Revealed Preference Valuation Compared to Contingent Valuation: radon-induced lung cancer prevention

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Introduction:

This paper explores and compares two methods of economic valuation, revealed preference and contingent valuation, with the purpose of ultimately informing the use of two tools of economic evaluation, CEA and CBA. The valuation methods are applied to radon-induced lung cancer prevention as a case study. The paper outlines the use of radon-induced lung cancer prevention data to examine the methods and the unique characteristics of the data sets, which make them particularly suited for use in these analyses. The data and studies referred to in this paper come from a larger work on economic analysis techniques applied to radon-induced lung cancer prevention (PhD thesis).

Comparing Valuation Methods

In the hierarchy of different types of validity for WTP methods, Mitchell and Carson (1989) and Hill (1988) suggest that construct validity is the most objectively determined type of external validity. This is true for all measured WTP welfare estimates since direct observation of the actual welfare change, the compensating or equivalent variation, is not possible (except perhaps in some experimental tests). Indeed, some environmental economists (Bishop, Champ and Mullarkey 1995; Hill 1988) have defined convergent validity for WTP measures as a comparison of a hypothetical, or contingent valuation, estimates with that which is derived indirectly from actual market observations, or revealed preference estimates. This is the situation faced with the estimates from the valuation studies encountered here.

Previous Studies:

Contingent valuation (CV) estimates have been compared systematically with travel cost method (TCM) estimates in the environmental literature. A meta-analysis of 70 studies was undertaken by Carson and colleagues in 1996. More recently they were also compared in a breast cancer mammography study by Clarke (1997). Carson and others found that the ratio of CV to TCM estimates was about .75. Clarke (1997) found a significant discrepancy between his CV and TCM point estimates[1] of approximately 1.6, which were opposite results from the Carson study. Hill (1988) was the first health economist to compare WTP results from a CV study to those from a similar RP study for breast cancer prevention through mammography. Similarly, he found the CV estimates to be about 1.5 times higher than the revealed preference estimates, and they were found to be significantly different. Where the CV estimates have been found to differ significantly from the revealed preference or travel cost estimates an implicit questioning of the external validity of CV methods has taken place. Revealed preference methods are sometimes thought to produced more 'truthful' and reliable estimates of WTP than stated preference (direct) or CV methods. CV estimates are thought to be more vulnerable to bias than indirect market-based estimates (Arrow et al 1993).

Below, two studies estimating valuations for life years gained from radon-induced lung cancer prevention are reported and discussed.

[1] 95% confidance intervals were also reported for these point estimates (Clarke 1998) based on the Duffield and Patterson (1991) approach.

Radon Gas:

Radon is a naturally occurring radioactive, odourless, colourless gas that usually arises as a decay product from trace uranium found in bedrock throughout the world. Most times radon poses no problem to people but when it enters buildings and concentrates there, it can pose a human health hazard. It is now known to produce an increased risk of lung cancer in those exposed (Darby et al 1998). Several regions throughout the UK have been identified as Radon-Affected Areas where indoor radon concentrations are of concern. These include for example: Cornwall, Devon, Northamptonshire, North-Oxfordshire, Aberdeenshire, and parts of Ireland. Relatively simple actions can be taken to remediate buildings against radon, thus reducing the risk to inhabitants of radon-induced lung cancer. Actual (indirect revealed preference) and hypothetical (direct contingent valuation) decisions regarding household radon remediation are studied here.

Revealed Preference

Indirect methods for willingness to pay valuations involve observing the behaviour of individuals in actual markets where goods or money related to health risks are traded. In this way, individual preferences are revealed *through* the market mechanism. One particularly useful indirect method of willingness to pay valuation is the revealed preference method where actual decisions on safety devices and risk averting intervention purchases in the marketplace are observed and WTP (Willingness to Pay) estimates are estimated. The risk reductions are purchased directly on a market for risk reduction devices. The purchase of radon remediation is an example of this type of decision used in estimating WTP (Akerman et al 1991).

There are two main problems in using risk averting behaviour observations in revealed preference: 1) differentiating between mortality and morbidity changes, and 2) deriving a complete demand profile from what is often a discrete decision to purchase a good at a single price. However, these two limitations can be overcome using the radon remediation data used in this study.

Limitations Overcome

The first of the two limitations alluded to above highlights the problem that often exposure to a risk results in both various morbidity and mortality from disease(s). For example, exposure to air pollution can cause or aggravate any number of adverse health outcomes (eg: asthma, chronic bronchitis, ect). Unlike general air pollution, radon exposure is proven to cause a *single* disease- lung cancer. Not only does radon only cause lung cancer, but lung cancer has particular prognoses that simplify the distinction between mortality and morbidity outcomes. The expected survival at two years post-diagnosis is 5%. The only morbidity associated with the disease is that experienced in the time around diagnosis and between diagnosis and death[2]. The fact that radon is known to cause only *one* disease simplifies the risk communication information used to inform the public about radon gas. It results in our ability to use absolute risk of radon-induced lung cancer estimates along side exposure levels. The poor survival prognosis upon diagnosis of lung cancer further simplifies the communication of radon risk to the public for economic valuation

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[2] Some health research scientists have argued that this morbidity impact may be large for that short time period (a measure of the median survival 2 years post-diagnosis was not available from OCIU, the most recently published survival figures also do not include the 95% confidence intervals but the 1999 survival estimates currently being calculated will be published with the 95% confidence intervals though they are not yet available (per com OCIU, Sandra Edwards)), however, no estimates exist for quality of life changes for the relatively short period between diagnosis and death for lung cancer

exercises because it is easy to approximate lung cancer diagnosis with mortality. The public is told that radon causes lung cancer which results in 95% of people with lung cancer dying in the first two years post-diagnosis. Social science researchers can then more easily infer from this situation that radon-induced lung cancer risk reduction actions are indeed approximately mortality risk reductions. So mortality risk reductions can be approximately inferred from observations of people valuing radon risk reductions[3].

The second limitation often facing revealed preference studies of health goods and services is that people either do not face any price for the goods or services (provided by the government or co-insured), or that if they do, they often face a single price for a good or service that is apparently indivisible. Neither of these describes the case in this radon study. The arrangement in the United Kingdom is that although there may be some government-sponsored radon testing in homes (free or subsidised), if an elevated radon level is found, the householder is solely responsible for any radon remediation costs[4]. Householders face many radon remediation options which all come at different prices. All produce a radon level reduction to some degree, they vary in effectiveness (Naismith 1999). This results in each household facing any number of prices for radon reduction, and the option of purchasing any level of radon risk reduction. One of the main assumptions here is that all the options are equal in

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(Guyatt, Feeny and Patrick 1993; Feeny, Torrance and Furlong 1996; Feeny, Furlong and Torrance 1999).

[3] In the radon case, the only option for reducing radon-induced lung cancer is some sort of radon remediation in the house. A fundamental restriction in the use of market-based data to derive WTP values is the assumption that radon remediation is *essential* to produce a reduction in risk of mortality from radon-induced lung cancer (Smith 1991, p.48). Other options of reducing lung cancer in general such as tobacco smoking cessation are ignored because information regarding this option was not included in the education materials sent to households in the sample. Smoking cessation, however, is accounted for in the CEA ratio comparison study included.

[4] Other European countries have established preferential loans and grant schemes for all homes that test over their Action level, for example Sweden and Switzerland (Akerblom 1999), but other than for those in council housing, no such schemes are known to have been successfully implemented in the UK.

their constituent attributes. In this study, all households upon testing over the action level, were provided information on the prices and costs of various remediation options.

The householders were faced with at least six prices for radon remediation. Indeed, they may have faced more, if the purchase of radon risk reduction is perceived as being on a continuous scale so that it was possible to purchase a completely divisible quantity of risk reduction using any remediation measure. By facing a decision between many different prices for remediation and the ability to purchase any amount of risk reduction (subject to the initial radon level in the home), it is possible to derive a mostly complete demand profile for radon risk reduction from this data and therefore estimate a more complete welfare change associated with the risk change.

Questionnaire and Sample:

A questionnaire was designed to gather information on householders' experiences with radon gas. The sampling relied on the assistance of the National Radiological Protection Board in the UK. The NRPB randomly chose 1000 records from their database of homes who had tested over the action level of 200 Bq m^{-3} between 1989 and 1998 in Northamptonshire (n=5461). They sampled with replacement for those homes which were sampled in the pilot survey (n=43) and for those who were known to have moved or deceased (n=41). These 1043 homes (the 43 from the pilot study and the 1000 from the NRPB database) were sent a postal questionnaire in the Spring of 1999. The response rate was 47%. Pre and post remediation radon levels were known from the NRPB database for all households in the sample, though not all homes were identified by address because of confidentiality requests. The full sampling protocol is available from the author.

Estimating the households' welfare change, or valuation of outcome, due to their purchase of a radon risk reduction can be done using the information collected in the household radon questionnaire. There are two models suggested here, one for estimating the WTP associated with the subjective measure of risk reduction, and the other associated with the objective risk reduction.

A household's decision to remediate or not can be described a binary good: to buy the remediation, or not to buy the remediation. For a divisible good, such as radon remediation, the prices paid for remediation can provide information on the benefits gained by householders of their purchase of the risk reduction. The change in benefits is the compensating variation (CV), the area to the left of the ordinary Marshallian demand curve between the start and end prices. Therefore, to quantify the welfare change associated with the purchase or not of radon remediation (risk reduction) a simple limited dependent dichotomous choice model specification can be chosen to predict the probability that an individual household would remediate given several characteristics. A binary probit model was chosen over the logit model here because the probit generally produces a slimmer tail, making the integration under the curve more precise (Greene 2000, p.815).

By using a probit model, each individual's equation for predicted probability of remediating can be estimated. By varying the cost parameter over the range of the pamphlet prices (remediation prices on the remediation options provided to the households at the time of testing), two points on the cumulative density function of the standard normal distribution for the average demand in the sample are pinpointed. From this average predicted probability demand curve, it is then possible to integrate under the demand curve to get the welfare change observed for the average individual in the sample. The average welfare change is calculated assuming that the individual welfare changes from the households can be aggregated simply.

Linear Specification

In order to estimate the linear specification, information on prices faced by the households was needed. This information was gathered in the sample by asking what households 'thought' they would have to pay for remediation[5].[6] In this way, a 'price' term was observed for all the households in the sample completing that question, including even those who did not remediate. Information was also needed on the risk reductions associated with the remediation (as an explanatory variable). Observations on subjective (perceived) risk reductions were available for all responding households; however, objective risk reduction observations were only available for those households who remediated.

Overcoming the partially observed objective risk problem

To overcome the problem of observing objective risk estimates on the remediators only, since only they have realised a risk reduction through remediation, an OLS-Probit, two-stage model (Madala 1983, p.240) was employed. The two stage OLS- Probit model used here is based on the approach outlined in Clarke (1998), where a two stage model is required, because travel costs have one of the same

[5] This is considered the appropriate price measure to use in the model since it is price on which the household based their remediation decision.
[6] There are several important decisions made about parameter specification: whether to use the subjective risk perceptions or the objective risk calculations, and whether to use what the households

limitations to risk reduction where they cannot be observed when an individual does not purchase the good. This allowed an OLS regression to be used to estimate a *predicted objective risk* for all the households in the sample from the remediator's information. The predicted risk variable is then included as an explanatory variable in the regular probit. The use of the predicted parameter in place of the actual (not available) introduces another source of random variation which affects the co-variance matrix of the probit. This can be corrected for using an adjustment procedure employed by Clarke (1998, p.776-777) given in Madala (1983, p.245).

Previous attempts in the literature

Akerman and others (1991)[7] simply estimated a binary logit explaining whether a household would be a remediator or a non-remediator. They found the median WTP estimate by solving for the cost variable where half the households would be induced to choose remediation and then calculated the implicit value of life using a Rosen (1988) and BEIR IV dose-response function. However, this method is not used here for two reasons: 1) actual observed costs, household characteristics and subjective risks are available in this sample and 2) the median has been found to be inferior to the mean as the best measure of WTP (Alberini 1995). It will be possible to estimate a model that gives a more accurate measure of welfare change and ultimately of the valuation of the radon risk reduction.

'thought' it would cost to remediate or what they actually paid, or what the pamphlet, sent to all households, estimated, based on the initial radon levels reported to the householders.

Estimation of the Models

As alluded to above, two different models were estimated, one each using the subjective risk reductions and the predicted objective risk reductions. Both models are presented in the following paragraphs, starting with the simpler of the two, the model using subjective risk reductions.

The Probit Model-using subjective risks

The dependent variable chosen was whether or not a household remediated indicated as Y=1 for remediating household, and Y=0 for a non-remediating household.

Choice of explanatory variables

Factors influencing the households' behaviour to remediate or not to remediate should conceivably be used in the model equation (on the right hand side), including a cost parameter and a risk parameter.

Comparing the results from several different variable and estimation specifications offers information about the true nature of the empirical modelling of revealed preference models in order to gain valuations of health and safety. This data set of radon remediation behaviour provides a unique opportunity for exploring such difficulties of consumer market based revealed preference, as have been highlighted by Johansson (1995) and Adamowicz and others (1999). Two models are reported below, a full model incorporating all hypothesised 'important' explanatory variables,

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[7] They did not have any remediation cost information and so constructed a cost variable from expert opinion.

and a reduced model incorporating only those parameters in the full model found to be significant at the alpha=.05 level.

Variable Specification:

The arithmetic means or the medians of the variables used in the model are listed in Table 1. The hypothesised (priors) signs on the coefficients are also given in table 1.

Model Specification:

Observed remediation decisions in a market context reveal information about individual preferences for radon-induced cancer risk reductions. A model of state-dependent utility is suggested to characterise the demand for risk reduction. A simple linear utility state dependent demand model for health from the purchase of radon remedial measures (remediation) was used. Assuming that the purchase of a radon remedial measure is the same as purchasing a preventive health measure, purchasing a preventive health measure means purchasing more life.

There are two options: remediate and reduce the risk of radon-induced lung cancer while incurring the remediation cost or, do not remediate and keep the risk of radon-induced lung cancer but not incurring the remediation cost. The probability of remediating depends on whether or not more utility is gained through the risk reduction or the remediation costs. In the probit model employed below, the probability of remediating is the cumulative density function for the utility from remediating being greater than the utility from not remediating, where both are a function of household income, household characteristics, remediation cost and risk reduction.

Explanatory variables:

The explanatory variables were: AGE (age of individual respondent[8]), COST (the total remediation cost the household faced (for the remediators it is what they actually faced and for the non-remediators it is what they thought it would cost, for those not answering the question the mean pamphlet cost was inputted)), lniLEVEL natural log of the initial radon level, INCOME annual household income (numerical income), LEDU level of education attained (categorical variable), DUMSMOKE=1 for if there is more than one smoker in the house, HEALTH self-reported health status[9], FAMLC=1 for if a family member has had lung cancer, DUMCHILD=1 for if there is more than one child in house, and FIREDET=1 if there is a fire detector in the home (for an indication of attitude towards reducing household risks).

(Probability of remediating Prob=1 or O) = f(age, lnilevel, cost, health, smoke, children, income, Leduc, famlc, firedet)

Table 1: Descriptives for Variables

Variable	Variable Description	Mean, Median or %	Standard Deviation or IQ ranges	Prior
COST	Expected remediation costs	670.02	553.42	-
AGE	Age of responder in years	55.14	14.52	? + or -
logilevel	Natural log of initial radon level (Bq m^{-3})	5.90 350.72 Bq m^{-3}	.48546	+
FAMLC	Dummy for family member	18% yes		+

[8] The variable for number of children in the household was not included in the model because it was too highly collinear with the AGE variable and caused problems of multicollinearity. A dummy for the presence or not of children was included.

[9] Other variables from the data set were also used in model specifications however none produced significant estimates. For example I included permutations of: dummies for fire detector, fire extinguisher, double glazing and central heating, family member suffered from lung cancer, age when left school, age of home, length of time in home (years) and social status measures.

	had lung cancer	82% no		
HEALTH	Self-reported health status	2 (good)	2,2,2	-
INCOME	Annual household income	21 561.59	11106.42	+
LEDU	Highest level of education attained	3	1,3,4	+
DUMSMOKE	Dummy for people if smoke in house	18.7% yes 80.7% no		+ or -
SUBJRISK	Subjective Risk Reduction	.0038895		+
FIREDET	Presence of smoke/fire detector	76% yes 20.9% no		+
DUMCHILD	One or more children in house	23.6% yes 73.9% no		+

The mean income was about £21 500 which corresponds to the 4th income category on the questionnaire. This shows how different this sample is with respect to the larger Northamptonshire population, where the mean annual income is £18 550. Also, the mean reported for the initial level of radon from this sample is 350 Bq m^{-3}, much higher than the mean for the Northamptonshire housing stock ~50 Bq m^{-3} (Bradley et al 1997)[10]. The log base 10 of the initial radon level was taken because radon measurements are distributed log-normally in regional surveys (Kendall et al 1994) and this transformation helped to achieve an approximately normal distribution.

Probability of Remediating: the influencing factors:

See Table 2 below for the probit model results. All models were estimated using LimDep Version 7.0.

[10] These two factors would generally lead one to expect an inflated WTP figure from this sub-sample compared to the true population WTP.

Table 2: The full and reduced probit models (subjective risk) of factors determining the probability of remediation against radon in the home

	Full Probit Model (n=134/326)			**Reduced Probit Model (n=138/326)**		
Variable	**Beta Coeff.**	**SE of coeff.**	**p-value**	**Beta-coeff.**	**SE of coeffi.**	**p-value**
lniLEVEL	1.17	.3235	.0003***	1.230	.3022	.0000***
COST	-.00171	.00049	.0004***	-.001566	.000450	.0005***
HEALTH	.5181	.2031	.20			
SMOKE	-.4794	.3563	.18			
INCOME	.000045	.000016	.0043***	.00003414	.0000128	.0077***
AGE	.034	.0138	.014**	.03509	.01054	.0009***
LEDU	.0421	.125	.735			
FAMLC	.341	.348	.326			
FIREDET	-.147	.345	.670			
DUMCHILD	-.014	.373	.969			
SUBJRISK	41.455	15.71	.0084***	42.32	15.23	.0055***
CONSTANT	-9.73	.2.26	.0000***	-9.08	1.999	.0000***

Notes Full:

-2*LL=128.44, so LL=-64.22

Notes Reduced:

-2*LL=141.52, so LL=-70.76

Stars indicate significance using a two-tailed t-test: ***=.01, **=.05, *=.10

Regression Diagnostics

Regression diagnostics are used to explore the results for any individual outlying observations that are having undue influence on the coefficients in the regression. Cook's regression statistics and leverage test were run on the regression (STATA 6.0 manual vol 3, p.199).

Two observations were found to have unreasonably high influence factors (Cook's statistic over 2). These two observations were examined and the outlying problem was found in the subjective risk variable for each. The first perceived a risk reduction of .10 and the second reported a very large cost associated with a minute perceived risk reduction.

Rejecting these two households increased the fit and the coefficients and their significance in the model up to 50 fold. The gains in the coefficients of the model were considered to outweigh the losses from increased variance due to a decrease in sample observations (from 140 to 138 households).

The fit of the model is considered as adequate for the purposes of the study. The models were tested for multiplicative heteroscedasticity (Greene 2000). The null hypothesis was homoscedasticity and all test statistics were below the critical values at an alpha=.05 level, so the null hypothesis was not rejected.

Results:

As the expected cost of remediation increased, households were less likely to remediate (statistically significant at the alpha= .01 level). This is an important finding if the economic theory validity of the model is to be preserved. As was expected, when annual household income was higher, households were statistically significantly more likely to remediate. But the elasticities were tiny.

The signs on the coefficients retain their meaning in a probit estimation. The sign on the AGE coefficient is positive and highly significant (alpha=.05 level), indicating that as the responder ages, the household is more likely to remediate. This may reflect Rosen's (1988) argument: "Older persons may nonetheless put greater value on some risks than younger people because the risk is more immediate"[11]. Although, Shepard and Zeckhauser (1982) proposed that the marginal rate of substitution follows an 'inverted U-shape', with a peak at 40 years and Jones-Lee (1985) confirmed this finding a peak at approximately 45 years, no evidence of a U-shape relationship is found here.

Initial radon level is influential, the sign on its coefficient is positive, so that as initial radon level increases, householders are more likely to be remediators. Similarly, as a household's perceived risk reduction from remediation increases they are more likely to remediate.

All the other coefficients on the explanatory variables were not found to be statistically significant at either the alpha= .01, .05 or.10. It is still possible to attempt to explain the direction of signs on the coefficients (to see if the hypothesised signs were correct), though no conclusions about the relationships are to be held up as true and fast as they are not statistically significant at the levels chosen before the analysis.

The coefficient for the HEALTH variable is as can expected, the better the health status, the less likely a household is to remediate. This may reflect that the person is at a sufficiently high health status as not to need to purchase more by way of remediating their home (threshold argument of Jones-Lee (1976)).

The sign of the coefficient on the education level variable was positive, so as education level increased, the more likely a household was to remediate. Education

[11] Regardless of how effective the risk reduction at that stage may be.

may act to influence the household's decision in terms of ability to learn about radon risks.

The variable, SMOKE, was included to capture overall household sentiments towards decisions about lung cancer risk. The sign on this variable's coefficient was negative, indicating that if a household has at least one smoker, the household was less likely to be a remediator. It could be that smoking households have less concern for lung cancer risk than non-smoking households, or that their attitudes towards lung cancer risks are fundamentally different.

Reporting that a family member had been diagnosed with lung cancer seems to increase a household's probability of remediating, though it is not significant. Fears about lung cancer are perhaps more honed in that group and so they possibly see radon remediation as an easy way to decrease the risk of lung cancer. A household was less likely to be a remediator if they had any children. This is contrary to what was initially expected based on the qualitative study, but it was not statistically significant coefficient. The presence of a fire or smoke detector was also not a statistically significant factor, where if a household had a detector, they were less likely to be a remediator.

Valuation estimates:

Where the consumer surplus, or compensating variation is defined to be the area under the demand curve, the integral value weighted for the marginal utility of money (as per Small and Rosen 1981 and the template LIMDEP code was developed by Clarke 1997) was found to be £697.29. This is the WTP for radon remediation. To change this into a value of a statistical life (VOSL) the amount is divided by the average lung cancer risk reduction in the sample (.003881) to give £179 688.81, or £13 300.43 per life year gained.

The OLS-Probit Model-using objective risks

This was a two-step model, where an OLS regression was used first to predict objective risk reduction for all households and then used as the risk variable in a probit model.

OLS-Probit Model:

The dependent variable for the OLS regression[12] was the objective risk reduction achieved by the remediating households. The explanatory variables chosen were age, family lung cancer, smoke, health status, expected cost and log of initial radon level. See Table 3 for a summary of the OLS results.

[12] OLS regression has been employed in many other WTP analyses of health interventions (O'Brien and Viramontes 1994; Berwick and Weinstein 1985; Johannesson et al 1993; Clarke 1998). But they did not have the problem of not observing WTP for the non-purchasers. The solution provided here for the problem of not observing any risk reductions for non-remediators is based on the travel cost work of Clarke 1998. The relationship between variables such as age, income, baseline risk and health status and WTP have been explored in other studies (Jones-Lee 1985). Theoretical predictions on the signs have been made and are included in the discussion below.

Table 3: The OLS model to predict objective risk reduction (n=309)

Variable	Beta Coeff.	SE of coeff.	Mean	p-value
lniLEVEL	.021866	.00269	5.85	.0000***
COST	-.000002316	.00000229	671.76	.3121
HEALTH	.0008239	.001942	2.0	.6717
SMOKE	-.002306	.003529	17%	.5140
AGE	-.0001954	.0000940	58.40	.0385**
FAMLC	.006021	.003805	12.95%	.1146
CONSTANT	-.11030	.1634		.0000***

Notes OLS:

R-squared=.194

Stars indicate significance using a two-tailed t-test: ***=.01, **=.05, *=.10

Probit Model:

The dependent variable for the probit was the same as above whether or not a household remediated indicated as Y=1 for remediating household, and Y=0 for a non-remediating household.

Explanatory variables:

The explanatory variables were also the same as above, except that subjective risk reduction was replaced by a vector of predicted values for objective risk reduction. See Table 4 for the model results.

Table 4: The Reduced Probit model using predicted objective risk reduction (n=294)

Variable	Beta Coeff.	SE of coeff.[a]	Mean	p-value
lniLEVEL	-1.948	.7936	5.85	.0141**
COST	-.001341	.000264	675.79	.0000***
AGE	.03861	.009670	57.943	.0001***
OBJRISK	129.29	36.311	.009847	.0004***
INCOME	.00004322	.00000896	19 050.676	.0000***
CONSTANT	7.4358	3.960		.0604*

Notes:

-2*LL=307.36 or LL=-153.87

Stars indicate significance using a two-tailed t-test: ***=.01, **=.05, *=.10

[a]These are the unadjusted SE and significances. Madala's adjustments to the standard errors to get the true asymptotic covariance matrix involve complex matrices manipulation (see Madala 1983, p.245). The coefficients are correct and do not require adjustment. It is only the coefficients which are used to calculate the WTP estimates, so the SE adjustments were not calculated here.

Discussion:

The fit of the model is poor with a very large log-likelihood (-153.87). All the signs on the coefficients are the same as in the subjective risk model, except the sign on the log of the initial radon level which has become negative, indicating that as the initial radon level increases the household is less likely to remediate. This is contrary to the prior hypothesis. This model was estimated on many more households (n=294) than the subjective risk model (n=138) because of the use of predicted values for objective risk reduction. The inclusion of the predicted values in place of the unknown true values may have influenced the probit results.

Welfare estimates:

The integral value was weighted for the marginal utility of money (as per Clarke 1997, after Small and Rosen 1981) and was found to be £458.84. This is the WTP for radon remediation using the predicted objective risk reduction. To change this into a value of a statistical life (VOSL) the amount is divided by the average lung cancer risk reduction in the sample (.009847) to give £46 597.77, or £3 449.13 per life year gained.

Confidence Intervals for the mean WTP estimates

The 95% confidence intervals for the WTP estimates were calculated as the parameter estimates used to calculate the welfare measures are random variables. Duffield and Patterson (1991) suggest a method for calculating the confidence intervals using the bootstrapping method. And following Clarke (1997, p.169)[13], this method was employed here for both the subjective risk and objective risk mean WTP welfare estimates (and for the welfare estimates from the contingent valuation study in the next chapter). The predicted-Y, or predicted probabilities of Y=1 were calculated using the main regression model (usually a probit). Then a new dependent variable is formed by randomly drawing from the binomial distribution for each household. The model is re-estimated using the new dependent variable and the welfare estimate is calculated. Done for large numbers of replications (500), this produces a vector of 500 WTP estimates from which the 95% confidence interval is given by dropping 13 (=(500(1-.05)/2)) observations at either tail of the distribution. For the subjective risk mean WTP estimate of £697.29 the 95% confidence interval

[13] Clarke granted the author access to his LIMDEP codes used for the bootstrapping process and these provided the template for the confidance intervals calculated here.

was (£558.041, £957.907). For the objective risk mean WTP estimate of £458.84 the 95% confidence interval was (£375.831, £551.130). These are interpreted as amounts per life year gained

Which WTP estimate to use?

The ability to calculate two mean WTP per life year estimates from the same revealed preference data opens up a whole new dimension to the subsequent analyses where the valuations will be compared with those found in the contingent valuation study and then used to calculate cost-benefit analyses.

Contingent Valuation Study

Sample

The study was conducted amongst residents in a radon affected area on the border with Northamptonshire. Residents of the Banbury Area in North Oxfordshire were targeted. Anyone living North of Deddington (inclusive of the village of Deddington) and South of Daventry were deemed to be living in the Banbury area for the purposes of the study.

Viscusi (1998) had described the use of a convenience sample generating strategy that produced close to a population representative sample. Viscusi has used this type of strategy for contingent valuation studies for the purpose of value of a statistical life generation many times (for a review of the studies see Viscusi 1998). It involved setting up a table in a shopping mall and approaching passers-by. Interviews would be conducted standing in the mall hallway. This strategy was chosen for this study due to its similarities to Viscusi's risk work. All passers-by would be approached by the interviewer(s) and asked "Were they from the Banbury area?". Those stating yes were subsequently told that the interviewer was a researcher conducting a survey about radon gas among residents from the Banbury area and that the survey involved a few questions that would take no longer than 3-5 minutes to complete. If the person stated that they were interested, the interview was begun as per the questionnaire.

The final revised wording of the first WTP question was:

Imagine that your own home is tested for radon and the level is found to be at 400 Bequerels per meter cubed (twice the recommended action level). Your extra risk of developing lung cancer due to radon would be about 2 in 500. Would you be willing to pay _____ for radon remediation in your home that would reduce the radon concentration to 200 Bequerels per meter cubed and reduce the risk of developing radon caused lung cancer by half to 1 in 500?

The question was then followed by an appropriate bid-level follow-up. If the respondent answered yes they were asked a second question: Would you be willing to pay ____ ?, where the bid was slightly higher than the first bid. If they answered no to the first bid, a second, slightly lower bid was presented. The magnitude of the difference between the first and follow-up bids was approximately 50% (or £150 either way), this was set based on the need for the follow-up bids from the first bids to overlap, or at least cover the amounts in between each bid interval.

Selecting First Bids:

The selection of starting bids in a contingent valuation study has always proved problematic in empirical studies (Carson and Mitchell 1989). Ideally, the 'true' WTP estimates could be known and then the range of bids chosen could be distributed symmetrically (or non-symmetrically, depending on the parameter you wish to minimise) around the ‘true’ value (Albertini 1995a and b)[14]. If the ‘true’ mean or median WTP value is not known, then the researcher must chose a set of bids that may be expected to encompass almost all the preferences of the surveyed population. In this study, the starting bid vector for the WTP estimates were the observed estimates from the revealed preference study at the 25%, 50%, and 75% interquartile ranges (as per the recommendations of Albertini (1995b) and Nyquist (1992). These were: 227.22, 392.21, and 699.21, respectively (for those who remediated).

The estimates from those that remediated were chosen over the full sample because of plausibility. The estimates from the whole sample provided estimates that were far below the price that would be faced for a reduction from 400 to 200 Bq m^{-3} in any real setting. For example, it would be practically impossible to achieve a successful 200 Bqm^{-3} reduction with an expenditure of less than £100 on remediation[15].

The bid vector used for the first 31 respondents was therefore: £250, £400, and £700. A random list consisting of 50 of these three bids was generated using Excel. The bids were entered onto the questionnaires and administered according to the order on the list. The questionnaires were used consecutively as each respondent was approached (questionnaires were not presented to non-responders because they refused to take part). Optimal design strategies for contingent valuation studies can be enacted as an iterative process, and this was the format employed here (details available from author). After the initial bid vector was used for the first 31 respondents a review of the demand curve was made and it was determined that two

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[14] The sensitivity of the models to assumptions about the distributions of WTP is well documented in the literature (Carson et al 1996; Albertini 1994).

other bids should be added to the vector in order to get better estimates in the tails of the distribution. Two bids (£100 and £1500) were therefore added to the bid vector. These did seem to improve the responses and information for the tails of the distribution (a high bid acceptance rate for the £100 bid and a low acceptance rate for the £1500 bid).

A second, more technical review[16] was made after 80 surveys had been completed. At this stage, an optimal design model for minimising the variance on the truncated mean estimate of WTP (thus maximising efficiency, and minimising bias) was applied to the data (as described by Duffield and Patterson 1991). A final sample size of 150 observations was chosen (due to budgetary constraints and based on sample sizes for other contingent valuation studies undertaken in health fields (Donaldson 2000)).

Responses and Analyses

Bid responses

Table 5 lists the responses to the initial and follow-up bid questions as well as the true zero questions. For example, if someone was faced with an initial bid of £400 and if they accepted the bid, they were then asked if they would be willing to pay

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[15] This is why in the third follow-up question a smaller risk reduction was described (do it yourself sealing cracks in the basement).

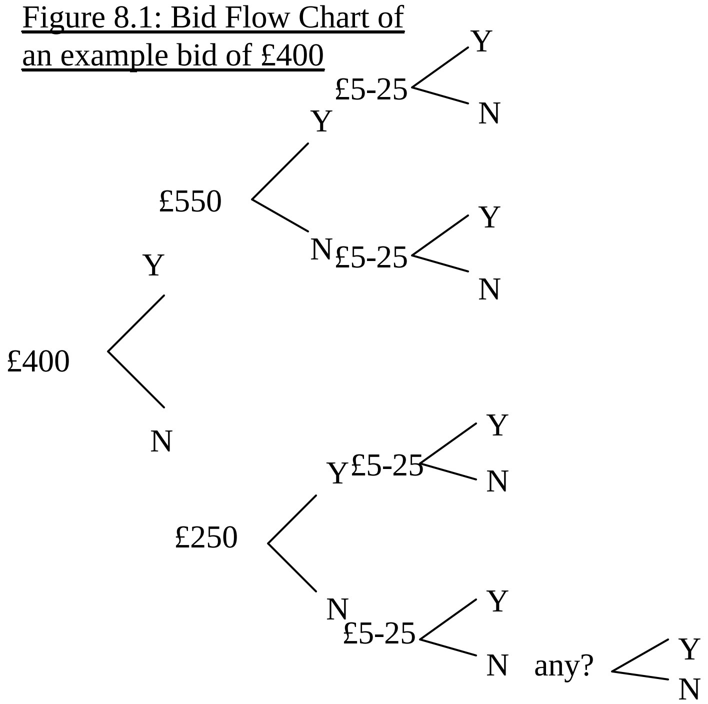
[16] Based on the model of Cochrane (1963), the optimal sample size (n_b) for each bid (x_b) was calculated. Where N is the total sample size, p_i is the probabilities of positive responses, and the subscript b indicates an individual bid parameter and subscript g indicates the rest of the vector of bids.

$$n_b = N \frac{x_b\,[p_b(1-p_b)]^{1/2}}{x_g\,[p_g(1-p_g)]^{1/2}}$$

The results from this exercise were as follows (rounded up to whole numbers):
Bid £100 = 16
Bid £250 = 21
Bid £400 = 39
Bid £700 = 36
Bid £1500 = 38
These results indicated that more observations were needed in the three largest bids and the number of surveys used in the subsequent collection used primarily the largest three bids. However, a truncated

£550. Each initial bid was followed by either a higher (or lower) bid depending on if the person had accepted (or rejected) the initial bid. All persons were then asked if they would be willing to pay a smaller (£5-£25) amount of money for a smaller (1/8 decrease) risk. All those responding ‘no’ to the previous three bid questions were then asked if they would be willing to pay anything to reduce radon in their home, those responding no were interpreted as expressing a true willingness-to-pay of zero. Those who responded that although they were not willing-to-pay a small amount like £5-£25 for a small reduction, they would pay ‘something’. The ‘something’ was interpreted as greater than zero, but less than £5 for a 1.25/5000 risk reduction (1/8 of the risk reduction presented in the initial WTP question). See Figure 5 for a diagrammatic explanation example of bid responses.

Figure 8.1: Bid Flow Chart of an example bid of £400



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mean would not be used in the analysis so the calculated sample sizes were only used as a guide and not followed exclusively.

The last option point, after saying no to all bids, is the ‘pay anything?’ question.

Table 5: Summary of responses to the WTP questions

	Initial Bid Response		%	Follow-up Bid	Response		%	Small Amount?		Anything (yes)	True Zero
£100	Yes	8	67	£250	Yes	4	50	Yes 4	No 0		-
					No	4	50	Yes 2	No 2		-
	No	4	33	£50	Yes	0	0	-	-		-
					No	4	100	Yes 1	No 3	0	3
£250	Yes	17	54.8	£400	Yes	9	53	Yes 5	No 4		-
					No	8	47	Yes 4	No 4		-
	No	14	45.2	£100	Yes	8	57	Yes 8	-		-
					No	6	43	Yes 3	No 3	1	2
£400	Yes	18	51.4	£550	Yes	9	50	Yes 7	No 2		-
					No	9	50	Yes 6	No 2		-
	No	17	48.6	£250	Yes	3	17.6	Yes 1	No 2		-
					No	14	82.3	Yes 9	No 6	1	5
£700	Yes	14	35.9	£1000	Yes	6	42.8	Yes 5	No 1		-
					No	8	57.2	Yes 6	No 2		-
	No	25	64.1	£550	Yes	2	8	Yes 2	-		-
					No	23	92	Yes 14	No 9	2	7
£1500	Yes	2	8	£1750	Yes	1	50	Yes 1	-		-
					No	1	50	Yes 1	-		-
	No	23	92	£1000	Yes	1	4.3	Yes 1	-		-
					No	22	95.7	Yes 17	No 4	0	4

Parametric Analyses

Model

The questionnaire was designed to be able to calculate a double bounded model. Economists, for example Calia and Strazzera (2000), have summarised the advantages and disadvantages of the single bound (SB) versus double bound (DB) methods for generating WTP welfare amounts. DB is more efficient but has the problem of requiring the assumption that the probability of refusing the follow-up bid is independent of the magnitude of the initial bid (i.e. that for both questions there is a single underlying valuation process). This assumption can be tested for using the parametric test outlines in Hanemann and Kanninen (1999) and is done so in a section below. The structure of the analysis of this contingent valuation data follows that of Clarke's (2000) contingent valuation study of mobile mammography units[17], starting with the single-bounded model, employing the same parametric test for consistency, through the double-bounded model.

WTP Estimates from a contingent valuation study:

Three estimates of the WTP for radon remediation risk reduction were made. Firstly, a non-parametric estimate of median and mean was made based on the initial bid question. Secondly, a parametric single-bounded model was estimated using information on the acceptance or rejection of the initial bid. And finally, a third model, a one-way resentment double-bounded model, was estimated using the information on both the initial bid and the follow-up bid.

The same linear specification as used in the revealed preference study is used here. It allows the bid(s) to be included as an explanatory variable for behaviour in a probit model. The probability of accepting a bid is therefore specified as a function of the change in welfare which is a function of many characteristics. All households can be assumed to draw their WTP from an approximately similar distribution, save for differing incomes and experiences (including family member ages).

[17] Indeed, whole portions of Clarke's LIMDEP code template were used in both the single-bounded and in the double-bounded analysis that follows.

Single-bounded Model

The dependent variable is equal to one if the respondent accepted the initial bid, and zero otherwise. See table 6 below for a description of the variables used in the models (both full and reduced). Observations on 142 households were available for all variables, except income, where one household refused to answer that question. The sample size, therefore, for the single-bounded full model was n=141, but it was n=142 for the reduced model.

Table 6: Descriptives for Variables

Variable	Variable Description	Mean, Median or %	Standard Deviation or IQ range	Prior
DUMRADON	Dummy=1 if person had heard of radon and could describe it	49.3% yes 50.7% no		+
BID	Value of the initial bid	617.96 median=400	451.88 250,400,700	-
PEOPLE	Number of people in the household	2.70	1.30	+
HSTATUS	Self-reported health status	Median= 2 (good)	2,2,2	-
LCHANCE	Chance of developing lung cancer	Median =1 (average)	1,1,1	+
POSTSEC	Dummy=1 if postsecondary or vocational training reported	38.7%		+
DUMSMOKE	Dummy for people if smoke in house	52.1% yes		+
AGE	Respondent’s age	41.57	17.39	+
INCOME	Household income	£18 078.01	£10 286.83	+
DUMTEST	Dummy=1 if household has tested for radon gas	27.5% yes		+

The variables chosen are similar to those chosen for the revealed preference probit analysis and the priors on the explanatory variables are the same.

Income Variable Assumptions:

Assumptions surrounding the appropriateness of including the income term as an explanatory variable in the linear specification versus a Box-Cox specification was tested using a likelihood ratio test of the two models (proposed by Gertler et al 1987 but first employed in this way by Clarke 2000). The LIMDEP code used for the specification test was based on the template designed by Clarke 1997. Lamda was found to equal .93662 and the Chi-squared test was below its critical value, indicating that the income term is fine in the linear specification. Regardless, the income term was not found to be significant at the alpha=.10 level in the full model and was therefore not included in the final reduced model.

Table 7: The full and reduced probit models (subjective risk) of factors determining the probability of remediation against radon in the home

Full Probit Model (n=141)				**Reduced Probit Model (n=142)**		
Variable	**Beta Coeff.**	**SE of coeff.**	**p-value**	**Beta-coeff.**	**SE of coeffi.**	**p-value**
CONSTANT	-.5315	.8394	.5266	.0846	.2315	.356
DUMRADON	.02353	.2680	.9300			
BID	-.00143	.000351	.0001***	-.001549	.0003343	.0000***
PEOPLE	.0271	.1150	.8141			
HSTATUS	.0561	.1771	.7512			
LCHANCE	-.1022	.1384	.4603			
POSTSEC	.4782	.2694	.076*	.5352	.2463	.0298**
DUMSMOKE	.7567	.2605	.0037**	.6992	.2399	.0036***
AGE	.00128	.00908	.8883			
INCOME	.0000150	.000013	.2467			
DUMTEST	.3722	.2956	.2079			

Notes Full:

Log-Likelihood=-77.11

Notes Reduced:

Log-Likelihood=-79.52

Stars indicate significance using a two-tailed t-test: ***=.01, **=.05, *=.10

Single-bounded Model Results

The results of the single-bounded probit model are presented in table 7.

Welfare changes:

Using the cumulative distribution function(s) for each individual in the model, it is possible to calculate the compensating variation (CV) of an individual household. The method is similar to that employed in Clarke (2000). The mean WTP is calculated by estimating the integral under the probability of accepting the bid curve for the positive range of WTP[18]. The cumulative density function (cdf) was truncated at £1750 since only one respondent accepted this bid (in the follow-up). The mean WTP calculated using the single-bounded model was £538.83.

Double-bounded model

Format:

Using the information from both the initial and the follow-up questions a double-bounded model is estimated. Using the following formulations outlined in Hanemann and Kanninen (1999, p.379), the mean WTP was estimated. The respondent's answers to both questions fall into one of the following four intervals:

0-£Bid_{min}	(no/no)
£Bid_{min}-£$Bid_{initial}$	(no-yes)
£$Bid_{initial}$-£Bid_{max}	(yes/no)
£Bid_{max}-	(yes/yes)

[18] This type of calculation assumes that WTP is non-negative and this can lead to problems (see Johansson, Kristrom and Maler 1989). Two other models were put forward by Clarke (1997), the log-normal model and the spike model. These are not estimated here since it is highly unlikely that households have a negative WTP for radon remediation risk reductions.

And the double-bounded response probability formulas take the following forms where K is a vector of explanatory characteristics from the linear specification:

Prob(yes/yes) = (U(Bid_{max},K)
Prob(yes/no) = (U($Bid_{initial}$,K)- (U(Bid_{max},K)
Prob(no/yes) = (U(Bid_{min},K)- (U($Bid_{initial}$,K)
Prob(no/no) = 1- (U(Bid_{min},K)

This type of model is an interval data probit model (Alberini 1995). See table 8 below for a description of the dependent and explanatory variables used in the model.

Table 8: Descriptives for Variables used in the DB Model and the Bivariate Probit Models

Variable	Variable Description	Mean, Median or %	Standard Deviation or IQ range
BIDFUP	Value of follow-up bid	554.93 median=550	345.55 250,550,1000
BID	Value of the initial bid	617.96 median=400	451.88 250,400,700
POSTSEC	Dummy=1 if postsecondary or vocational training reported	38.7%	
DUMSMOKE	Dummy for people if smoke in house	52.1% yes	

Assumption Problem:

Before the double-bounded model could be estimated, a test of consistency was performed (Clarke 1997). One of the assumptions implied when employing the double-bounded model is that the responses from the initial bid and the follow-up bid come from the same stochastic process. This would mean that there is no anchoring problem in terms of whether the follow-up bid is higher or lower than the initial bid. The validity of this assumption can be tested two ways: using a non-parametric test to test for the consistency of the responses (Clarke 1997 after Hanemann and Kanninen 1999), or using a parametric test treating the answers to the two bids as related goods and employing a bivariate probit analysis where the linkages between the two bids are taken into account (Cameron and Quiggin 1994). The later test was employed here, as the first kind of test can only be employed where there are overlapping bid vectors.

The results from the bivariate probit models are reported below in table 9. The dependent variables were initial bid (1=yes, 0=no) and follow-up bid (1=yes, 0=no). To test if they are actually from the same underlying stochastic process (distribution) a likelihood ratio test was used. The null hypothesis in a likelihood ratio test (LR) (Greene 1998, p.165) is that the two models have the same underlying stochastic process. The first bivariate probit is estimated and then a restricted version of the bivariate probit, where the coefficients are constrained to equal the first model, is estimated. The LR test of the first model (log likelihood function=-153.69) versus the restricted model (log likelihood function=-182.79) produced a Chi-squared test statistic of 58.21, far above the critical value at the alpha=.05 level. The null hypothesis that they had the same underlying process was rejected. The probability of accepting the bid differs between the initial and follow-up question. This result is similar to that found by Clarke (1997) in his study of mobile mammography screening.

Table 9: FIML Results for the Bivariate Probit Models (n=142)

Bivariate Probit Model				Restricted Bivariate Probit Model		
Variable	**Beta Coeff.**	**SE of coeff.**	**p-value**	**Beta-coeff.**	**SE of coeffi.**	**p-value**
1[a]CONSTANT	.02897	.3571	.9353	-.5103	.1380	.0002***
1BID	-.00108	.00109	.3262	-.000178	.000225	.4288
1POSTSEC	.4709	.3184	.1391	.2850	.1356	.0355**
1DUMSMOKE	.5587	.3355	.096*	.2126	.1352	.1157
2CONSTANT	-1.013	.2574	.0001***	-.5103	.1380	.0002***
2BID1	.005563	.00385	.1486	-.000178	.000225	.4288
2POSTSEC	.4127	.4618	.3715	.2850	.1356	.0355**
2DUMSMOKE	-.6903	.7875	.3807	.2126	.1352	.1157

[a]1 or 2 indicate equation number in the bivariate probit.

Notes Full:
Log-Likelihood=-153.69
Rho=-.5139 (.3665)

Notes Restricted:
Log-Likelihood=-182.79

Stars indicate significance using a two-tailed t-test: ***=.01, **=.05, *=.10

Inconsistency detected: solving the problem

There are several ways to overcome the problem of inconsistency, described by both Hanemann and Kanninen (1999) and Alberini and others (1997). Given the assumption problem, it may be better to simply take the single-bounded estimate as the mean WTP. Otherwise, it may still be correct to pool the first and second bids despite the inconsistency because although it produces biased coefficient estimates, it may also provide a gain in efficiency (Alberini 1995b). Indeed, this is echoed in the view of Hanemann and Kanninen (1999, p.388)

> we would recommend using the double-bounded model approach, even if it produces some bias compared with the single-bounded approach, the experience to date generally suggests that the bias is in a conservative direction and is greatly outweighed by the gain in efficiency in terms of minimizing overall mean squared error.

Resentment Model:

Another way of looking at this situation is to consider that this effect is produced because the follow-up question comes either as a surprise to the respondent, or that the respondent feels challenged by the follow-up question to assert their feelings expressed in the initial question. The respondent may feel resentment towards being asked a larger (smaller) bid after their initial answer is given as ‘yes’ or ‘no’ (Hanemann and Kanninen 1999). The resentment model was first employed to health interventions by Clarke (1997). The second bid may lead to a shift in the location parameter of the WTP distribution making the second response.

This can be modelled using the Cameron-Quiggin model (1994) where a background disposition to say ‘no’ is included for the second response. The background probability of saying ‘no’ if they answered ‘yes’ to the initial question is $_u$ and the background probability of saying ‘no’ if they answered ‘no’ to the initial question is $_d$. According to Hanemann and Kanninen (1999), under a resentment hypothesis, $_u$>0 and $_d$ >0. It was expected that this sample would exhibit $_u$-type of resentment (based on the results of other contingent valuation studies such as Clarke 1997; Alberini et al 1997). A one-way resentment model for the double-bounded model is estimated below[19].

[19] A two-way model was also attempted to confirm that $_d$ would not be significant but the model would not converge even after scaling the bid values four ways, changing the start values and going to 200 iterations.

Double-bounded Model Results

The results of the model are presented in table 10 below[20].

[20] The LIMDEP code templates used were written by Clarke (1997).

Table 10: Results for the One-way u Double-bounded Probit Model (n=142)

Variable	Beta Coeff.	SE of coeff.	p-value
CONSTANT	1.280	.4578	.0052***
BID	-.00198	.000610	.0012***
POSTSEC	.8663	.3912	.0268**
DUMSMOKE	.9229	.3584	.0100***
u	.4973	.06802	.0000***

Notes:
Log-Likelihood=-92.64

Stars indicate significance using a two-tailed t-test: ***=.01, **=.05, *=.10

Valuation:

The mean WTP calculated using the one-way resentment double-bounded model was £766.75.

Confidence Intervals for the welfare estimates:

The 95% confidence intervals for the single-bounded model mean WTP and the one-way double-bounded mean WTP were calculated as per the revealed preference estimates using the bootstrap technique. For the SB mean WTP estimate of £538.83 the 95% confidence interval was (£402.34, £685.03). For the one-way double bounded model mean WTP estimate of £766.75 the 95% confidence interval was (£610.899, £877.892).

Limitations:

Most environmental studies comparing two valuation methods apply the two methods to the same sample population. However, in this study it was not possible to identify most of the householders who received the questionnaire (confidentiality requirements) and it was not feasible to re-interview those who had responded for the CV study (no identifying information was collected in order to increase response rate). Efforts were made to sample very similar random population samples for both the CV and the RP studies. The degree to which this effort succeeded is evident in the similar descriptive statistics available for the samples[21].

The mean income of the two samples was very similar, at £18 078 (CV) and £19 016 (RP). These span the actual mean income level of the county of £18 855. The self reported health status and gender profiles were also very close in each group. The variables on which the two samples differed considerably were in mean age, socio-economic profile and the percentage of homes with at least one smoker. The mean age in the CV sample was 41.57 years, much younger than that for the RP sample at 58.41 years. The potential impact of this difference depends on if age factors in the valuation process. From the regression analyses done in chapter 7 and 8 age is not a variable that remains important in the analyses. Similarly, the socio-economic profiles are not included in the valuation regressions. There were many more retirees in the RP sample (48.5%) than in the CV sample (16.2%) and double the percentage of post graduate-educated people in the RP sample. The percentage of homes with at least one smoker was very different for the two samples (52% in CV and 17% in RP), and they both differed greatly from the county average percentage of 28%. The two samples were obviously not the same in composition, but were they similar enough in order to compare their valuations? It is assumed here that they are and the test for convergence of the valuation estimates is undertaken below.

[21] Though not all important statistics were known for all the respondents and non-respondents in each of the samples, such as radon testing, or radon levels (CV sample).

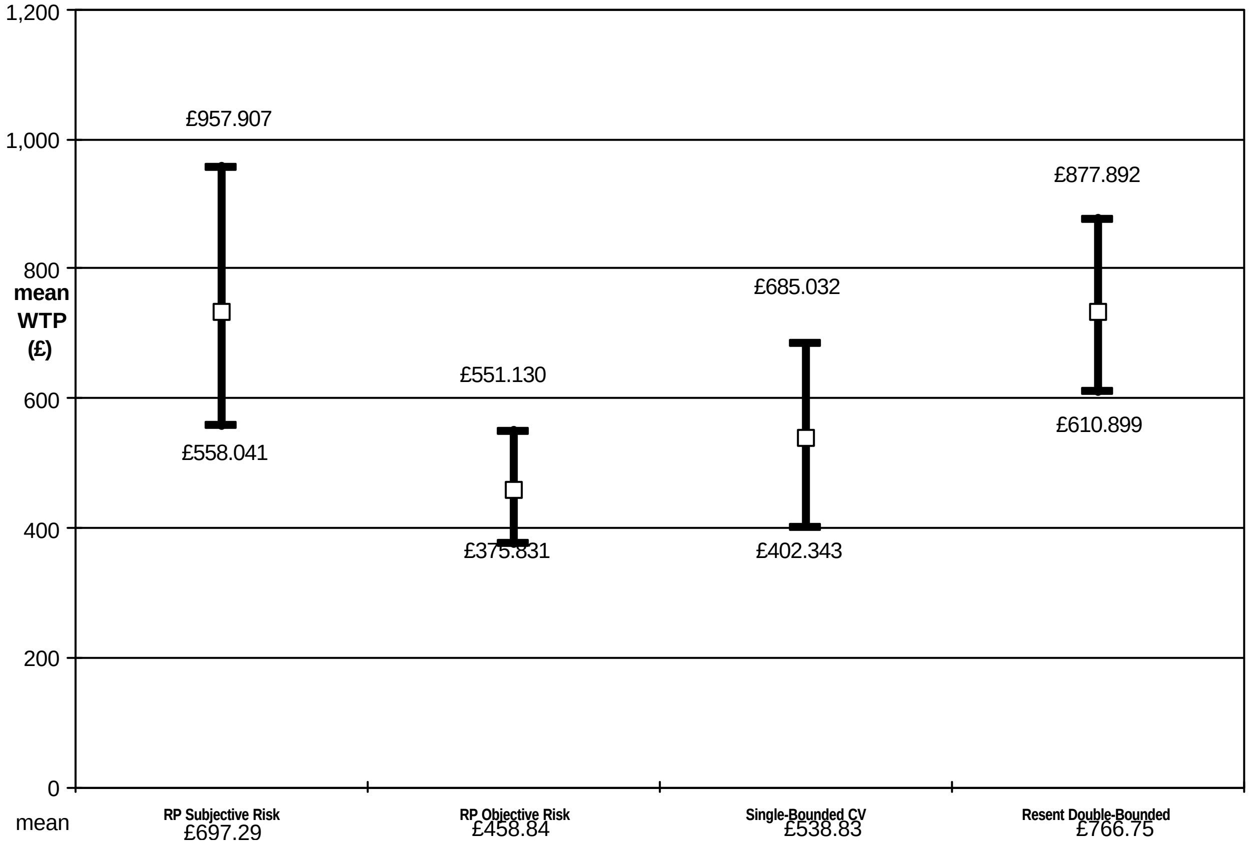
The CV study did not include identification/measurement costs and neither did the RP since in both instances they were free to the householders (NRPB study). But in time, the free testing as part of the pilot studies will end[22] and householders will be responsible for testing costs. This will result in this study being an underestimate of value if householders and/or government are forced to pay more for the same risk reduction.

Hypothesis testing for convergent validity of the RP and the CV methods

See Figure 6. The RP subjective risk mean WTP and the RP objective risk mean WTP are not equal at the alpha=.05 level (their 95% confidence intervals (CI) do not overlap). However, the 95% CI's for all the mean WTP estimates from the RP and the CV methods and models do overlap indicating that they are statistically similar, except the objective risk RP estimate and the one-way double-bounded model estimate.

[22] As it did in some parts of Northamptonshire in 1999.

Figure 6: Mean WTP estimates and their 95% CI's



Discussion and Conclusion

The difference between the objective and subjective risk RP estimates can be found in the very different risk estimates used. The difference found between the RP subjective risk estimate and the one-way double-bounded (DB) model estimate is not as easily explained.

The two most theoretically defensible estimates are the RP subjective risk valuation and the DB model estimate, as they come theoretically closest to capturing the consumer preferences for radon risk reductions on which people base their remediation decisions (if consumer sovereignty is upheld). The question remains whether or not the objective or the subjective RP estimates should be used in the economic evaluation(s) when they are to be used to inform public policy decisions (use what people think is true as opposed to what scientists know is true with regards to risk). Both valuation methods have produced similar results, indicating that they do hold some external validity as assessed by convergent validity.

References:

Adamowicz, M.L. Boxall, P.C. Louviere, J.J. Swait, J. and Williams, M. (1999) "Stated-Preference Methods for Valuing Environmental Amenities" in *Valuing Environmental Preferences*. Bateman I.J. and Willis K.G. (eds.) pp.460-482, OUP:Oxford.

Akerblom, G. (1999) "Legislation on Radon", *Radon in the Living Environment' International EC Directorate General for Science, Research and Development Radiation Research Unit Workshop* National Technical University of Athens: Athens, Greece.

Åkerman, J. Johnson, F.R. and Bergman, L. (1991) "Paying for safety: Voluntary reduction of residential radon risks", *Land Economics*, 67, pp. 435-46.

Alberini, A. (1995a) "Optimal designs for discrete choice contingent valuation Surveys: Single-bounded, double Bounded and bi-variate models", *Journal of Environmental Economics and Management*, 28, pp. 287-306.

Alberini, A. (1995b) "Efficiency vs Bias of Willingness to Pay Estimates: Bivariate and Interval Data Models", *Journal of Environmental Economics and Management*, 29, pp. 169-180.

Alberini, A. Kanninen, B. and Carson, R.T. (1997) "Modeling Response Incentive Effects in Dichotomous Choice Contingent Valuation Data", *Land Economics*, 73(3), pp. 309-24.

Arrow, K.J. Solow, R. (co-chairs) Leamer, E. Portney, P. Radner, R. and Schuman, H. (1993) "Report of the NOAA Panel on contingent valuation" *Federal Register*, 58, No. 10, Friday January 15 1993.

Bishop, R.C. Champ, P.A. Mullarkey, D. J. (1995) "Contingent valuation", in D.W. Bromley (ed) *The Handbook of Environmental Economics*, Basil Blackwell: Oxford.

Bradley, E.J. Lomas, P.R. Green, B.M.R. and Smithard, J. (1997) *Radon in Dwellings in England 1997 Review*. NRPB-R293, Chilton: London TSO.

Calia and Strazzera 2000.

Carson, R.T. Flores, N.E. Martin, K.M. and Wright, J.L. (1996) "Contingent valuation and revealed preference methodologies: Comparing the estimates for quasi-public goods", *Land Economics*, 72, pp. 80-99.

Cameron, T.A. and Quiggin, J. (1994) "Estimation using contingent valuation data from a 'Dichotomous choice with follow-up' questionnaire", *Journal of Environmental Economics and Management*, 27, 218-234.

Clarke, P.M. (1997) *Valuing the Benefits of Health Care in Monetary Terms with Particular Reference to Mammographic Screening*. PhD. Dissertation, Australian National University, Canberra.

Clarke, P.M. (1998)

Clarke, P.M. (2000) Valuing the benefits of mobile mammographic screening using the contingent valuation method *Applied Economics*, 32, 1647-1655.

Cochrane, W.G. (1963) *Sampling Techniques*. Wiley: NewYork.

Darby, S., Whitley, E., Silcocks, P., Thakrar, B., Green, M., Lomas, P., Miles, J., Reeves, G., Fearn, T. and Doll, R. (1998) "Risk of lung cancer associated with residential radon exposure in south-west England: A case-control study", *Br J Cancer* 78(3), pp. 394-408

Donaldson et al 1999 EuroWil papers from ihea

Duffield, J.W. and Patterson, D.A. (1991) "Inference and optimal design for a welfare measure in dichotomous choice contingent valuation", *Land Economics*, 67, pp. 225-39.

Gertler, P. Locay, L. and Sanderson, W. (1987) "Are user fees regressive?: Welfare implications of health care financing proposals in Peru", *Journal of Econometrics*, 36, 67-88.

Greene, W.H. (1992) *Econometric Analysis*, Second Edition, Macmillian Publishing Company: New York.

———. (1998) *LIMDEP Version 7.0*, Econometric Software, Inc. 1998.

Hanemann, W.M. and B. Kanninen, (1999) "The statistical analysis of discrete response CV data", in *Valuing Environmental Preferences*. Bateman I.J. and Willis K.G. (eds.) pp.302-441, OUP:Oxford.

Hill, J. W. (1988) "Valuing reductions in the risk of breast cancer mortality: A comparison of revealed preference and contingent valuation methods" PhD. Dissertation, University of Wisconsin, Madison.

Johannesson, M. (1993) "The contingent valuation method- Appraising the appraisers", *Health Economics*, 2, pp. 357-359.

Johansson, P.-O. Kriström, B. and Mäler, K.G. (1989) "Welfare evaluation in contingent valuations experiments with discrete response data: Comment", *American Journal of Agricultural Economics*, 71, pp. 1054-1056.

Johansson, P.-O.(1995) *Evaluating Health Risks: An Economic Approach*, Cambridge University Press: Cambridge.

Jones-Lee, M.W. (1976) *The Value of Life: an economic analysis*. Martin Robertson:London.

Jones-Lee, M.W. Hammerton, M. and Philips, P.R. (1985) "The value of safety: results of a national sample survey", *Economic Journal*, 95, pp. 49-72.

Maddala, G.S. (1983) *Limited Dependent and Qualitative Variables in Econometrics*, Econometrics Society Monographs, Cambridge University Press: Cambridge.

Mitchell R.C. and Carson R.T. (1989) *Using Survey Methods to Value Public Goods: the Contingent Valuation Method*, Resources for the future: Washington D.C.

Naismith, S.P. Miles, J.C.H. and Scivyer, C.R. (1999) "The Influence of House Characteristics on the Effectiveness of Radon Remedial Measures". *Health Physics*, 75(4), pp.410-416.

Nyquist, H. (1992) "Optimal designs of discrete response experiments in contingent valuation studies", *Review of Economics and Statistics*, 74, pp. 559-62.

O'Brien, B. and Viramontes, JL. 1994 Willingness to pay: a valid and reliable measure of health state preference?. *Medical Decision Making.* 14(3):289-97.

Rosen, S. (1988) "The Value of Changes in Life Expectancy", *J Risk and Uncertainty*, 1, pp.285-304.

Small, K.A. and Rosen, H.S. (1981) "Applied welfare economics with discrete choice models", *Econometrica*, 49, pp. 105-130.

Sheppard and Zeckhauser 1982.