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Abstract

We provide a contingent valuation of a major cycling event, viz. the Tour of Flanders. Starting from survey data, we estimate several models with different assumptions about (1) the latent willingness to pay distribution and (2) the change in willingness to pay when responding to the follow-up question in a double-bounded dichotomous framework. We relate the individual figures to explanatory factors and find that people residing in the event's core region as well as spectators have a higher valuation. Incorporating the spatial effect, we arrive at an estimated aggregate value of 24.3 million euro.

Introduction

In this paper we provide a contingent valuation (CV) of the 'Tour of Flanders', a one-day +250 km road race for professional elite cyclists that is part of the international UCI World Tour and one of the most prominent one-day events on the cycling sport's calendar. First held in 1913, it is one of the five so-called 'Monuments', each year attracting hundreds of thousands of spectators along the course, and a multiple of that in terms of worldwide TV audience.

The valuation of major sporting events usually is done by means of a so-called economic impact analysis. As indicated by that very label, such analyses basically seek to quantify the additional economic activity (extra spending, extra jobs, extra revenues,...) that is generated by a specific event (see e.g. Collins & Jackson, 1999 or Gratton, Shibli & Coleman, 2005 for a literature overview, and Desbordes (2007) for an overview of economic impact studies of the Tour de France). It is however well-known that, by essentially focusing on market effects, this approach falls short of capturing other possible but far less tangible sources of additional value. The national prestige that comes with hosting, e.g., the Olympic Games is an often cited example of the latter.

Ironically, economic impact studies sometimes serve the practical purpose of stressing the need for *public* funding. Yet, from a normative perspective it are non-market benefits (or market failures more generally) that may justify government intervention. That major sporting events, despite their essentially private character, benefit from government intervention is clear. The ‘Tour of Flanders’ itself is considerably subsidized by different levels of government, both financially and in kind.¹ In point of fact, a +250 km road race on an open circuit is both non-rival in consumption and non-excludable.² Its public good nature calls for a valuation method that is especially fit to capture ‘non-use’ value components not transmissible via the standard market mechanism.³

Specifically, this paper uses a CV approach so as to include these non-marketable sources in an estimate of the event’s total economic value. Contingent valuation has hitherto been applied more often in environmental or cultural evaluation studies than in sports economics. Applications in sports include the valuation of the Olympic Games 2012 (Atkinson, Mourato, Szymanski & Ozdemiroglu, 2008; Walton, Longo & Dawson, 2008) and sports stadiums (Johnson & Whitehead, 2000; Johnson, Mondello & Whitehead, 2007; Groothuis, Johnson & Whitehead, 2004). Studying the ‘Tour of Flanders’ adds to this literature by focusing on a (yearly recurring) one day ‘Big Event’ in an increasingly popular sport.

To derive an accurate estimate of median and average willingness to pay (WTP) in our sample we compare the fit of models with different assumptions about the latent WTP distribution and select the best one. Moreover, to correct for a possible bias in the WTP estimate, we investigate different assumptions about a change in WTP when responding to the follow-up question.

For model estimation, both a classical approach (using posterior maximization) and a fully Bayesian approach were used. Relative to more standard (maximum-likelihood) approaches, which build on asymptotic theory, a fully Bayesian approach has the advantage of allowing for the computation of posterior confidence intervals of parameters that are also valid in small samples. Moreover, this small-sample validity carries over to the distribution of any function of the parameters, including the median and average WTP for the entire sample, 95% posterior confidence intervals, etc.

The estimated individual valuations will be linked to other individual characteristics in a regression analysis. Among these we include information about a respondent's place of residence, allowing for an analysis of potential spatial effects. In its capacity as a public good, it is instructive to know the geographical extent of the benefits the event generates. Put otherwise, identifying such effects is important when establishing the total number of beneficiaries. If, for instance, there is a strong 'distance decay' in individual valuation, then this must be taken into account when calculating aggregate benefits (Hanley, Schäpfler & Spurgeon, 2003).

To be clear, this paper is concerned with an empirical assessment of the Tour of Flanders' total economic value, and not with the empirical decomposition of that value into so-called use and non-use (sub-)components as such. Basically, this is because the former assessment is called for whereas the latter is far more controversial, as we will briefly explain below. Still, we do provide some information about particular 'non-use motivations' indicated by our survey respondents.

2. Survey methodology

In a perfect market setting, and assuming consumer sovereignty, WTP can be estimated from observations of price/quantity combinations. In settings such as the one studied in this paper such data are clearly absent. Still, two alternative routes can be taken to determine WTP: revealed preference methods and stated preference methods.

Revealed preference methods infer the WTP from observed behavior on complementary or substitution markets. By construction, revealed preference methods can only provide estimates for the use value of an event. Arguably though, major and classic sporting events like the Tour of Flanders also encompass some non-use aspects that bear on the event's value. In such instances, a survey based stated preference method is certainly appropriate. Specifically, we employ a CV method, in which respondents are questioned directly about their WTP.⁴

Data for our study were collected in 2009 as part of the 'Participation Survey' ('PaS'09) that was organized by the Policy Research Centre for Culture, Youth and Sport, a research consortium funded by the Flemish government. The PaS'09 interviewed a representative sample of the Flemish population, in which 4697 addresses were used to realize 3194 interviews (response rate = 68.0%).⁵ Within this sample, one out of six respondents, aged 18 or more, received questions on their WTP for the Tour of Flanders in a face-to-face interview. Since 7 respondents out of these 461 did not fully complete the survey, the analysis is performed on 454 respondents.

The survey sample contains more users than non-users: just over 70% of the respondents have been (live or TV) spectators of the event at least once, with 44% of the respondents declaring they have seen the Tour of Flanders several times. We will refer to that last group as 'intensive users'. Less than 9% were unacquainted with the event, while about 20% knows it but has never seen it.⁶

Each respondent was asked questions about his or her WTP for the Tour of Flanders, using a so-called double-bounded dichotomous approach (see e.g. Mitchell & Carson, 1989; Arrow et al., 1993; Bateman et. al., 2002). The Tour of Flanders is first briefly described, followed by the following hypothetical question:

Assume that due to cost increases, the Tour of Flanders is no longer profitable and will no longer be organized in the future . If everyone pays a similar amount, the Tour of Flanders can continue to exist. That amount will be collected through an increase in the income taxes.

Are you willing to contribute annually ... euro, by means of extra taxes, to ensure that the Tour of Flanders will continue to exist?

It should be noted that the ‘Big Event’ nature of the Tour of Flanders is quite crucial for the credibility of this question. That is, if the event would be considered by our respondents as one for which substitutes are easily available, then this would probably bear on the quality of the answers they provide. Yet it is safe to say that this particular sporting event has a ‘cultural heritage’ –aspect quite similar to events as the Cup Final, the Superbowl, etc. Flemish media, politicians, artists, and the audience at large repeatedly and explicitly depict the Tour of Flanders as a Flemish cultural icon.⁷

The interviewer suggests a start amount and the respondent answers with yes or no. In case of a positive answer, the interviewer repeats the same question with a higher follow up amount and in case of a negative answer with a lower follow up amount. We used three different start amounts⁸ S_c ($c=1,...,3$) each with its respective higher and lower follow up amount (denoted as H_c and L_c respectively). Specifically, we used as (S, H, L) triplets $(5, 11, 1)$, $(9, 16, 3)$, and $(13, 20, 7)$. Each respondent arbitrarily received one of the three bid cards; each card was used for about one third of the respondents (see Table 1 below).

The two consecutive dichotomous questions lead to four different answer combinations: no-no, no-yes, yes-no or yes-yes. Table 1 gives a first indication of the willingness to pay by showing the percentage of respondents for each of three (S , H , L) combinations used. Almost 15% of the respondents with bid card 3, for example, answer yes-yes, signifying that they are willing to pay at least 20 euro per year to avoid the Tour's disappearance. Similarly, 55% of the bid card 2 respondents reveal by their no-no answer a WTP between 0 and 3 euro. Table 1 reveals that the percentage of no-no answers increases with the initial amount on the bid card. There is thus no apparent framing effect in that presenting the respondent with a higher initial amount does not induce a higher stated willingness to pay.

Table 1. Percentage of respondents for each answer combination

	no-no	no-yes	yes-no	yes-yes	(N)
Bid card 1 (5 – 11 – 1)	42,8%	15,7%	19,9%	21,7%	166
Bid card 2 (9 – 16 – 3)	54,7%	12,9%	18,7%	13,7%	139
Bid card 3 (13 – 20 – 7)	67,8%	2,7%	14,8%	14,8%	149

3. Estimating the distribution, mean and median of individual willingness to pay

3.1 Standard analysis of contingent valuation data

To describe the modeling of the contingent valuation responses, we first introduce some notation. The WTP value of respondent i ($i=1, \dots, I$) will be denoted as θ_i . It is assumed that the true WTP values of respondents are sampled from a latent distribution $p(\theta|\phi)$, with ϕ a set of unknown parameters that specify the form of the latent distribution. For instance, when assuming

a Normal distribution for WTP, $\boldsymbol{\varphi} = (\mu, \sigma^2)$ comprises the mean and variance of the Normal distribution. Furthermore, the binary variable Z_{ic} equals 1 if respondent i has been assigned bid card c ($c=1, \dots, C$) with start- and follow-up amounts (S_c, H_c, L_c) , and 0 otherwise. The binary response variables Y_{i1} and Y_{i2} (1=yes, 0=no) are used to code the response of person i to the initial and the follow-up question, respectively.

From the survey set-up, it follows that the probability of each response pattern (i.e. no-no, no-yes, yes-no and yes-yes) can be computed as a part of the surface under the WTP distribution, that is,

$$\pi_{00c} = P(Y_{i1} = 0, Y_{i2} = 0 | Z_{ic} = 1) = P(0 < \theta_i \leq L_c) = F(L_c | \boldsymbol{\varphi})$$

$$\pi_{01c} = P(Y_{i1} = 0, Y_{i2} = 1 | Z_{ic} = 1) = P(L_c < \theta_i \leq S_c) = F(S_c | \boldsymbol{\varphi}) - F(L_c | \boldsymbol{\varphi})$$

$$\pi_{10c} = P(Y_{i1} = 1, Y_{i2} = 0 | Z_{ic} = 1) = P(S_c < \theta_i \leq H_c) = F(H_c | \boldsymbol{\varphi}) - F(S_c | \boldsymbol{\varphi})$$

$$\pi_{11c} = P(Y_{i1} = 1, Y_{i2} = 1 | Z_{ic} = 1) = P(H_c < \theta_i) = 1 - F(H_c | \boldsymbol{\varphi}),$$

with $F(\cdot | \boldsymbol{\varphi})$ the cumulative distribution function of WTP.

To estimate the parameters of the latent distribution one may maximize the posterior distribution:

$$\begin{aligned} p(\boldsymbol{\varphi} | \mathbf{y}, \mathbf{z}) &\propto p(\boldsymbol{\varphi}) p(\mathbf{y} | \mathbf{z}, \boldsymbol{\varphi}) \\ &\propto p(\boldsymbol{\varphi}) \int_{\boldsymbol{\theta}} p(\mathbf{y} | \mathbf{z}, \boldsymbol{\theta}) p(\boldsymbol{\theta} | \boldsymbol{\varphi}) \end{aligned} \quad (1)$$

Note that in (1) $p(\mathbf{y} | \mathbf{z}, \boldsymbol{\varphi})$ represents the likelihood of the model:

$$p(\mathbf{y} | \mathbf{z}, \boldsymbol{\varphi}) = \prod_{c=1}^C \left\{ \prod_{i=1}^I (\pi_{00c})^{(1-y_{i1})(1-y_{i2})} \pi_{01c}^{(1-y_{i1})y_{i2}} \pi_{10c}^{y_{i1}(1-y_{i2})} \pi_{11c}^{y_{i1}y_{i2}} \right\}^{z_{ic}}$$

and $p(\boldsymbol{\varphi})$ represents the prior distribution for the parameters of the latent distribution. Classical maximum likelihood estimates are obtained by specifying a flat prior (i.e., $p(\boldsymbol{\varphi}) \propto 1$) for the parameters of the latent distribution.

In addition to maximizing the posterior distribution one may also adopt a fully Bayesian approach and use Markov chain Monte Carlo methods such as Gibbs sampling to compute a sample of the posterior distribution (see e.g., Araña & León, 2005, 2007; Fernández, León, Steel & Vázquez-Polo, 2004; Li, Jenkins-Smith, Silva, Berrens, & Herron, 2009; Yoo, Kwak & Kim, 2001; Yoo, 2004;). Computing a sample of the posterior distribution may be advantageous for several reasons (see Araña & León, 2007): First, with large samples, a fully Bayesian approach yields the same results as traditional maximum likelihood methods, but it can be more accurate with small samples because it does not rely on asymptotic approximations to the posterior distribution. Second, besides providing point estimates and posterior intervals of the model parameters, the posterior sample allows to simulate and summarize the distribution of any function of the parameters. (e.g. the median WTP value). Third, adopting a fully Bayesian approach provides less complex estimation procedures in some cases (calculation of multiple integrals, impose ordinal constraints on category boundary parameters in ordinal regression models,...).

3.2 Accounting for starting point bias, or a shift in WTP when responding to the follow-up question

In the above presented standard modeling, it is assumed that a respondent's responses to the initial and the follow-up question are driven by the same WTP value. However, it has been argued that the individual WTP value of a respondent may shift when responding to the follow-up question, as the information conveyed to the respondent is different in both questions. Carson and Groves (2007) provide an overview of the different plausible assumptions about response strategies and of the type of shift they would cause in the WTP distribution for the second question.

More specifically, a first plausible assumption is that the perceived cost of the good by the respondent is a weighted average of the costs presented at the first and the second question, and that the second question is answered on the basis of this average cost. As a result, the perceived cost of the follow-up question will be higher for respondents with an initial negative response and their WTP distribution for the second question will shift to the left (i.e. in the opposite direction of the initial bid or “starting-point”). Using the same reasoning, the perceived cost of the follow-up question will be lower for respondents with an initial positive response and their WTP distribution will shift to the right (i.e. in the opposite direction of the starting-point).

A second plausible assumption, which uses a Bayesian perspective about the decision maker, is that the initial bid provides an anchor about the value of the good for the uncertain respondent. As a result, respondents will update their initial WTP in the direction of the starting-point when responding to the follow-up question (Czajkowski, 2009; Herriges & Shogren, 1996; McLeod & Bergland, 1999). It is easy to see that the predictions made by this Bayesian decision model are exactly opposite to the predictions made by the “average cost” assumption (namely a shift of WTP in the opposite direction of the starting-point).

Finally, other plausible assumptions about the response strategy of respondents (i.e. risk aversion because of uncertainty about the price, or a tendency to bargain after being offered a second price) still make other predictions, namely a downward shift of the WTP distribution for all respondents. In sum, different response strategies yield predictions that have a different effect on the WTP distribution. Therefore, in order to account for different types of shifts in the WTP distribution when responding the follow-up question, we propose a model which allows to capture shifts that differ depending on the value of the initial response and that can be both upward or downward.

To describe the model, let θ_i denote the WTP value used when person i answers the initial question. Further, we assume that, when responding to the follow-up question, the WTP value of person i equals $\theta_i + \tau_c^L$ if an initial negative response was given ($Y_{i1} = 0$) and that it equals $\theta_i + \tau_c^H$ if an initial positive response was given ($Y_{i1} = 1$). As explained before, a shift in the WTP distribution corresponds to an opposite shift in the cost presented at the follow-up question. In particular, $\xi_c^L = L_c - \tau_c^L$ denotes the shifted cost for the follow up question in case of an initial negative response and, in the same way, $\xi_c^H = H_c - \tau_c^H$ indicates the shifted cost of the follow-up question in case of an initial positive response. Furthermore, as each response pattern (No-No, No-Yes, Yes-No, Yes-Yes) should have a positive probability to occur, it is natural to assume that $0 < \xi_c^L < S_c$ and that $S_c < \xi_c^H < +\infty$. Hence, it also follows from these constraints that $L_c - S_c < \tau_c^L < L_c$ and $-\infty < \tau_c^H < H_c - S_c$.

The joint probability of providing negative responses to both the initial response and the follow-up question can now be derived as follows:

$$P(Y_{i1} = 0, Y_{i2} = 0 | Z_{ic} = 1) = P(\theta_i \leq S_c, \theta_i + \tau_c^L \leq L_c) = P(\theta_i \leq L_c - \tau_c^L) = P(\theta_i \leq \xi_c^L) = F(\xi_c^L | \boldsymbol{\varphi}),$$

In the same way one may derive the probabilities to observe the other response patterns:

$$P(Y_{i1} = 0, Y_{i2} = 1 | Z_{ic} = 1) = P(\xi_c^L < \theta_i \leq S_c) = F(S_c | \boldsymbol{\varphi}) - F(\xi_c^L | \boldsymbol{\varphi})$$

$$P(Y_{i1} = 1, Y_{i2} = 0 | Z_{ic} = 1) = P(S_c < \theta_i \leq \xi_c^H) = F(\xi_c^H | \boldsymbol{\varphi}) - F(S_c | \boldsymbol{\varphi})$$

$$P(Y_{i1} = 1, Y_{i2} = 1 | Z_{ic} = 1) = P(\xi_c^H < \theta_i) = 1 - F(\xi_c^H | \boldsymbol{\varphi})$$

Several authors have presented related models: Alberini, Kanninen and Carson (1997) proposed a shift model which assumes the same structural shift in the WTP distribution for

respondents with a negative or a positive initial response (i. e. $\tau_c^L = \tau_c^H$). Flachaire and Hollard (2007) present a “range” model which involves specific structural shifts for respondents with a positive or a negative initial response, but which constrains the shifts to be in a certain direction (i.e. the range model implies that $\tau_c^L \geq 0$ and $\tau_c^H \leq 0$). Our model thus allows for a richer set of possible scenarios.

3.3 Analysis

In the present study we consider models that assume different types of latent distributions, and that make different assumptions about the shift in WTP when responding to the follow-up question. In particular, we consider three latent distributions for WTP: (1) A Normal distribution, (2) a truncated Normal distribution (i.e. truncated to the left at zero to exclude negative WTP values), and (3) a Weibull distribution; and three assumptions concerning the shift in WTP: (1) no shift (i.e. $\tau_c^L = \tau_c^H = 0$), a model that assumes the same (positive or negative) structural shift for positive and negative initial responses (i.e. $\tau_c^L = \tau_c^H = \tau$) (see also Alberini, Kanninen & Carson, 1997), and a model that estimates different (upward or downward) shifts depending on the response to the initial question (i.e. τ_c^L and τ_c^H are only constrained to be within certain boundaries).

Table 2 presents estimates of mean and median WTP based on a maximization of the posterior distribution. In order to enhance comparison with a fully Bayesian analysis, (very weak) prior distributions are assumed on the estimated parameters.⁹ All the models in Table 2 were estimated using the SAS procedure NLMIXED (SAS Institute Inc., 2008). As an example, Appendix 1 lists the SAS code for estimating M₆. As shown in Table 2, a model with a Normal distribution (M₁, with $\mu = 1.9, \sigma = 14.4$) turns out to be rather unrealistic as it implies WTP to be

negative for almost half of the respondents in the sample. Therefore, this model is not further considered.

Table 2: Estimated median and mean WTP value for models with different assumptions about the distribution of WTP and a shift in WTP when responding to the follow-up question.

Model	Distribution	Shift model	Median	95%CI	Mean	95% CI	Distribution parameters	Shift parameters	BIC
M ₁	Normal	No shift	1.9	(0.1,3.7)	1.9	(0.1,3.7)	$\mu = 1.9$ $\sigma = 14.4$	/	1085
M ₂	Truncated Normal	No shift	5.1	(4.5,5.6)	7.2	(6.4,7.9)	$\mu = -181.2$ $\sigma = 37.3$	/	1259
M ₃	Truncated Normal	Same shift for Y _{il} =0 and Y _{il} =1	6.5	(5.8,7.3)	9.2	(8.1,10.1)	$\mu = -157.9$ $\sigma = 40.1$	$\tau_1 = -2.3^{**}, \tau_2 = -3.3^{**}, \tau_3 = -4.5^{**}$	1111
M ₄	Truncated Normal	Specific shift for Y _{il} =0 and Y _{il} =1	5.7	(5.0,6.4)	7.9	(7.0,8.8)	$\mu = -93.9$ $\sigma = 29.3$	$\tau_1^L = -2.4^{**}, \tau_2^L = -3.4^{**}, \tau_3^L = -4.9^{**}$ $\tau_1^L = 0.9, \tau_2^L = 0.5, \tau_3^L = 1.9$	1106
M ₅	Weibull	No shift	2.2	(1.6,2.9)	11.5	(7.8,15.2)	$k = 0.46$ $\lambda = 4.93$	/	1103
M ₆	Weibull	Same shift for Y _{il} =0 and Y _{il} =1	4.2	(3.2,5.3)	10.2	(8.3,12.2)	$k = 0.65$ $\lambda = 7.46$	$\tau_1 = -1.6^{**}, \tau_2 = -2.4^{**}, \tau_3 = -4.4^{**}$	1074
M ₇	Weibull	Specific shift for Y _{il} =0 and Y _{il} =1	3.7	(2.3,5.1)	12.9	(6.3,19.5)	$k = 0.54$ $\lambda = 7.32$	$\tau_1^L = -1.2^{**}, \tau_2^L = -1.7^{**}, \tau_3^L = -4.2^{**}$ $\tau_1^L = -3.7, \tau_2^L = -8.6, \tau_3^L = -7.0$	1088

* P<0.05, ** P<0.01

Furthermore, as indicated by the BIC values, a Weibull distribution (models M_5 , M_6 and M_7) should be preferred to a truncated Normal distribution (models M_2 , M_3 and M_4) as it generally yields a better fit. Finally, the estimated shift parameters indicate that there is evidence for a decrease in WTP when responding to the follow-up question. As ignoring this type of response bias would cause an underestimation of WTP values, inclusion of the shift effect may help to correct the estimated WTP values in the opposite direction. This is confirmed by the significant increase in median WTP values for models with a structural shift in WTP versus models without shift effect (i.e., $\text{Median}(M_3) > \text{Median}(M_2)$, and $\text{Median}(M_6) > \text{Median}(M_5)$). As model M_6 has the lowest BIC value ($\text{BIC}=1074$) we will select this model for further analysis.

A fully Bayesian analysis is conducted for M_6 using the R-package R2WinBUGS (Sturtz, Ligges, & Gelman, 2005). Appendix 2 lists the R-code for running this analysis. Note that the Gibbs sampling algorithm used in the Bayesian analysis generates, in each iteration, a value for each of the model parameters (i.e. the parameters of the Weibull distribution, the shift parameters and the individual WTP values). In particular, we run four chains of 10000 iterations using random starting points and use evenly spaced draws from the second halves of the chains to construct a sample of 2000 iterations. Using the constructed sample to summarize the distribution of parameters (i.e. across the 2000 iterations) we obtain results that are very similar to those obtained by

maximizing the posterior distribution: The estimated median WTP equals 4.2 euro with 95% posterior interval (3.4,4.9), and the estimated mean WTP equals 10.3 euro with 95% posterior interval (9.0,11.9). The estimated shift parameters equal $\tau_1 = -1.6, \tau_2 = -2.4, \tau_3 = -4.2$ with 99% posterior intervals (-2.4,-0.7), (-3.8,-0.8) and (-5.5,-2.0), respectively.

4. Determinants of willingness to pay

4.1. Explanatory factors

A next step is to examine possible relations between individual characteristics and WTP via a regression analysis. Some socio-economic characteristics may be expected to have an influence on an individual's valuation. The variables **gender**, **age** and **income** represent a first type of such characteristics. One could expect that men prefer watching the Tour of Flanders more than women and, therefore, through their higher use value, have a higher WTP. Note that half of the respondents in the sample are males. Furthermore, in order to capture a possible nonlinear relationship between age and WTP, age is included as a categorical variable with age groups '18-34', '35-54', '55-64' and '65+' each of which contains 22%, 37%, 18% and 23% of respondents, respectively. To code the effects of age categories in the regression, we use dummy (0/1) coding with the age group '18-34' as the reference category. Income is measured as the net monthly household income of the respondent.¹⁰ For the entire sample the average income equals 2592 euro with a standard deviation of 1261. To reduce the effect of outliers, we include the centered natural logarithm of income as a continuous variable in the analysis.

A second type of socio-economic variables deals with a respondent's participation in the event as a user as well as in sports more generally. The

variable **intensive user** (44% of the respondents) identifies respondents that have watched the Tour of Flanders either on tv or along the track several times. Relative to infrequent and non-users, we expect a higher use value and thus a higher WTP. Next, we make a distinction between respondents that engage in sport activity only irregularly, and active sport enthusiasts either with **cycling** (18% of the respondents) or any **other sports** (32% of the respondents) as their most regular sports activity. We expect the latter two groups to have a higher valuation of the event, relative to the former.

Another set of potential explanatory variables are included so as to check for the presence of spatial effects. The question here is whether individuals living closer to the event have a systematically different valuation than others, and, if so, whether this is a higher or a lower valuation. The former result is indicative of the so-called ‘distance decay effect’, whereas the latter would point towards preponderant negative externalities (e.g., traffic congestion) as experienced by those living nearby the event. As we will show in more detail in the next section, finding such systematic differences is also important when it comes to aggregating individual valuations over the entire (Flemish) population.

Since we are dealing here with a +250 km road race that largely takes place in two out of five existing Flemish provinces and that crosses several municipalities, we discern multiple ways of deciding whether a respondent lives

‘on the event’s track’. All these variables are dummies. The variable **track** (8% of the respondents) refers to respondents living in a municipality where the 2009 edition of the Tour of Flanders passed. Over the years, there are some minor variations in this track, but the fundamental structure of the event has not been altered over the last decades. There is a +/-100km run-up in the flat (but sometimes windy) coastal area, after which the race turns towards its typical final section, a winding track filled with short but steep hills and cobblestoned roads. As this section attracts most of the visitors, and is located in the so-called “Flemish Ardennes”, we set the dummy variable **Flemish Ardennes** at one for those respondents living in a municipality situated in the event’s core region *and* where the Tour actually passes. Since the event is strongly associated with this particular region in general (and is, in fact, rather instrumental in attracting regional tourism) we allow for a broader spatial effect: respondents living in a municipality next to one considered by the former variable, but without the event actually passing, are indicated as such by the dummy **Region FA**. A final dummy within this spatial set refers to ‘special’ villages along the track, viz. the departure city (Bruges), the arrival city (Meerbeke) and all villages that have carried the title ‘village of the Tour of Flanders’. ¹¹ For the observed sample, the variables Flemish Ardennes, Region FA, and ‘special’ villages along the track apply to 2%, 10% and 5% of the respondents in the sample, respectively.

As just stated, two opposing spatial effects may influence a person’s WTP. People living close to the track or in the event’s core region have lower (travel) costs to visit the Tour of Flanders, which increases their ‘option value’ relative to others. Similarly, they may be more proud of ‘their’ event or, more mundanely, have a more direct stake in its economic impact. Conversely, they

are more confronted with negative external effects such as traffic jams, noise pollution,... which would lower their WTP.

Two variables related to the survey set-up are also included. Interviews for the survey were carried out through the whole year 2009, while the event itself was held in April 2009. About 67% of the respondents were interviewed after the event. This information on the timing of the survey is included in the regression by the dummy variable **2009 Tour** (1 = interview carried out after the event, 0 = interview before the event). The **protest** variable is a dummy, indicating respondents that may have not stated their true WTP for the Tour of Flanders. It is possible that respondents state a low or a zero WTP in the survey but have a higher WTP in reality, or vice versa. The usual way to differentiate between protest valuations and genuine zero valuations is to present a set of debriefing questions to the respondents. A frequently cited ‘wrong’ motivation for a low WTP is the protest against the payment vehicle (Morrison et. al., 2000). The literature is unclear about which motivations lead to protest-answers¹² and how these protest-answers should be treated. We follow the suggestion from Jorgensen and Syme (2000) and Meyerhoff and Liebe (2005) and include the protest variable (which equals 1 for 6% of the respondents in the sample) in our estimation of the WTP.

Map 1. Variables Track, Region and ‘Special’ villages

4.2. Results

While the characteristics listed above are readily observable from a respondent's answers to the survey, the individual WTP attributed to this respondent, θ_i , has been found using the fully Bayesian analysis (see Appendix

2). A regression could use a point estimate of these 454 values as dependent variable (e.g. posterior mean of each θ_i computed across iterations of the Gibbs sampler) and relate these to corresponding explanatory variables such as gender, income, place of residence, etc. But since such a procedure would ignore the uncertainty in the WTP estimates of respondents, it would also underestimate the uncertainty of the corresponding estimated regression coefficients. A natural way to deal with this problem is to exploit the Monte Carlo nature of the fully Bayesian analysis. Specifically, since each iteration of the Gibbs sampling algorithm yields a vector of estimated θ_i -values, we can run a regression for each of these WTP vectors. In turn, this generates multiple values for each estimated coefficient—one value for each original iteration—, so generating a distribution for each regression coefficient. This allows us to present its average value as well as confidence intervals.

We report results for four different models. An initial model focuses on the spatial effects and survey related variables only. A second model further includes the effect of the respondent's personal characteristics namely gender, age, income and active sports participation. A third model further includes an interaction between age and gender. Finally, a fourth model also includes the intensive user variable.

Table 3 shows the mean value of the estimated coefficients as obtained after running 2000 OLS regressions (i.e., one for each draw of WTP vectors). As the track variable did not have a significant contribution on top of the other spatial variables, it was not included in the analysis. Furthermore, there is a positive effect for inhabitants from the event's Flemish Ardennes core region in models 1 and 2. Note however that this effect just falls below the boundary of significance when the interaction between age and gender is included (model 3), and that it is especially further mitigated in both statistical significance and size once the intensive user variable is added (model 4).¹³ The latter indicates that people living in the Flemish Ardennes partly have a higher WTP because of their increased probability to be a spectator. The "departure/arrival/special village" variable on the other hand is significantly negative in all four models. This is consistent with the hypothesis that people residing in such municipalities experience, on balance, more than others the negative external effects of the Tour of Flanders. As can be seen from the significant interaction between age and gender (model 3 and 4), there is evidence that the effect of age on WTP is different for men and women. In particular, as indicated by the main-effect of 'men', men aged between 18 and 34 value the Tour of Flanders significantly more than women in this age category. Furthermore, the main-effects of the age categories indicate that the average WTP of women aged between 18 and 34 is significantly lower than for women in other age categories. Finally, using posterior simulations to summarize the distribution of a sum of model parameters (e.g. 'age 35-34 versus 18-34' + 'men*age 35-34 versus 18-34') it can further be derived that average WTP is not significantly different for men aged between 18-34 and for men in other age categories. In sum, especially women between 18-34 turn out to have a lower valuation of the Tour of Flanders compared to men in the same age category, or compared to men or women older than 35.

Table 3: Estimated regression coefficients for four different models

Variable type	variable	Model 1	Model 2	Model 3	Model 4
Spatial variables	intercept	11.4**	7.8**	5.7**	4.0**
	Flemish Ardennes	6.2*	6.1*	5.4	2.2
	Region Flemish Ardennes	4.6**	4.5**	4.1*	3.7*
	Departure village, arrival village or 'village of the tour'	-5.4*	-5.9*	-6.9**	-6.8**
Survey	2009 Tour	-1.4	-1.9	-1.9	-1.6
Socio-economic	Protest	-8.8**	-8.2**	-8.3**	-8.7**
	Men		2.2*	6.7**	4.5**
	Age 35-54 versus 18-34		2.3	6.6**	6.0**
	Age 55-64 versus 18-34		2.8	3.2**	2.5*
	Age 65+		2.9*	5.7**	5.0**
	Men* Age 35-54 versus 18-34			-8.5**	-7.9**
	Men* Age 55-64 versus 18-34			-0.5	-0.9
	Men* Age 65+ versus 18-34			-5.1*	-5.9*
	Centered Ln(income)		3.0**	3.0**	1.9*
Sports Participation	Cycling		5.0**	4.8**	4.4**
Event Participation	Other sports		-0.4	-0.8	-0.6
	Intensive user				7.3**
R ²		0.03	0.07	0.08	0.13

* P<0.05

** P<0.01

The protest variable has a significantly negative effect on the WTP, which is to be expected as we are mainly dealing with no-no respondents. Income, after controlling for other effects, has a significant and positive impact on the WTP. Being acquainted with the event, not so much because of living nearby but because one likes cycling, also has a clear positive impact. The intensive user effect is visible as such in model 4 (where we have already indicated that its inclusion corrects for overstated spatial effects). As for sports participation, we note that this effect is limited to cycling as people practicing other sports have no significantly higher WTP.

5. Estimating Total Economic Value

Given that Flanders has about 2.6 million households, and recalling from section 3 our sample estimate of average WTP of 10.3 euro, a naïve extrapolation would lead to a total economic value of 26.8 million euro (with an associated 95% confidence interval ranging from about 23.4 euro million euro to about 30.9 million euro). It is however clear from section 3 that this overall average builds on some right-tail outliers.¹⁴ More fundamentally, as this average is based only on the information gathered in Table 1, it abstracts from the underlying components we studied in the previous section.

Against this background, we estimate the total economic value of the Tour of Flanders accruing to the Flemish population by first estimating a value for each municipality separately.¹⁵ To achieve this, we use the regression results from model 3 in the previous section. That model takes the effect of the place of residence as well as the personal characteristics of the respondent into account.¹⁶ Specifically, we reconstruct the WTP of the average household in a specific municipality as the basis for further aggregation.

Hence, for each municipality, we multiply the estimated coefficient associated with a regression variable with the particular value taken on by that variable in the municipality. Thus, for example, the average household residing in a village in the ‘Flemish Ardennes’ is assigned a WTP (*ceteris paribus*) that equals the value of the estimated coefficient of the variable ‘Flemish Ardennes’. Values for other geographical factors are obtained similarly. For the gender variable, the percentage of men for each municipality was calculated based on official census data. The same database was used to calculate the proportions of the age groups (35-54, 55-64 and 65+) in the total population of the municipality

older than 18 years. For the income variable, the income of an average household was calculated by dividing the total taxable net income of the municipality by the total number of households. For the variable ‘sport’, a uniform distribution across all villages was assumed. The percentage of people that indicated that cycling (or another sport) was their most regular sports activity in the sample was therefore taken as the percentage for each village.¹⁷

Summing up all these values render a village-specific predicted value for the WTP. Because our estimation procedure generates multiple values for each estimated coefficient (one value for each of the 2000 iterations – see section 4.2), we obtain for each municipality a distribution of the WTP of the average household. By taking the average value of this distribution we arrive at an estimated value for the average WTP in each village, which is presented in Map 2.

Map 2: Average willingness to pay per municipality (Flemish Region)

Map 2 shows that in most Flemish villages the average WTP is between 5.7 and 9.7 euro. It is furthermore immediate that the highest WTP figures are yielded in the region that constitutes the heart of the event, with the ‘Flemish Ardennes’ region displaying the highest valuation numbers. More remote villages with an associated estimate above 9,7 euro are revealed as such mainly by virtue of an high average income, e.g. suburban villages close to the Brussels Region (shaded area on the map).

Next, for each village the total WTP is calculated by multiplying the average WTP with the number of households in that village. Finally, by summing the WTP of all villages we obtain an estimate for the whole of the Flemish Region. Table 4 presents this estimate along with some region-specific components.

Table 4. Various regional breakdowns of total WTP estimates

Region	<i>Households</i>		Total willingness to pay		
	<i>Number</i>	<i>(%)</i>	in euro	<i>(%)</i>	(95% conf. interval)
Flanders (Flemish Region)	2.576.940	100%	24,263,879	100%	(21,489,785 – 27,885,980)
Flemish Ardennes	63.233	2,45%	803,879	3,3%	(469,114 – 1,482,879)
Region Flemish Ardennes	365.950	14,20%	4,704,850	19,4%	(3,613,822 – 6,397,344)
Province of East-Flanders	591.147	22,94%	6,515,766	26,9%	(5,441,130 – 7,991,796)
Brugge, Ninove and Wetteren	77.177	2,99%	250,884	1,03%	(1,170 – 591,840)

Inhabitants from Flanders are willing to pay 24.3 million euro annually (between 21.5 million euro and 27.9 million euro with a probability of 95%)¹⁸ to avoid the disappearance of the Tour of Flanders. Some clear geographic

concentration effects of this overall figure are also evident in table 4. The number of households in the event's core region (Flemish Ardennes + region Flemish Ardennes) comprises only 16,6% of the Flemish total, but their combined aggregate valuation of 5.5 million euro makes up almost one fourth of the total Flemish value. The notable exception to this positive proximity effect relates to the inhabitants of the departure city, the arrival city and the 'Village of the Tour 2009' (Brugge, Ninove and Wetteren).

6. Non-use motivations for different respondent groups

As we indicated in the introduction, the main comparative advantage of a stated preference analysis is taken to be that it allows to gauge total economic value rather than use value only. It is instructive to point out here that the non-use value can be decomposed further, at least conceptually. At this abstract level, it can be taken to include, *inter alia*, the event's bequest motive (underlying a positive willingness to pay for the mere reason that future generations will still be able to enjoy the event), its prestige value (a quite popular concept in the field of cultural economics, see e.g. Bille & Schulze, 2006; Frey & Meier, 2006, and referring to WTP because one is 'proud' of the event), the somewhat hybrid option value attributed to a potential future visit, and the like.

However, it is hard to sustain that such conceptually attractive (sub-)labels can be transformed into substantial empirical decompositions. Exactly this point was made by Cummings and Harrison (1995), who make the careful distinction between a wide range of (valid) *possible motives* underlying a nonuser's valuation and the impossibility of rendering value decompositions operationally meaningful given the inherent measurement problem of transforming these

motives into separable monetary values (other than in extremely imperfect ways).¹⁹ A similar point has been raised by Cooper, Poe and Bateman (2004).

Notwithstanding these important remarks, it should be recalled (i) that our sample contains both non-users and users, and (ii) that *both* types may have non-use motives for a strictly positive valuation. Hence, it is instructive to check to what extent some of the possible ('non-use') motives for a positive WTP differ across these two types.

Our survey also sheds some light on this issue. All respondents indicating a non-zero WTP at least once were asked to indicate their relevant motives, where multiple motives could be indicated from a set of alternatives.²⁰ Furthermore, whenever a respondent indicated more than one motive, she was subsequently asked to indicate her most important reason. The results are presented in Table 5.

Table 5. Motives for a positive willingness to pay (% of the respondents)

	Indicated by intensive users	Indicated by other users	χ^2 statistic and (<i>p</i> - value)	<i>most important for</i> <i>intensive users</i>	<i>most important</i> <i>for other users</i>	χ^2 statistic and (<i>p</i> -value)
“The ToF creates jobs”						
(Financial motive)	14.9%	14.1%	0.02 (0.87)	1.8%	6.5%	3.1 (0.08)
“I may become a future spectator”						
(Option value)	53.5%	8.7%	45.9 (0.00)	19.3%	0%	19.9 (0.00)
“The ToF must be available to future generations.”						
(Bequest motive)	58.8%	43.5%	4.7 (0.03)	32.5%	30.4%	0.1 (0.76)
“I enjoy the fact that other people watch the ToF.”						
(altruism)	33.3%	47.8%	4.5 (0.03)	7%	31.1%	20.7 (0.00)
“The ToF is something to be proud of.”						
(Prestige motive)	61.4%	39.1%	10.1(0.00)	35.1%	22.8%	3.7 (0.05)

From table 5 it is clear that non-use motives are more popular, in the sense of being mentioned more often, with intensive event spectators than with one-time and non-spectators. The financial motive is the only notable exception. The median (mean) number of motives indicated is 2 (2,325) for the intensive users and 1 (1.641) for one-time and non-users. In view of the hybrid character of the option value, and under the plausible assumption that there is a positive correlation between past and future use, the large difference between the two groups for this value source is hardly surprising. While the bequest value is indicated more often by intensive users, the percentage of respondents finding it their most important choice is similar. Similar findings are reported by Kniivilä (2006). The Prestige motive seems more important to users. Conversely, altruism figures as a relatively more prominent motive for non-users.

Finally, we point out that a similar comparison can be made between geographically distinct groups. In view of the foregoing, we briefly report here

on notable differences between inhabitants from the ‘Flemish Ardennes’ and the ‘Region Flemish Ardennes’ on the one hand and other Flemish respondents on the other hand. About half of both groups refers to the bequest motive. But the former point to the financial motive almost twice as often than the others (24.2% versus 12.4%; $X^2=3.0$ and $p=0.08$), refer to the option value more often (42.4% versus 32.4%; $X^2=1.4$ and $p=0.24$), and indicate more frequently that they are proud of (‘their’?) Tour of Flanders (57.6% versus 50.6%; $X^2=0.59$ and $p=0.443$).²¹

7. Conclusion

This paper presents a contingent valuation of the ‘Tour of Flanders’, a major cycling event. In a representative population survey 461 respondents were asked to state their WTP for the event. To derive an accurate estimate of median and average WTP several models with different assumptions about (1) the latent WTP distribution and (2) the change in WTP when responding to the follow-up question in a double-bounded dichotomous framework were estimated. Using the BIC criterion to select the model with the best balance between complexity and fit, a shift model (to correct for the follow-up question response bias) with a Weibull distribution was selected for further analysis. For model estimation, both a classical approach (using posterior maximization) and a fully Bayesian approach were used.

The estimated average WTP is 10.3 euro (with a 95% confidence interval between 9.0 euro and 11.9 euro), the estimated median WTP is 4.2 euro (with a 95% confidence interval between 1.4 euro and 4.9 euro). The results of the regression analysis showed that the individual valuation depends on place of residence. Inhabitants from the Flemish Ardennes (villages in the event's core region where the Tour actually passes) and the surrounding villages (villages in the event's core region but where the Tour does not pass) have a significant higher WTP. By contrast, inhabitants from the 'departure/arrival/special village' have a significant lower WTP for the Tour of Flanders. An extrapolation of the individual WTP that takes into account these spatial differences among other individual characteristics leads to a total economic value for the Tour of Flanders of 24.3 million euro.

Notes

1. In 2009, for example, the Flemish Community granted a subsidy of 150.000 euro, the province of East-Flanders provided 12.500 euro as subsidies, and in the local municipalities a total number of 675 police agents were present to guarantee the safety during the Tour of Flanders. (Figures taken from the Flemish Budget 2009 and from the May 6, 2009 session of the Parliamentary Commission on Internal and General Affairs and the Public Office.)
2. In principle, of course, certain attractive parts along the track can possess the rivalry and excludability characteristics of a private good and, hence, can be provided via a market. But for the kind of event studied in this paper, this is at best a local solution.
3. It should be noted that non-use values generated by the event, such as prestige, also possess the non-rivalry and non-excludability characteristics.

4. The other stated preference method is also survey-based and builds on so-called discrete choice experiments. For an application to sport stadiums, see Pedersen, Kiil and Kjaer (2011).
5. The ‘Participation Survey’ interviewed 3194 households face-to-face. The households were selected via a two-stage sampling design. First, 350 sample clusters were drawn using the zip code. In the second step, households were drawn from each sample cluster. The aim was to get an interview with 10 households in every sample cluster. For various reasons this was not realized in 46 clusters. The final sample was reweighted to match the distribution by sex, age and education in the Flemish population.
6. These figures corroborate the Tour’s degree of popularity in Flanders. Estimates of the number of spectators along the track yield numbers between 600,000 and 800,000. On average, 1,1 million spectators watched the 2010 edition live on Flemish television, peaking to almost 1,65 million in the final part of the event.
7. In fact, the city of Oudenaarde in the Vlaamse Ardennen region hosts the “Centre Ronde Van Vlaanderen”, a reality museum attracting thousands of visitors every year. For a scholarly analysis (in Dutch) of the relation between the Tour of Flanders and Flemish cultural identity, see Vanreusel (2006). See Thompson (2006) for a similar cultural analysis of the Tour de France.
8. Start amounts were determined by an open question during the pilot phase of the survey.
9. Weak prior distributions are assumed for the shift parameters and for the parameters of the latent WTP distribution. In particular, for the selected model

M_6 , each of the shift parameters (τ_1 , τ_2 and τ_3) is assigned a Normal prior distribution with $\mu=0$ and $\sigma^2=100$. In the fully Bayesian analysis, the shift parameters are truncated above and below to ensure that each response category has a positive probability to occur. Furthermore, a Uniform distribution on the interval (0.0001,100) is assumed for the parameters of the Weibull distribution k and γ with $\gamma = 1 / (\lambda^k)$.

10. In the survey 65 out of 461 respondents did not mention their income. In that case the income was estimated based on a regression on education, age and subjective income ($R^2=0.35$). The subjective income variable measures on a seven point scale the extent to which one can live comfortably off the household income.
11. Each year (since 2000) a village on the track is chosen to carry the title ‘Village of the Tour of Flanders’. In this village plenty of festivities are organized to remember and honor someone (e.g. Briek Schotte – Desselgem) or something (e.g. Molenberg – Zwalm) that influenced the history of the race.
12. In our application, the following motivations are considered to indicate a protest-answer: (1) ‘I already pay enough taxes’, (2) ‘I do not believe the raised money will go to the ToF’, (3) ‘I disagree with the willingness to pay question’, (4) ‘Government or sponsors need to take care of it’ and (5) ‘I like to contribute to good causes’.
13. As pointed out by one of the referees, the intensive user variable likely suffers from endogeneity bias and / or multicollinearity with the spatial variables. Including the intensive user variable mitigates the effect of the variable ‘Flemish Ardennes’ in both statistical significance and size. There is however no remarkable change in effect on the variables ‘Region Flemish Ardennes’ and ‘Departure village, arrival village and village of the tour’. There is a significant, but low, pair-wise correlation between ‘Intensive user’ and ‘Flemish Ardennes’ (0.12, sig = 0.01) and no correlation between ‘Intensive user’ and ‘Region

Flemish Ardennes' (0.04, sig = 0.40) or 'Departure village, arrival village and village of the tour' (0.04, sig = 0.43).

14. Recall that the estimated median is only 4,2 euro. In addition, one can infer from Table 1 that $(14.8\% \times 149) + (13.7 \times 139)$ respondents, i.e. almost 9% of all 454 respondents, indicate a willingness to pay of at least 16 euro.
15. It should be noted at this point that the event also attracts many non-Flemish spectators. However, our limitation to the Flemish population/taxpayers is consistent with the payment vehicle used in the survey.
16. We use model 3, rather than model 4, for our estimates because the latter model includes the valuation effect of being a spectator. The percentage of people that watch the Tour of Flanders is not available per village and is not uniformly distributed. The fact that people living close to the track are more likely to be spectators will thus be captured in the region variable of model 3.
17. We imputed an edition variable of 1 for all villages, which means that we implicitly calculated the total willingness to pay for respondents after the 2009 Tour.
18. For each iteration (2000 in total), we have multiplied the estimated effect of a variable with the particular value associated with that community. Thus, we have 2000 village-specific predicted values. From this distribution we have taken the mean and a 95% confidence interval.
19. For instance, Silberman et al. (1992) report empirical evidence that the "existence value" attributed to New Jersey beaches by users is not a pure existence value but includes a recreation value component.

20. While the list of motives was open (and some respondents indeed indicated other motives than those listed), it was at the same time non-exhaustive in the sense that a direct use motivation or a (non-use) “existence value”-type of motivation was not taken up.
21. More than one in three of the ‘Flemish Ardennes’-respondents identify prestige as their most important motive.

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Appendix 1: Estimation of M_6 with SAS PROC NLMIXED

SAS code

```
proc nlmixed data=tour technique=newrap noad maxiter=100
maxfunc=2000;
parms shape=1 scale=5 tau1=0 tau2=0 tau3=0;
if ((s=5) and (y=1)) then p=cdf('weibull',1-
tau1,shape,scale);
else if ((s=5) and (y=2)) then
p=cdf('weibull',5,shape,scale)-cdf('weibull',1-
tau1,shape,scale);
else if ((s=5) and (y=3)) then
p=cdf('weibull',11-tau1,shape,scale)-
cdf('weibull',5,shape,scale);
else if ((s=5) and (y=4)) then p=1-cdf('weibull',11-
tau1,shape,scale);
```

```

    if ((s=9) and (y=1)) then p=cdf('weibull',3-tau2,shape,scale);
else if ((s=9) and (y=2)) then
    p=cdf('weibull',9,shape,scale)-cdf('weibull',3-
tau2,shape,scale);
else if ((s=9) and (y=3)) then
    p=cdf('weibull',16-tau2,shape,scale)-
cdf('weibull',9,shape,scale);
else if ((s=9) and (y=4)) then p=1-cdf('weibull',16-
tau2,shape,scale);

    if ((s=13) and (y=1)) then p=cdf('weibull',7-
tau3,shape,scale);
else if ((s=13) and (y=2)) then
    p=cdf('weibull',13,shape,scale)-cdf('weibull',7-
tau3,shape,scale);
else if ((s=13) and (y=3)) then
    p=cdf('weibull',20-tau3,shape,scale)-
cdf('weibull',13,shape,scale);
else if ((s=13) and (y=4)) then p=1-cdf('weibull',20-
tau3,shape,scale);

*use a Normal(0,10000) prior distribution for shift parameters
tau1,tau2,tau3;

ltau1=-0.5*log(2*3.141593)-log(100)-0.5*(tau1/100)**2;
ltau2=-0.5*log(2*3.141593)-log(100)-0.5*(tau2/100)**2;
ltau3=-0.5*log(2*3.141593)-log(100)-0.5*(tau3/100)**2;

if (p>1e-8) then ll=log(p)+(1/454)*(ltau1+ltau2+ltau3);
else ll=-1e100;
model y ~ general(ll);
estimate 'mean WTP' scale*GAMMA(1+1/shape);
estimate 'median WTP' scale*log(2)**(1/shape);
estimate 'log prior distribution' ltau1+ltau2+ltau3;
run;

```

Comment

The SAS data set “tour” contains 454 records and two variables: the variable “s” indicates the start amount, and the variable “y” codes the response pattern of the respondent (y=1, 2, 3 and 4 for patterns No-No, No-Yes, Yes-No, and Yes-Yes, respectively). The parameters of the Weibull distribution are indicated as “shape” and “scale”, and the shift parameters are indicated as “tau1”, “tau2” and “tau3”.

Appendix 2: Estimation of M6 with the R-package R2WinBUGS

R-code

```

##load R-package
library(R2WinBUGS)

## describe WINBUGS model
model6<-function(){

```



```

for (i in 1:166){y[i]~dcat(p[i,])
p[i,1]<-1-exp(-gamma*pow(1-tau[1],shape))
p[i,2]<-exp(-gamma*pow(1-tau[1],shape))-exp(-gamma*pow(5,shape))
p[i,3]<-exp(-gamma*pow(5,shape))-exp(-gamma*pow(11-
tau[1],shape))
p[i,4]<-exp(-gamma*pow(11-tau[1],shape))}

for (i in 167:305){y[i]~dcat(p[i,])
p[i,1]<-1-exp(-gamma*pow(3-tau[2],shape))
p[i,2]<-exp(-gamma*pow(3-tau[2],shape))-exp(-gamma*pow(9,shape))
p[i,3]<-exp(-gamma*pow(9,shape))-exp(-gamma*pow(16-
tau[2],shape))
p[i,4]<-exp(-gamma*pow(16-tau[2],shape))}

for (i in 306:454){y[i]~dcat(p[i,])
p[i,1]<-1-exp(-gamma*pow(7-tau[3],shape))
p[i,2]<-exp(-gamma*pow(7-tau[3],shape))-exp(-
gamma*pow(13,shape))
p[i,3]<-exp(-gamma*pow(13,shape))-exp(-gamma*pow(20-
tau[3],shape))
p[i,4]<-exp(-gamma*pow(20-tau[3],shape))}

shape~dunif(0.0001,100)
gamma~dunif(0.0001,100)

## For the shift parameters, Normal(0,10000) distributions are
assumed which are truncated above and below to ensure that each
response category has a positive probability to occur

tau[1]~dnorm(0,0.0001)%_I(-4,1)
tau[2]~dnorm(0,0.0001)%_I(-6,3)
tau[3]~dnorm(0,0.0001)%_I(-20,6)

scale<-1/pow(gamma,(1/shape))
mean<-scale*exp(loggam(1+1/shape))
median<-scale*pow(log(2),1/shape)

ksil1<-1-tau[1]
ksilh<-11-tau[1]
ksi2l<-3-tau[2]
ksi2h<-16-tau[2]
ksi3l<-7-tau[3]
ksi3h<-20-tau[3]

for (i in 1:71) {theta[i]~dweib(shape,gamma)%_I(0,ksil1)}
for (i in 72:97) {theta[i]~dweib(shape,gamma)%_I(ksil1,5)}
for (i in 98:130) {theta[i]~dweib(shape,gamma)%_I(5,ksilh)}
for (i in 131:166) {theta[i]~dweib(shape,gamma)%_I(ksilh,)}

```

```

for (i in 167:242) {theta[i]~dweib(shape,gamma) %_I(0,ksi2l)}
for (i in 243:260) {theta[i]~dweib(shape,gamma) %_I(ksi2l,9)}
for (i in 261:286) {theta[i]~dweib(shape,gamma) %_I(9,ksi2h)}
for (i in 287:305) {theta[i]~dweib(shape,gamma) %_I(ksi2h,)}

for (i in 306:406) {theta[i]~dweib(shape,gamma) %_I(0,ksi3l)}
for (i in 407:410) {theta[i]~dweib(shape,gamma) %_I(ksi3l,13)}
for (i in 411:432) {theta[i]~dweib(shape,gamma) %_I(13,ksi3h)}
for (i in 433:454) {theta[i]~dweib(shape,gamma) %_I(ksi3h,)}
}

## save WINBUGS model to file
filename <- file.path(tempdir(), "model6.bug")
write.model(model6, filename)

## define data, initial values and parameters for "bugs" function
data<-list(y=y)
inits<-
function(){list(shape=runif(1,0.2,2),gamma=runif(1,0.3,0.8),tau=
runif(3,-0.5,0.5))}
parameters<-
c("shape","gamma","scale","mean","median","tau","theta")

## run the analysis: 10000 iterations are computed using 4 chains
with random starting points. A sample of 2000 iterations is
constructed using evenly spaced draws from the second half of each
chain.

model6.sim <- bugs(data, inits, parameters,
  model.file=model6,
  n.chains=4, n.iter=10000,n.sims=2000,
  bugs.directory="c:/Program Files/WinBUGS14/",
  working.directory="C:/temp")

```

Comments

The vector “y” codes the response pattern of the respondent (y=1, 2, 3 and 4 for patterns No-No, No-Yes, Yes-No, and Yes-Yes, respectively. The observations 1-166, 167-305 and 306-454 pertain to respondents who received start amounts 5, 9 and 13, respectively. The parameters of the Weibull distribution are indicated as “shape” and “gamma”, with $\gamma = 1/(\text{scale}^{\text{shape}})$. The shift parameters are indicated as “tau[1]”, “tau[2]” and “tau[3]”, and the latent WTP values are indicated as theta[i].