Do Scenario Context and Question Order influence WTP? The Application of a Model of Uncertain WTP to the Contingent Valuation of the Morbidity Impacts of Air Pollution

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Abstract

This paper presents a general framework for modelling responses to contingent valuation questions when respondents are uncertain about their 'true' WTP. These models are applied to a contingent valuation data set recording respondents' WTP to avoid episodes of ill-health. Two issues are addressed. First, whether the order in which a respondent answers a series of contingent valuation questions influences their WTP. Second, whether the context in which a good is valued (in this case the information the respondent is given concerning the cause of the ill-health episode or the policy put into place to avoid that episode) influences respondents' WTP.

The results of the modelling exercise suggest that neither valuation order nor the context included in the valuation scenario impact on the precision with which respondents answer the contingent valuation questions. Similarly, valuation order does not appear to influence the mean or median WTP of the sample. In contrast, it is shown that in some cases, the inclusion of richer context significantly shifts both the mean and median WTP of the sample. This result has implications for the application of benefits transfer. Since, WTP to avoid an episode of ill-health cannot be shown to be independent of the context in which it is valued, the validity of transferring benefits of avoided ill-health episodes from one policy context to another must be called into question.

Key words: Uncertainty, mixture models, contingent valuation, context, benefits transfer.

Introduction

This paper reports on a large-scale contingent valuation survey aimed at determining how much individuals are willing to pay to avoid the pain and discomfort that result from suffering an episode of ill-health. In particular, the good being valued is the avoidance of episodes of respiratory ill-health that might result from exposure to air pollution. Each respondent was asked to value three different ill-health episodes. The episodes differed in severity ranging from a mild symptom day, to a restricted activity day through to a hospital admission.

Clearly, it would be extremely advantageous if values estimated from a study such as this could be used by policy-makers in the evaluation of any project that impacts upon the number of episodes of respiratory ill-health suffered in a population. The validity of transferring values across studies depends, to a large extent, on the independence of the population's WTP from the exact details of the project being evaluated. If the population's WTP to avoid an ill-health episode is independent of the cause of that episode or the details of the project that is being considered to remedy that cause, then values can be safely transferred across projects.

To test the validity of benefits transfer exercises such as this, a split sample survey has been undertaken in which different sub-samples were presented with contingent valuation scenarios offering different levels of context. One sub-sample was asked to value the avoidance of each of the three ill-health episodes, but were given no details of the cause of this episode nor the policy that would be implemented to remedy the cause. A second sub-sample were given details of the cause of the ill-health episodes and a third sub-sample provided with details of the cause and the policy to be implemented to remedy the cause. One objective of this paper is to test whether WTP changes significantly when context is added to the contingent valuation scenario.

Of course, a second possible response to differences in the context in which a good is being valued would be to change the certainty with which respondents are able to state their WTP. For example, we might hypothesise that including details of the proposed policy in the valuation scenario may increase the certainty with which individuals state their maximum WTP, since they are made aware of exactly how paying money will result in avoidance of an episode of ill-health. To test this second hypothesis, an elicitation method is presented that explicitly allows for respondent uncertainty. Further, within the framework of a general model of uncertain WTP responses to contingent valuation questions, two models are presented that can be used to estimate the impact of context on both the level of WTP and the certainty with which this is stated.

A further issue that has worried contingent valuation practitioners is whether presenting respondents with a series of valuation questions impacts upon their response to any one of the questions. Naturally, it is more practical to include several valuation questions since this increases the quantity of relevant information that can be collected in one contingent valuation survey. However, if respondents' WTP for any one contingent good is dependent on where it is valued in a series of such valuation exercises, the practice of including multiple valuation exercises in one survey must be called into question. To test this hypothesis, the survey presented here contained a further sub-sample that were asked to value the same three episodes of ill-health (presented with no context) but in a different order.

Respondent Uncertainty and Population Heterogeneity in Models of WTP

Let us consider the process by which individuals estimate their maximum WTP for a good in response to a contingent valuation question. Following standard economic theory, we can define an indirect utility function, $V(\cdot)$, for a representative individual that depends on money wealth, Y, the prices of all other goods, P, and other demographic and economic factors that might influence an individual's ability to pay or constrain their behaviour, Z. We assume also that the quantity or quality of the good of interest, Q, enters this function influencing the individual's decisions in maximising utility.

The contingent valuation survey described here presents respondents with a scenario in which they are informed they will suffer from an episode of ill-health in the near future and are asked to express their WTP to avoid the pain and discomfort this will cause them. Representing the individual's current health status with regard to this ill-health episode as Q^0 and the addition of a further hypothetical episode by q, we can define the equality;

$$V(Y^0, P^0, Z^0, Q^0 + q) = V(Y^1 - C, P^1, Z^1, Q^0) = V \qquad (1)$$

Where the *0* superscript describes the values of the various factors influencing utility without the hypothetical improvement in health and the superscript *1* describes their values with the improvement. If we assume that avoidance of the ill-health episode is regarded as an improvement, C measures the compensating variation measure of welfare; the maximum WTP to achieve an improvement in health.

Assuming individuals are perfectly able and willing to solve the various aspects of this valuation problem we can define an individual's WTP as a function, $C(\cdot)$, of the proposed change in Q and the other factors that influence a person's value for a change in Q;

$$C = C(Q^0, q, Y^0, Y^1, P^0, P^1, Z^0, Z^1) \qquad (2)$$

Given that the change in health status described in the hypothetical scenario posited in the contingent valuation survey is instantaneous we can make the simplifying assumption that $Y^0 = Y^1 = Y$, $P^0 = P^1 = P$ and $Z^0 = Z^1 = Z$ such that equation (2) reduces to[1];

$$C = C(Q^0, q, Y, P, Z) \qquad (3)$$

Of course this formulation suggests that an individual is able to define their WTP perfectly. Clearly, this is a poor reflection of reality. In general we would expect a respondent to have some uncertainty over their preferences and WTP value. Such uncertainty may arise for numerous reasons, amongst which we might include;

1. *Characteristics of the Good (q)*. Frequently contingent valuation studies, present respondents with descriptions of goods with which they have little experience. Respondents are forced to rely on the necessarily limited descriptions of these goods provided by researchers. For such unfamiliar goods, it is likely that respondents will have poorly formed preferences.

   In the present study, where individuals are being asked to value the avoidance of the pain and discomfort associated with a hypothetical episode of ill-health, respondents are reliant on the researcher's descriptions to ascertain the symptoms and restrictions associated with each of the ill-health episodes[2]. For more familiar

[1] Should a contingent valuation survey ask individuals to express their WTP now for a future change in Q then these equalities may not necessarily hold.

[2] A separate but potentially important issue with the hypothetical nature of contingent valuation studies is whether respondents are entirely convinced by the hypothetical good described to them. If they have doubts as to whether the described change will actually be realised they will presumably allot some

episodes, such as a day coughing, respondents may be able to define reasonably accurately their preferences for q. On the other hand, respondents may have little personal experience of more severe episodes such as an episode of ill-health that requires admission to hospital. In such cases we would expect respondents to find it difficult to give precise estimates of their WTP.

At the same time, many other characteristics of the hypothetical good, when not clarified in the contingent valuation scenario, will likely induce uncertainty in respondents. Most notably, in the present study, the cause of the ill-health episode and the mechanism by which paying money will allow them to avoid it.

2. *Circumstances of Consumption (Y, P* and *Z)*. Typically, contingent valuation scenarios present respondents with a change in the provision or quality of a good that will be realised at some unspecified or inexact point in the future. For many consumption decisions the time of consumption will have a large impact on individuals' preferences. In terms of equation (3), we might expect the values of Y, P and Z to change or fluctuate over time. For instance, the value of Y of those in monthly waged work will decline over the course of the month in response to other consumption decisions. These individuals' ability to pay to avoid an episode of ill-health will, therefore, be different at different times of the month. A further illustration is provided by a question that was frequently raised in pretesting of the present survey; "Will I get this illness on a weekend or a weekday?". Presumably the impact of the illness on an individual will be very different if it involves having to take time off work[3]. In this case we are observing the attitudes of the individual (contained in the Z vector) changing over time[4].

   While respondents may, from past experience, have an idea of the range of values that might be taken by Y, P and Z they have no way of predicting exactly what values they will take at the unspecified point in the future when the good is to be consumed. Again we would expect this to result in respondents being uncertain of their WTP.

3. *Unfamiliarity with Contingent Valuation Technique*. For some respondents the hypothetical nature of the exercise and their unfamiliarity with expressing their values for goods in the manner demanded by the contingent valuation method may compound their uncertainty concerning their WTP.

4. *Bounded Rationality.* A further possible cause of respondent uncertainty is as a consequence of the limits of respondents cognitive abilities resulting in bounded rationality. That is, individuals may determine that it is not optimal for them to completely solve the valuation problem.

The first three points listed above are features of the contingent valuation method itself. The first two in particular result from lack of detail in the hypothetical scenario

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probability to the event and their reported WTP will consequently understate their WTP for the good consumed with full certainty.

[3] This despite the fact that respondents were asked to assume that they would not lose wages through suffering the episode.

[4] Other examples of factors that might induce uncertainty in respondents preferences and values for avoiding an episode of ill-health might include, their responsibilities and commitments at the point in time when the good is to be consumed, the time of year or even purely random events such as the weather.

description. Since no contingent behaviour scenario can completely describe all relevant details for all respondents some level of uncertainty must exist for the respondent.

In short, it seems likely that, for most respondents, uncertainty is likely to be a feature of the valuation problem presented to them in a contingent valuation survey. To reflect this fact, an individual's WTP, *C*, is probably better characterised as a random variable that we shall denote $\tilde{C}$.

Given that respondents have knowledge of the factors driving the randomness in *C*, it is reasonable to assume that they can approximate its probability density function (pdf). In other words, respondents are unlikely to be able to state an exact WTP but rather identify the probability that they would pay a certain amount, *C*. In mathematical notation;

$$\Pr(C) = g_{\tilde{C}}(C \mid \boldsymbol{X}) \tag{4}$$

Where $g_{\tilde{C}}(\cdot)$ is the probability density function (pdf) of the random variable $\tilde{C}$.

and $\boldsymbol{X}$ is the vector of factors (i.e. *Q*, *q*, *Y*, *P*, *Z*) that influence WTP.

Equation (4) presents a model of individual uncertainty. As described in greater detail below, this paper presents an elicitation procedure which explicitly allows for individuals to express this uncertainty in response to contingent valuation WTP questions.

So far we have looked at the problem solely from the perspective of the individual. The picture is somewhat more complex when viewed by the researcher attempting to model WTP responses to contingent valuation questions. Let $f_{\tilde{C}}(\cdot)$ be what the researcher assumes is the pdf of $\tilde{C}$ and $F_{\tilde{C}}(\cdot)$ be the corresponding cumulative density function (cdf). For simplicity, let us assume that $f_{\tilde{C}}(\cdot)$ is a simple pdf, defined by two parameters; a location parameter which we shall denote as $\eta_{\tilde{C}}$, and a variance which we shall denote by $\sigma^2_{\tilde{C}}$. Using data collected in a CV survey the researcher wishes to estimate these parameters. In contrast to equation (4), the researcher's model of individual uncertainty, therefore, can be defined as;

$$\Pr(C) = f_{\tilde{C}}(C; \eta_{\tilde{C}}, \sigma^2_{\tilde{C}} \mid \boldsymbol{X}) \tag{5}$$

This formulation implies that an individual's WTP may take any of a range of values. The greater an individual's uncertainty, the greater the range of values within which their WTP may lie. Indeed, we can consider the variance of this pdf, $\sigma^2_{\tilde{C}}$, to be a measure of an individual's imprecision.

Note that equation (5) allows both the location parameter, $\eta_{\tilde{C}}$, and the variance, $\sigma^2_{\tilde{C}}$, of the random variable $\tilde{C}$ to be functions of the $\boldsymbol{X}$ vector. In other words, the absolute level of an individual's WTP and the imprecision associated with this WTP will change according to the values taken by $\boldsymbol{X}$ (e.g. the qualities of the hypothetical good).

Suppose now that the researcher is unable to collect data on all the variables in the $\boldsymbol{X}$ vector, nor is it possible to measure with exact precision the values of those variables for which data exists. Further, the researcher can only postulate the exact functional form by which these variables influence the distribution of an individual's WTP. In such a case, $f_{\tilde{C}}(\cdot)$ involves an individual specific quantity υ, such that equation (5) must be reformulated as;

$$\Pr(C) = f_{\tilde{C}}(C \mid \boldsymbol{x}, v) = f_{\tilde{C}}(C \mid \boldsymbol{X}) \qquad (6)$$

Where $\boldsymbol{x}$ is the subset of the variables in $\boldsymbol{X}$ that are included in the researchers model,

and v is an individual specific quantity representing the variables not included in the model by the researcher and the inaccuracies introduced in measurement and through approximation of the functional form.

In practice v is both unmeasured (unknown) and varies over the population of interest. As such, we can follow the usual interpretation and describe v as the realisation of a random variable, $\tilde{V}$, that represents unobservable heterogeneity in the WTP of respondents.

Let the distribution function of $\tilde{V}$ over the population be described by a pdf denoted by $f_{\tilde{V}}\left(v; \eta_{\tilde{V}}, \sigma^2_{\tilde{V}} \mid \boldsymbol{x}\right)$. Where $\eta_{\tilde{V}}$ is the location parameter and $\sigma^2_{\tilde{V}}$ is the variance of the distribution that the researcher may wish to estimate. Describing $\tilde{V}$ as conditional on the $\boldsymbol{x}$ vector allows for the possibility that the data may display heteroskedasticity.

To be clear, we have already stated that to account for respondent uncertainty, WTP should be considered a random variable which we denote $\tilde{C}$. The vector of variables, $\boldsymbol{x}$, can be thought to act on this random variable in two ways; by shifting its distribution to higher or lower values or by increasing the range of values over which the distribution predicts a positive probability (i.e. the level of respondent imprecision). Moreover, the researcher must take account of population heterogeneity. That is, two respondents with identical values of $\boldsymbol{x}$, may express different WTP probability distributions. It is assumed that such differences in $\tilde{C}$, result from unobserved heterogeneity and further that this heterogeneity can be described by a second random variable $\tilde{V}$. In making $\tilde{V}$ conditional on $\boldsymbol{x}$ we allow for the fact that the unmeasured variability in $\tilde{C}$ may be related to measured characteristics. For example we might envisage that WTP distributions will show greater variability for those with relatively high incomes or less variability for those with greater prior experience of consuming the good being valued.

The distribution of WTP that the researcher witnesses in the population, therefore, must be modelled as the interaction of two random variables; $\tilde{C}$, the probability distribution of WTP caused by respondent uncertainty, and $\tilde{V}$, unobservable heterogeneity in the population. Such a distribution is termed a mixture distribution.

Let us denote the pdf of this mixture distribution $f_M(\cdot)$ and the corrsponding cdf $F_M(\cdot)$. From the researcher's point of view, therefore, the probability of observing a particular value of WTP given in response to a contingent valuation question is given by;

$$\Pr(C) = f_M\left(C; \eta_{\tilde{C}}, \sigma^2_{\tilde{C}}, \eta_{\tilde{V}}, \sigma^2_{\tilde{V}} \mid \boldsymbol{x}\right) \tag{7}$$

Equation (7) forms the basis for a general class of probabilistic models describing individual responses to WTP questions that accounts for both uncertainty and population heterogeneity.

Elicitation in the presence of Uncertain WTP

Given respondent uncertainty, elicitation methods commonly employed in contingent valuation surveys may appear ambiguous to the respondent. For example, the open-ended elicitation method which poses questions of the type "What is your maximum WTP for *q*?" is not clearly defined; maximum WTP could take one of a range of values. Similarly, referendum style elicitation methods requiring a "Yes" or "No" response to questions such as "Would you be WTP $*x* for *q*?" may be ambiguous if $*x* falls in the individual's zone of uncertainty; there is a probability that they would pay that amount and a probability that they would not.

Clearly, elicitation methods must be adapted to take account of uncertainty. A number of approaches have been presented in the literature. Svento (1993) and Huang (1997) both present referendum style elicitation questions that allow not only "Yes" or "No" responses but also "Don't Know" responses. It is assumed that respondents replying "Don't Know" to a particular bid level are uncertain as to whether they would pay this amount or not. A second approach advocated by Li and Mattson (1995) and Ready et al. (1995) is to append a certainty follow-up question to an initial referendum style elicitation question. Li and Mattson (1995), for example, followed a referendum style question with a follow-up question asking "How certain were you of your answer to the previous question?". Respondents were asked to state their confidence in their previous answer on a scale of 0% to 100%. In this paper we present a further approach to eliciting WTP when respondents are uncertain, through a payment card type approach that we shall term the *payment ladder* to reflect the fact that respondents are asked to consider each amount on a payment card sequentially.

The payment ladder lists a series of values, starting at low numbers and ending in reasonably high numbers. In the UK version of the survey the payment ladder consisted of 35 values ranging from 10p to £3,250[5]. Money amounts were chosen such that the size of each increment roughly followed an exponential progression[6], and such that the highest value included was larger than almost all WTP responses. Starting with the smallest value on the ladder, respondents were asked to consider each value in turn and tick the amounts they were "almost certain" they would pay, cross the amounts they were "almost certain" they would not pay and leave blank the amounts for which they could not say one way or the other. The highest tick and lowest cross, it is assumed, define the limits of the individuals range of uncertainty, whilst the respondent allots some positive probability to having a WTP that takes any of the values between these two amounts. Further, to take account of the interval nature of the payment card, we assume that the 10th percentile of the respondents WTP distribution ($G_{\tilde{C}}(\cdot)$ = 0.1) lies between the amount ticked and the next value on the payment card, whilst the 90th percentile of the distribution ($G_{\tilde{C}}(\cdot)$ = 0.9) lies between the amount crossed and the previous value on the payment card.

As illustrated in Figure (1), the payment ladder elicitation method returns four pieces of information concerning individual *i*'s WTP;

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[5] An earlier pretest of the survey had tested for payment card bias . In this pretest a second version of the payment card was presented to a sample of respondents displaying fewer values with larger increments. No systematic difference was found in the WTP of those using the short payment card from those using the long payment card used in the full-scale survey.

[6] Rowe, Schulze and Breffle (1995) provide theoretical justifications for such a payment card design.

- y_i^{HT-}, the highest amount they were almost certain they would pay – as marked by their *highest tick* on the payment ladder (where *HT* denotes Highest Tick),
- y_i^{HT+}, the next amount printed on the payment ladder,
- y_i^{LC+}, the lowest amount they were almost certain they would not pay – as marked by their *lowest cross* on the payment ladder (where *LC* denotes Lowest Cross).
- y_i^{LC-}, the previous amount printed on the payment ladder.

Also, we assume that;

$$G_{\tilde{C}}\left(y_i^{HT-}\right) \leq 0.1 > G_{\tilde{C}}\left(y_i^{HT+}\right)$$
$$\text{and} \tag{8}$$
$$G_{\tilde{C}}\left(y_i^{LC-}\right) \leq 0.9 > G_{\tilde{C}}\left(y_i^{LC+}\right).$$

Two other types of responses might be expected from this elicitation method. First we would expect that some respondents will be indifferent to the hypothetical change in Q[7]. Consequently, our models must account for those with zero WTP. Further, certain individuals, may associate a positive possibility to paying an amount greater than the highest amount printed on the payment card. In such cases, respondents will place a tick on the highest amount listed on the payment card. Again our model will have to account for this type of right censoring.

[7] We do not, however, allow for respondents having negative WTP In other words, we assume that respondents do not expect to be compensated (i.e. have a positive WTA compensation) for an improvement in their health.

Econometric Model

In the models presented here, zero responses are considered qualitatively different from responses with positive WTP. We assume, therefore, that the population consists of two distinct types, a group who are indifferent to the change in *Q*, and another group who have a varying but positive WTP. To take account of zero responses, therefore, we introduce a probability mass, or spike, at $C = 0$. That is equation (7) must be reformulated as;

$$\Pr(C) = (1-\gamma) + \gamma \cdot f_M(C \mid \boldsymbol{x}) \qquad C \geq 0 \qquad (9)$$

Where γ is the probability that $C > 0$. In this application, γ is modeled using a simple dichotomous probit model such that,

$$\Pr(C) = (1-\Phi(\alpha)) + \Phi(\alpha) \cdot f_M(C \mid \boldsymbol{x}) \quad C \geq 0 \qquad (10)$$

Where $\Phi(\cdot)$ is the cumulative standardised normal distibution and α is a parameter to be estimated.

Tacit in the formulation of equation (10) is the condition that the mixture distribution, $f_M(\cdot)$, is only defined for values that are greater than zero. More specifically we assume that that $f_{\tilde{C}}(\cdot)$ is only defined for positive values. A family of distributions that have this property, and which might be employed to formulate models of uncertain WTP, generate what can be termed log-linear models of the random variable $\tilde{C}$ (see Lancaster; 1990, pp 40-41).

For a group of two parameter distributions[8] within the log-linear family of models, the probability of observing a particular value for *C* is given by;

$$\Pr(C) = f_{\tilde{C}}\left(\frac{\ln(C) - \eta_{\tilde{C}}}{\sigma_{\tilde{C}}}\right) \qquad (11)$$

where $(\ln(y) - \eta_{\tilde{C}})/\sigma_{\tilde{C}}$ represents a standardised deviate and our objective is to estimate the parameters of the distribution of $\tilde{C}$, i.e. the location parameter $\eta_{\tilde{C}}$ and the variance $\sigma^2_{\tilde{C}}$.

Further, the probability that an individual's 'true' WTP, *C*, will be less than or equal to a certain value, *y*, is given by;

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[8] Included in this group is the log normal , the exponential, the weibull distribution, the logistic and the gamma distributions.

$$\{\Pr(C) \leq y\} = F_{\tilde{C}}\left(\frac{\ln(y) - \eta_{\tilde{C}}}{\sigma_{\tilde{C}}}\right) \tag{12}$$

We can use the relationships given in (8) to build a model that describes the probability of observing an individual returning the highest tick and lowest cross that they marked on the payment ladder. First we note that the standard deviate defining the 10th and 90th percentiles of $\tilde{C}$ are given by $F_{\tilde{C}}^{-1}(0.1)$ and $F_{\tilde{C}}^{-1}(0.9)$ respectively. Such that, given values for $\eta_{\tilde{C}}$ and $\sigma_{\tilde{C}}^2$, the probability of a respondent placing their highest tick at y_i^{HT-}, is given by;

$$\Pr\left\{F_{\tilde{C}}\left(y_i^{HT-}\right) < 0.1 < F_{\tilde{C}}\left(y_i^{HT+}\right)\right\} = F_{\tilde{C}}\left(\frac{\ln\left(y_i^{HT+}\right) - \eta_{\tilde{C}}}{\sigma_{\tilde{C}}} - F_{\tilde{C}}^{-1}(0.1)\right) - F_{\tilde{C}}\left(\frac{\ln\left(y_i^{HT-}\right) - \eta_{\tilde{C}}}{\sigma_{\tilde{C}}} - F_{\tilde{C}}^{-1}(0.1)\right) \tag{14}$$

and the probability of them placing their lowest cross at y_i^{LC+}, is given by;

$$\Pr\left\{F_{\tilde{C}}\left(y_i^{LC-}\right) < 0.9 < F_{\tilde{C}}\left(y_i^{LC+}\right)\right\} = F_{\tilde{C}}\left(\frac{\ln\left(y_i^{LC+}\right) - \eta_{\tilde{C}}}{\sigma_{\tilde{C}}} - F_{\tilde{C}}^{-1}(0.9)\right) - F_{\tilde{C}}\left(\frac{\ln\left(y_i^{LC-}\right) - \eta_{\tilde{C}}}{\sigma_{\tilde{C}}} - F_{\tilde{C}}^{-1}(0.9)\right) \tag{15}$$

Equation (7) presented a general form for the mixture distribution formed by the interaction of individual's preference uncertainty and unobserved population heterogeneity when the uncertainty and heterogeneity are characterised by two parameter probability distributions. To generate specific parametric mixture models, three assumptions must be made by the researcher; how heterogeneity enters the valuation function, the distribution of individual WTP, $\tilde{C}$, and the distribution of population heterogeneity, $\tilde{V}$. Two possible models are presented here.

Model 1: The Additivie Heterogeneity Model

Returning to equation (6), we can make the assumption that heterogeneity can be modelled as an additive error term;

$$\Pr(C) = f_{\tilde{C}}(C \mid \boldsymbol{x}, v) = f_{\tilde{C}}(C \mid \boldsymbol{x}) + v \tag{16}$$

Further we assume that $\tilde{C}$ is distributed log normally, (i.e. $\tilde{C} \sim$ LN($\eta_{\tilde{C}}$, $\sigma_{\tilde{C}}^2$)) and that that $\tilde{V}$ is distributed normally with a mean of zero (i.e. $\tilde{V} \sim$ N(0, $\sigma_{\tilde{V}}^2$)). This is essentially the model of Li and Mattson (1995).

Given these assumptions, we can define each individual's likelihood contribution as the joint probabilty of an individual stating that the 90th and 10th percentiles of their

WTP distibution lie between y_i^{HT-} and y_i^{HT+}, and between $y_i^{LC-}$and y_i^{LC+}, respectively. Using (17) and (15) this can be written as;

$$
\begin{aligned}
l_i = &\left(\Phi\left(\frac{\ln\left(y_i^{HT+}\right) - \eta_{\tilde{C}}}{\sigma_{\tilde{C}}} - \Phi^{-1}(0.1) \Big/ \frac{\sigma_{\tilde{V}}}{\sigma_{\tilde{C}}} \right) - \Phi\left(\frac{\ln\left(y_i^{HT-}\right) - \eta_{\tilde{C}}}{\sigma_{\tilde{C}}} - \Phi^{-1}(0.1) \Big/ \frac{\sigma_{\tilde{V}}}{\sigma_{\tilde{C}}} \right) \right) \\
\times &\left(\Phi\left(\frac{\ln\left(y_i^{LC+}\right) - \eta_{\tilde{C}}}{\sigma_{\tilde{C}}} - \Phi^{-1}(0.9) \Big/ \frac{\sigma_{\tilde{V}}}{\sigma_{\tilde{C}}} \right) - \Phi\left(\frac{\ln\left(y_i^{LC-}\right) - \eta_{\tilde{C}}}{\sigma_{\tilde{C}}} - \Phi^{-1}(0.9) \Big/ \frac{\sigma_{\tilde{V}}}{\sigma_{\tilde{C}}} \right) \right)
\end{aligned} \tag{17}
$$

Where l_i is the likelihood contribution of individual, i, and Φ is the standard normal cdf.

Model 2: The Multiplicative Heterogeneity Model

Drawing on the substantial literature concerning the analysis of durations (see, for example, Lancaster, 1990), a second approach to modelling heterogeneity is for it to enter the valuation function multiplicatively according to;

$$
\Pr(C) = f_{\tilde{C}}(C \mid \boldsymbol{x}, v) = f_{\tilde{C}}(C \mid \boldsymbol{x}) \cdot v \tag{18}
$$

For reasons of mathematical tractability, it is often assumed that $\tilde{C}$ follows a Weibull distribution, (i.e. $\tilde{C} \sim$ W($\eta_{\tilde{C}}$, $\sigma^2_{\tilde{C}}$)) and that that $\tilde{V}$ follows a Gamma distributed with a mean of one (i.e. $\tilde{V} \sim$ G(1, $\sigma^2_{\tilde{V}}$)).

Given these assumptions, each individual's likelihood contribution is given by the joint probabilty;

$$
\begin{aligned}
l_i = &\left(\begin{array}{l} \left(1 + \sigma^2_{\tilde{V}} \exp\left(\ln\left(y_i^{HT-}\right) - \eta_{\tilde{C}} / \sigma_{\tilde{C}} - \ln(-\ln(1-0.1))\right)\right)^{-1/\sigma^2_{\tilde{V}}} \\ -\left(1 + \sigma^2_{\tilde{V}} \exp\left(\ln\left(y_i^{HT+}\right) - \eta_{\tilde{C}} / \sigma_{\tilde{C}} - \ln(-\ln(1-0.1))\right)\right)^{-1/\sigma^2_{\tilde{V}}} \end{array} \right) \\
\times &\left(\begin{array}{l} \left(1 + \sigma^2_{\tilde{V}} \exp\left(\ln\left(y_i^{LC-}\right) - \eta_{\tilde{C}} / \sigma_{\tilde{C}} - \ln(-\ln(1-0.9))\right)\right)^{-1/\sigma^2_{\tilde{V}}} \\ -\left(1 + \sigma^2_{\tilde{V}} \exp\left(\ln\left(y_i^{LC+}\right) - \eta_{\tilde{C}} / \sigma_{\tilde{C}} - \ln(-\ln(1-0.9))\right)\right)^{-1/\sigma^2_{\tilde{V}}} \end{array} \right)
\end{aligned} \tag{19}
$$

One potential weakness of the two models presented here is that they do not allow for the panel nature of the data. In other words, the observation on the 10th percentile of an individual's WTP distribution is assumed to be completely independent of the observation on the 90th percentile. Though it is possible to account for this shortcoming by modelling the upper and lower boundary observations as coming from a joint distribution, this is not presented here.

Combining (17) or (19) with the participation model given in (10) provides the full model of the mixture distribution used for analysis in this paper.

The models described above require the estimation of four parameters:

- α; the parameter of the simple probit model used to model the probability mass at zero (i.e. the probability of having zero WTP).
- $\eta_{\tilde{C}}$; the location parameter of the individual's uncertain WTP distribution (i.e. the random variable $\tilde{C}$)
- $\sigma^2_{\tilde{C}}$; the variance of the individual's uncertain WTP distribution (i.e. the random variable $\tilde{C}$)
- $\sigma^2_{\tilde{V}}$; the variance of the distirbution of random heterogeneity in the population (i.e. the random variable $\tilde{V}$).

To shed more light on the factors that influence WTP for the avoidance of ill-health events it is possible to model each of these parameters as functions of $\boldsymbol{x}$ (i.e. the vector of characteristics of the individual, the ill-health episode and the contingent valuation scenario).

Survey and Data

Epidemiological evidence supports the contention that air pollution results in individuals suffering from episodes of ill-health. This paper reports on a large-scale contingent valuation survey aimed at determining how much individuals are WTP to avoid the pain and discomfort that result from suffering such an episode. In particular, the good being valued was avoidance of episodes of respiratory ill health. Three different episodes were valued. These were described in detail to the respondent, and were written by an MD to reflect typical episodes that would be classified as a restricted activity day, a bed episode or a hospital admission in an epidemiological study to estimate exposure-response relationships between air pollution and human health. Table 1 presents brief synopses of the three episodes descriptions.

Table 1: Ill-Health Episode Descriptions

Episode Name	Epidemiological End Point	Description
COUGH	Restricted Activity Day	*One day with persistent phlegmy cough, some tightness in the chest, and some breathing difficulties. Patient cannot engage in strenuous activity, but can work and do ordinary daily activities*
BED	Bed Episode	*Three days with flu-like symptoms including persistent phlegmy cough with occasional coughing fits, fever, headache and tiredness. Symptoms are serious enough that patient must stay home in bed for the three days*
HOSPITAL	Hospital Admission	*Admission to a hospital for treatment of respiratory distress. Symptoms include persistent phlegmy cough, with occasional coughing fits, gasping breath, fever, headache and tiredness. Patient stays in the hospital receiving treatment for three days, followed by 5 days home in bed*

Three different versions of the survey were administered which differed in the amount of information presented to the respondent concerning the cause of the ill-health episode and the measures that the respondent would be paying for in order to avoid the episode.

Each of the three versions began with background questions concerning the respondents own health state, and past experience of various types of respiratory ill health. Next, the episodes were presented, and the respondent was asked to rank them based on which episodes would be worse to experience[9]. The ranking exercise was intended to force respondents to carefully consider all episodes before valuing any of them[10].

The three versions of the survey differed only in the section of the questionnaire in which respondents were asked to place values on avoidance of the different ill-health

[9] Three additional illness episodes, a symptom day with itchy, runny eyes, a symptom day suffering from an upset stomach and an emergency room visit, were also described and ranked.

[10] This sequence of tasks is the same as that used by Tolley et al. DATE

episodes. In the first survey (*the full context survey*) the respondent was informed that the episode of ill-health would result from air pollution (*the causal context*) and was then asked to express their WTP for a policy measure (*the policy context*) that would reduce pollution to a level that would ensure that they would not suffer the ill-health episode. In the second survey (*the causal context survey*) respondents were told that the episode of ill-health would result from air pollution but were simply asked to express a WTP to reduce pollution to a level that would ensure that they did not suffer the episode, but were not presented with a specific policy designed to achieve this. The third survey (*the non-contextual survey*) was completely context free, respondents were simply asked for their WTP to avoid the described episode of ill-health.

In each survey, all three episodes were valued in the order BED followed by HOSPITAL followed by COUGH. In addition, however, a further version of the non-contextual survey was administered in which the order of valuation was changed to COUGH, HOSPITAL, BED.

The four versions of the survey are summarised in Table 2 along with the total number of each version administered.

Table 2: The Four Different Versions of the UK Survey

Version	Context	Order	Number
A	Non-Context	Order I: Bed – Hosp – Cough	139
B	Non-Context	Order II: Cough – Hosp – Bed	141
C	Causal Context	Order I: Bed – Hosp – Cough	205
D	Causal and Policy Context	Order I: Bed – Hosp – Cough	209
			694

The objectives of this study, therefore, are twofold; to use the models described in the previous section to investigate how individuals' WTP is impacted by changes in context and by changes in the order that individuals were asked to value the good. Both issues are important for the use of contingent valuation studies in policy decision making;

- If the order in which the episodes are valued impacts upon individual's WTP then this suggests that problems exist in the current design and administration of contingent valuation surveys and consequently casts doubts upon the validity of their results.

- If context does not significantly impact on individuals' WTP then this greatly increases the validity of benefits' transfer exercises. In the current context, our interest is in valuing improvements in health status. One aim of non-market valuation is to provide values that can be used by decision-makers to guide policy decisions. In the present case we can think about policies that might bring about improvements in health such as reducing air pollution or increasing spending on primary health care. Though both policies may result in the same change in health status for a particular individual, the context in which this change is achieved is very different. Clearly if values are not influenced by context then this allows decision makers to apply the same values for the avoidance of ill-health events in the consideration of policies with very different context. Such benefits' transfer exercises reduce the need for costly valuation studies.

Results

Surveying was conducting between February and May 1998 by a professional survey company on a random sample of 694 UK residents aged 18 or older.

As shown in Table 3, 576 (83%) of the respondents reported a positive WTP to avoid the COUGH episode, 611 (88%) had positive WTP to avoid the BED episode and 615 (89%) had a positive WTP to avoid the HOSPITAL episode. Positive WTP is defined as those who ticked a value greater than zero on the payment ladder.

There are many reasons why people would not be willing to pay anything to avoid an episode of ill-health. Those who reported a zero WTP were asked a follow-up question to establish their reasons for not wanting to pay. A breakdown of these reasons is provided in Table 3.

The responses in Table 3 have been divided into three categories; those with a positive WTP, those with zero WTP who replied with genuine economic reasons for not wanting to pay to avoid the episode of ill-health and those who were simply rejecting the contingent market. In terms of the analysis of WTP the latter group have to be discarded from the sample since their response to the CV questions, whilst entirely valid, cannot be treated merely as a zero WTP.

Table 3: Breakdown of WTP Responses according to Positive or Negative WTP and by Reasons for Negative WTP

Reason	Cough	Bed	Hospital
Those reporting positive WTP			
	576	*611*	*615*
Valid Reasons for not Participating in Contingent Market			
Can't afford to pay anything	*12*	*13*	*11*
Ill-health episode not bad enough	*39*	*5*	*2*
	51	*18*	*13*
Rejection of Contingent Market			
Can't say how much avoiding ill-health episode is worth	*5*	*4*	*6*
Paying to avoid ill-health is unrealistic	*32*	*33*	*32*
Not used to making decisions like this	*2*	*2*	*3*
Other	*19*	*16*	*16*
No reason given	*9*	*10*	*9*
	67	*65*	*66*

As would be expected Table 3 illustrates how those expressing a valid economic reason for having a zero WTP declines as the severity of the ill-health event increases. At the same time the number rejecting the contingent market for each ill-health event remains relatively similar. Remember these are the same individuals valuing all three ill-health events so that is likely that the similarity in the number rejecting the contingent market reflects the fact that the same individuals have refused to put a value on any of the three ill-health episodes.

In Table 4, responses have been further subdivided according to whether respondents were presented with the non-contextual valuation scenario or one of the contextual scenarios. Whilst the percentage of respondents returning valid zeros is relatively similar in the different sub-samples, notice how the percentage of respondents rejecting the contingent market is considerably higher for those answering the contextual survey compared to those presented with the non-contextual survey. It would appear that one of the responses that results from embedding WTP questions in a richer context is to increase the number of respondents rejecting the contingent market and refusing to express their WTP. This observation is not pursued further in this paper.

Table 4: Percentage Breakdown of WTP responses according to whether Respondents Answered the Contextual or Context-Free Surveys

Reason	**Cough**		**Bed**		**Hospital**	
	Context	**No Context**	**Context**	**No Context**	**Context**	**No Context**
Participate	*76%*	*93%*	*83%*	*95%*	*83%*	*96%*
Valid Zero	*9%*	*5%*	*2%*	*3%*	*2%*	*2%*
Rejection of Contingent Market	*13%*	*2%*	*12%*	*2%*	*13%*	*2%*
No Answers	*2%*	*0%*	*2%*	*0%*	*2%*	*0%*

Having removed those rejecting the contingent market from the sample, the models described above were estimated separately for each of the three ill-health events. Table 5 presents the estimation results for a simple constants only model. As would be expected for such a simple model, all the parameters for both models for each of the ill health episodes are significant at greater than a 1% level of confidence.

Reaffirming the results presented in Table 3, the parameter of the simple probit model of positive WTP (α) is greater for the Bed episode than for the Cough episode and greater still for the Hospital episode. Since α represents the standard deviate of a normal distribution, the parameter can easily be reinterpreted as a probability, confirming the observation that 91% of the sample have a positive WTP for the Cough episode and 97% have a positive WTP for the Bed and Hospital episodes.

The parameters of the individual's uncertain WTP distribution, are similarly significant. Notice first that in both models the location parameter of the WTP distribution, $\eta_{\tilde{C}}$, is larger for the Bed episode than the Cough episode and larger still for the Hospital episode. This would conform to our expectation that the WTP distribution is shifted to higher values the greater the severity of the ill-health event avoided.

The variance of the WTP distribution, $\sigma^2_{\tilde{C}}$, which we interpret as a measure of individual imprecision, is also highly significant but in comparison to the variance of population heterogeneity, $\sigma^2_{\tilde{V}}$, is relatively small.

Table 5: Constants only models

	Model 1: Additive Heterogeneity			**Model 2: Multiplicative Heterogeneity**		
	COUGH	**BED**	**HOSPITAL**	**COUGH**	**BED**	**HOSPITAL**
Positive WTP:						
α	*1.367**** *(.073)*	*1.833**** *(.099)*	*1.959**** *(.109)*	*1.367**** *(.073)*	*1.833**** *(.099)*	*1.959**** *(.109)*
WTP:						
$\eta_{\tilde{C}}$	*2.312**** *(.041)*	*3.442**** *(.043)*	*4.169**** *(.046)*	*2.063**** *(.056)*	*3.268**** *(.063)*	*4.052**** *(.064)*
$\sigma_{\tilde{C}}$	*.158**** *(.032)*	*.131**** *(.033)*	*.106**** *(.036)*	*.426**** *(.016)*	*.503**** *(.018)*	*.557**** *(.018)*
Heterogeneity:						
$\sigma_{\tilde{V}}$	*1.340**** *(.029)*	*1.446**** *(.031)*	*1.557**** *(.033)*	*1.720**** *(.057)*	*1.643**** *(.054)*	*1.602**** *(.049)*
Number of Obs	*594*	*599*	*598*	*594*	*599*	*598*
Log Likelihood	*-3178.5*	*-3644.1*	*-3821.8*	*-3282.4*	*-3817.7*	*-4019.5*

*significant at the 10% level

**significant at the 5% level

***significant at the 1% level

The relationship between the different sources of variance in the model are more clearly illustrated in Figures 1 through 6. Figures 1, 3 and 5 provide graphical presentations of the pdf of uncertain WTP (dotted line) and of the mixture distribution inclusive of heterogeneity (solid line), for the additive heterogeneity model for each of the episodes. Figures 2, 4 and 6 provide the same information for the multiplicative heterogeneity model. Notice that the horizontal WTP axis is log transformed.

In both the additive and multiplicative heterogeneity models the uncertain WTP distribution, $\tilde{C}$, is centred around £10 for the Cough episode, between £10 and £100 for the Bed episode and up towards £100 for the Hospital episode. The shapes of the uncertain WTP distributions are quite different for the two models. Compared to the lognormal distribution depicted for the additive model, the Weibull distribution of the multiplicative model appears to suggest a greater variance to uncertain WTP whilst greater weight to the left hand tail of the distribution.

Clearly, from the figures, the variance of the uncertain WTP distribution is relatively small compared to that of the mixture distribution suggesting that the majority of variability in the data is a result of population heterogeneity rather than individual uncertainty. Notice how for the mixture distribution the multiplicative model has thicker right hand tails than the additive model. As we shall discuss later, this presents some problems in the estimation of mean WTP from this model.

Figure 1: Estimated PDFs for the Additive Heterogeneity Model for Cough Episode

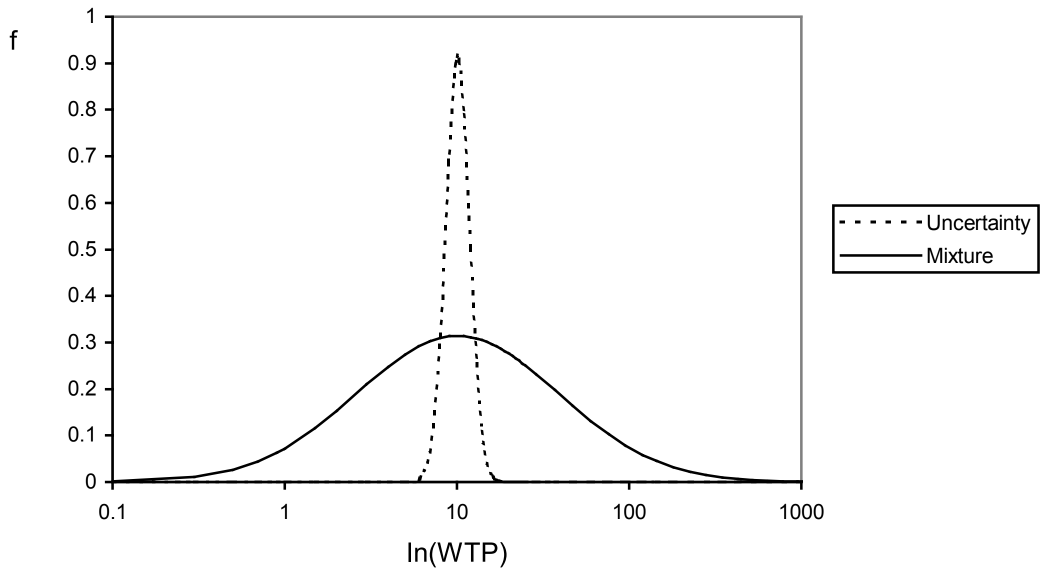


Figure 2: Estimated PDFs for the Multiplicative Heterogeneity Model for Cough Episode

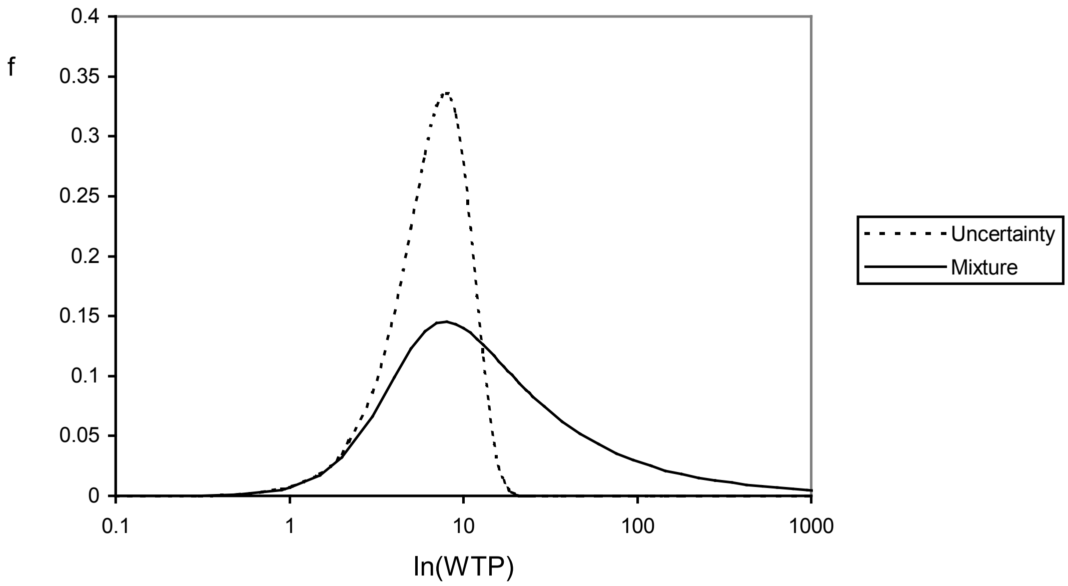


Figure 3: Estimated PDFs for the Additive Heterogeneity Model for Bed Episode

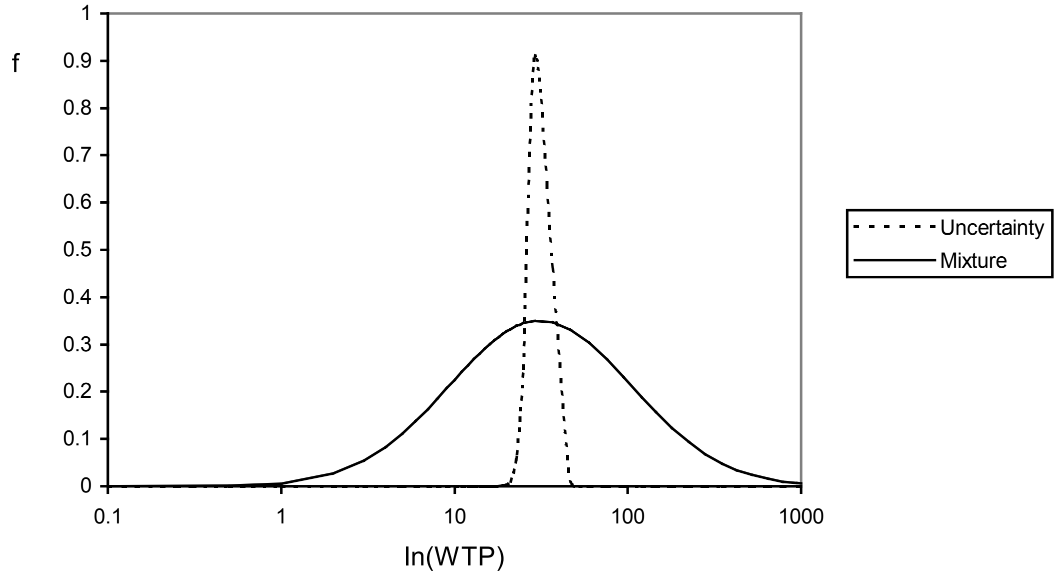


Figure 4: Estimated PDFs for the Multiplicative Heterogeneity Model for Bed Episode

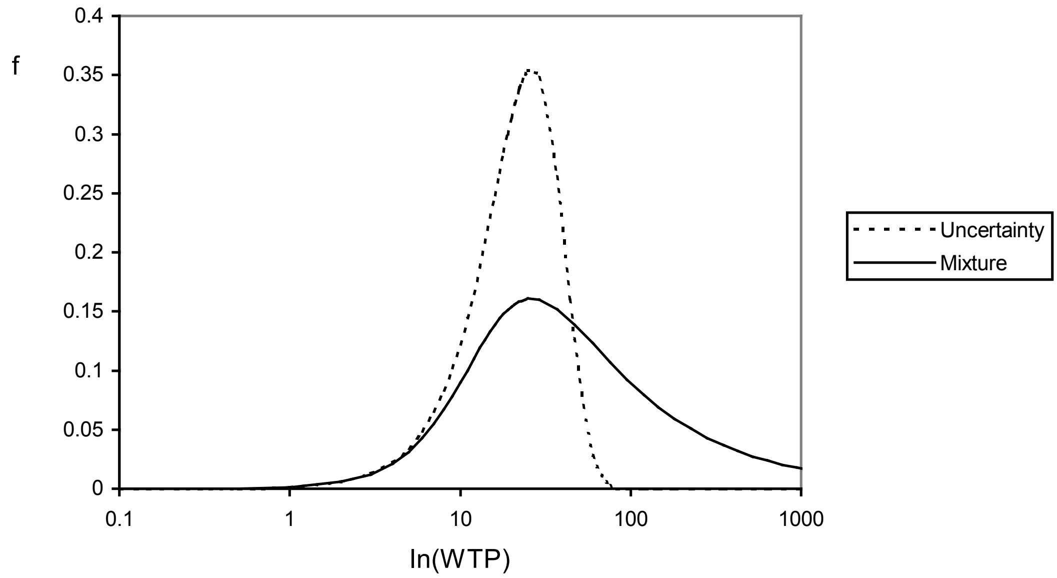


Figure 5: Estimated PDFs for the Additive Heterogeneity Model for Hospital Episode

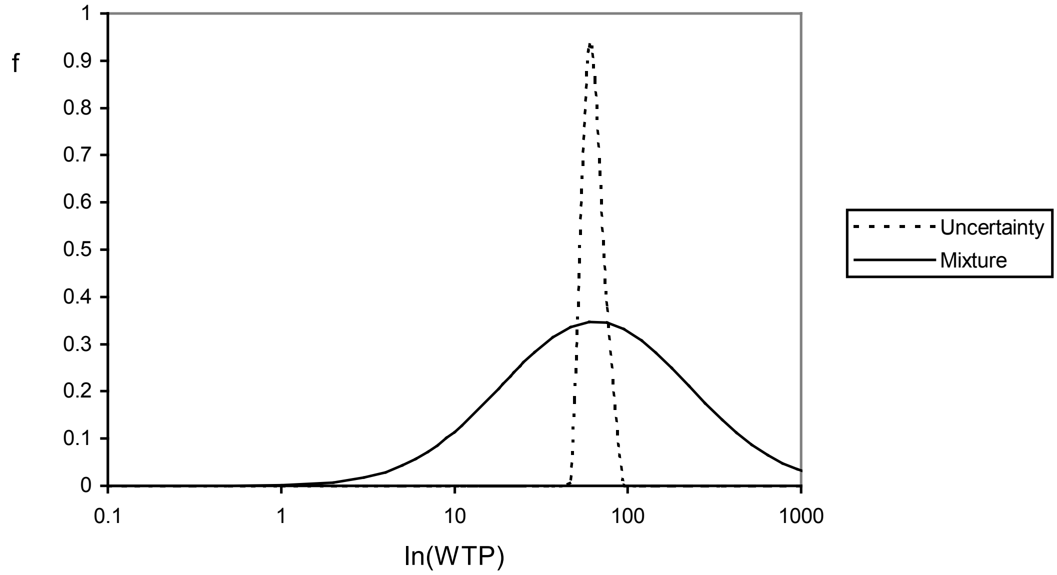
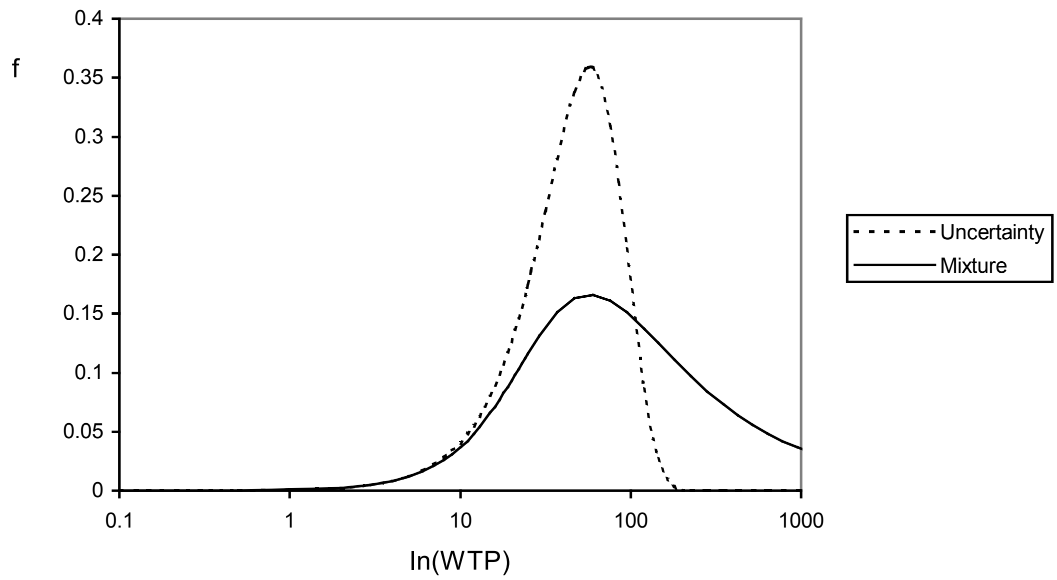


Figure 6: Estimated PDFs for the Multiplicative Heterogeneity Model for Hospital Episode



Tables 6 and 7 provide details of the parameterised models for the additive heterogeneity and multiplicative heterogeneity models respectively. A number of different types of variables might be important in explaining the WTP reported by an individual respondent. In particular, we include three different types;

- Dummy variables for those answering the four different versions of the survey. The non-contextual survey with episodes valued in the order Bed, Hospital, Cough (Version A) is taken as the baseline and a dummy included for the Version B survey (non-contextual but with episodes valued in order Cough, Hospital, Bed), Version C survey (Causal Context) and Version D survey (Causal and Policy Context).
- Variables relating to the socio-economic characteristics of the respondent. Variables for income, age, sex, years in education, a dummy for having children, and a dummy for whether the individual was self-employed were included. Also, a dummy variable is included for those who refused to respond to the income question in the survey.
- A final set of variables are those relating to the respondent's health. A dummy is included distinguishing those who suffer from either asthma or chronic bronchitus and a further dummy is included for those that smoke. A final variable relates to individuals' experience of the ill-health episode being valued. For the Cough episode this is defined as the number of days during the last month that the respondent had suffered from a persistent cough, for the Bed event this was defined as the number of days during the last month that the respondent had had to miss work or had to restrict their activities as a result of respiratory illness, and for the Hospital episode this was defined as whether the respondent had ever visited casualty or been admitted to hospital due to respiratory illness.

To investigate the impact of context and order on individuals' responses to WTP questions, the dummy variables relating to the survey version were used to parameterise the location parameter ($\eta_{\tilde{C}}$) and variance ($\sigma^2_{\tilde{C}}$) of the WTP distribution and also the parameter of the probit model (α) determining the probability of having positive WTP. Further, the socio-economic and health variables were included in the parameterisation of $\eta_{\tilde{C}}$ to investigate the extent to which these might explain shifts in individual's WTP.

Both the additive and multiplicative heterogeneity models result in similar conclusions concerning the impacts of context and order on responses to WTP quesitons. It would appear that the addition of context or the changing of the order in which valuation questions are answered does not impact on the probability of respondents having a positive WTP, since for both models and for all episodes none of the dummy variables used to parameterise α are significant.

A similar conclusion can be drawn for the impact of context and order on imprecision. In the additive model, none of the dummy variables used to parameterise $\sigma_{\tilde{C}}$, are significant. Whilst in the multiplicative model only one parameter, that on the order dummy variable for the Cough episode returns a significant coefficient. In this case, the negative coefficient indicates that respondents asked to value the Cough episode first in a series of such valuation exercises are more precise in their answers than those asked to value it third in a series.

In contrast, the dummy variables for context and order used to parameterise the location parameter of the WTP distribution, $\eta_{\tilde{C}}$, are in all but one case significant at the 5% level of confidence. In both models and for all episodes, the introduction of 'causal' and 'causal and policy' context shifts the WTP distribution upwards to higher values, though we are yet to determine whether these changes result in significant changes in the mean of the overall mixture distribution of WTP (see next section).

Table 6: Parameterised Additive Heterogeneity Models

	Model 1: Additive Heterogeneity					
	COUGH		BED		HOSPITAL	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Positive WTP:						
α						
Cause	*-.285*	*(.211)*	*.101*	*(.264)*	*-.005*	*.292*
Policy	*-.165*	*(.214)*	*.199*	*(.271)*	*.109*	*.302*
Order	*.142*	*(.246)*	*.313*	*(.306)*	*.293*	*.353*
Constant	*1.478****	*(.167)*	*1.691****	*(.190)*	*1.876****	*.217*
WTP:						
$\eta_{\tilde{C}}$						
Cause	*.550****	*(.112)*	*.169*	*(.117)*	*.378****	*.124*
Policy	*.669****	*(.112)*	*.244***	*(.119)*	*.318***	*.126*
Order	*.033*	*(.117)*	*.243***	*(.123*	*.199*	*.130*
Income	*2.9E-05****	*(6.57E-06)*	*3.7E-05****	*(4.81E-06)*	*4.4E-05****	*5.12E-06*
Income Missing	*.062*	*(.122)*	*.671****	*(.127)*	*.846****	*.135*
Age	*.011****	*(.003)*	*.010****	*(.003)*	*.015****	*.003*
Sex	*.238****	*(.083)*	*-.122*	*(.084)*	*.061*	*.089*
Years of Education	*.026***	*(.013)*	*.038****	*(.014)*	*.063****	*.015*
Children	*.132*	*(.091)*	*.310****	*(.095)*	*.304****	*.100*
Self Employed	*-.034*	*(.157)*	*.256*	*(.165)*	*.208*	*.174*
Asthma or Bronchitus	*.247****	*(.094)*	*.345****	*(.097)*	*.188**	*.110*
Health Experience	*.006*	*(.009)*	*.006*	*(.023)*	*.237*	*.200*
Smoker	*.050*	*(.087)*	*.109*	*(.091)*	*.066*	*.096*
Constant	*.733****	*(.240)*	*1.689****	*(.253)*	*1.680****	*.270*
$\sigma_{\tilde{C}}$						
Cause	*.004*	*(.087)*	*.043*	*(.091)*	*.035*	*.096*
Policy	*-.021*	*(.086)*	*.012*	*(.090)*	*.020*	*.095*
Order	*.022*	*(.090)*	*.012*	*(.095)*	*.011*	*.101*
Constant	*.158***	*(.065)*	*.113**	*(.068)*	*.091*	*.072*
Heterogeneity:						
$\sigma_{\tilde{V}}$	*1.270****	*(.028)*	*1.369****	*(.029)*	*1.457****	*.031*
Number of Obs	*594*		*599*		*598*	
Log Likelihood	*-3119.8*		*-3581.6*		*-3745.4*	

*significant at the 10% level

**significant at the 5% level

***significant at the 1% level

Table 7: Parameterised Multiplicative Heterogeneity Models

	Model 2: Multiplicative Heterogeneity					
	COUGH		BED		HOSPITAL	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Positive WTP:						
α						
Cause	*-.285*	*.211*	*.101*	*.264*	*-.005*	*.292*
Policy	*-.165*	*.214*	*.199*	*.271*	*.109*	*.302*
Order	*.142*	*.246*	*.313*	*.306*	*.293*	*.353*
Constant	*1.478****	*.167*	*1.691****	*.190*	*1.876****	*.217*
WTP:						
$\eta_{\tilde{C}}$						
Cause	*.638****	*.107*	*.275***	*.116*	*.437****	*.120*
Policy	*.710****	*.112*	*.300***	*.122*	*.405****	*.127*
Order	*.117*	*.107*	*.299***	*.122*	*.292***	*.129*
Income	*2.8E-05****	*6.59E-06*	*4E-05****	*4.70E-06*	*4.2E-05****	*4.93E-06*
Income Missing	*.154*	*.113*	*.728****	*.126*	*.893****	*.131*
Age	*.005**	*.003*	*.007***	*.003*	*.015****	*.003*
Sex	*.232****	*.076*	*-.093*	*.081*	*.065*	*.086*
Years of Education	*.010*	*.013*	*.036***	*.014*	*.064****	*.015*
Children	*.086*	*.087*	*.363****	*.093*	*.412****	*.097*
Self Employed	*.064*	*.140*	*.371***	*.155*	*.308**	*.167*
Asthma or Bronchitus	*.292****	*.084*	*.286****	*.092*	*.251***	*.104*
Health Experience	*.009*	*.008*	*.019*	*.021*	*.206*	*.191*
Smoker	*-.018*	*.081*	*.076*	*.091*	*.057*	*.094*
Constant	*.917****	*.231*	*1.603****	*.255*	*1.521****	*.271*
$\sigma_{\tilde{C}}$						
Cause	*-.020*	*.032*	*-.042*	*.035*	*-.041*	*.037*
Policy	*.028*	*.033*	*.003*	*.036*	*.018*	*.038*
Order	*-.066***	*.031*	*-.046*	*.036*	*-.011*	*.040*
Constant	*.427****	*.027*	*.508****	*.030*	*.532****	*.031*
Heterogeneity:						
$\sigma_{\tilde{V}}$	*1.669****	*.056*	*1.587****	*.052*	*1.569****	*.049*
Number of Obs	*594*		*599*		*598*	
Log Likelihood	*-3221.4*		*-3744.6*		*-3935.2*	

*significant at the 10% level

**significant at the 5% level

***significant at the 1% level

In the additive heterogeneity model, the dummy variable for order is only significant for the Bed episode and then only at 5% level of confidence. In the multiplicative heterogeneity model the order dummy is significant for the Bed episode and the Hospital episode. It would seem that whilst it makes little difference to respondents whether they value the cough episode first or third in a series of valuation exercises, the values reported for the Bed episode are comparatively lower when it is valued first in the series than when it is valued third in a series after the relatively more severe Hospital episode.

Though it can be seen from these results that context and order do impact on WTP, we leave to the next section a more thorough test of whether the significant differences in the location parameter of the WTP distribution shown in the modeling exercise translate into significant shifts in the WTP of the sample.

The other variables used to parameterise the location parameter of the WTP distribution generally have the expected sign. Income, age and years of education all shift the WTP distribution upwards to higher values and in the most part are highly significant. In both models sex is only significant for the Cough episode, suggesting that the WTP distribution of women for the avoidance a day spent coughing is greater than that of men, though no significant difference exists between the sexes in their WTP to avoid the more severe Bed and Hospital episodes.

In contrast, the parameter estimated on the dummy variable for the respondent having children is not significant in either model for the Cough episode. However, having children does significantly shift the WTP distribution for avoidance of the more serious episodes that result in restrictions in activities. This would accord with an expectation that those responsible for children are more likely to wish to avoid ill-health events that restrict their ability to carry out parental duties.

For similar reasons, the coefficients on the self-employed dummy for the Bed and Hospital episodes are positive and, at least in the multiplicative heterogeneity model, significant. Again it would appear that the responsibilities associated with self-employment are likely to shift upwards respondents' WTP distribution for the avoidance of episodes of ill-health that restrict the ability to work.

In both models, those who suffer from asthma or chronic bronchitus are WTP significantly more to avoid respiratory ill-health episodes, though for neither model for any of the episodes does a respondents' current experience of the ill-health episode significantly alter their WTP. It would also appear that being a smoker does not impact on WTP.

Notice that for each episode, the additive model outperforms the multiplicative model in terms of the value of the maximised log-likelihood. It would appear that the additive model provides a better fit to the data than the multiplicative model.

Willingness to Pay

The heterogeneity models presented above can be used to derive estimates of the WTP to avoid episodes of ill-health. For both models we estimate the sample's WTP as the mean of the mixture distribution.

For the additive heterogeneity model the mixture distribution is defined by the pdf:

$$\Pr(C) = \Phi(\alpha) \cdot \phi\left(\frac{\ln(C) - \eta_{\tilde{C}}}{\sigma_{\tilde{C}}} \bigg/ \frac{\sigma_{\tilde{V}}}{\sigma_{\tilde{C}}} \right) \quad (20)$$

the mean of this distribution, therefore, is given by;

$$E[C] = \int_0^\infty \Phi(\alpha) \cdot \phi\left(\frac{\ln(C) - \eta_{\tilde{C}}}{\sigma_M} \right) dC \quad (21)$$

Where $\sigma_M = \left(\sigma_{\tilde{V}}^2 + \sigma_{\tilde{C}}^2\right)^{\frac{1}{2}}$ is the standard deviation of the mixture distribution. The integral yields the analytical solution:

$$E[C] = \Phi(\alpha) \cdot \exp(\eta_{\tilde{C}}) \cdot \exp\left(\sigma_M^2 / 2\right) \quad (22)$$

For the multiplicative heterogeneity model the mixture distribution is defined by the pdf:

$$\Pr(C) = \Phi(\alpha) \cdot \left(1 + \sigma_{\tilde{V}}^2 \exp\left(\frac{\ln(C) - \eta_{\tilde{C}}}{\sigma_{\tilde{C}}} \right) \right)^{-\left(\frac{1}{\sigma_{\tilde{V}}^2} + 1\right)} \cdot \exp\left(\frac{\ln(C) - \eta_{\tilde{C}}}{\sigma_{\tilde{C}}} \right) \quad (23)$$

Such that the mean of the mixture distribution is given by the integral:

$$E(C) = \int_0^\infty \Phi(\alpha) \cdot \left(1 + \sigma_{\tilde{V}}^2 \exp\left(\frac{\ln(C) - \eta_{\tilde{C}}}{\sigma_{\tilde{C}}} \right) \right)^{-\left(\frac{1}{\sigma_{\tilde{V}}^2} + 1\right)} \cdot \exp\left(\frac{\ln(C) - \eta_{\tilde{C}}}{\sigma_{\tilde{C}}} \right) dC \quad (24)$$

Which can be shown to have the analytical solution (Lancaster, 1990, p 68):

$$E(C)=\Phi(\alpha)\cdot\frac{1}{\exp\left(-\eta_{\tilde{C}}\right)^{\sigma_{\tilde{C}}}}\frac{\Gamma\left(1+\sigma_{\tilde{C}}\right)}{\sigma_{\tilde{V}}^{2\left(1+\sigma_{\tilde{C}}\right)}}\frac{\Gamma\left(1/\sigma_{\tilde{V}}^{2}-\sigma_{\tilde{C}}\right)}{\Gamma\left(1/\sigma_{\tilde{V}}^{2}+1\right)} \tag{25}$$

where Γ is the gamma function. The analytical solution in (25) is only defined for values of $\sigma_{\tilde{C}}$ and $\sigma_{\tilde{V}}^{2}$ that meet the condition:

$$-\sigma_{\tilde{C}} < 1 < \sigma_{\tilde{C}}/\sigma_{\tilde{V}}^{2} \tag{26}$$

In the models estimated here, $\sigma_{\tilde{V}}^{2}$ is always larger than $\sigma_{\tilde{C}}^{2}$, such that the right hand inequality condition in (26) is not met and no analytical solution to the mean of the mixture distribution is defined. In effect, in the models estimated here, the right hand tail of the distribution does not converge to zero and the mixture distribution predicts positive probabilities to all values greater than zero (to a certain extent, this can be seen graphically in Figures 2, 4 and 6). To overcome this problem the mean of the distribution has been calculated through numeric integration. Using the Newton-Cotes algorithm the integral in (24) is calculated, integrating between 0 and the highest value on the payment ladder, £3,250. To ensure consistency in the reported results, the mean of the additive heterogeneity models are also calculated using numeric integration truncating the distribution at £3,250.

A further measures of the central tendency of the sample WTP is the median of the mixture distribution. The median measures the amount that half of the sample would be willing to pay. For the additive heterogeneity model the median is given by:

$$Median[C]=\Phi(\alpha)\cdot\exp\left(\Phi^{-1}\left(\frac{1}{2}\right)\cdot\left(\sigma_{\tilde{C}}^{2}+\sigma_{\tilde{V}}^{2}\right)^{\frac{1}{2}}+\eta_{\tilde{C}}\right) \tag{27}$$

and for the multiplicative heteogeneity model by:

$$Median[C]=\Phi(\alpha)\cdot\exp\left(\sigma_{\tilde{C}}\ln\left(\frac{2^{\sigma_{\tilde{V}}^{2}}-1}{\sigma_{\tilde{V}}^{2}}\right)+\eta_{\tilde{C}}\right) \tag{28}$$

Estimates of mean and median WTP are taken at the sample means of the regressors. A confidence interval for these estimates has been constructed using a bootstrap procedure. Each bootstrap sample is generated by drawing with replacement from the whole sample of households. For each bootstrap sample, the model is re-estimated and mean and median WTP computed. If a sufficiently large number of bootstrap samples are created, the set of generated estimated means or medians can be used to compute a bootstrap confidence interval.

The results of the estimated mean and median WTP measures are presented in tables 8, 9 and 10.

Table 8: Measures of WTP to Avoid COUGH Episode

WTP Measure	All	No Context Order I	No Context Order II	Causal Context	Causal & Policy Context
	(£)	(£)	(£)	(£)	(£)
Mean:					
MODEL 1: Additive Heterogeneity	*26.17*	***18.82***	*19.77*	*30.94*	*35.64*
	(3.01)	*(3.29)*	*(2.73)*	*(4.52)*	*(5.41)*
MODEL 2: Multiplicative Heterogeneity	*17.29*	*9.28*	*14.20*	*18.98*	*28.35*
	(1.97)	*(2.37)*	*(3.48)*	*(3.91)*	*(6.35)*
Median:					
MODEL 1: Additive Heterogeneity	*9.33*	*6.70*	*7.01*	*11.02*	*12.79*
	(.52)	*(.85)*	*(.69)*	*(1.15)*	*(1.54)*
MODEL 2: Multiplicative Heterogeneity	*10.47*	*7.22*	*7.77*	*12.67*	*14.57*
	(.62)	*(.93)*	*(.88)*	*(1.39)*	*(1.56)*

Table 9: Measures of WTP to Avoid BED Episode

WTP Measure	All	No Context Order I	No Context Order II	Causal Context	Causal & Policy Context
	(£)	(£)	(£)	(£)	(£)
Mean:					
MODEL 1: Additive Heterogeneity	*101.18*	***84.45***	*109.43*	*100.81*	*109.69*
	(10.19)	*(13.51)*	*(14.74)*	*(12.33)*	*(14.19)*
MODEL 2: Multiplicative Heterogeneity	*48.87*	*45.63*	*45.68*	*45.87*	*57.47*
	(4.55)	*(9.39)*	*(8.01)*	*(8.79)*	*(9.53)*
Median:					
MODEL 1: Additive Heterogeneity	*30.11*	*25.02*	*32.72*	*29.89*	*32.80*
	(1.61)	*(3.14)*	*(3.50)*	*(3.08)*	*(3.36)*
MODEL 2: Multiplicative Heterogeneity	*29.99*	*23.97*	*31.97*	*31.09*	*32.93*
	(2.25)	*(3.48)*	*(4.41)*	*(3.55)*	*(3.88)*

Table 10: Measures of WTP to Avoid HOSPITAL Episode

WTP Measure	All	No Context Order I	No Context Order II	Causal Context	Causal & Policy Context
	(£)	(£)	(£)	(£)	(£)
Mean:					
MODEL 1: Additive Heterogeneity	*231.23* (18.86)	***186.00*** (26.88)	*224.50* (27.62)	*259.01* (29.37)	*248.71* (28.35)
MODEL 2: Multiplicative Heterogeneity	*91.92* (8.08)	*77.00* (13.88)	*91.60* (14.67)	*88.50* (15.60)	*107.37* (15.01)
Median:					
MODEL 1: Additive Heterogeneity	*62.76* (3.64)	*49.20* (6.89)	*60.75* (7.33)	*71.79* (8.02)	*68.47* (8.11)
MODEL 2: Multiplicative Heterogeneity	*64.54* (5.14)	*47.70* (7.12)	*64.72* (8.97)	*72.83* (8.14)	*72.48* (8.47)

As we would expect from log-linear specifications of the mixture distribution, for both models and all episodes, median WTP is considerably lower than mean WTP. The mean is skewed to the right as a result of a proportion of the sample being willing to pay a relatively large amount to avoid the ill-health episode.

Whilst the medians of the additive and multiplicative models are in all cases very similar, the mean values for the multiplicative model are universally smaller than those estimated by the additive model. It would appear, that both models fit the mass of the data concentrated around the median relatively well, however, the multiplicative model only provides a poor approximation to the underlying data at higher values of WTP. As has been mentioned previously, the right hand tail of the distribution suggested by the multiplicative model is "thick"; the estimated distribution forces too much of the probability mass into higher values. By truncating at £3,250, a significant portion of the WTP distribution is ignored in the estimation of the mean from the multiplicative model, and the estimated values are, therefore, relatively low.

For this reason we concentrate on the results from the additive model in the following discussion.

The non-contextual means, as would be expected, are extremely similar to those calculated using a somewhat different modelling approach in Chapter ????. These values are highlighted in tables 8, 9 and 10. As way of comparison the equivalent figures in the previous chapter were; £19.89 (compared to £18.82, here) for avoidance of the Cough episode, £82.96 (compared to £84.45, here) for avoidance of the Bed episode and £163.90 (compared to £186.00, here) for avoidance of the Hospital episode.

Also, the non-contextual values with few exceptions, provide lower estimates of mean and median WTP than do the contextual values. Using the results of the bootstrap procedure, Table 11 presents results of a paired comparison of the means and medians estimated for the additive model. The figures in the table present tests of the two-tailed hypothesis that the means and medians of the non-contextual data (with episodes valued according to Order I – Bed, Hospital, Cough) are significantly different from those estimated for the other sub-samples.

Table 11: Probability that the Mean WTP and Median WTP of the Non-Contextual (Order I) Sub-Sample is different from those of the other Sub-Samples (highlighted figures are those significant at <5% level of significance)

	No Context Order II	Causal Context	Causal & Policy Context
Cough:			
Mean	*.770*	***.003***	***.001***
Median	*.780*	***.002***	***.000***
Bed:			
Mean	*.095*	*.251*	*.089*
Median	*.098*	*.274*	*.095*
Hospital:			
Mean	*.266*	***.031***	*.060*
Median	*.277*	***.035***	*.068*

Using the usual 5% level of significance, it is apparent from Table 11 that the Order of valuation does not significantly influence mean or median WTP for any of the episodes.

The same conclusion cannot be reached for the addition of contextual information to the valuation scenario. For the Cough episode, both the mean and median WTP are significantly larger when context is added. For the Hospital episode the same is true, but only for the scenario containing just causal context. On the other hand, the inclusion of richer context in the valuation scenario does not appear to significantly effect the mean or median WTP of the sample to avoid the Bed episode.

Clearly, the results in Table 11, suggest that the inclusion of richer contexts in the presentation of scenarios in contingent valuation exercises can significantly influence WTP for the avoidance of ill-health episodes. This would appear to be more apparent in the valuation of less severe ill-health events (Cough episode) than for those involving greater suffering and inconvenience (Bed and Hospital episodes).

Summary and Conclusions

This paper has examined two aspects of the contingent valuation of a series of ill-health episodes. First, whether the order in which the ill-health episodes are valued influences respondents' WTP to avoid those episodes. And second, whether respondents' WTP to avoid episodes of ill-health are influenced by the inclusion within the valuation scenario of contextual information concerning the cause of the ill-health episode or, alternatively, the cause of the ill-health episode and a policy package that would remedy that cause.

One of a number of responses to changes in valuation order or the inclusion of richer context were hypothesised,

- that respondents may become more or less likely to state a zero WTP for avoidance of an ill-health episode
- that respondents' WTP would shift up or down
- that respondents' would become more or less uncertain of their WTP

A general model of WTP in the face of respondent uncertainty was presented. From the general specification, two specific models were derived; the additive heterogeneity model and the multiplicative heterogeneity model. These models provide a rich framework in which to examine the responses of individuals to contingent WTP questions. Though both models gave qualitatively similar results, the additive model was shown to provide a better fit to the data especially in the right-hand tail of the distribution.

Though some qualitative evidence exists to suggest that more respondents rejected the contingent valuation scenario when context is added, this observation is not followed-up in this paper.

The inclusion of context or the changing of the order of valuation were shown to have no significant impact on either the probability that respondents would report a zero WTP or on the precision with which respondents stated their WTP. However, the results of the modelling exercise do provide evidence that WTP to avoid ill-health episodes may shift in response to changes in the valuation order or the valuation scenario context.

Bootstrap procedures were employed to test the hypothesis that the mean and median WTP of the sample changed significantly when the order of valuation altered or when context is added to the scenario. These tests reveal that the order in which the episodes were valued does not significantly change the mean or median WTP of the sample.

In contrast, significant increases in WTP were evident in the mean and median WTP of the sample when context is included in the valuation scenario. These shifts were most marked for avoidance of the Cough episode, the least severe of the ill-health episodes valued here.

The implications of these findings are twofold. First, the fact that the order of valuation does not significantly change respondents' WTP supports the use of multiple valuation exercises.

The second implication relates to the use of benefits transfer in project appraisal. Benefits transfer can only be considered a reliable tool if the WTP for a non-market good can be shown to be independent of the context in which the good is presented.

Since evidence is presented here that suggests that WTP may change with the introduction of context, doubt must be cast on the validity of transferring benefits across contexts.

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