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How wrong can you be? Implications of incorrect utility function specification for welfare measurement in choice experiments.

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Abstract

Despite the vital role of the utility function in welfare measurement, the implications of working with incorrect utility specifications have been largely neglected in the choice experiments literature. This paper addresses the importance of specification with a special emphasis on the effects of mistaken assumptions about the marginal utility of income. Monte Carlo experiments were conducted using different functional forms of utility to generate simulated choices. Multi-Nomial Logit and Mixed Logit models were then estimated on these choices under correct and incorrect assumptions about the true, underlying utility function. Estimated willingness to pay measures from these choice modelling results are then compared with the equivalent measures directly calculated from the true utility specifications. Results show that for the parameter values and functional forms considered, a continuous-quadratic or a discrete-linear attribute specification is a good option regardless of the true effects the attribute has on utility. We also find that mistaken assumptions about preferences over costs magnify attribute mis-specification effects.

Keywords: utility specification, attributes, welfare measurement, accuracy, efficiency, choice experiments, Monte Carlo analysis.

JEL classification: C51, D69, C99, C15.

1. Introduction

Since the early 1990's, Choice Experiments (CE) have been increasingly used in the field of environmental valuation. One of their most important advantages is their ability to estimate willingness-to-pay (WTP) for changes in the attributes of an environmental good. In this context, decisions the researcher makes concerning the way in which these attributes are assumed to be related to utility are important. Decisions on how attributes enter the utility function involve which attributes to include, their nature (continuous or discrete) and the number of levels which attributes can take [1].

Given that attribute specification within the utility function assumed for a representative individual determines both the econometric approach taken to estimating choice models and the experimental design from which estimation proceeds, decisions over how to model the effects of changes in biodiversity, or air quality, or noise on utility may well have a significant impact on the accuracy and precision of marginal WTP estimates, and on the estimates of Compensating Surplus (CS) which can be derived from these. Decisions concerning the effects attributes have on utility are thus likely to be important, and an interesting question concerns the extent to which researchers produce inaccurate (biased) welfare measures by mistaken assumptions over the nature of the underlying utility function. Surprisingly, this question has not been addressed in the choice modelling literature.

Given that choice modellers must make decisions about the nature and the number of levels of attributes in a context of uncertain knowledge about the true preferences of individuals, this raises the question of the implications of working with incorrect utility specifications. As is well known, the parameter of the *Cost* attribute, usually interpreted

as the negative of the marginal utility of income, plays a key role in welfare measurement. Specification issues related to the *Cost* variable include decisions over whether to assume a constant parameter or not.¹ Problems related to the assumption of a non-constant *Cost* parameter² have led many researchers to assume it be a constant when specifying the utility function [2]. However, this is unlikely to be true in all cases [3]. Assuming as homogeneous a parameter that is likely to be heterogeneous could have important implications for welfare estimates. In this context, examining the sensitivity of attribute mis-specification effects should include mistaking assumptions about how the *Cost* parameter varies across individuals.

The objective of this paper is therefore to investigate the consequences of utility mis-specification for CE estimates of welfare change, with a special emphasis on the effects of mistaken assumptions about the marginal utility of income. To do this, Monte Carlo (MC) experiments have been conducted where different attribute specifications and assumptions for both the *Cost* and an environmental quality parameter – that is, different functional forms of utility – have been used to generate simulated choices. Multi-Nomial Logit (MNL) and Mixed Logit (MXL) models have been estimated on these simulated choices under correct and incorrect assumptions about the true, underlying utility function (clearly, such tests are not available using real data, since the researcher cannot know the true form of utility). Inferred values for WTP from simulated choice data have then been compared with true WTP values obtained directly from the underlying utility specifications. This procedure has been repeated 1,000 times to examine the robustness of results.

¹ The *Cost* variable tends to enter the utility function as a continuous attribute in most CEs reported in the environmental economics literature.

² These problems include calculating implicit prices as a ratio of two distributions.

The structure of the rest of this paper is as follows. The next section provides a review of the environmental valuation literature which has used Monte Carlo methods to assess specification, design and estimation issues. Section 3 discusses the methodology used and the data employed for the experiments. Results on attribute mis-specification, using one environmental attribute as an example, are reported in section 4. In section 5, the sensitivity of welfare measures to mistaken assumptions about the marginal utility of income is analysed. We also consider the implications of assuming constant error variances when this is not true. Next, a section on the errors in WTP involved from incorrectly assuming that the true, underlying utility function is additive is presented. Conclusions are drawn in section 7.

2. Utility specification issues in the environmental valuation literature

Despite the central role of utility function specification in welfare measurement, interest in choice modelling has thus far been restricted to the analysis of the impacts of alternative experimental designs under different utility specifications. Indeed, surprisingly little attention has been paid to utility specification issues in research on other valuation approaches based on random utility models, such as recreation demand models and dichotomous choice contingent valuation.

Recognition of the need for analyzing the accuracy of welfare estimates [4; 5] led researchers to investigate issues such as the specification of the recreation demand function in travel costs (TC) models, and WTP elicitation in the contingent valuation (CV) approach. These early studies were largely concerned with the factors affecting welfare measurement in revealed preference methods and dealt with the effects of different approaches to TC modelling. Thus, Kling [6] looks at the impacts on WTP

estimates for quality changes in the Chesapeake Bay from the use of four different recreation demand models. Parameters from recreation surveys are combined with a utility function to simulate a TC data set to which the four alternative approaches are applied. Kling [6] finds that all approaches underestimate the true mean welfare change. A related paper is Kling [7], who again uses MC analysis to compare three different true utility specifications with alternative functional forms for the demand function in TC models. The paper shows that rather simple specifications for TC models can actually yield relatively small errors in welfare estimation.

Issues of functional form choice in TC models are also central to papers by Adamowicz et al [8] and Kling [9]. The former article looks at effects on the variance of welfare estimates, comparing linear, semilog, log-log and restricted Box-Cox forms, and finds that impacts on both variance and mean can be substantial. In the latter paper, Kling [9] focuses on the magnitude of errors in WTP estimates from incorrect choice of functional form and finds that the choice of functional form is less important for small than big price changes. A related area of concern is decisions over appropriate nesting structures in multiple site recreation demand models. Kling & Thomson [10] show that parameter estimates depend on both nesting structure and estimation method (sequential or Full Information Maximum Likelihood), whilst Herriges & Kling [11] report the sign and size of bias from inappropriate nesting structures and analyze the ability of conventional goodness-of-fit tests to identify the best model.

Concerns about the accuracy and precision of welfare estimates can also be found in CV. Thus, Kling [12] uses MC analysis to investigate the advantages of combining TC and CV data in terms of the bias and precision of welfare measures, and Alberini [13]

analyzes, by undertaking MC experiments, the gains from using a double-bounded discrete choice model in the CV context, relative to a bivariate probit model and finds the double-bounded approach produces gains in terms of lower bias and greater precision. Scarpa & Bateman [14] also use MC methods to analyse the design of follow-up questions in multiple-bounded question formats, and to investigate the efficiency gains from asking such follow-up questions, whereas Park et al [15] investigate the effects of functional form on WTP estimates within a discrete choice set-up.

Turning specifically to specification issues in CEs, many studies using simulation have been focused on the effects of different experimental design strategies. Thus, Ferrini & Scarpa [16] use MC analysis to compare simple, shifted (orthogonal) designs with D-efficient designs and cast light on both the use of prior information in undertaking experimental design, and the issue of whether the nature of the actual data generating process is consistent with that assumed by the analyst in choosing their econometric approach. Scarpa & Rose [17] also analyze the performance of different design strategies, undertaken under the assumption that a prior belief on the range of values for the utility parameters can plausibly be defined, with a focus on efficiency of WTP estimates from a MNL model. Carlsson & Martinsson [18] use MC analysis to compare three kinds of experimental design (orthogonal, cyclical and D-optimal) in terms of bias and mean squared error for three different true utility functions. In a similar vein is a paper by Lusk & Norwood [19] who also use MC experiments to compare the effects of specifying utility as a continuous function of attributes, with a step-wise specification, in terms of the implications of alternative experimental designs. Their main finding is that true and estimated WTP are insignificantly different for all experimental designs

considered, and that higher sample sizes always improve the fit of actual and estimated WTP.

A conclusion reached from this review is that the question of how important the specification of the utility function is for welfare measurement in CEs has received little attention. Given the key role of utility specification in welfare calculation, efforts need to be made to fulfil this gap. Indeed, some authors have argued that addressing the effects of misspecifying the underlying utility function – for example, using a linear form when true utility is non-linear – is an important area for future research [19].

3. Designing MC experiments to examine the importance of attribute specification

3.1 The experimental design

The attribute data employed to create the experimental design used in this paper come from a CE study on recreational beach use in Santa Ponça Bay, a small Mallorcan tourism area.³ We consider three non-monetary, environmental attributes (X_1 , X_2 and X_3) and a cost attribute (X_4) varying at 3 levels each.⁴ The design has been generated under a D-efficiency criterion. As explained by Lusk & Norwood [19], D-efficiency is a common measure of design efficiency representing a function of the geometric mean of the eigen values of $(X'X)^{-1}$. It is formally given by $100 \cdot 1/N |(X'X)^{-1}|^{1/A}$, where X is the matrix of attributes used in the design, N is the number of observations in a design

³ For a detailed description of the attributes and their levels, see [20].

⁴ Two variations on the levels of X_1 have also been considered to examine the effects of changing the number of levels: the first one with 2 levels and the second one with 5 levels. However, 2 levels only serve to identify a unique utility jump. Thus, the resulting attribute values have been the same under all the assumed attribute specifications regardless of the *true* effects X_1 has on utility. On the other hand, assigning 5 levels to X_1 – a rather seldom practice in the literature – has led to similar results as those derived from assigning 3 levels. For all these reasons, these results on varying attribute levels have not been reported in the paper.

and A is the number of attribute x levels in the design. The design has also been generated allowing for main effects (ME) only. According to Louviere et al. [21], this kind of design typically explains about 70-90% of the variance in choice. The final design consisted of 36 pairs of attribute combinations. These have been then blocked into different versions each of 6 choice sets of 2 alternatives plus a business-as-usual (BAU) option. The main features of the design are shown in Table 1.⁵

3.2 Underlying utility functions and true welfare measures

At the first stage of the MC analysis, three different generic utility functions with the same explanatory variables (X_1, X_2, X_3 and X_4) and known parameters have been specified. The effects of utility function mis-specification are examined for the attribute X_1 , which represented a measure of water quality in the CE. Thus, for a scenario in which X_1 has a true linear effect, a linear specification has been employed (Equation 1). To consider non-linear effects two different specifications have been used: a quadratic form (Equation 2); and a step-wise function (Equation 3) where the marginal utility of X_1 takes three constant values between 0 and c_2 .⁶

$$U_{ji} = \alpha_1 X_{j1} + \beta X_{j2} + \phi X_{j3} + \omega X_{j4} + \varepsilon_{ji} \quad (1)$$

⁵ A number of 36 pair combinations has been the result from application of a SAS. Given the BAU levels have been considered constant across the choice sets, only pair combinations have been optimized when creating the design. The BAU alternative has been added to the generated choice sets after the optimization process. However, the BAU levels (except €0 level for the *Cost* attribute) have not been for the exclusive use of the BAU option. Therefore, they have also been employed to generate the optimized pair combinations, this leading to a 3⁴ experimental design for each of the two alternatives.

⁶ These utility function specifications are the most widely used in the literature when specifying an estimation model. In this context, if we consider researchers expect their utility specifications to fit well the data, it seems reasonable to use them to generate choices. Note that a utility specification matching Equation (3) for estimation purposes is given by a utility function where X_{j1} is codified as discrete by creating two dummy variables. Thus, if we want to identify the utility changes α_1 and α_2 with respect to when $X_{j1} \geq c_2$, the utility specification would be as follows:

$$U_{ji} = \alpha_1 1(X_{j1} < c_1) + \alpha_2 1(c_1 \leq X_{j1} < c_2) + \beta X_{j2} + \phi X_{j3} + \omega X_{j4} + \varepsilon_{ji}$$

$$U_{ji} = \alpha_1 X_{j1} + \alpha_2 X_{j1}^2 + \beta X_{j2} + \phi X_{j3} + \omega X_{j4} + \varepsilon_{ji} \quad (2)$$

$$U_{ji} = \alpha_1 (X_{j1} < c_1) + \alpha_2 (c_1 \leq X_{j1} < c_2) + \alpha_3 (X_{j1} \geq c_2) + \beta X_{j2} + \phi X_{j3} + \omega X_{j4} + \varepsilon_{ji} \quad (3)$$

where U_{ji} is the indirect utility of alternative j for individual i , α_1 , α_2 , α_3 , β , ϕ , ω are the known parameters of the attributes (ω is the marginal utility of income), c_1 and c_2 are the critical attribute values delimiting the three steps of the step-wise marginal utility of X_1 and ε_{ji} is the error term associated with alternative j and individual i .

Following Hanemann [22], the true CS value of X_1 , defined as the WTP for a change in the attribute from the BAU scenario, has been calculated for the linear, quadratic and step-wise utility specifications as shown in Equations (4), (5) and (6):

$$CS = -\frac{1}{\omega} [\alpha_1 (X_{1_1} - X_{1_0})] \quad (4)$$

$$CS = -\frac{1}{\omega} [\alpha_1 (X_{1_1} - X_{1_0}) + \alpha_2 (X_{1_1}^2 - X_{1_0}^2)] \quad (5)$$

$$CS = -\frac{1}{\omega} (\alpha_y - \alpha_z); \quad y, z=1, 2, 3 \quad (6)$$

where X_{1_1} and X_{1_0} are the policy-on and policy-off levels of X_1 , respectively, and y and z represent one of the three ranges of the three-stepwise function and depend on the values of c_1 and c_2 .

Table 2 shows the true utility specifications, the known parameters, the critical values c_1 and c_2 for the step-wise function and the true WTP values for a hypothetical change

in X_1 from the BAU level (a value of 6, as shown in Table 1) to a situation in which it takes the level 2, indicating a reduction in pollution. As seen in Table 2, two different quadratic specifications have been considered. These show two different degrees of non-linearity when X_1 has true quadratic effects on utility: a low degree (quadratic 1) and a high degree (quadratic 2). Using these two quadratic specifications will allow an examination of whether the intensity of true non-linearities has some influence on bias in the estimated attribute values.

3.3 MC experiments and estimated welfare measures

At the second stage of the analysis, MC experiments have been undertaken to estimate the CS value of the change in X_1 and compare it with the true value. Therefore, choices have been simulated for each type of true utility specification (linear, quadratic 1, quadratic 2 and step-wise). The utility of each alternative for each choice occasion has been calculated by combining the known parameters of the utility function with the attribute levels and an error term. These error terms have been generated from a type I extreme value distribution and a unique error has been randomly drawn not only for each alternative but also for each observation in the sample.⁷

This procedure generated 4 sets of simulated choices (one for each type of true utility function specification or data generating process). For each choice task, the simulated choice has been assigned to that alternative in the choice set providing the highest utility level. In the simulation, 600 individuals have been considered. Given each individual faces 6 choice tasks, 3,600 (600x6) observations have been created by this process for

⁷ In an initial analysis, we tested the effects of changing the relative contribution of the error terms to total utility on the accuracy of welfare measures, but found that “small”, “large” and “very large” error percentages gave rather similar accuracies for welfare measures. So, the main analysis in this new version of the paper uses just one error proportion– “small”.

each of the 4 data generating processes (DGP). Using these simulated samples, MNL models have then been estimated which encompass the range of true utility function specifications: that is, we estimate linear, quadratic and step-wise in X_1 MNL models.

Taking into account the types of true attribute specification (linear, quadratic 1, quadratic 2, stepwise) and attribute specification in the estimation model (continuous-linear, continuous-quadratic and discrete (step-wise)-linear), we have 12 different MC experiments (4x3). The CS value for the same change in X_1 has been estimated for each MC experiment following Equations (4), (5) and (6) according to the attribute specification assumed in the model. This process has been repeated 1,000 times, leading to a distribution of 1,000 estimated WTP values for the change in X_1 for each MC experiment. From each distribution, the mean WTP value of X_1 has been calculated as the average of the sum of the values obtained in each MC experiment over these 1,000 repetitions.

The importance of attribute specification has been examined by quantifying the errors in the estimated CS. To do this, bias and mean squared error (MSE) have been calculated. As shown in Equations (7) and (8), bias is defined as the average over 1,000 repetitions of the difference between the estimated and the true WTP for X_1 . The MSE represents the average over 1,000 repetitions of the square of the bias and gives an idea of the variance of the estimates.⁸

⁸ Note that $MSE = Bias^2 + var(CS^e)$, where the variance is defined as the spread of the estimates about the mean of the estimates.

$$BIAS = \frac{1}{R} \left[\sum_{r=1}^R (CS_r^e - CS^t) \right] \quad (7)$$

$$MSE = \frac{1}{R} \left[\sum_{r=1}^R (CS_r^e - CS^t)^2 \right] \quad (8)$$

where R is the number of repetitions of each MC experiment, CS_r^e is the estimated CS in repetition r and CS^t is the true CS.

Relative bias, defined as the ratio between our measure of bias and the true marginal value of X_1 , has also been calculated to make comparable results from all the MC experiments. In what follows, we focus on relative bias as the measure of error in welfare estimation.⁹

4. Results: mis-specifying how an environmental attribute affects utility.

The results of relative bias in the estimated WTP value of X_1 for each MC experiment are presented in Table 3. As stated above, these values refer to a hypothetical change in X_1 from the BAU level of $X_1 = 6$ to a level of $X_1 = 2$. Relative bias measures are shown in terms of the true utility specification (linear, quadratic 1, quadratic 2, stepwise) and the specification assumed in the estimation model (continuous-linear, continuous-quadratic and discrete-linear) used in the simulations. We focus discussion on results where the assumed attribute specification does not match the true one.

As shown in Table 3, relative biases are highest when X_1 has true non-linear effects but a linear specification is assumed by the researcher. This is especially so when the

⁹ In the interest of brevity, only results of relative bias are reported in the paper. Values for bias and MSE for all the MC experiments are provided in the Appendix.

attribute has true quadratic effects with a marked degree of non-linearity (i.e. quadratic 2). In contrast, when X_1 has true linear effects and a quadratic or a discrete specification is erroneously assumed, relative biases are practically zero. That relative biases resulting from attribute misspecification increase when X_1 has true non-linear effects is not surprising as the linear specification is a particular case of the quadratic. Indeed, estimation results show that the quadratic model fits choice data from a true linear model well, yielding an insignificant squared parameter. In this context, and taking into account that preferences are in practice unknown, opting for a discrete or a quadratic attribute specification in estimation seems to be a good strategy when the researcher does not know the true underlying utility function.¹⁰

To analyze the sensitivity of results to the magnitude of welfare change, the MC experiments have been repeated considering a smaller attribute change than that used above. The analysis was repeated for a hypothetical change in X_1 from the BAU level (6, see Table 1) to a level of 4, rather than 2. Results show that for this smaller welfare change, attribute mis-specification when X_1 has true non-linear effects leads to less precise estimates than in the case for a bigger change in the attribute level. Again, when the attribute has true quadratic effects with a high degree of non-linearity the value of relative bias increases substantially when linear models are used. It seems then more risky to erroneously assume a linear specification when the welfare change considered is smaller. These results reinforce the idea that, in a context of uncertain preferences, the use of a quadratic or a discrete attribute specification is the best option.

¹⁰ In particular, if the environmental attribute is quantitative, opting for a quadratic specification would probably lead to a better preference representation.

5. Mistaken assumptions about the *Cost* parameter

The sensitivity of attribute mis-specification effects to mistaken assumptions about the marginal utility of income (ω) has been examined under the hypothesis that this parameter varies across individuals. In this context, for each true attribute specification (linear, quadratic 1, quadratic 2, step-wise, as used in the previous section), choices have been simulated. This has led to 4 sets of 600 simulated individuals. The utility of each alternative in each choice occasion has been calculated by combining the attribute levels with the known parameters of Table 2 except that of ω .¹¹ Heterogeneity of the marginal utility of income has been incorporated under the assumption that the *Cost* parameter is lognormally-distributed with a mean of 0.8 and a variance of 0.2.¹²

To assess attribute mis-specification effects under mistaken assumptions about the marginal utility of income, two erroneous assumptions an analyst might make about the *Cost* parameter have been considered. First, we consider what happens when the analyst makes the assumption of homogeneity in ω , when this is not true. Second, we consider the effects of assumptions concerning the distribution for ω , where again the analyst “gets it wrong”. As Balcombe et al. [3] note, there is considerable variation in the empirical literature about what distributional assumptions are made in MXL models. Empirically, this has been done by applying firstly a MNL model (reflecting a mistaken assumption that there is no variation in ω across respondents) and secondly a MXL model to the simulated choices. In the latter case, a triangular distribution has been

¹¹ To avoid problems related to the calculation of WTP values from the ratio of two distributions, the known parameters for the attributes other than *Cost* have been kept constant for all the simulated individuals. In other words, only heterogeneity in the true *Cost* parameter has been considered.

¹² The authors are aware that this is one of the many ways to incorporate heterogeneity into the marginal utility of income when it randomly varies across individuals. Indeed, although it is not surprising that people value income differently at the margin, there is no certainty about the true distribution of the *Cost* parameter.

assigned to ω -this represents the analyst making the wrong distributional assumption.¹³

In each estimation model, X_1 has been codified as continuous-linear, continuous-quadratic and discrete-linear to match equations (1), (2) and (3), respectively.

The results obtained by “incorrectly” applying the MNL and MXL models to the 4 sets of simulated choices have been compared with those derived from a correct application of the MXL model (i.e. where the analyst correctly assumes a lognormal distribution for ω to match the underlying DGP). Thus, three assumptions about ω have been considered: one correct and two erroneous. Across the possible types of true attribute specifications, assumed attribute specification and assumption about the *Cost* parameter there are 36 different MC experiments (4x3x3). The CS of a change in X_1 from a level of 6 to a level of 2 has been estimated for each experiment following Equations (4), (5) and (6). Again, this process has been repeated 1,000 times leading to a distribution of 1,000 estimated WTP values for X_1 for each MC experiment. From each distribution, the WTP value of X_1 has been calculated as the average of the sum of the values obtained in each MC experiment over 1,000 repetitions.¹⁴

The results of relative bias in the estimated value of the change in X_1 for each of these MC experiments are presented in Table 4. Recall that these represent a hypothetical change in X_1 from the BAU level of 6 (Table 1) to a level of 2. As seen in Table 4,

¹³ Like the lognormal distribution, the triangular distribution can be constrained to have the same sign for the parameter of interest. This is why it can also be assigned to a random *Cost* parameter when the lognormal distribution is not assumed. Given that the Matlab code by Kenneth Train to estimate the MXL model has been used in this paper, the triangular distribution for the *Cost* parameter has been defined as follows: $\omega \sim \text{Triangular}(\mu + \sigma t)$ where t is triangular between -1 and 1, and μ and σ are estimated.

¹⁴ Like for the calculation of the simulated value of X_1 , the estimated value for each MC experiment when the MXL model is applied has been obtained by averaging the sum of the individual marginal values over all the individuals of the sample.

when the heterogeneity in the marginal utility of income is correctly captured by the researcher (third column), attribute misspecification always leads to higher relative biases. This is especially true when a linear specification is assumed in a context in which X_1 has true non-linear effects. In this case, the higher the non-linearity of the true quadratic effects, the less accurate the researcher's estimates.

Looking at the results from erroneously assuming that the *Cost* parameter is constant across respondents (fourth column), it is easy to see that decisions about attribute specification gain importance for welfare measurement. Indeed, all relative biases increase in magnitude in comparison with those of the third column. This indicates that mistakes over the presence of preference heterogeneity for costs magnify mistakes over functional form, in some cases by a factor of 3.5. Results show that, in general, WTP errors due to attribute misspecification are again higher when the attribute has true non-linear effects. It is then generally worse to erroneously assume a linear specification than to erroneously assume a quadratic or a discrete one. Again, this is especially marked when X_1 has a true "quadratic 2" specification.

Finally, allowing for preference heterogeneity but with an incorrect distribution (fifth column) does not always lead to higher relative biases than those of the third column. In particular, this is so when X_1 has true quadratic effects and a linear specification is assumed. It would seem that mistaking the distribution of the *Cost* parameter partly compensates for the effects of attribute mis-specification in this case. Note that under an erroneous distributional assumption about ω , codifying X_1 as continuous-linear is

always advantageous when it has true non-linear effects. Likewise, attribute misspecification under true, linear effects seems to be a non-relevant issue.

By looking at results of Table 4, the importance of working under incorrect assumptions about the marginal utility of income is easily seen. In this sense, assuming this parameter to be constant when it actually varies across individuals is more critical than mistaking its distribution. Indeed, despite not always leading to higher relative biases, it makes attribute mis-specification a non-trivial issue in all cases.

The sensitivity of results on cost preference heterogeneity to the magnitude of the welfare change has also been examined. Again, the MC experiments have been repeated considering a hypothetical change in X_1 from the BAU level of 6 to a level of 4: that is, for a smaller change in environmental quality. In contrast to a high welfare change, values of relative bias show that mistaking the distribution of the *Cost* parameter makes relevant attribute mis-specification effects in all the cases. Indeed, it always leads to less precise estimates when ω is assigned a triangular distribution. On the other side, erroneously assuming constant the *Cost* parameter only makes attribute misspecification a non-trivial issue when X_1 has true, quadratic effects. Additionally, relative biases derived from a mis-specified X_1 increase with respect to a high welfare change in most of cases. This is especially so when it has true quadratic effects, this reinforcing the appropriateness of opting for quadratic or discrete specifications. Therefore, results for a small welfare change show that working under incorrect assumptions about the marginal utility of income leads to higher attribute mis-specification effects in most of cases. In other words, the consequences of attribute mis-specification where preferences

are heterogeneous seem to depend on the size of environmental quality change being valued.

5.1 Overlooking scale heterogeneity in the *Cost* parameter

In CEs, preference heterogeneity is commonly understood on the basis of MXL models. When the *Cost* parameter is that assumed to be heterogeneous, MXL assumptions imply the existence of a mean *Cost* attribute weight in the population. It is assumed each person-specific marginal utility of income represents the mean attribute weight plus the person-specific deviation from that mean. However, heterogeneity in ω could also be driven by scale heterogeneity. Indeed, some authors argue that true error variances are likely to be non-constant, thus explaining heterogeneity in attribute preferences [23].

The sensitivity of attribute mis-specification effects to mistaken assumptions about the marginal utility of income should then be analyzed under the hypothesis that the true heterogeneity in ω is also driven by a non-constant scale of the error.¹⁵ To do this, four sets of choices have been simulated following the DGP steps from section 5 but considering variation in the *Cost* parameter across individuals in the terms described in [23] for Generalized Multinomial Logit (G-MNL) models. That is, heterogeneity in ω has been considered as being caused by both scale heterogeneity (lognormally-distributed with 1 mean and 0.9 standard deviation) and lognormally-distributed mean heterogeneity (as described in section 5, with 0.8 mean and 0.2 standard deviation, independent of the variation induced by scale).¹⁶

¹⁵ The authors are grateful to an anonymous reviewer who suggested testing for this.

¹⁶ G-MNL models are presented as nested structures combining both the MXL model and the scale-heterogeneity model [23]. According to this, the true *Cost* parameter can be written as $\omega_i = \sigma_i(\omega + \eta_i) = \sigma_i\omega + \eta_i^*$, where the random variable σ_i captures scale heterogeneity and η_i^* captures

The assessment of attribute mis-specification effects under mistaken assumptions about the marginal utility of income has been focused on two types of erroneous assumptions. First, as in section 5, the assumption of homogeneity in ω . Again, this has been empirically done by applying MNL models to the simulated choices. Second, an erroneous assumption about the source of heterogeneity in ω , where the analyst overlooks scale heterogeneity. Here, MXL models have been applied by assigning both a lognormal and a triangular distribution to the *Cost* parameter to test for potential effects of distributional assumptions. Given MXL models assume the idiosyncratic error is independent and identically distributed extreme value, these models could be flawed in such cases leading to important implications for welfare measurement. In each estimation model, X_1 has again been codified as continuous-linear, continuous-quadratic and discrete-linear to match Equations (1), (2) and (3), respectively. The true and assumed attribute specifications and the mistaken assumptions about ω have led to 36 different MC experiments (4x3x3), from which the CS of a high and a small change in X_1 has been calculated (as in previous sections).

Table 5 shows the relative biases in the estimated value of the high change in X_1 under each mistaken assumption about ω .

When comparing these values with those from Table 4, one observes that decisions about attribute specification gain importance for welfare measurement.¹⁷ Indeed, all

residual taste heterogeneity. For the purpose of our paper, we have considered the standard deviation of η_i^* is proportional to σ_i , that is, we have worked on the G-MNL-II model introduced in [23] (i.e. $\gamma = 0$).

¹⁷ By comparing Tables 4 and 5, we examine the performance of MNL and MXL model applications to choices simulated under DGPs only differing from the source of heterogeneity in the *Cost* parameter. Thus, we compare values from third and fourth columns in Table 5 with those from fourth and third columns in Table 4, respectively, and those from fifth columns in both tables.

relative biases increase in magnitude in most of cases when the analyst mis-specifies the attribute. However, only under the erroneous assumptions of homogeneity in ω (third column) and a lognormal-distributed ω (fourth column) attribute mis-specification becomes a non-trivial issue. In these cases, errors in WTP from attribute mis-specification are higher when X_1 has true, non-linear effects, this indicating again that quadratic and discrete specifications seem to be a good option when the researcher is uncertain.¹⁸

Relative biases show that the loss of accuracy is especially marked when applying a MXL model under the assumption of a triangular distribution for the *Cost* parameter, followed by erroneously assuming it be a constant.¹⁹ Interestingly, comparisons of these values with those from Table 4 show that the lowest increases in relative biases occur under the application of a MXL model assuming a lognormally-distributed *Cost* parameter. This suggests that the relevance of mistaking the source of heterogeneity depends on the distributional assumptions for the *Cost* parameter. Indeed, under a scenario of scale heterogeneity in ω , assuming constant error variances (i.e. erroneously applying MXL models) is less critical when the distribution assigned to ω matches that of the heterogeneity in ω independent of the variation induced by scale. Although a smaller welfare change leads in general to less accurate estimates, especially under the erroneous assumptions of homogeneity in ω and a lognormal-distributed ω ,

¹⁸ Note that only assuming a quadratic specification under true, linear effects makes attribute mis-specification a relevant issue when assigning a triangular distribution to the *Cost* parameter (fifth column).

¹⁹ Results of MSE show a very high impact on the variance of the estimated welfare measures for these cases.

only in few cases attribute mis-specification becomes a non-trivial issue.²⁰ Thus, the accuracy losses related to a smaller welfare change seem to be compensated by the gains in terms of a less relevance of attribute specification.

6. A note on mistaken additive assumptions about the true utility functional form

Assuming a utility function which is additive in its attributes is common practice in CEs.²¹ Our MC analysis has thus revolved around the implications for welfare measurement of erroneous assumptions about the true effects attributes have on utility on the basis of additive specifications. In this sense, we have opted for quadratic and step-wise functional forms to simulate choices from DGPs following non-linear attribute specifications. However, non-linear effects on utility can also be derived from non-additive attribute relationships. As true preferences are unknown, this raises the question of what the WTP errors from making the common additive assumptions would be if individuals used non-additive strategies to make choices.²² To shed light on this, we have repeated the analysis from previous sections using true, non-additive utility functions.²³

²⁰ This happens under true, quadratic effects and estimation through a MXL model assuming a lognormally-distributed *Cost* parameter, and under true, linear effects and the assumption of a triangular-distributed *Cost* parameter when specifying X_1 in a quadratic way.

²¹ This explains our focus on additive utility specifications both to simulate choices and to specify the estimation models in the MC experiments as well as our use of a ME only experimental design.

²² Note that under DGPs following non-additive attribute specifications, linear, quadratic and discrete functional forms represent mistaken additive utility assumptions.

²³ The authors are grateful to an anonymous reviewer who asked for testing for this. He argued that restricting the analysis within the belief system of additive utility specifications could be somehow limiting as individuals could also use non-additive strategies to make choices.

In this sense, we have simulated choices under a utility specification where X_1 depicts a Cobb-Douglas relationship with X_2 , the remaining attributes (X_3 and X_4) entering in an additive, linear way, as shown by Equation 9:

$$U_{ji} = \alpha X_{j1}^\rho X_{j2}^{1-\rho} + \phi X_{j3} + \omega X_{j4} + \varepsilon_{ji} \quad (9)$$

Table 6 shows the known parameters used and the true WTP values for the high change in X_1 from the BAU level (6) to a level of 2, at each level of X_2 .

As seen, two types of Cobb-Douglas utility functions have been considered to test for the effects on WTP bias from mistaken additive attribute specifications of different values for ρ (i.e. different contributions to utility of X_1 at each level of X_2 , regardless of the value of α).²⁴ Based on these known parameters and Equation (9), choices have been simulated according to the DGP steps described in previous sections and all the MC experiments repeated²⁵.

²⁴ Technically, ρ determines the slope of the indifference curves for X_1 and X_2 . With X_1 in Y axis and X_2 in X axis, when X_1 and X_2 are *goods* lower values of ρ imply the indifference curves are flatter and hence individuals are willing to give up less quantity of X_1 for one additional unit of X_2 . This means the part-worth utility of X_1 is higher for lower values of ρ at each level of X_1 , increasing with the level of X_2 . However, note that α is negative, indicating X_1 and X_2 act as *bads*, thus depicting a part-worth *disutility* from their Cobb-Douglas relationship. In this case, a lower value of ρ implies a higher (lower) part-worth disutility (utility) of X_1 at each level of X_1 , increasing (decreasing) with the level of X_2 . Note that by using these values for ρ , we move away from common two-way attribute interactions considered sometimes in CEs. Additionally, note that the true value of the change in X_1 is higher under a Cobb-Douglas 1 utility function at each level of X_2 . Indeed, given this function is steeper, it implies a higher variation of disutility between two given levels of X_1 and, hence, a higher WTP for a change in the attribute.

²⁵ The analyses leading to Tables 3, 4 and 5 have been repeated under these true, non-additive utility functions. Note that the value 0.8 for the *Cost* parameter represents the mean of a lognormal distribution when it varies across individuals in the terms described in sections 5 and 5.1. Relative bias, bias and MSE for each MC experiment are reported in the Appendix at each level of X_2 , both for a high and small welfare change in X_1 .

The analysis of the effects from mistaken additive utility assumptions when true preferences on cost are homogeneous shows that the level of X_2 is critical in determining the WTP errors. Despite this, the estimates are less accurate under a true Cobb-Douglas 2 utility specification at each level of X_2 . Results also show a better performance of the linear specification in most cases, although the quadratic and discrete ones seems to be the best option for a smaller welfare change. Comparison of relative biases from mistaken additive assumptions under DGPs based on both additive and non-additive utility functional forms leads to an interesting conclusion. It shows that erroneously assuming linear, quadratic and discrete specifications does not necessarily imply less accurate estimates if the DGP follows a non-additive scheme. Indeed, cases can be found where erroneously assuming an additive attribute specification gives a lower WTP bias under a true, Cobb-Douglas utility functional form. The role of ρ and X_2 is then critical in determining the relevance of mistaken additive assumptions. In other words, it is the type of non-additive relationship between attributes and not the simple fact that the true, utility function is non-additive which counts.

This conclusion above can also be drawn from the analysis of the sensitivity of the effects from mistaken additive specifications to mistaken assumptions about the marginal utility of income. In contrast, the quadratic and discrete specifications seem to be better for a higher welfare change. Similarly as in previous sections, when the true *Cost* parameter is lognormally-distributed, the mistaken assumptions of homogeneity and distribution magnify the WTP errors derived from mistakenly considering additive specifications. In this sense, the level of X_2 is critical in determining which mistaken assumption about the marginal utility of income leads to less accurate estimates.

Likewise, erroneous assumptions about the *Cost* parameter when it is also driven by scale heterogeneity also make higher WTP bias. In addition, results from this analysis show again that the relevance of mistaking the source of heterogeneity in the *Cost* parameter (i.e. assuming constant error variances) depends on distributional assumptions. In other words, overlooking scale heterogeneity in the *Cost* parameter seems to be not so critical when the distributional assumption of deterministic effects matches that of the underlying true heterogeneity, independent of scale-induced variation.

7. Conclusions

When choice experimenters set out to value changes in environmental goods, they need to make assumptions about the utility function of people whose preferences they are trying to estimate. Researchers need to do this both with regard to constructing an experimental design and with regard to choice model estimation (these issues are of course closely linked with each other). However, it has been unclear to date how much bias can be introduced to welfare estimation by making the wrong assumptions: wrong assumptions on functional form, and wrong assumptions on preference heterogeneity. By applying MC analysis, this paper has investigated the importance of the specification of environmental attributes in the utility function for estimating their marginal value. Moreover, given that the *Cost* parameter plays a key role in welfare measurement, we have also investigated the sensitivity of attribute mis-specification effects to mistaking assumptions about the existence of heterogeneity in preferences towards cost, the distribution of preferences, and the source of heterogeneity. Results show that attribute mis-specification leads to mistakes in welfare estimates, especially in a context in which the attribute has true non-linear effects, both additive and non-additive. In this sense, the

type of non-linearity is critical in determining the magnitude of bias. Indeed, the higher the true quadratic effects or the lower the value of ρ , the greater the potential bias in welfare measurement from mis-specification.

Mistaken assumptions about the *Cost* parameter can amplify environmental attribute mis-specification effects. This seems to be mainly so for assuming a constant parameter on cost, rather than getting the distribution wrong, although results are sensitive to size of the environmental changes being valued. When the *Cost* parameter is also driven by scale heterogeneity, distributional assumptions when applying a MXL model determine if erroneously assuming homogeneity is more critical than mistaking the source of heterogeneity (i.e. assuming constant error variances). Interestingly, results show that not accounting for scale heterogeneity is not so relevant when the distribution assigned to the *Cost* parameter matches that of its heterogeneity, independent of the scale-induced variation.

Taking all results together, it would seem as though opting for quadratic or step-wise utility functions leads to the lowest overall degree of relative bias, compared to linear forms. Robustness to this is given by fact that additive attribute specifications do not necessarily lead to less accurate estimates if individuals use non-additive strategies to make choices. Yet linear utility functions are very common in choice models reported in the literature to date.

These results, however, are subject to the data employed in these MC experiments. That is, our conclusions are possibly specific to the experimental design, true utility attribute specifications, known parameters, error structures, and attribute specifications assumed

in our models, and the assumptions about the marginal utility of income considered here. Although this suggests results may not be generalizable to all cases, the experimental design and methods of analysis employed here as “exemplars” are hardly un-common. Indeed, continuous and discrete non-monetary attributes with 3 levels and main effects only designs are features that can be found in many CE studies reported in the literature. Additionally, the analysis of the effects derived from erroneously assuming constant a *Cost* parameter that actually varies across individuals is an interesting result. It provides evidence of the magnitude of bias that can result when models are specified, as traditionally done, under the assumption of a constant marginal utility of income.

In a context in which utility specification issues have been largely overlooked in stated preference studies, this paper is only a first step on the long path to fill this gap. Although our results seem promising, it would be interesting to analyze the sensitivity of findings to different values of the known parameters. Likewise, the results for alternative attribute specifications, consideration of more than one non-monetary attributes varying across utility specifications, and experimental designs constructed on different efficiency criteria or allowing for interaction effects remain to be tested. Further research on these issues could help to examine the robustness of the conclusions drawn here. This will contribute to testing issues that, although being at the core of discrete choice studies, have been largely ignored in the literature to date.

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Table 1. Features of the experimental design

Experimental design factors		Design
	X₁	2 4 6*
Attribute levels	X₂	3 6 8*
	X₃	0.3 1* 2
	X₄	3 10.5 24 (0*)
Alternatives		2+BAU
Choice sets per individual		6
Blocks		6
Block replications		100
Total observations^a		3,600

*Starred numbers correspond to the levels for the BAU option.

^aTotal observations are the number of choice sets x the number of blocks x the number of block replications.

Table 2. True utility specifications and true CS

Parameters	Linear	Quadratic 1	Quadratic 2	3-Stepwise
α_1	-2.1	-2	-5.5	-4.5
α_2		0.1	0.5	-9
α_3				-13
β	-0.7	-0.7	-0.7	-0.7
ϕ	0.4	0.4	0.4	0.4
ω	-0.8	-0.8	-0.8	-0.8
c_1				3
c_2				5
True value of the change in X_1	10.5	6	7.5	10.6

Table 3. Relative bias in the estimated value of a hypothetical change in X_1 (over 1,000 repetitions)

True utility specification	Assumed utility specification	Relative bias
Linear	Linear	-0.0002
	Quadratic	-0.0003
	Discrete	-0.0003
Quadratic 1	Linear	-0.0245
	Quadratic	-0.0001
	Discrete	-0.0001
Quadratic 2	Linear	-0.0674
	Quadratic	0.0002
	Discrete	0.0002
3-Stepwise	Linear	-0.0119
	Quadratic	-0.0008
	Discrete	-0.0008

Table 4. Relative bias in the estimated value of a change in X_1 under each assumption about ω when the true *Cost* parameter is lognormally-distributed (over 1,000 repetitions)

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal	Constant	Triangular
Linear	Linear	-0.0148	-0.0570	0.1133
	Quadratic	-0.0170	-0.0604	0.1134
	Discrete	-0.0170	-0.0604	0.1135
Quadratic 1	Linear	-0.0394	-0.0655	0.0259
	Quadratic	-0.0148	-0.0474	0.0580
	Discrete	-0.0148	-0.0474	0.0580
Quadratic 2	Linear	-0.0868	-0.1104	-0.0297
	Quadratic	-0.0134	-0.0590	0.0487
	Discrete	-0.0134	-0.0590	0.0487
3-Stepwise	Linear	-0.0297	-0.0677	0.0846
	Quadratic	-0.0178	-0.0610	0.1142
	Discrete	-0.0178	-0.0610	0.1153

Table 5. Relative bias in the estimated value of a change in X_1 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity (over 1,000 repetitions)

True utility specification	Assumed utility specification	Constant	Mistaken heterogeneity source	
			Lognormal	Triangular
Linear	Linear	-0.4943	-0.0380	-0.4470
	Quadratic	-0.4941	-0.0390	-2.6501
	Discrete	-0.4941	-0.0390	0.0628
Quadratic 1	Linear	-0.5028	-0.0759	-0.7775
	Quadratic	-0.4876	-0.0536	-1.1724
	Discrete	-0.4876	-0.0536	-0.8075
Quadratic 2	Linear	-0.4978	-0.0700	-0.6105
	Quadratic	-0.4753	-0.0512	-0.7724
	Discrete	-0.4753	-0.0512	1.0816
3-Stepwise	Linear	-0.4961	-0.0431	-0.6343
	Quadratic	-0.4934	-0.0377	-1.0623
	Discrete	-0.4934	-0.0377	-0.9978

Table 6. True, non-additive utility specifications and true CS

Parameter values		Cobb-Douglas 1	Cobb-Douglas 2
	α	-2.1	-2.1
	ϕ	0.4	0.4
	ω	-0.8	-0.8
	ρ	0.8	0.2
True value of the change in X_1	$X_2=8$	9.76	3.91
	$X_2=6$	9.21	3.11
	$X_2=3$	8.02	1.78

APPENDIX TO PAPER

Bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 (over 1,000 repetitions)

True utility specification	Assumed utility specification	Bias
Linear	Linear	-0.0025
	Quadratic	-0.0034
	Discrete	-0.0034
Quadratic 1	Linear	-0.1467
	Quadratic	-0.0005
	Discrete	-0.0005
Quadratic 2	Linear	-0.5059
	Quadratic	0.0016
	Discrete	0.0016
3-Stepwise	Linear	-0.1269
	Quadratic	-0.0081
	Discrete	-0.0081

MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 (over 1,000 repetitions)

True utility specification	Assumed utility specification	MSE
Linear	Linear	0.0291
	Quadratic	0.0316
	Discrete	0.0316
Quadratic 1	Linear	0.0363
	Quadratic	0.0167
	Discrete	0.0167
Quadratic 2	Linear	0.2727
	Quadratic	0.0175
	Discrete	0.0175
3-Stepwise	Linear	0.0448
	Quadratic	0.0318
	Discrete	0.0318

Relative bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 (over 1,000 repetitions)

True utility specification	Assumed utility specification	Relative bias
Linear	Linear	-0.0002
	Quadratic	-0.0004
	Discrete	-0.0004
Quadratic 1	Linear	0.1707
	Quadratic	-0.0009
	Discrete	-0.0009
Quadratic 2	Linear	1.7977
	Quadratic	-0.0017
	Discrete	-0.0017
3-Stepwise	Linear	0.0498
	Quadratic	0.0003
	Discrete	0.0003

Bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 (over 1,000 repetitions)

True utility specification	Assumed utility specification	Bias
Linear	Linear	-0.0012
	Quadratic	-0.0021
	Discrete	-0.0021
Quadratic 1	Linear	0.4266
	Quadratic	-0.0022
	Discrete	-0.0022
Quadratic 2	Linear	2.2471
	Quadratic	-0.0021
	Discrete	-0.0021
3-Stepwise	Linear	0.2490
	Quadratic	0.0016
	Discrete	0.0016

MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 (over 1,000 repetitions)

True utility specification	Assumed utility specification	MSE
	Linear	0.0073
Linear	Quadratic	0.0178
	Discrete	0.0178
	Linear	0.1857
Quadratic 1	Quadratic	0.0147
	Discrete	0.0147
	Linear	5.0535
Quadratic 2	Quadratic	0.0197
	Discrete	0.0197
	Linear	0.0692
3-Stepwise	Quadratic	0.0181
	Discrete	0.0181

Bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 under each assumption about ω when the true *Cost* parameter is lognormally-distributed (over 1,000 repetitions)

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Linear	Linear	-0.2079	-0.8003	1.5917
	Quadratic	-0.2394	-0.8482	1.5929
	Discrete	-0.2395	-0.8481	1.5943
Quadratic 1	Linear	-0.3162	-0.5260	0.2077
	Quadratic	-0.1191	-0.3808	0.4658
	Discrete	-0.1191	-0.3808	0.4658
Quadratic 2	Linear	-0.8709	-1.1083	-0.2981
	Quadratic	-0.1347	-0.5917	0.4886
	Discrete	-0.1347	-0.5916	0.4886
3-Stepwise	Linear	-0.4228	-0.9628	1.2025
	Quadratic	-0.2533	-0.8667	1.6228
	Discrete	-0.2533	-0.8666	1.6392

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 under each assumption about ω when the true *Cost* parameter is lognormally-distributed (over 1,000 repetitions)

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Linear	Linear	0.0959	0.6812	6.2945
	Quadratic	0.1143	0.7613	31.7297
	Discrete	0.1144	0.7613	31.5773
Quadratic 1	Linear	0.1280	0.3015	0.1174
	Quadratic	0.0458	0.1716	0.2933
	Discrete	0.0458	0.1716	0.2933
Quadratic 2	Linear	0.7892	1.2547	0.1756
	Quadratic	0.0551	0.3817	0.3309
	Discrete	0.0551	0.3816	0.3309
3-Stepwise	Linear	0.2338	0.9697	19.9077
	Quadratic	0.1245	0.7964	30.0161
	Discrete	0.1245	0.7964	35.2770

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

Relative bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 under each assumption about ω when the true *Cost* parameter is lognormally-distributed (over 1,000 repetitions)

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Linear	Linear	-0.0148	-0.0570	0.1133
	Quadratic	-0.0085	-0.0423	0.1245
	Discrete	-0.0085	-0.0423	0.1246
Quadratic 1	Linear	0.1527	0.1214	0.2310
	Quadratic	-0.0121	-0.0953	0.0157
	Discrete	-0.0121	-0.0953	0.0157
Quadratic 2	Linear	1.7396	1.6687	1.9109
	Quadratic	-0.0120	-0.3936	-0.0390
	Discrete	-0.0119	-0.3935	-0.0390
3-Stepwise	Linear	0.0309	-0.0095	0.1524
	Quadratic	-0.0081	-0.0431	0.1254
	Discrete	-0.0081	-0.0431	0.1265

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

Bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 under each assumption about ω when the true *Cost* parameter is lognormally-distributed (over 1,000 repetitions)

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Linear	Linear	-0.1039	-0.4002	0.7959
	Quadratic	-0.0598	-0.2971	0.8746
	Discrete	-0.0598	-0.2971	0.8753
Quadratic 1	Linear	0.5109	0.4060	0.7729
	Quadratic	-0.0404	-0.3189	0.0524
	Discrete	-0.0404	-0.3189	0.0524
Quadratic 2	Linear	2.9096	2.7909	3.1960
	Quadratic	-0.0200	-0.6582	-0.0652
	Discrete	-0.0119	-0.6582	-0.0652
3-Stepwise	Linear	0.2067	-0.0633	1.0194
	Quadratic	-0.0542	-0.2880	0.8386
	Discrete	-0.0541	-0.2881	0.8464

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 under each assumption about ω when the true *Cost* parameter is lognormally-distributed (over 1,000 repetitions)

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Linear	Linear	0.0240	0.1703	1.5736
	Quadratic	0.0345	0.1159	8.8220
	Discrete	0.0345	0.1159	8.7641
Quadratic 1	Linear	0.2680	0.1711	0.6159
	Quadratic	0.0266	0.1333	0.0398
	Discrete	0.0266	0.1333	0.0398
Quadratic 2	Linear	8.4733	7.7957	10.2360
	Quadratic	0.0353	0.4765	0.0441
	Discrete	0.0353	0.4764	0.0441
3-Stepwise	Linear	0.0565	0.0147	5.6546
	Quadratic	0.0339	0.1118	6.8939
	Discrete	0.0339	0.1118	8.0835

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

Bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity (over 1,000 repetitions)

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Linear	Linear	-19.2057	-1.4768	-17.3696
	Quadratic	-19.1984	-1.5167	-102.9669
	Discrete	-19.1984	-1.5164	2.4399
Quadratic 1	Linear	-11.1626	-1.6853	-17.2622
	Quadratic	-10.8263	-1.1885	-26.0303
	Discrete	-10.8263	-1.1891	-17.9273
Quadratic 2	Linear	-13.8144	-1.9416	-16.9421
	Quadratic	-13.1914	-1.4222	-21.4376
	Discrete	-13.1913	-1.4223	30.0175
3-Stepwise	Linear	-19.5031	-1.6941	-24.9399
	Quadratic	-19.3969	-1.4838	-41.7674
	Discrete	-19.3969	-1.4832	-39.2300

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity (over 1,000 repetitions)

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Linear	Linear	368.965	5.141	165705.648
	Quadratic	368.688	5.288	4635943.747.
	Discrete	368.687	5.289	593152.422
Quadratic 1	Linear	124.675	3.739	7246.187
	Quadratic	117.283	2.329	67190.985
	Discrete	117.283	2.330	15305.266
Quadratic 2	Linear	190.920	5.077	353936.979
	Quadratic	174.090	3.218	10402.740
	Discrete	174.090	3.218	3180365.102
3-Stepwise	Linear	380.475	5.809	98446.925
	Quadratic	376.342	5.180	21156.974
	Discrete	376.342	5.178	185120.038

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

Relative bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity (over 1,000 repetitions)

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Linear	Linear	-0.4943	-0.0380	-0.4470
	Quadratic	-0.4968	-0.0312	-2.7142
	Discrete	-0.4968	-0.0312	0.0977
Quadratic 1	Linear	-0.4033	0.1089	-0.7330
	Quadratic	-0.6297	-0.0524	-1.1745
	Discrete	-0.6297	-0.0524	-0.7989
Quadratic 2	Linear	0.5067	1.7901	0.1686
	Quadratic	-1.0613	-0.0533	-0.7468
	Discrete	-1.0613	-0.0533	1.2315
3-Stepwise	Linear	-0.4646	0.0167	-0.6115
	Quadratic	-0.5011	-0.0299	-1.0587
	Discrete	-0.5011	-0.0299	-1.0029

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

Bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity (over 1,000 repetitions)

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Linear	Linear	-9.6028	-0.7384	-8.6848
	Quadratic	-9.6514	-0.6068	-52.7292
	Discrete	-9.6514	-0.6064	1.8978
Quadratic 1	Linear	-3.7311	1.0075	-6.7809
	Quadratic	-5.8251	-0.4843	-10.8649
	Discrete	-5.8251	-0.4846	-7.3904
Quadratic 2	Linear	2.3437	8.2801	0.7799
	Quadratic	-4.9089	-0.2466	-3.4541
	Discrete	-4.9089	-0.2466	5.6965
3-Stepwise	Linear	-8.5952	0.3093	-11.3136
	Quadratic	-9.2704	-0.5537	-19.5887
	Discrete	-9.2704	-0.5533	-18.5557

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity (over 1,000 repetitions)

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Linear	Linear	92.241	1.285	41426.412
	Quadratic	93.227	1.241	1258587.256
	Discrete	93.227	1.241	158128.883
Quadratic 1	Linear	13.939	1.240	1783.032
	Quadratic	34.021	0.507	12239.674
	Discrete	34.022	0.507	2816.109
Quadratic 2	Linear	5.514	68.887	88413.094
	Quadratic	24.224	0.299	262.178
	Discrete	24.224	0.299	102677.237
3-Stepwise	Linear	73.903	0.831	24584.229
	Quadratic	86.020	1.103	4977.505
	Discrete	86.021	1.103	44091.296

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

Relative bias in the estimated value of a change in X_1 from the BAU level (6) to a level of 2 under true, non-additive utility specifications (over 1,000 repetitions)

True utility specification	Assumed utility specification	Relative bias		
		$X_2=8$	$X_2=6$	$X_2=3$
Cobb-Douglas 1	Linear	-0.0731	-0.0182	0.1278
	Quadratic	-0.0752	-0.0205	0.1252
	Discrete	-0.0752	-0.0205	0.1252
Cobb-Douglas 2	Linear	-0.1271	0.0988	0.9131
	Quadratic	-0.1196	0.1082	0.9294
	Discrete	-0.1196	0.1082	0.9295

Bias in the estimated value of a change in X_1 from the BAU level (6) to a level of 2 under true, non-additive utility specifications (over 1,000 repetitions)

True utility specification	Assumed utility specification	Bias		
		$X_2=8$	$X_2=6$	$X_2=3$
Cobb-Douglas 1	Linear	-0.7128	-0.1673	1.0249
	Quadratic	-0.7340	-0.1885	1.0037
	Discrete	-0.7340	-0.1885	1.0037
Cobb-Douglas 2	Linear	-0.4972	0.3068	1.6293
	Quadratic	-0.4679	0.3361	1.6585
	Discrete	-0.4679	0.3361	1.6585

MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 under true, non-additive utility specifications (over 1,000 repetitions)

True utility specification	Assumed utility specification	MSE		
		$X_2=8$	$X_2=6$	$X_2=3$
Cobb-Douglas 1	Linear	0.5275	0.0475	1.0698
	Quadratic	0.5593	0.0561	1.0279
	Discrete	0.5592	0.0561	1.0280
Cobb-Douglas 2	Linear	0.2591	0.1061	2.6665
	Quadratic	0.2312	0.1252	2.7629
	Discrete	0.2312	0.1252	2.7630

Relative bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 under true, non-additive utility specifications (over 1,000 repetitions)

True utility specification	Assumed utility specification	Relative bias		
		$X_2=8$	$X_2=6$	$X_2=3$
Cobb-Douglas 1	Linear	-0.0217	0.0363	0.1904
	Quadratic	-0.0041	0.0548	0.2117
	Discrete	-0.0041	0.0548	0.2117
Cobb-Douglas 2	Linear	0.1053	0.3913	1.4224
	Quadratic	-0.0463	0.2004	1.0901
	Discrete	-0.0464	0.2004	1.0901

Bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 under true, non-additive utility specifications (over 1,000 repetitions)

True utility specification	Assumed utility specification	Bias		
		$X_2=8$	$X_2=6$	$X_2=3$
Cobb-Douglas 1	Linear	-0.1002	0.1582	0.7230
	Quadratic	-0.0191	0.2393	0.8041
	Discrete	-0.0191	0.2393	0.8041
Cobb-Douglas 2	Linear	0.1626	0.4800	1.0022
	Quadratic	-0.0716	0.2459	0.7681
	Discrete	-0.0716	0.2459	0.7681

MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 under true, non-additive utility specifications (over 1,000 repetitions)

True utility specification	Assumed utility specification	MSE		
		$X_2=8$	$X_2=6$	$X_2=3$
Cobb-Douglas 1	Linear	0.0149	0.0299	0.5276
	Quadratic	0.0171	0.0740	0.6633
	Discrete	0.0171	0.0740	0.6633
Cobb-Douglas 2	Linear	0.0294	0.2334	1.0074
	Quadratic	0.0236	0.0790	0.6085
	Discrete	0.0237	0.0790	0.6085

Relative bias in the estimated value of α of a hypothetical change in X_1 from the BAU level (6) to a level of 2 under each assumption about ω when the true *Cost* parameter is lognormally-distributed and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Cobb-Douglas 1	Linear	-0.0788	-0.1005	-0.0261
	Quadratic	-0.0750	-0.1032	-0.0182
	Discrete	-0.0750	-0.1032	-0.0182
Cobb-Douglas 2	Linear	-0.1144	-0.2763	-0.0386
	Quadratic	-0.1054	-0.2576	0.0321
	Discrete	-0.1054	-0.2576	0.0310

*Results for $X_2=8$

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

Bias in the estimated value of α of a hypothetical change in X_1 from the BAU level (6) to a level of 2 under each assumption about ω when the true *Cost* parameter is lognormally-distributed and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Cobb-Douglas 1	Linear	-1.0280	-1.3112	-0.3409
	Quadratic	-0.9790	-1.3466	-0.2370
	Discrete	-0.9793	-1.3466	-0.2370
Cobb-Douglas 2	Linear	-0.5987	-1.4457	-0.2022
	Quadratic	-0.5517	-1.3479	0.1679
	Discrete	-0.5516	-1.3478	0.1624

*Results for $X_2=8$

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 when the true *Cost* parameter is lognormally-distributed and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Cobb-Douglas 1	Linear	1.0974	1.7571	0.2212
	Quadratic	1.0008	1.8532	0.1650
	Discrete	1.0014	1.8533	0.1650
Cobb-Douglas 2	Linear	0.3797	2.1208	139.5348
	Quadratic	0.3270	1.8486	6.8542
	Discrete	0.3269	1.8485	7.4081

*Results for $X_2=8$

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Relative bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 when the true *Cost* parameter is lognormally-distributed and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Cobb-Douglas 1	Linear	-0.0277	-0.0506	0.0279
	Quadratic	-0.0449	-0.0356	-0.0096
	Discrete	-0.0449	-0.0356	-0.0096
Cobb-Douglas 2	Linear	0.1214	-0.0836	0.2173
	Quadratic	-0.0548	-0.4990	0.1033
	Discrete	-0.0548	-0.4990	0.1022

*Results for $X_2=8$

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^b ω is erroneously considered constant, so a MNL model is estimated

Bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 when the true *Cost* parameter is lognormally-distributed and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Cobb-Douglas 1	Linear	-0.1712	-0.3127	0.1724
	Quadratic	-0.2777	-0.2201	-0.0594
	Discrete	-0.2778	-0.2201	-0.0593
Cobb-Douglas 2	Linear	0.2507	-0.1727	0.4490
	Quadratic	-0.1132	-1.0311	0.2135
	Discrete	-0.1132	-1.0310	0.2113

*Results for $X_2=8$

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MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 when the true *Cost* parameter is lognormally-distributed and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Cobb-Douglas 1	Linear	0.0395	0.1073	0.0560
	Quadratic	0.1036	0.0774	0.0476
	Discrete	0.1037	0.0774	0.0476
Cobb-Douglas 2	Linear	0.0682	0.0376	35.0751
	Quadratic	0.0449	1.0953	1.2251
	Discrete	0.0449	1.0952	1.3163

*Results for $X_2=8$

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

Relative bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 when the true *Cost* parameter is lognormally-distributed and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Cobb-Douglas 1	Linear	-0.0242	-0.0472	0.0316
	Quadratic	-0.0202	-0.0501	0.0440
	Discrete	-0.0202	-0.0501	0.0400
Cobb-Douglas 2	Linear	0.1148	-0.0890	0.2102
	Quadratic	0.1261	-0.0655	0.2992
	Discrete	0.1261	-0.0655	0.2978

*Results for $X_2=6$

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

Bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 when the true *Cost* parameter is lognormally-distributed and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Cobb-Douglas 1	Linear	-0.2982	-0.5813	0.3889
	Quadratic	-0.2492	-0.6108	0.4928
	Discrete	-0.2495	-0.6108	0.4928
Cobb-Douglas 2	Linear	0.4770	-0.3699	0.8736
	Quadratic	0.5241	-0.2721	1.2436
	Discrete	0.5241	-0.2721	1.2381

*Results for $X_2=6$

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 when the true *Cost* parameter is lognormally-distributed and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Cobb-Douglas 1	Linear	0.1296	0.3759	0.2562
	Quadratic	0.1044	0.4203	0.3516
	Discrete	0.1045	0.4203	0.3517
Cobb-Douglas 2	Linear	0.2488	0.1677	140.2571
	Quadratic	0.2973	0.1059	8.3726
	Discrete	0.2973	0.1059	8.9147

*Results for $X_2=6$

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

Relative bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 when the true *Cost* parameter is lognormally-distributed and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Cobb-Douglas 1	Linear	0.0299	0.0057	0.0888
	Quadratic	0.0117	0.0215	0.0491
	Discrete	0.0116	0.0215	0.0491
Cobb-Douglas 2	Linear	0.4115	0.1536	0.5323
	Quadratic	0.1898	-0.3694	0.3889
	Discrete	0.1898	-0.3693	0.3875

*Results for $X_2=6$

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

Bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 when the true *Cost* parameter is lognormally-distributed and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Cobb-Douglas 1	Linear	0.1746	0.0330	0.5181
	Quadratic	0.0681	0.1257	0.2864
	Discrete	0.0680	0.1257	0.2864
Cobb-Douglas 2	Linear	0.6755	0.2521	0.8738
	Quadratic	0.3116	-0.6063	0.6383
	Discrete	0.3116	-0.6063	0.6361

*Results for $X_2=6$

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 when the true *Cost* parameter is lognormally-distributed and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Cobb-Douglas 1	Linear	0.0406	0.0106	0.2947
	Quadratic	0.0312	0.0448	0.1261
	Discrete	0.0312	0.0448	0.1261
Cobb-Douglas 2	Linear	0.4617	0.0713	35.6370
	Quadratic	0.1292	0.3998	1.5869
	Discrete	0.1292	0.3997	1.6763

*Results for $X_2=6$

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

Relative bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 when the true *Cost* parameter is lognormally-distributed and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Cobb-Douglas 1	Linear	0.1209	0.0945	0.1849
	Quadratic	0.1255	0.0912	0.1946
	Discrete	0.1254	0.0912	0.1946
Cobb-Douglas 2	Linear	0.9409	0.5862	1.1070
	Quadratic	0.9606	0.6271	1.2620
	Discrete	0.9606	0.6271	1.2597

*Results for $X_2=3$

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

Bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 when the true *Cost* parameter is lognormally-distributed and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Cobb-Douglas 1	Linear	1.2970	1.0139	1.9841
	Quadratic	1.3460	0.9784	2.0880
	Discrete	1.3457	0.9784	2.0880
Cobb-Douglas 2	Linear	2.2465	1.3995	2.6430
	Quadratic	2.2935	1.4973	3.0131
	Discrete	2.2935	1.4973	3.0075

*Results for $X_2=3$

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 when the true *Cost* parameter is lognormally-distributed and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Cobb-Douglas 1	Linear	1.7229	1.0659	4.0416
	Quadratic	1.8540	0.9971	4.4685
	Discrete	1.8532	0.9971	4.4685
Cobb-Douglas 2	Linear	5.0678	1.9895	146.4794
	Quadratic	5.2828	2.2738	15.9045
	Discrete	5.2829	2.2739	16.4269

*Results for $X_2=3$

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

Relative bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 when the true *Cost* parameter is lognormally-distributed and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Cobb-Douglas 1	Linear	0.1831	0.1552	0.2506
	Quadratic	0.1621	0.1734	0.2051
	Discrete	0.1621	0.1734	0.2051
Cobb-Douglas 2	Linear	1.4576	1.0085	1.6679
	Quadratic	1.0716	0.0980	1.4181
	Discrete	1.0716	0.0981	1.4158

*Results for $X_2=3$

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

Bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 when the true *Cost* parameter is lognormally-distributed and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Cobb-Douglas 1	Linear	0.9303	0.7887	1.2738
	Quadratic	0.8238	0.8814	1.0421
	Discrete	0.8237	0.8814	1.0421
Cobb-Douglas 2	Linear	1.3742	0.9507	1.5725
	Quadratic	1.0103	0.0924	1.3370
	Discrete	1.0103	0.0924	1.3347

*Results for $X_2=3$

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 when the true *Cost* parameter is lognormally-distributed and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Correct assumption	'Mistaken assumptions'	
		Lognormal ^a	Constant ^b	Triangular ^a
Cobb-Douglas 1	Linear	0.8756	0.6316	1.6489
	Quadratic	0.7051	0.8058	1.1300
	Discrete	0.7050	0.8058	1.1301
Cobb-Douglas 2	Linear	1.8938	0.9117	37.3462
	Quadratic	1.0527	0.0407	2.9670
	Discrete	1.0528	0.0407	3.0533

*Results for $X_2=3$

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

Relative bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Cobb-Douglas 1	Linear	-0.4722	-0.0865	-0.6127
	Quadratic	-0.4688	-0.0790	-0.6706
	Discrete	-0.4688	-0.0790	-0.9674
Cobb-Douglas 2	Linear	-0.7725	-0.1098	-0.7988
	Quadratic	-0.7484	-0.0952	-0.7428
	Discrete	-0.7484	-0.0952	-0.4184

*Results for $X_2=8$

^a Heterogeneity in ω is modelled through a MXL model

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Bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Cobb-Douglas 1	Linear	-17.0461	-3.1221	-22.1160
	Quadratic	-16.9214	-2.8534	-24.2089
	Discrete	-16.9214	-2.8534	-34.9233
Cobb-Douglas 2	Linear	-11.1796	-1.5884	-11.5593
	Quadratic	-10.8309	-1.3782	-10.7497
	Discrete	-10.8308	-1.3774	-6.0553

*Results for $X_2=8$

^a Heterogeneity in ω is modelled through a MXL model

^b ω is erroneously considered constant, so a MNL model is estimated

MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Cobb-Douglas 1	Linear	290.675	11.747	29820.553
	Quadratic	286.437	10.222	52803.643
	Discrete	286.437	10.222	7894.947
Cobb-Douglas 2	Linear	125.048	3.100	2011.415
	Quadratic	117.377	2.501	823.753
	Discrete	117.376	2.499	3224.095

*Results for $X_2=8$

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Relative bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Cobb-Douglas 1	Linear	-0.4429	-0.0358	-0.5912
	Quadratic	-0.4974	-0.0786	-0.6450
	Discrete	-0.4974	-0.0786	-0.9634
Cobb-Douglas 2	Linear	-0.7120	0.1272	-0.7452
	Quadratic	-1.0322	-0.1363	-0.7595
	Discrete	-1.0322	-0.1361	-0.4341

*Results for $X_2=8$

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^b ω is erroneously considered constant, so a MNL model is estimated

Bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Cobb-Douglas 1	Linear	-7.5749	-0.6129	-10.1098
	Quadratic	-8.5055	-1.3448	-11.0297
	Discrete	-8.5055	-1.3447	-16.4744
Cobb-Douglas 2	Linear	-4.0685	0.7272	-4.2583
	Quadratic	-5.8985	-0.7786	-4.3404
	Discrete	-5.8985	-0.7780	-2.4807

*Results for $X_2=8$

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MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Cobb-Douglas 1	Linear	57.405	0.875	7435.068
	Quadratic	72.431	2.363	13664.030
	Discrete	72.431	2.362	1904.534
Cobb-Douglas 2	Linear	16.569	0.673	487.583
	Quadratic	34.849	0.975	118.267
	Discrete	34.849	0.974	382.930

*Results for $X_2=8$

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Relative bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Cobb-Douglas 1	Linear	-0.4410	-0.0324	-0.5897
	Quadratic	-0.4373	-0.0245	-0.6511
	Discrete	-0.4373	-0.0245	-0.9655
Cobb-Douglas 2	Linear	-0.7137	0.1206	-0.7467
	Quadratic	-0.6833	0.1389	-0.6763
	Discrete	-0.6833	0.1390	-0.2679

*Results for $X_2=6$

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Bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Cobb-Douglas 1	Linear	-15.0278	-1.1037	-20.0977
	Quadratic	-14.9030	-0.8351	-22.1905
	Discrete	-14.9030	-0.8351	-32.9049
Cobb-Douglas 2	Linear	-8.2045	1.3867	-8.5843
	Quadratic	-7.8558	1.5969	-7.7746
	Discrete	-7.8558	1.5977	-3.0802

*Results for $X_2=6$

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MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Cobb-Douglas 1	Linear	225.938	3.218	29735.351
	Quadratic	222.204	2.777	52709.992
	Discrete	222.204	2.777	7758.046
Cobb-Douglas 2	Linear	67.379	2.500	1951.486
	Quadratic	61.782	3.152	768.642
	Discrete	61.782	3.154	3192.474

*Results for $X_2=6$

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Relative bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Cobb-Douglas 1	Linear	-0.4100	-0.0213	-0.5670
	Quadratic	-0.4676	-0.0241	-0.6239
	Discrete	-0.4676	-0.0241	-0.9612
Cobb-Douglas 2	Linear	-0.6374	0.4190	-0.6793
	Quadratic	-1.0406	0.0873	-0.6973
	Discrete	-1.0405	0.0874	-0.2877

*Results for $X_2=6$

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Bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Cobb-Douglas 1	Linear	-6.6187	0.3433	-9.1537
	Quadratic	-7.5493	-0.3887	-10.0735
	Discrete	-7.5494	-0.3885	-15.5182
Cobb-Douglas 2	Linear	-2.8937	1.9019	-3.0835
	Quadratic	-4.7237	0.3962	-3.1656
	Discrete	-4.7237	0.3968	-1.3059

*Results for $X_2=6$

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MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Cobb-Douglas 1	Linear	43.834	0.618	7416.648
	Quadratic	57.080	0.705	13643.852
	Discrete	57.080	0.705	1873.944
Cobb-Douglas 2	Linear	8.390	3.762	478.958
	Quadratic	22.371	0.525	109.450
	Discrete	22.371	0.526	377.298

*Results for $X_2=6$

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Relative bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Cobb-Douglas 1	Linear	-0.3578	0.1115	-0.5287
	Quadratic	-0.3536	0.1206	-0.5993
	Discrete	-0.3536	0.1206	-0.9604
Cobb-Douglas 2	Linear	-0.5015	0.9511	-0.5590
	Quadratic	-0.4486	0.9829	-0.4363
	Discrete	-0.4486	0.9831	0.2746

*Results for $X_2=3$

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Bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Cobb-Douglas 1	Linear	-10.6161	3.3079	-15.6860
	Quadratic	-10.4914	3.5766	-17.7789
	Discrete	-10.4914	3.5766	-28.4933
Cobb-Douglas 2	Linear	-3.3111	6.2802	-3.6908
	Quadratic	-2.9624	6.4903	-2.8812
	Discrete	-2.9623	6.4912	1.8132

*Results for $X_2=3$

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MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 2 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Cobb-Douglas 1	Linear	112.806	12.982	29577.486
	Quadratic	110.173	14.872	52533.661
	Discrete	110.173	14.872	7487.178
Cobb-Douglas 2	Linear	11.028	40.017	1891.419
	Quadratic	8.844	42.726	716.498
	Discrete	8.844	42.737	3172.820

*Results for $X_2=3$

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Relative bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Cobb-Douglas 1	Linear	-0.3222	0.1731	-0.5026
	Quadratic	-0.3884	0.1210	-0.5680
	Discrete	-0.3884	0.1211	-0.9554
Cobb-Douglas 2	Linear	-0.3687	1.4706	-0.4415
	Quadratic	-1.0706	0.8930	-0.4730
	Discrete	-1.0706	0.8933	0.2402

*Results for $X_2=3$

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Bias in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Cobb-Douglas 1	Linear	-4.5288	2.4332	-7.0637
	Quadratic	-5.4594	1.7013	-7.9836
	Discrete	-5.4594	1.7014	-13.4283
Cobb-Douglas 2	Linear	-0.9614	3.8342	-1.1513
	Quadratic	-2.7914	2.3285	-1.2333
	Discrete	-2.7914	2.3291	0.6263

*Results for $X_2=3$

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MSE in the estimated value of a hypothetical change in X_1 from the BAU level (6) to a level of 4 under each assumption about ω when the true *Cost* parameter presents scale heterogeneity and the true utility specification is non-additive (over 1,000 repetitions)*

True utility specification	Assumed utility specification	Constant ^b	Mistaken heterogeneity source	
			Lognormal ^a	Triangular ^a
Cobb-Douglas 1	Linear	20.536	6.421	7382.755
	Quadratic	29.892	3.448	13606.113
	Discrete	29.893	3.449	1813.447
Cobb-Douglas 2	Linear	0.941	14.846	470.775
	Quadratic	7.849	5.790	100.950
	Discrete	7.849	5.793	373.079

*Results for $X_2=3$

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