.
$Nhouse$	Number of persons in the respondent's household (children + adults)
Age	Age of the respondent
$Protest$	Binary variable taking the value 1 if the respondent is identified as protester

Table 13: Parametric estimates of WTP central tendency

Distribution	CDF	Mean	Median
Normal	$\Phi(\alpha + x_i\beta + \gamma Bid_i)$	$-\frac{\hat{\alpha + \bar{x}\hat{\beta}}}{\hat{\gamma}}$	$-\frac{\hat{\alpha + \bar{x}\hat{\beta}}}{\hat{\gamma}}$
Logistic	$\frac{1}{1+exp(-(\alpha+x_i\beta+\gamma Bid_i))}$	$-\frac{\hat{\alpha + \bar{x}\hat{\beta}}}{\hat{\gamma}}$	$-\frac{\hat{\alpha + \bar{x}\hat{\beta}}}{\hat{\gamma}}$
Log-Normal	$\Phi(\alpha + x_i\beta + \gamma ln(Bid_i))$	$exp(\frac{-\hat{\alpha + \bar{x}\hat{\beta}}}{\hat{\gamma}})exp(\frac{1}{2\hat{\gamma^2}})$	$exp(-\frac{\hat{\alpha + \bar{x}\hat{\beta}}}{\hat{\gamma}})$
Log-Logistic	$\frac{1}{1+exp(-(\alpha+x_i\beta+\gamma ln(Bid_i)))}$	$exp(-\frac{\hat{\alpha + \bar{x}\hat{\beta}}}{\hat{\gamma}})\Gamma(1-\frac{1}{\hat{\gamma}})\Gamma(1+\frac{1}{\hat{\gamma}})$	$exp(-\frac{\hat{\alpha + \bar{x}\hat{\beta}}}{\hat{\gamma}})$
Spike model	$\begin{cases} CDF & \text{if } WTP > 0 \\ p & \text{otherwise} \end{cases}$	$(1-p)Mean$	$\begin{cases} 0 & \text{if } p \geq 0.5 \\ CDF = (0.5-p) & \text{if } p < 0.5 \end{cases}$

Table adapted from Aizaki et al. (2014, p.27)

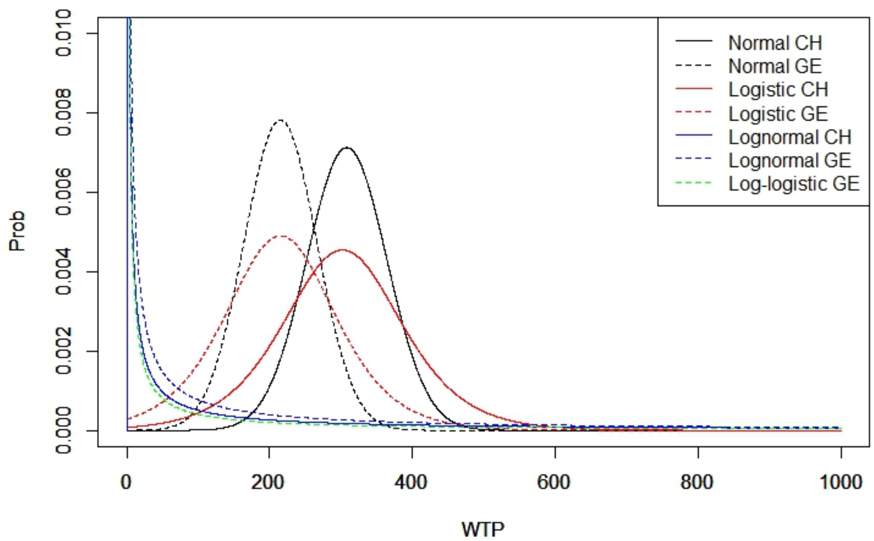

Figure 3: Approximated empirical WTP distributions

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