Discussion Paper No. 13-059

Accounting for Uncertainty in Willingness to Pay for Environmental Benefits

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Centre for European
Economic Research

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Non-technical Summary

In environmental economics there is a growing literature on the valuation of environmental externalities using consumer willingness to pay, which is a relevant input for welfare analysis of projects targeting sustainability. Discrete choice models based on random utility maximization are particularly interesting for determining consumer valuation of environmental goods for which there is no market price. A large number of studies concerned with determining willingness-to-pay (WTP) measures using discrete choice models report only point estimates, without correct standard errors or other measures of uncertainty. However, the analysis of reliability of the estimates of interest – willingness to pay, consumer benefits, market shares, elasticities – is essential for inferring actual benefits.

In this paper, we contribute to the literature on characterizing the distribution of WTP measures by exploring Bayesian inference on parameter ratios, and by analyzing the implications of considering individual random effects on the determination of confidence intervals. We show that these implications are not trivial and have an impact on how to summarize the WTP distributions. As an application, we study the distribution of the WTP for reducing CO_2 emissions for two empirical situations: choice of heating versus insulation, and adoption of ultra-low emission vehicles. Therefore, this paper elucidates the value of Bayesian techniques for environmental evaluation.

Das Wichtigste in Kürze

Innerhalb der umweltökonomischen Literatur gewinnt die Bewertung von Umweltgütern (für die es keinen Marktpreis gibt) mithilfe von Zahlungsbereitschaftsanalysen immer mehr an Bedeutung. Die Ergebnisse solcher Studien können einen wichtigen Beitrag bei der Abschätzung von Kosten und Nutzen von umweltpolitischen Maßnahmen liefern. Von besonderem methodischem Interesse sind dabei vor allem sog. diskrete Entscheidungsmodelle. Viele der Studien, die mithilfe diskreter Entscheidungsmodelle Zahlungsbereitschaften ermitteln, geben allerdings nur Punktschätzer an und informieren somit nicht über Unsicherheiten, die mit der geschätzten Zahlungsbereitschaft verbunden sind. Gerade das Wissen um diese Unsicherheiten ist jedoch maßgeblich für eine belastbare Politikfolgenabschätzung.

Das vorliegende Diskussionspapier trägt in zweierlei Hinsicht zur einschlägigen Zahlungsbereitschafts-Literatur bei: Zum einen wird gezeigt, wie man mit Bayesschen Verfahren nicht nur Punktschätzer, sondern gleich die Verteilung von Zahlungsbereitschaften (die letztlich nichts anderes als das Verhältnis zweier geschätzter Parameter sind) ermitteln kann. Zum anderen wird untersucht, wie sich die Berücksichtigung von Heterogenität in unbeobachteten Faktoren auf die Bestimmung von Bayesschen Konfidenzintervallen auswirkt. Die Analyse erfolgt dabei anhand zweier empirischer Fallstudien: die Zahlungsbereitschaft deutscher Konsumenten für eingesparte CO_2-Emissionen a) bei energetischen Sanierungen und b) beim Pkw-Kauf. Insgesamt verdeutlicht diese Arbeit damit den Nutzen Bayesscher Methoden bei der Bewertung von Umweltaspekten.

Accounting for uncertainty in willingness to pay for environmental benefits

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May 2013

Abstract

Previous literature on the distribution of willingness to pay has focused on its heterogeneity distribution without addressing exact interval estimation. In this paper we derive and analyze Bayesian confidence sets for quantifying uncertainty in the determination of willingness to pay for carbon dioxide abatement. We use two empirical case studies: household decisions of energy-efficient heating versus insulation, and purchase decisions of ultra-low-emission vehicles. We first show that deriving credible sets using the posterior distribution of the willingness to pay is straightforward in the case of deterministic consumer heterogeneity. However, when using individual estimates, which is the case for the random parameters of the mixed logit model, it is complex to define the distribution of interest for the interval estimation problem. This latter problem is actually more involved than determining the moments of the heterogeneity distribution of the willingness to pay using frequentist econometrics. A solution that we propose is to derive and then summarize the distribution of point estimates of the individual willingness to pay under different loss functions.

JEL classification: C25; D12; Q51

Keywords: Discrete Choice Models; Willingness to Pay; Credible Sets

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1 Introduction

In environmental economics there is a growing literature on the valuation of environmental externalities using consumer willingness to pay either for renewable energy or for energy-efficiency gains, which is a relevant input for welfare analysis of projects targeting sustainability. Discrete choice models based on random utility maximization (see McFadden, 2001) are particularly interesting for determining consumer valuation of environmental goods for which there is no market price (cf. Boxall et al., 1996). Hence, the use of these models in environmental economics applications has expanded in recent years (for example Goett et al., 2000; Brouwer et al., 2008; Banfi et al., 2008; Kwak et al., 2010; Scarpa and Willis, 2010).

A large number of studies concerned with determining willingness-to-pay (WTP) measures using discrete choice models report only point estimates, without correct standard errors or other measures of uncertainty. However, the analysis of reliability of the estimates of interest – willingness to pay, consumer benefits, market shares, elasticities – is essential for inferring actual benefits. For instance, it is relevant to provide confidence sets for WTP measures since, at the limit, one would like to assess whether individuals are really willing to pay for the qualitative improvement or not (i.e. a test of statistical significance). Even more, having confidence sets for WTP measures is necessary for comparing the results of competing models, or for determining whether there is heterogeneity in the WTP of different segments of the population. The latter problem is particularly important for policy-making and cost-benefit analysis in non-market valuation problems. In effect, if different segments have different valuations of a resource, then one should account for this heterogeneity by assuming a certain distribution of the benefits of an environmental project. In addition, upper and lower bounds of the benefits of a project should also be determined to better inform decision-making. Informed decision-making also requires the derivation of standard errors and intervals with good statistical properties. A few studies do provide WTP confidence intervals, using standard statistical tools such as the delta method. However, as shown in Dufour (1997), Brownstone (2001), and Bolduc et al. (2010), and as discussed in more detail below, this method may provide a wrong answer in specific situations. The use of simulation, as in Krisky and Robb (1986), for determining WTP intervals may provide an erroneous answer as well, because a finite moment may be obtained when that moment does not actually exist. Additionally, the problem of how to derive standard errors and confidence intervals of WTP in models with random parameters – for which two layers of uncertainty can be identified – in an open research question.

1.1 Discrete choice models and willingness to pay

The microeconomic formulation of discrete choice models is based on a reformulated consumer problem with one discrete good and a set of standard continuous goods. Following a framework of hedonic demand modeling, for individual i the discrete good j is characterized by alternative-varying qualitative attributes $\mathbf{q}_{ij}$ as well as by price of the discrete good p_{ij}. By solving the consumer problem with discrete choice, it is possible to derive the truncated conditional indirect utility function of the discrete good j for individual i: $V_{ij} = V(I_i - p_{ij}, \mathbf{q}_{ij})$, where I_i represents the income of the individual. V_{ij} is called the deterministic utility of alternative j for individual i. Random utility models are obtained by assuming an error term that adds to the deterministic utility $U_{ij} = V(I_i - p_{ij}, \mathbf{q}_{ij}) + \varepsilon_{ij}$, where U_{ij} is the random utility of alternative j for individual i.

The subjective value of an attribute, or willingness to pay (WTP), is the marginal rate of substitution between that attribute and money. WTP represents the amount of money that a consumer is willing to pay for a qualitative improvement (e.g. how much money consumers will pay for energy-efficiency gains). Considering V_{ij}, the WTP for an additional unit of attribute q_{kij} is

$$WTP_{q_{kij}} = \frac{\partial V_{ij}/\partial q_{kij}}{\partial V_{ij}/\partial I_i}. \tag{1}$$

Note that $\partial V_{ij}/\partial I_i$ is the marginal utility of income. Because V_{ij} depends on the disposable income $I_i - p_{ij}$, then the marginal utility of income – which can be labeled as λ or the multiplier of the budget constraint – equals the additive inverse of the marginal utility of the monetary cost of the discrete good, i.e. $\lambda = \partial V_{ij}/\partial I_i = -\partial V_{ij}/\partial p_{ij}$. Therefore, the WTP for the increase of an attribute that increases utility can be rewritten as:

$$WTP_{q_{kij}} = -\frac{\partial V_{ij}/\partial q_{kij}}{\partial V_{ij}/\partial p_{ij}}. \tag{2}$$

If a linear specification $V_{ij} = \mathbf{q}'_{ij}\boldsymbol{\beta} - \lambda p_{ij}$ is assumed, then the WTP point estimation problem reduces to inference on parameter ratios: $WTP_{q_{kij}} = \beta_k/\lambda$. This parameter ratio represents the simplest expression of a WTP. Nonlinear utility functions entail more involved expressions for consumer valuation of attributes. In addition, note that even though estimates of the marginal utilities of a discrete choice model are hard to interpret, the ratio representing consumers' WTP is a meaningful function with a clear economic interpretation.

1.2 WTP: inference on parameter functions

The reason for the general omission of WTP intervals in most empirical research is that constructing a confidence set for WTP measures does not have a clear answer even for the simplest case of a parameter ratio. For instance, the ratio of the marginal utilities – which are asymptotically normal – is locally almost unidentified.[1] Because conventional techniques, such as the delta method, break down even for large samples (Dufour, 1997; Brownstone, 2001), Bolduc et al. (2010) propose variants of the frequentist Fieller's method for identification of robust confidence sets for inference on parameter ratios. Even though Fieller's method performs better than the delta method, there are at least four potential problems: the solution may be unbounded, discontinuous, sometimes occurs with an undesired sign, and exhibits properties that are asymptotically valid. Other proposed methods include simulation (Krisky and Robb, 1986; Ettema et al., 1997) or Bootstrapping (Brownstone, 2001; Pakes, 2003), and two specific Fieller-type methods using either explicit inversion of the asymptotic t-test (Zerbe et al., 1982; Armstrong et al., 2001) or implicit inversion of the likelihood ratio test (Garrido and Ortúzar, 1994). Nevertheless, these frequentist methods are valid only for one simple parameter ratio, underlying a linear specification for the utility function, may mask problems (such as producing a finite specific moment for a distribution that lacks that moment) and are not applicable to determining multidimensional confidence sets. In this paper we discuss how Bayesian tools can be used to propose a solution to these problems, from a completely different paradigm. To the best of our knowledge, no previous research has looked at the behavior of Bayesian confidence sets of multiple parameter ratios of a discrete choice model.

[1] Weak identification due to a marginal utility of income being close to zero.

In addition, there is a further associated research problem in applied economics regarding inference on the distribution of parameter ratios when the parameters are assumed random in the context of preference heterogeneity. Several authors have analyzed this problem from a frequentist perspective (Algers et al., 1998; Revelt and Train, 1998; Hensher and Greene, 2003; Train and Sonnier, 2004; Hess et al., 2005; Sillano and Ortúzar, 2005; Cirillo and Axhausen, 2006; Meijer and Rowendal, 2006).[2] Some of the problems that arise are WTP heterogeneity distributions that may be unbounded or, even more problematically, may lack finite moments. Partial solutions that have been proposed include constraining the marginal utility of income to be a fixed parameter,[3] trying alternative parametric distributions (such as assuming lognormally distributed parameters),[4] estimating the median of the heterogeneity distribution instead of its mean,[5] and working with a reparameterization from the original preference space to a consumer surplus or WTP space. However, these assumptions are not always realistic. For example, a fixed parameter for the marginal utility of income or for a price parameter may be a reasonable assumption only when working with a very specific segment of consumers. Furthermore, no previous research dealing with the WTP heterogeneity distribution has looked at the interval estimation problem, which is one of the research questions that we aim at answering in this paper. (In the case of random parameter models, some authors provide bounds for the WTP for the population parameters only.)

In sum, even though the general problem of how WTP is distributed has been studied, the answers that have been proposed are valid only for certain specific cases. Additionally, no previous study has tried to solve the WTP interval estimation problem when random taste variation is assumed. In this paper we contribute to the literature on characterizing the distribution of WTP measures by exploring Bayesian inference on parameter ratios (cf. Brownstone, 2001), and by analyzing

[2]Most of these studies have analyzed the heterogeneity distribution of the consumer valuation of travel time savings (also known as value of time), which is a relevant measure for transportation policy analysis. The value of travel time is the WTP for reducing travel time in one unit.

[3]In this case, and working with a linear specification, the distribution of the parameter ratio is given by the distribution of the numerator.

[4]The ratio of two lognormally distributed parameters is also lognormally distributed.

[5]For distributions that are asymmetric, the median is more robust to skewness than the mean because it avoids to some extent the problems induced by the long tails of the resulting ratio distribution.

the implications of considering individual random effects on the determination of confidence intervals. We show that these implications are not trivial and have an impact on how to summarize the WTP distributions. Despite the extensive use of mixed logit models in practice, the implications that we discuss here are currently neglected, and we think it is important to raise awareness of the problems we identify.

We propose to use credible regions, which are the Bayesian answer to the statistical problem of interval estimation. Bayesian confidence intervals are attractive for the problem of parameter ratio inference because credible regions can be obtained from the posterior as a direct output of the estimation process, are bounded, their associated properties work for finite samples, and the interpretation of the results is much more intuitive. In addition, although Bayesian econometrics and statistics have become standard practice in some specific fields, in environmental economics Bayes estimators have not been fully exploited yet. This paper contributes in elucidating the value of Bayesian techniques for environmental evaluation.

A central contribution of this paper is our discussion of the advantage of postprocessing now standard MCMC (Markov chain Monte Carlo) Bayes estimators of discrete choice models for inference on parameter ratios, as well as on other functions of the original parameters (cf. Edwards and Allenby, 2003). In particular we address the complexities that arise when random effects are taken into account. Note that Sonnier et al. (2007) have also used postprocessing, but for transforming the parameters from utility-space to WTP-space and not for deriving credible regions. To our knowledge, the present paper is the first to summarize posterior marginal density of high dimensions, which is the case of hierarchical models of unobserved taste variations.

We use two empirical case studies on consumer preferences for durable goods that are energy intensive: household decisions of energy-efficient heating versus insulation, and purchase decisions of ultra-low-emission vehicles. Although both case studies are choice experiments (stated preferences), the discussion is valid for any source of the data, including revealed preferences. We first explore the case of deterministic consumer heterogeneity using the Bayes estimator of a probit model (section 2). We then explore unobserved consumer heterogeneity using the hierarchical Bayes estimator of a random parameter mixed logit model (section 3). The two case studies follow the same structure. We describe first the data, we show the Bayes estimates of the choice model, and then we analyze the willingness-to-pay estimates for reducing carbon dioxide emissions. We show that deriving credible regions using the posterior distribution of the WTP is straightforward in the first case. However, when using individual estimates, which is the case for the random parameters of the mixed logit model, it is complex to define – and thus to summarize – the distribution of interest. This latter problem is actually more involved than determining the moments of the heterogeneity distribution of the WTP using frequentist econometrics. A partial solution that we propose is to derive the distribution of the point estimates of the individual willingness to pay. Section 4 concludes.

2 Case study I: Deterministic consumer heterogeneity

To account for different consumers having different preferences, different strategies for market segmentation can be applied within the discrete choice modeling framework. Deterministic consumer heterogeneity or observable taste variations is the simplest strategy for identifying homogenous consumer segments (Swait and Bernardino, 2000; Murdock, 2006). Systematic taste heterogeneity is modeled using fixed taste parameters, following the assumption of standard models, such as the conditional logit, nested logit, generalized extreme value, and probit. The strategy is to identify a discrete number of segments, typically using socioeconomic variables as indicators. Reference groups are set, and then for the other segments taste parameters representing taste variations with respect to the reference group are defined and estimated. In this section we derive parameter-ratio credible sets that represent WTP of deterministic segments.

2.1 Heating data description

The data on preferences for energy-saving measures in residential buildings comes from a June 2009 survey among more than 400 owner-occupiers of single-family detached houses, semidetached houses and row houses in Germany. The survey was carried out by the market research company GfK Group in two stages; after recruiting individuals with telephone interviews, they were visited at their homes for computer-assisted face-to-face interviews (CAPI method). During the telephone screening, the individuals had been explicitly asked whether they were involved in household energy-related decisions, such as the choice of electricity supplier or heating technology. Only those who affirmed their involvement were finally recruited and interviewed.

The survey contained a choice experiment involving home energy retrofits in which respondents could choose either a modern heating system or an improved thermal insulation for their house. Note that neither the concrete energy source (i.e. gas, oil, coal, wood, other biomass, solar-, air-, water- or geothermal-heat) nor the part of the house for the insulation measure (façade/exterior wall, roof, top ceiling, cellar ceiling or windows) were specified; rather, respondents were asked to imagine the respective technology they would like to have for their home. The alternatives to choose from were described by seven attributes: acquisition costs; annual energy-saving potential; payback period; CO_2 savings; opinion of an independent energy adviser; public and/or private funding; and period of guarantee (see Table 1 for more details).[6] A fractional factorial design was employed, using Sawtooth software, so that respondents were presented with 12 choice sets and asked to choose the alternative that they preferred most. A more detailed description of the sample and the experimental design can be found in Achtnicht (2011).

2.2 Bayes probit estimates

We use the heating versus insulation choice data to study WTP for carbon dioxide reductions in the context of deterministic consumer heterogeneity. The underlying choice model is a binary probit with some interactions between attributes, including alternative-specific constants, and sociodemographic characteristics of the individuals. The model is estimated using the probit Gibbs sampler outlined in Albert and Chib (1993), McCulloch and Rossi (1994), McCulloch and Rossi (2000), and McCulloch et al. (2000).

Table 2 reports the point estimates of the Bayesian probit model, which correspond to the empirical mean of the MCMC sample. Although we adopted the

[6] It should be noted that while the energy-saving potential was calculated with current energy prices, the payback period also included a supposed energy price development. Respondents were informed about this context by the interviewer at the beginning of the experiment.

same specification as in Achtnicht (2011) for the deterministic utility, in this paper we assumed a different error structure.[7] Whereas the attributes energy-saving potential, recommendation of an independent energy adviser, funding, and period of guarantee have positive marginal utilities, the effect of both acquisition costs and payback period is a decrease in utility. These results are in line with the economic interpretation of the parameters of the model, which represent structural preferences. A very interesting result is that West and East Germans have different marginal utilities of income, West Germans being less sensitive to the acquisition costs. This result is derived from the adopted specification with deterministic taste variations. In this case, the marginal utility of acquisition costs of West Germans is set as reference, and $\beta_{\text{Acquisition costs}}$ represents this marginal utility. The marginal utility of East Germans is determined by the reference value and the taste variation with respect to this reference, so the marginal utility of acquisition costs of East Germans is $\beta_{\text{Acquisition costs}} + \beta_{\text{Acquisition costs} \times \text{East}}$. Since the marginal utility of income is decreasing, this result can be explained by lower income levels of East Germans.[8]

Another interesting result is that the valuations of carbon dioxide savings are alternative-specific. Consumers evaluate positively the carbon dioxide savings of both alternatives, as shown by the obtained positive marginal utility. However, the point estimate is larger for the heating option. One possible explanation is that environmental externalities of burning fuel for heating are perceived as being more tangible than larger emissions due to poor insulation. Hence, consumers value more highly carbon dioxide savings for the heating option.

Moreover, there is a series of variables that interact with the alternative-specific constant of the heating option. On the one hand, if the current heating system was installed after the year 2000 (new heating), or if the system uses a cheaper fuel (wood-burning), then households are less likely to replace their heating. On the other hand, if the state of insulation is already good, then households are more likely to replace their current heating system. Additionally, young interviewees are more likely to choose heating, whereas more educated people are more likely to choose insulation first. Finally, if fuel prices are expected to rise considerably,

[7] A probit instead of a mixed logit model.

[8] Note that the percentage of low-income households (i.e., monthly net income below €1,000) is larger in the East German subsample (10 percent) than in the West German subsample (4 percent).

then the probability of choosing to purchase a more energy-efficient heating system increases.

2.3 Willingness-to-pay estimates

Using the MCMC sample of the posterior of the marginal utilities, we obtained a posterior sample of the WTP for reducing carbon dioxide emissions. The calculation was done by evaluating the ratio (of the marginal utility of CO_2 reductions and the marginal utility of income) for each sample of the Markov chain, following a postprocessing procedure (Edwards and Allenby, 2003). Table 3 summarizes the derived WTP posterior using the mean and specific quantiles. This posterior distribution represents uncertainty regarding knowledge of the true compensating variation induced by a one percent reduction in the production of carbon dioxide, given the observations in the sample.

Because the valuation of acquisition cost is different for West and East Germans, and since the marginal utility of carbon dioxide savings turned out to be alternative-specific, the WTP for CO_2 reductions varies by alternative and by region of Germany.

Figure 1 (Appendix) depicts the MCMC trace and the nonparametric estimation of the WTP posterior, disaggregated by both region and alternative. Analysis of the trace supports convergence of the chain. The posterior density is unimodal and symmetric with a Gaussian shape. Note that the 2.5% and 97.5% quantiles in Table 3 represent the lower and upper bounds respectively of the region that contains 95% of the mass of the posterior, i.e. the 95% credible interval of the WTP for reductions in CO_2. Whereas the 95% credible interval for heating contains only positive values and is reasonably bounded for both West and East Germans, the 95% credible interval of insulation contains a zero WTP. Consequently, we cannot reject the hypothesis that consumers are not willing to pay for carbon dioxide reductions coming from investments in better insulation. This result is related to the lower marginal utility of CO_2 savings for the insulation alternative, which may be explained by emissions being an indirect derived effect in this case. In the case of the heating alternative, the WTP point estimates are €162.5 (West Germans) and €101.1 (East Germans) per one percent reduction in CO_2. The standard errors are 20.59 and 12.76, respectively. These values lie between the mean and the median obtained for a frequentist mixed logit model with lognormally distributed parameters for the carbon dioxide savings in Achtnicht (2011) (see Table 4).[9]

An additional feature of the Bayesian approach is that the posterior is a joint distribution that contains enough information to derive credible sets, i.e. the multivariate generalization of the unidimensional credible intervals. In Figure 2 we show level curves of four different bidimensional projections of the joint WTP posterior. The bold contours show the 95% credible region.

From the 95% credible regions shown in the first two graphs of Figure 2, it can be seen that the WTP for CO_2 reductions for both West and East Germans are positively correlated. Beyond scale effects, it is clear that this correlation is stronger for the WTP obtained for the insulation alternative. However, it is not possible to reject the null hypothesis of a zero WTP in this case.[10] The WTP for CO_2 savings for heating and insulation appear to be independent. The independence holds for both regions of Germany.

Another relevant WTP measure is consumers' monetary valuation of energy efficiency (cf. Hausman, 1979; Train, 1985; Jaffe and Stavins, 1994). The Bayes point estimate of the WTP for energy efficiency, measured in terms of the annual monetary saving potential in energy costs, is €12.4 and €7.7 for West and East Germans, respectively, for energy savings of one euro per year. The 95% credible intervals are [€8.2,€16.4] for West Germans, and [€5.2,€10.6] for East Germans (Figure 3).

The bold contours in both graphs of figure 3 show the 95% credible region of the WTP for both energy efficiency gains and carbon dioxide savings, disaggregated by region. As before, these graphs were obtained by postprocessing the MCMC sample of the posterior of the parameters of the choice model.

In sum, although the idea of postprocessing has been used before, former applications have been centered on ensuring identification (McCulloch et al., 2000). The only application closest to the use of postprocessing that we propose in this paper is the work of Sonnier et al. (2007), where the authors use the Markov chain draws of the posterior to recast the model in WTP space, i.e. for analyzing heterogeneity distributions. However, this paper is the first application of postprocessing

[9]The large values of the standard deviation obtained in Achtnicht (2011) are due to the long tail of the lognormal distribution.

[10]This result is compatible with the unidimensional credible intervals, which correspond to the projection of the 95% credible region contour on each axis.

for deriving credible sets of parameter ratios, and we have shown that the derived credible sets exhibit good properties.

3 Case study II: random consumer heterogeneity

The usual approach to addressing unobserved taste heterogeneity is to adopt parametric assumptions regarding the continuous distribution of taste parameters that are assumed random (Revelt and Train, 1998; Train, 1998, 2001; Greene and Hensher, 2003; Murdock, 2006). For instance, if a parameter β_k is expected to vary across individuals, one assumes an associated parametric density function $\beta_k \sim f(\beta_k|\boldsymbol{\theta}_{\beta_k})$, where $\boldsymbol{\theta}_{\beta_k}$ are the parameters that describe the probability distribution. These parameters usually are the first and second moments. Note that even though the modeler cannot observe $\beta_{k,i}$ – the actual taste parameter of individual i – it is possible to determine how these individual random effects are distributed. In this section we discuss the problem of deriving credible sets of parameter ratios when individual random effects are accounted for. Note that the addition of the heterogeneity distribution adds a second layer of uncertainty to the problem that has been neglected in previous research.

3.1 Vehicle data description

The data on preferences for alternative-fuel vehicles comes from a Germany-wide survey among potential car buyers. The survey was conducted via computer-assisted personal interviewing (CAPI), from August 2007 to March 2008. The approximately 600 interviews took place in showrooms of car dealers of different brands and in selected offices of the technical inspection authority. The respondents were picked randomly subject to a certain age and having a valid driving license. The sample covers individuals from different regions in Germany (Eastern vs. Western Germany, urban vs. rural areas) and various demographic and socioeconomic groups (in terms of age, gender, education, income etc.); it thus provides a broad cross-section of the target population, i.e. potential car buyers in Germany, though it is not entirely representative.[11]

The core of the survey was a choice experiment involving alternative-fuel vehicles, in which each respondent faced six choice sets. Each choice set included seven hypothetical vehicles, each characterized by six attributes: purchase price; fuel costs per 100km; engine power; CO_2 emissions per km; fuel availability (given by the size of the service station network); and fuel type[12] (see Table 5 for details on the attribute levels).[13] Respondents were asked to assume that the presented hypothetical alternatives only differ in these attributes, but are otherwise identical. The fractional factorial design of the choice experiment was generated by Sawtooth software. For more details on the data, the interested reader is referred to Achtnicht (2012).

3.2 Bayes mixed logit estimates

In this second case study the utility specification – which we assumed linear – considers only the experimental attributes, i.e. all heterogeneity is assumed to be random and hence represented by individual random effects that interact with a subset of the attributes. From a Bayesian perspective, models such as the mixed logit belong to the family of hierarchical models.[14] We adopt the hierarchical Bayes estimator of Allenby (1997) as generalized by Train (2001). An important feature of hierarchical models is that they allow estimation of individual parameters (Revelt and Train, 2000; von Haefen, 2003).

We considered three different distributions for the random parameters, namely a normal, lognormal, and a symmetric Johnson S_B distribution (see Hess et al., 2005, for a discussion about what motivates the use of these parametric assumptions). In addition, we assumed random taste variation for fuel costs, fuel avail-

[11]For example, more educated individuals are over-represented, whereas women and individuals aged 40 to 49 years are under-represented in the sample.

[12]Note that each fuel type (i.e. gasoline, diesel, hybrid, LPG/CNG, biofuel, hydrogen, and electric) was covered exactly once in each choice set. This allows for studying alternative-specific effects, since the choice experiment is thus (quasi-)labeled (Hensher et al., 2005).

[13]The attribute levels of "purchase price" and "engine power" were customized: Respondents were asked beforehand to characterize the vehicle they intended to buy. This characterization in particular referred to upper and lower bounds for purchase price and engine power, which were then averaged and used as individual reference or pivot.

[14]In a hierarchical model, data comes from different segments but the parameters have the same parametric distribution.

ability, power, and carbon dioxide emissions.[15] Results of the estimation of each mixed logit model are presented in Table 6. The estimates of the marginal utilities show expected results. On average, the probability of choosing a specific vehicle for purchase increases as purchase price and fuel cost become cheaper, as the density of the network for refueling with the appropriate fuel increases, as more horsepower is offered, and as the emission levels are reduced. These average effects are true for the whole population when the random parameters are assumed to have either a lognormal or an S_B distribution. However, when normally distributed parameters are considered, then a portion of the population exhibits unexpected marginal utilities. In effect, according to the results of the model with marginal utilities that are normally distributed, 43% of consumers prefer less power; 32%, a less dense fuel network; 19%, more expensive fuel; and 42% of consumers prefer more polluting vehicles. These unexpected results are a well-known problem of normally distributed parameters (cf. Murdock, 2006), and the use of bounded distributions such as the uniform, lognormal, or Johnson SB distribution has been proposed. We would like to emphasize here that when modelers assume a bounded distribution to constrain the domain of a parameter, these modelers are introducing prior knowledge to the estimation process.

There is a very important distinction between random parameters for a heterogeneous population and random parameters for addressing uncertainty about the data-generating process of the model. The first one – random parameters to represent random taste variations – is common to both frequentist and Bayesian econometrics. The second one is an exclusive characteristic of the Bayesian approach. Suppose that random taste variations are represented through a distribution with mean μ and standard deviation σ. Then, different consumers will have a taste parameter that is drawn from this heterogeneity distribution. Using frequentist econometrics, the true μ and σ are fixed constants. Conversely, in Bayesian econometrics the true μ and σ are random and therefore inference is based on the posterior distributions $p(\mu|\mathbf{y})$ and $p(\sigma|\mathbf{y})$ that update beliefs according to observed

[15]Even though it is a contestable assumption, we decided not to consider an individual random effect for the marginal utility of purchase price. This assumption is compatible with the model specified in Achtnicht (2012) and supported by the fact that the standard deviation of the random taste variation of cost did not result to be statistically significant. In addition, this constraint controls for potential confounding effects in the derivation of the WTP, while following a procedure that has become standard in frequentist estimation (Revelt and Train, 1998, 2000).

data. Since we adopted the Bayesian approach for estimation of the mixed logit models, we find a posterior distribution not only for the population means but also for the population variations.

3.3 Willingness-to-pay estimates

Even though the model is extremely rich in the information it provides, it becomes nontrivial how to summarize the information contained in the derived high dimensional posterior (cf. von Haefen, 2003). For instance, a direct result of the hierarchical estimation algorithm is the posterior distribution of the WTP for each consumer in the sample. The problem is how to summarize 598 individual WTP distributions. We could focus on particular individuals if there are reasons to do so. For instance, following some criteria one could define representative individuals for different clusters and then analyze the heterogeneity distribution that distinguish the individual WTP. However, it is not clear how to define the necessary criteria for defining clusters a priori, especially given that a model with random heterogeneity is assumed. To provide a general idea of the individual WTP distributions, in Table 7 we present the point estimates and selected quantiles for the first five individuals in the sample.

In Figure 4 (Appendix) selected credible regions are displayed. The first graph in the upper left represents the confidence region of the WTP for carbon dioxide abatement of individuals one and two, whereas the graph in the upper right is the confidence region of the WTP of individuals two and three, both under the assumption of normally distributed individual random effects. The graphs are completed with the same credible regions but assuming lognormally and S_B distributed random parameters. Note that for these two latter assumptions, the credible regions are forced to not contain negative values. Figure 5 (Appendix) represents the trace and nonparametric estimation of the posterior density of the WTP for the first three individuals.

Note that the results show a remarkable level of variation. (This variability can also be seen in the spread depicted in the box plots of Figure 6.) For example, the 95% credible intervals of the WTP for carbon dioxide reductions of individuals three and five, for the case of the model with a lognormal distribution, are [€4.51,€141.40] and [€37.50,€608], respectively. Thus, the 95% credible intervals that are derived from the posterior distribution of the individual WTP for CO_2 reductions are both wide and highly variable. In fact, in the case of the normally distributed marginal utilities, for some individuals not only does the WTP present negative values, but the mean is also negative. For instance for individual 3, note that with normally distributed parameters less than 26% of the mass of the WTP posterior contains positive values. The possibility of negative WTP is ruled out in models with lognormally and S_B distributed parameters. However, the problem remains of how to summarize the individual-level results.

An immediate solution would involve analyzing the distribution of the WTP obtained by considering the parameters that represent the mean valuations in the sample, i.e. the average conditional distribution (cf. Allenby and Rossi, 1999). The problem with this strategy is that all the heterogeneity information is lost and thus one neglects the actual range of possible WTP. A second immediate solution is to describe the distribution of the entire WTP sample, i.e. to treat all the individual WTP samples as one Markov chain sample of the same posterior (see Table 8). This solution however also masks heterogeneity among individuals and the range of variation is extremely wide.

A partial solution that we propose is to describe the distribution of specific quantiles or moments of the individual WTP measures. For instance, the distribution of the point estimates represents the possible values of the average WTP in the sample. Table 9 displays the distribution of the mean and selected quantiles of the individual WTP measures.

This strategy summarizes the posterior distributions of the respective quantiles or moments of interest of the WTP obtained for each individual in the sample. For example, in Figure 7 (Appendix) the posterior distribution of the mean is displayed, for the normally, lognormally, and S_B distributed individual random effects. These histograms are simple nonparametric estimates of the probability distribution of the values obtained for the mean WTP for each of the 598 individuals in the sample, and show the high level of variability encountered. Figure 8 (Appendix) contains the nonparametric estimates of the distribution of the median WTP.

In sum, to generate draws of the parameter ratio, we have shown that the Bayesian approach offers the possibility of postprocessing the MCMC sample generated by the Bayes estimator of a discrete choice model. Although the idea of postprocessing an MCMC sample is not new, this is the first application that analyzes the posterior behavior of credible sets of parameter ratios. In addition, this addresses the problem that is encountered when a heterogeneity distribution is added. We have shown that samples from the posterior distribution of already well-known Bayes estimators of choice models can be used to obtain WTP credible sets, which are the Bayesian answer to the statistical interval estimation problem. A credible set is a fixed area containing the true parameter with a specified coverage probability, conditional on the observed data. The frequentist confidence set is a completely different concept with a much less straightforward interpretation, and non-desirable properties in the case of parameter ratios. First, under a classical perspective the true parameter is fixed and thus there is no sense in constructing a region based on its distribution. Second, a non-Bayesian confidence region is constructed using the unobserved sampling distribution of the estimator. This sampling distribution, which reflects the idea that different point estimates are generated over independent repeated replications of the data, depends on the distribution of unobserved realizations of the data and cannot be obtained for small samples. In addition, weak identification of a parameter ratio entails frequentist confidence sets that may be unbounded or discontinuous.

4 Summary and conclusion

Inference on parameter ratios emerges as fundamental in the field of non-market valuation and yet empirical research rarely provides a correct answer to the interval estimation problem: confidence intervals for willingness to pay or consumer surplus measures are either not reported or based on methods that may exhibit problems (these methods include popular tools such as the Delta method, and the Krinsky and Robb method). In effect, parameters of discrete choice models represent consumer preferences with marginal utilities that can be interpreted as taste parameters. These taste parameters serve to rank alternatives, but they lack a direct economic meaning. However, taste parameter ratios can be used to determine the willingness-to-pay (WTP) measures that are essential for the economic assessment (cost-benefit analysis, policymaking) of consumer choices. Some researchers have been engaged in studying two problems related to the distribution of parameter ratios: determination of robust confidence intervals (focusing on models with fixed parameters or analyzing just the population parameters neglecting the heterogeneity distribution) and inference on parameter ratios when the parameters are random (focusing on the heterogeneity distribution, but not on measures of uncertainty). Despite the popularity of mixed logit models in empirical work, the interval estimation problem of WTP for models with random parameters – which involves a ratio of not just parameters but of distributions – has been widely neglected. Additionally, previous research has been almost exclusively focused on frequentist models, for which confidence intervals are related to the sampling distribution of the estimates and random parameters appear when accounting for unobserved taste heterogeneity, failing to make the connection that in random parameter models there are two levels of uncertainty that need to be accounted for. We have instead adopted Bayes estimators in this work.

In this paper we have studied the posterior distribution of the WTP for reducing CO_2 emissions for two empirical situations: choice of heating versus insulation, and adoption of ultra-low emission vehicles. Although both datasets have been used before, the analysis of the interval estimation that we perform here is new. In the first case study, we adopted a probit model with deterministic taste variations. In the second case study, we adopted a mixed logit model for random taste variations.

On the one hand, the procedure for making inference on parameter ratios with deterministic taste variations is straightforward: the joint posterior distribution – a result of the estimation process – can be used to derive credible sets for each consumer segment by determining the area that covers the preset credibility level.

On the other hand, it is not clear how to make inference on parameter ratios when modeling unobserved consumer heterogeneity via random taste variations is introduced. Individual parameters can be obtained easily, and the same procedure for deterministic taste variations can be used to build credible regions for each individual. This result can be helpful when the analysis looks at distributional effects. However, for Hicksian cost-benefit analysis it is often the case that the WTP of a representative individual is needed. Determining a WTP point estimate is relatively simple (and has been discussed in previous research), but if one is interested in WTP standard errors or in providing an interval to account for uncertainty then the answer is not straightforward (and this problem is absent in the literature). As we have discussed, when adding heterogeneity distributions it becomes nontrivial how to summarize the credible sets obtained for every individual in a microdata sample. A solution proposed here is to describe the distribution of specific quantiles of the individual WTP measures under different loss functions. Nevertheless, due to the complications that random heterogeneity imposes to inference on the WTP distribution – including the derivation and analysis of credible sets – we suggest to fully exploit systematic heterogeneity as well as scale heterogeneity before exploring random taste variations.

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A Appendix : credible intervals

Bayesian estimation results in the posterior distribution of the parameters, i.e., the distribution of the parameters given the data. Using the MCMC draws found in estimation, which are equivalent to a posterior sample, it is possible to find the region of possible values for the random true parameter with a specified probability. This region is known as a credible region, which is the standard measure to describe uncertainty in the parameter estimates using Bayesian econometrics.

Definition 1 *Credible region or Bayesian confidence region. A subset of the parameter space* $\mathcal{C} \subseteq \Theta$ *such that*

$$P(\boldsymbol{\theta}_0 \in \mathcal{C}) = \int\limits_{\mathcal{C}} p(\boldsymbol{\theta}|\mathbf{y}) d\mu(\boldsymbol{\theta}) = 1 - \alpha, \tag{3}$$

where $(1-\alpha)$ *is a credibility level (Geweke, 2005).*

When the posterior distribution has a closed-form, assuming without loss of generality that the dimension of $\boldsymbol{\theta}_0$ is 1, a 100(1-α)% credible interval is found by determining the values $\theta^{(\alpha/2)}$ and $\theta^{(1-\alpha/2)}$ such that

$$\int_{-\infty}^{\theta^{(\alpha/2)}} p(\theta|\mathbf{y}) d\mu(\theta) = \frac{\alpha}{2} \text{ and } \int_{\theta^{(1-\alpha/2)}}^{\infty} p(\theta|\mathbf{y}) d\mu(\theta) = 1 - \frac{\alpha}{2}. \tag{4}$$

However, parameters of discrete choice models do not have a closed-form posterior and as outlined in the previous section, MCMC methods are used to sample draws of the posterior of interest. When working with an MCMC sample of the posterior, the most direct method to obtain a credible interval is to sort the MCMC output in increasing order and then determine the upper and lower bound of the interval. Supposing that the MCMC sampler has been run for R times, then $\theta^{(\alpha/2)} = \theta_{R(\alpha/2)}$ and $\theta^{(1-\alpha/2)} = \theta_{R(1-\alpha/2)}$, where $\theta_{R(\alpha/2)}$ and $\theta_{R(1-\alpha/2)}$ are the $R(\alpha/2)$ and $R(1-\alpha/2)$ elements of the sorted chain, respectively.

Tables

Table 1: Attributes and attribute levels for the heating choice experiment.

Attribute	Measure	Levels
Acquisition costs (including, if any, public and/or private funding)	Heating system Insulation	€10,000, €20,000, €30,000 €10,000, €20,000, €30,000, €40,000
Annual energy-saving potential at current energy prices (including fuel and electricity costs related to heating)	Heating system Insulation	25%, 50%, 75% of reference[a] (in €) 25%, 50%, 75% of reference[a] (in €)
Payback period (number of years after which the measure will pay off)	Heating system Insulation	10 years, 20 years, 30 years 10 years, 20 years, 30 years
CO_2 savings	Heating system Insulation	0%, 25%, 50%, 75%, 100% 25%, 50%, 75%
Opinion of an independent energy adviser	Heating system Insulation	recommendable, *blank* recommendable, *blank*
Public and/or private funding	Heating system Insulation	Yes, No Yes, No
Period of guarantee	Heating system Insulation	2 years, 5 years, 10 years 2 years, 5 years, 10 years

[a] current annual heating energy costs indicated by the respondent; if respondents did not know or did not state their fuel bill (15.6% of final regression sample), annual costs of €14 per square meter have been reasonably assumed

Table 2: Point estimates of the probit model for the heating data.

	Bayesian probit	
Variable	Estimate	Standard error
Acquisition costs	−0.0237***	0.001
Acquisition costs × East	−0.0148***	0.003
Energy-saving potential	0.0003***	0.000
Payback period	−0.0110***	0.001
CO_2 savings × Heating	0.0031***	0.001
CO_2 savings × Insulation	0.0027***	0.001
Energy adviser	0.1010***	0.021
Funding	0.0750***	0.020
Guarantee period	0.0129***	0.004
Heating system	−0.0602	0.001
New heating × Heating	−0.0024***	0.001
Age<46 × Heating	0.0025***	0.001
Education × Heating	−0.0014**	0.001
Wood-burning × Heating	−0.0021**	0.001
Price expectations × Heating	0.0007	0.001
State of insulation × Heating	0.0042***	0.001
Observed choices	4548	
Individuals	379	
Simulated loglikelihood	-2708.464	
Pseudo ρ^2	0.141	

Note: Standard errors in parentheses. Asterisks denote statistical significance at the *** p< 0.01, ** p< 0.05, * p< 0.1 level.

Table 3: Summary of the posterior distribution of the WTP for reducing CO_2 emissions (in €).

	WTP for CO_2 savings [€]				
Variable	Mean	2.5 %	25 %	75%	97.5%
Heating					
West Germans	162.50	123.37	148.45	176.10	204.30
East Germans	101.10	75.48	91.71	110.00	129.50
Insulation					
West Germans	67.71	−9.84	41.56	94.19	144.46
East Germans	42.17	−6.10	25.64	58.50	90.71

Table 4: Mixed Logit WTP point estimates for saved CO_2 (in €).

	Mean	Median	SD
West Germans	200.3***	88.0***	409.2**
	(30.8)	(21.6)	(164.4)
East Germans	150.6***	66.2***	307.8**
	(25.6)	(16.8)	(125.9)

Note: Standard errors (in parentheses) were calculated using the Delta method. Asterisks denote statistical significance at the *** $p < 0.01$, ** $p < 0.05$ level.

Table 5: Attributes and attribute levels for the vehicle choice experiment.

Attribute	Number of levels	Levels
Fuel type	7	Gasoline, Diesel, Hybrid, LPG/CNG, Biofuel, Hydrogen, Electric
Purchase price	3	75%, 100%, 125% of reference[a] (in €)
Engine power	3	75%, 100%, 125% of reference[a] (in hp)
Fuel costs per 100km	3	€5, €10, €20
CO_2 emissions per km	5	no emissions[b], 90g, 130g, 170g, 250g
Fuel availability	3	20%[c], 60%, 100% of service station network

[a] average of the lower and upper bounds for the next car indicated by the respondent
[b] only applied to non-fossil fuel types (i.e. biofuel, hydrogen, and electric)
[c] not applied to conventional fuel types (i.e. gasoline and diesel)

Table 6: Bayes point estimates of the mixed logit models.

	Mixed logit - normal		Mixed logit - lognormal		Mixed logit - S_B	
Variable	Estimate	(s.e.)	Estimate	(s.e)	Estimate	(s.e.)
Purchase price	−0.0648	(0.005)	−0.0443	(0.004)	−0.0445	(0.004)
Fuel costs (mean)	−0.0162	(0.010)	−2.7468	(0.094)	−2.6954	(0.117)
Fuel costs (SD)	0.0333	(0.0036)	1.6301	(0.254)	2.5471	(0.448)
Fuel availability (mean)	0.0275	(0.003)	−4.6768	(0.114)	−4.6700	(0.113)
Fuel availability (SD)	0.0036	(0.0002)	1.5347	(0.293)	1.6178	(0.297)
Engine power (mean)	0.0131	(0.003)	−5.7128	(0.287)	−5.6810	(0.299)
Engine power (SD)	0.0037	(0.0003)	1.9505	(0.583)	1.9607	(0.601)
CO_2 emissions (mean)	−0.0088	(0.002)	−5.7889	(0.124)	−5.8012	(0.128)
CO_2 emissions (SD)	0.0020	(0.0001)	1.3396	(0.230)	1.3789	(0.236)
Gasoline	−0.1713	(0.070)	−0.1132	(0.068)	−0.1087	(0.057)
Hybrid	−0.5050	(0.081)	−0.2907	(0.072)	−0.2838	(0.064)
LPG/CNG	−0.5466	(0.083)	−0.3624	(0.068)	−0.3689	(0.062)
Biofuels	−1.4762	(0.097)	−0.9088	(0.090)	−0.9010	(0.078)
Hydrogen	−0.9596	(0.084)	−0.5703	(0.080)	−0.5640	(0.074)
Electric	−1.9593	(0.106)	−1.2696	(0.088)	−1.2509	(0.069)
Observed choices	4186		4186		4186	
Individuals	598		598		598	
Simulated loglikelihood	-6270		-5840		-5842	
Pseudo ρ^2	0.099		0.161		0.160	

Table 7: Quantile estimates of the individual WTP (in €) for an emission reduction of 1g of CO_2 per km.

Individuals	Normal				
	Mean	2.5%	25%	75%	97.5%
Individual 1	205.79	31.81	141.80	262.70	405.70
Individual 2	179.03	−30.11	107.54	246.19	410.50
Individual 3	−70.61	−284.08	−137.47	0.42	128.70
Individual 4	104.50	−99.45	34.14	172.72	313.20
Individual 5	417.69	150.34	293.35	517.14	821.70
Individuals	Lognormal				
	Mean	2.5%	25%	75%	97.5%
Individual 1	108.81	10.02	45.19	154.24	312.20
Individual 2	118.90	9.13	45.55	170.67	349.10
Individual 3	46.23	4.51	19.21	62.85	141.40
Individual 4	72.16	6.06	27.07	99.13	234.00
Individual 5	277.11	37.50	169.33	362.48	608.00
Individuals	S_B				
	Mean	2.5%	25%	75%	97.5%
Individual 1	109.00	8.84	45.13	154.16	305.40
Individual 2	118.80	9.87	46.06	168.33	358.00
Individual 3	45.80	4.66	18.28	62.98	141.80
Individual 4	70.00	5.77	26.68	96.13	227.50
Individual 5	278.80	35.80	171.84	365.03	594.40

Table 8: Summary of the individual WTP measures (in €).

Variable	Mean	2.5 %	25 %	75%	97.5%
Normal	108.60	−355.26	−38.28	274.40	815.41
Lognormal	70.25	6.81	31.80	155.56	628.27
S_B	68.81	6.47	30.83	153.58	620.32

Table 9: Quantile estimates the entire WTP sample (in €).

Variable	Mean	2.5 %	25 %	75%	97.5%
			Normal		
2.5% quantile	−136.50	−641.68	−275.38	20.56	293.00
Mean	136.60	−256.13	−21.63	265.60	727.20
Median	132.80	−242.97	−19.54	257.16	698.70
97.5% quantile	430.70	11.67	209.45	570.75	1338.40
			Lognormal		
2.5% quantile	16.85	4.39	5.61	10.39	143.80
Mean	133.42	40.44	59.79	142.10	536.80
Median	109.24	31.25	44.85	110.05	501.90
97.5% quantile	385.68	129.76	195.48	442.54	1241.80
			S_B		
2.5% quantile	16.42	4.13	5.36	9.79	139.50
Mean	130.90	39.89	58.95	139.97	527.20
Median	107.57	30.72	44.21	108.12	497.90
97.5% quantile	376.03	128.97	192.81	435.58	1168.40

Figures

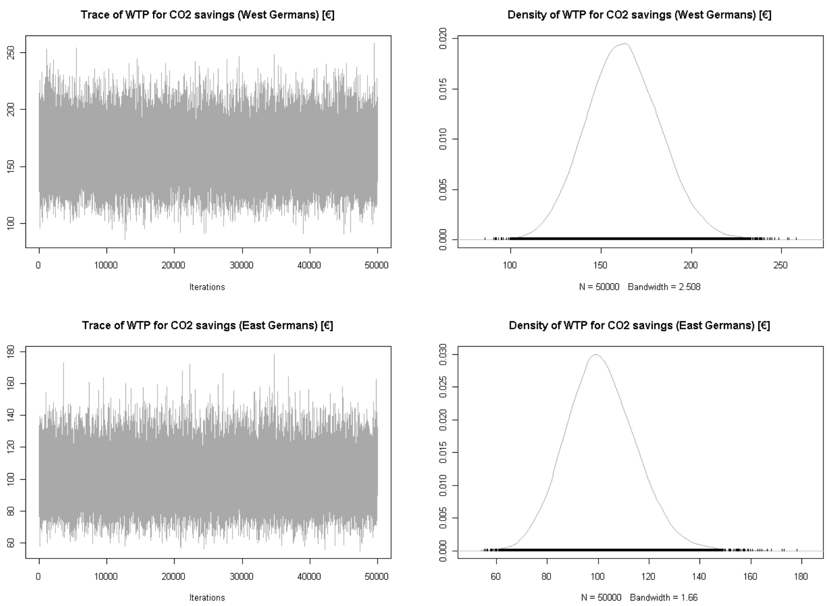

Figure 1: Trace and density of the WTP for reducing CO_2 emissions – heating vs. insulation data.

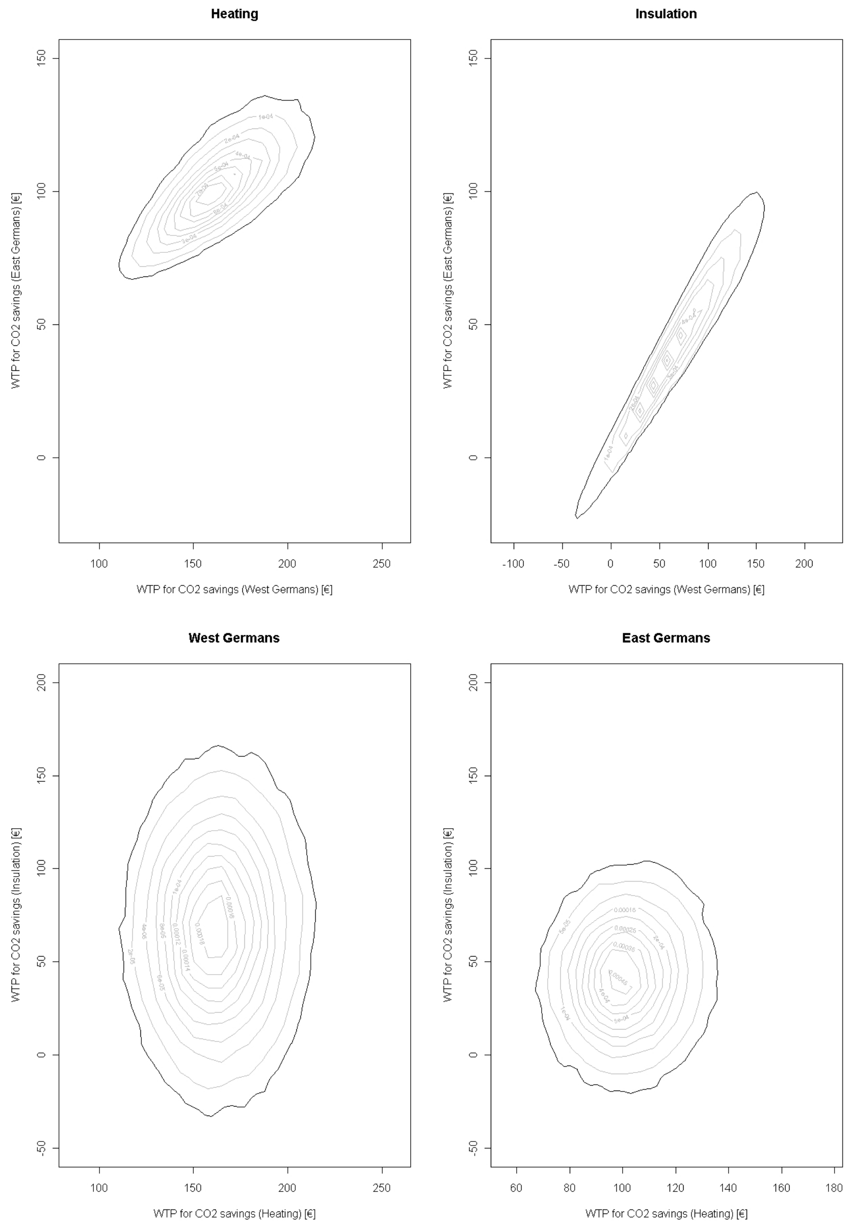

Figure 2: 95% credible regions of the WTP for reducing CO_2 emissions – heating vs. insulation data.

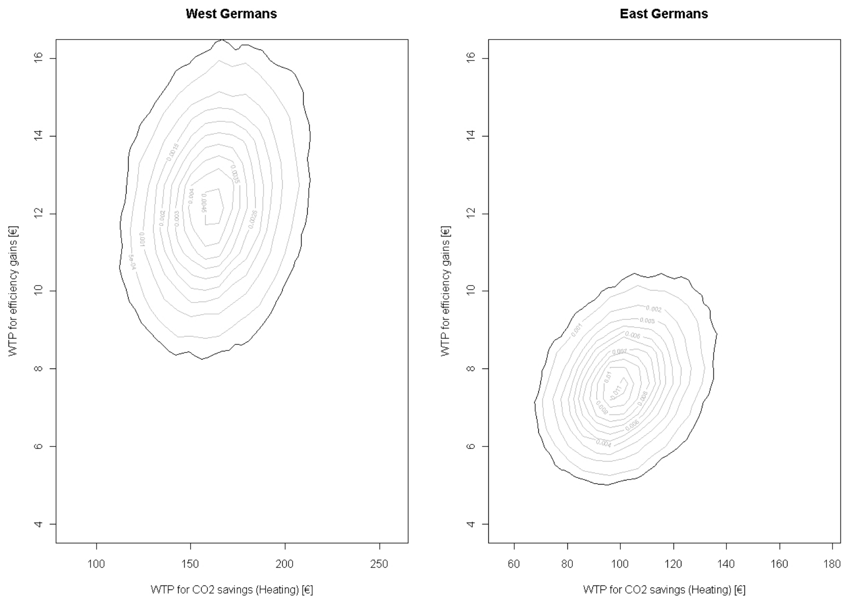

Figure 3: 95% credible regions of the WTP for both energy efficiency and CO_2 savings – heating vs. insulation data.

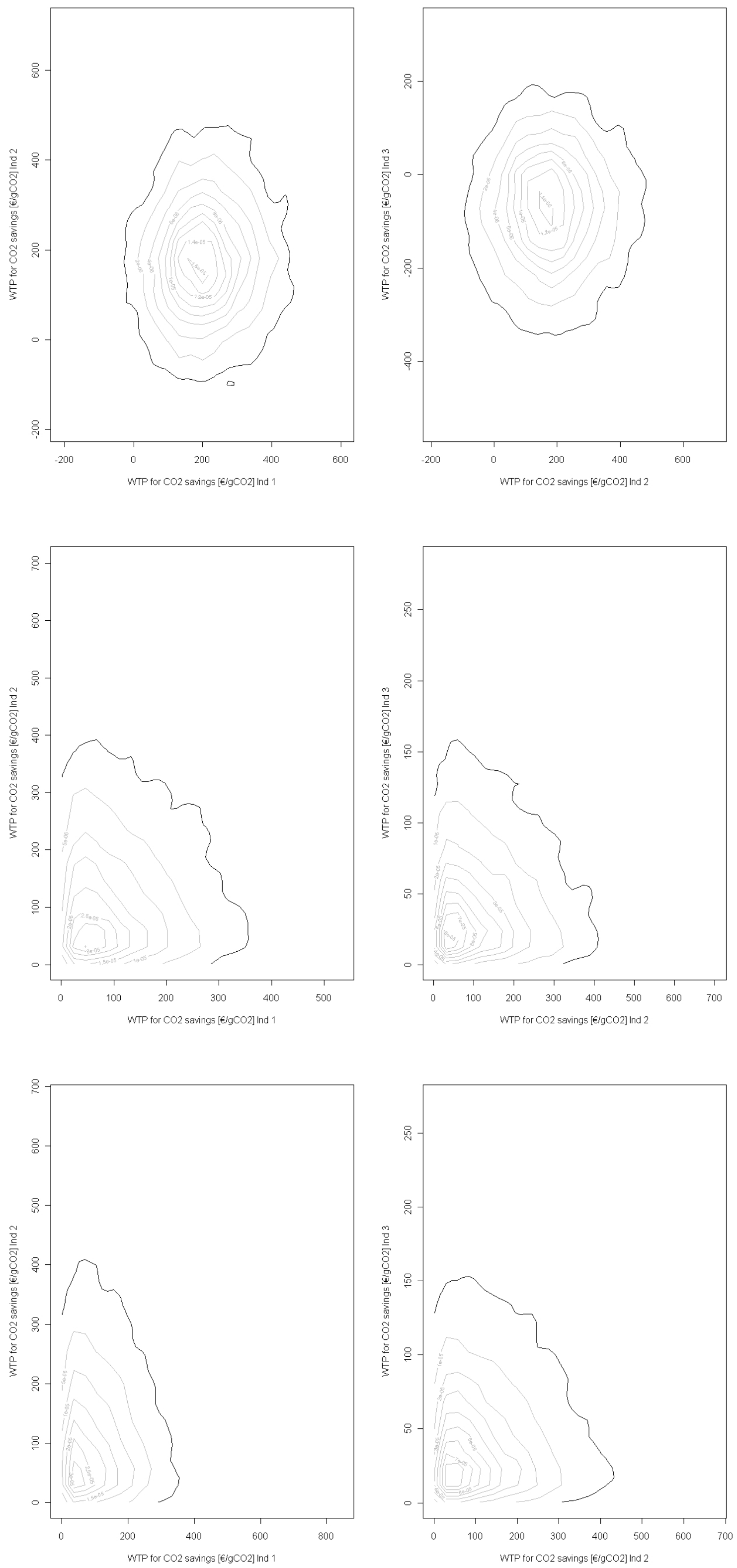

Figure 4: 95% credible regions of the WTP for CO_2 savings – vehicle choice data. (Upper: normal, middle: lognormal, bottom: S_B.)

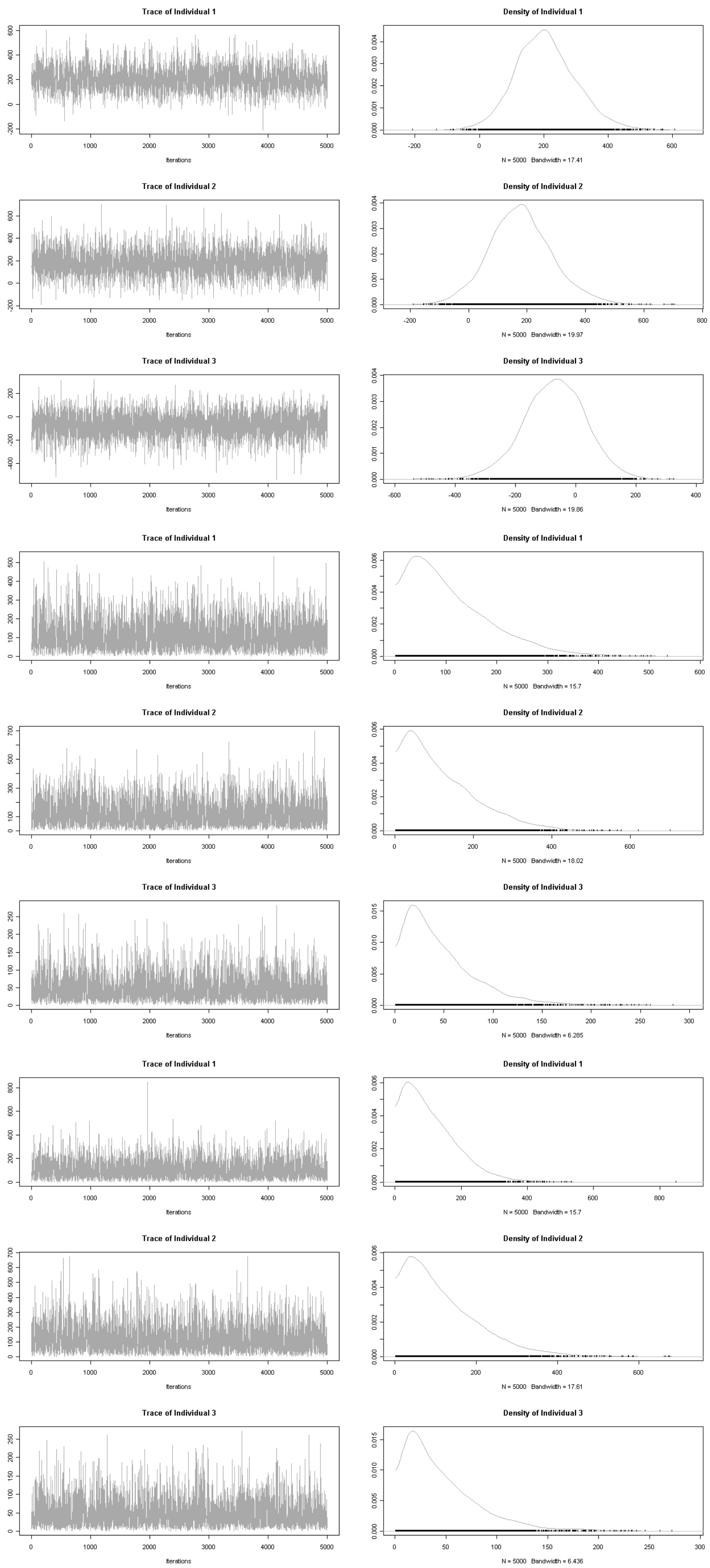

Figure 5: Trace and posterior density of the WTP for CO_2 savings – vehicle choice data. (Upper: normal, middle: lognormal, bottom: S_B.)

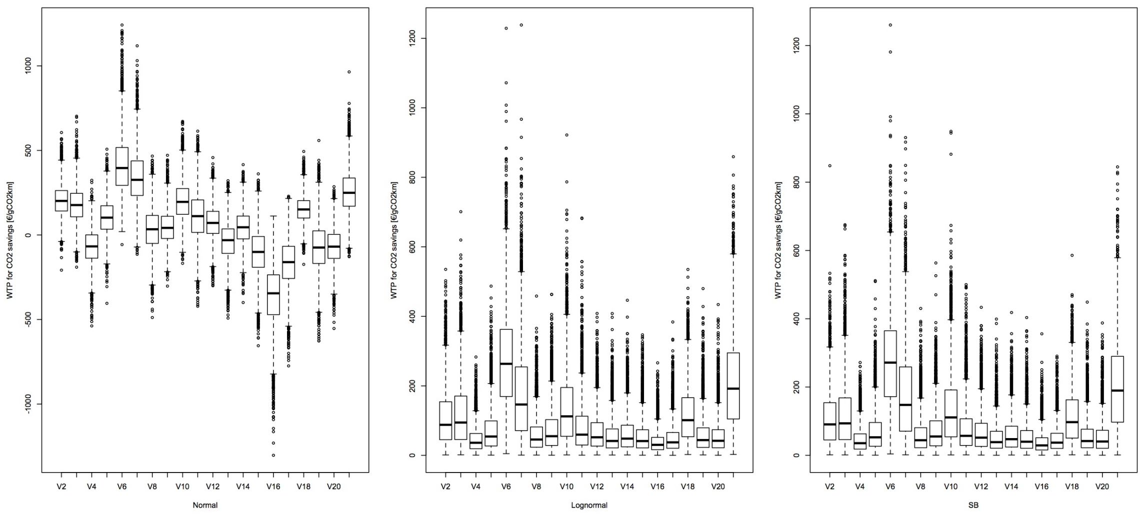

Figure 6: WTP posterior distribution of the first 20 individuals using a normal, lognormal, and S_B heterogeneity distribution

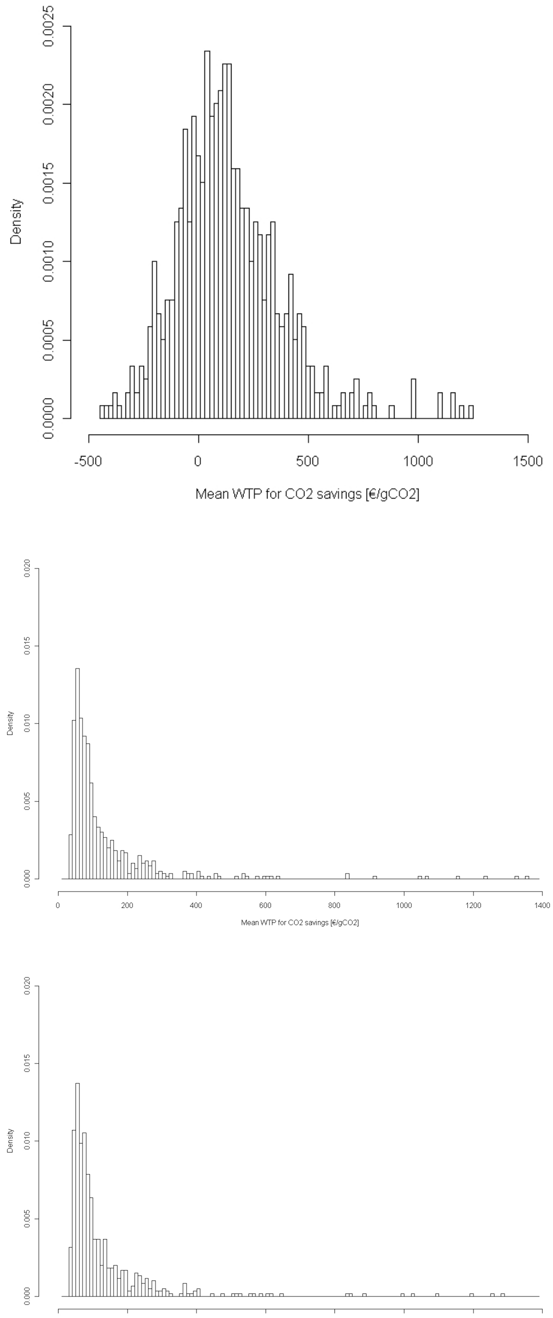

Figure 7: Posterior distribution of the mean of the individual WTP for CO_2 savings – vehicle choice data. (Upper: normal, middle: lognormal, bottom: S_B.)

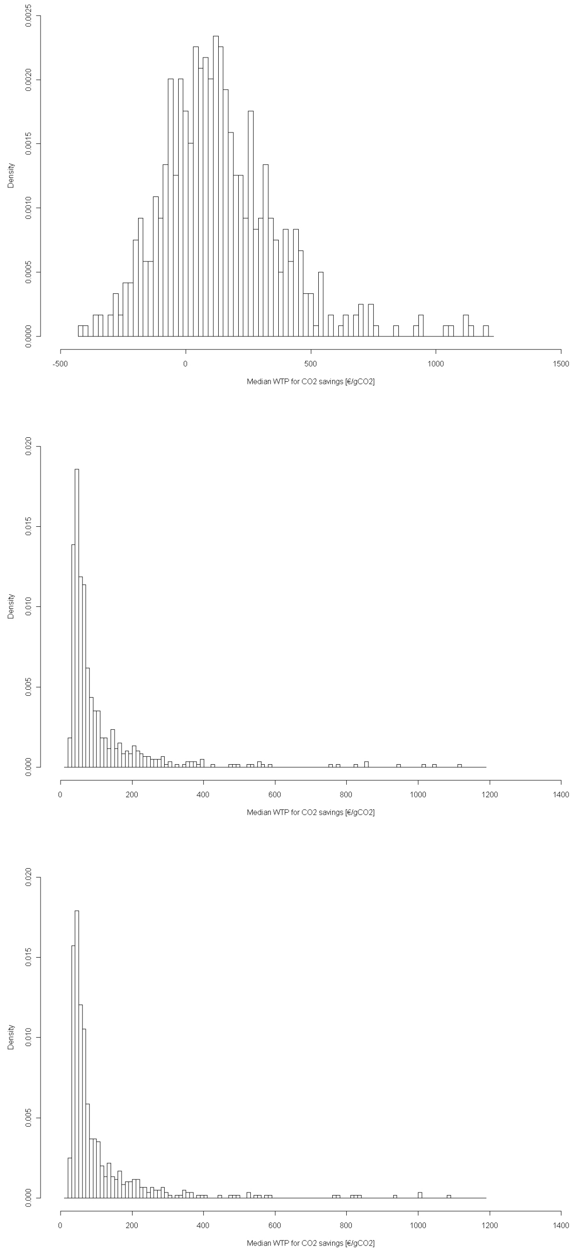

Figure 8: Posterior distribution of the median of the individual WTP for CO_2 savings – vehicle choice data. (Upper: normal, middle: lognormal, bottom: S_B.)