**Supplemental Information for:**

**Risk Perception, Learning and Willingness to Pay to Reduce Heart Disease Risk**

Mark Dickie, Wiktor Adamowicz, Shelby Gerking, Marcella Veronesi

**Appendix A-1.** *Supplemental information on survey and sample.*

The sample of 3155 adults included 505 respondents used in a pretest and 434 matched pairs of spouses/partners living together. Observations from the pretest are excluded because the final version of the survey differed from the pretest. The second spouse recruited for each matched pair was excluded so that observations would be independent. Data from the matched pairs were analyzed in Adamowicz et al. (2014).[[1]](#footnote-1) Retaining the first person recruited from each matched pair plus the 1782 living in different households gives a sample of n=2216. Twelve respondents did not answer all survey questions. Persons with a prior history of heart disease were excluded to focus on *ex ante* perception and valuation of risk. Data collected from parents about their children are not used here, because the analysis relies on differences in risks of heart disease by presence/absence of risk factors for the disease. Few children were reported to have diabetes, high blood pressure, high cholesterol; the survey did not assess children’s smoking; and levels of body mass index that define overweight and obesity for adults do not apply to children. Data on children were examined in Adamowicz et al. (2014) and Gerking et al. (2017).

The survey was developed in stages based on a pilot study with 815 residents of the Orlando, Florida area, followed by two focus groups with 25 Orlando residents, a pretest with 25 subjects from the KN panel, and the final pretest with 505 KN subjects. Additionally, Dr. David Carpenter, a cardiologist from SUNY-Albany, provided valuable advice on risk of coronary artery disease.

**Appendix A-2**. *Supplemental information and analysis: initial and revised risk perceptions.*

Table A-2-1 Perceived Risk of Coronary Artery Disease Diagnosis before Age 75 (chances in 100): Summary of distributions by gender

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Men (n=746) | |  | Women (n=1458) | |
|  | Initial | Revised |  | Initial | Revised |
| Mean | 37.42 | 35.40 |  | 35.24 | 32.69 |
| Std. Dev. | 23.18 | 20.14 |  | 22.19 | 19.02 |
| Min | 0 | 1 |  | 0 | 0 |
| 25th %tile | 20 | 21 |  | 20 | 20 |
| Median | 33 | 30 |  | 30 | 28 |
| 75th %tile | 50 | 50 |  | 50 | 45 |
| Max | 100 | 100 |  | 100 | 100 |

Table A-2-2 Perceived Risk of Coronary Artery Disease Diagnosis before Age 75 (chances in 100): Relative frequency distribution pooled over gender

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Chances in 100 | | Perceived Risk | |  |
| From | Through | Initial | Revised |  |
| 0 | 19 | 0.230 | 0.187 |  |
| 20 | 39 | 0.336 | 0.482 |  |
| 40 | 59 | 0.588 | 0.203 |  |
| 60 | 79 | 0.143 | 0.101 |  |
| 80 | 100 | 0.041 | 0.026 |  |
|  | Mean | 35.97 | 33.61 |  |
| Standard Deviation | | 22.55 | 19.44 |  |

*Supplemental information on revised risk perceptions*

Table A-2-3 presents additional summary tabulations of revisions of initial risk assessments. Data are pooled over gender because differences between the sexes are insubstantial. Panel A tabulates mean prior risks and updates by the direction of updating. Means of initial risk assessments are largest for persons who revise risk downward and smallest for those who revise upward. Despite the small overall average revision, absolute magnitudes of non-zero revisions are sizeable. Upward updates average 11, and downward updates average 18, chances in 100.

Panel B of Table A-2-3 cross-tabulates the direction of updating (reducing, not changing, or increasing the prior) by the level of risk initially perceived relative to the overall population objective risk of 27 chances in 100. As shown in the last column, 55% of respondents initially believed their risk was higher than the population average, whereas 45% of respondents believe their risk was lower. A chi-square test indicates that the direction of updating is related systematically at the 1% level to information provided on objective risk by gender.

Table A-2-3. Updates of Prior Risk Assessments.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| |  |  |  |  |  | | --- | --- | --- | --- | --- | | 1. Means of Initial Risk Assessment and Revision (chances in 100) Cross-Tabulated by Direction of Revision | | | | | |  |  | | |  | | Direction of Revision: | Mean of Initial risk | Mean of Revision | Number of Observations | | | Downward revision | 51.03 | -18.48 | 566 | | | No revision | 35.71 | 0 | 1164 | | | Upward revision | 18.66 | 11.06 | 474 | | | All observations | 35.98 | -2.37 | 2204 | | |  |  |  |  | | | | | | |
|  | | | | |
|  | | | | |
| B. Direction of Revision Cross-Tabulated by Whether Initial Risk Assessment is  Less than, Equal to, or Greater than Objective Riska (Relative Frequencies) | | | | |
|  | Direction of Revision: | | | |
| Initial risk: | Down | None | Up | Total |
| Initial risk < Objective risk | 0.025 | 0.241 | 0.180 | 0.446 |
| Initial risk = Objective risk | 0.000 | 0.001 | 0.00 | 0.001 |
| Initial risk > Objective risk | 0.231 | 0.286 | 0.035 | 0.553 |
| Total | 0.257 | 0.529 | 0.215 | 1 |
| Chi-square(4) | 570.78 |  |  |  |

aObjective risk = the overall population risk of 27 chances in 100.

*Supplemental information on Bayesian learning model*

Equation (1) gives the mean of the posterior risk distribution when perceived risks have a beta distribution (Pratt *et al*. 1975).[[2]](#footnote-2) The relative precision parameters are defined aswhereand denote precision of the prior and therisk estimate, and The individual acts as if her prior assessment were derived fromBernoulli trials in whichindicated presence of heart disease, and as if each risk estimate were derived fromBernoulli trials in whichindicated heart disease. Discussion of equation (1) assumes the new risk estimatesare independent. If instead they are drawn from overlapping information (for example, if subjects believe that the estimates rely in part on common data), theare adjusted for overlapping information, so that they represent the information content that is unique to each risk estimate. However, the mean posterior risk remains a weighted average of the prior risk and the new risk estimates and equation (2) remains valid, although with a somewhat modified interpretation of the weights (Viscusi 1997).

*Supplemental discussion of information gap variables*

For blood pressure and cholesterol, information gap measures were constructed assuming that the objective risk estimate applicable to people who have not been told to do something about the condition equals the risk in the lowest-risk category, whereas the risk estimate for those who have the condition equals the risk in the highest risk category. Lloyd-Jones et al. (2006) reported estimates of objective risk for quantitative measures of blood pressure and cholesterol. Because respondents would not be expected to know their blood pressure or cholesterol readings, the survey therefore inquired only if a medical professional had said to do something to lower blood pressure or cholesterol and if so whether medication was being taken for this purpose.

For example, supposeandrepresent the unknown objective risks with and without a family history of heart disease, History/Nohistory are indicators for presence/absence of this risk factor, denotes the overall population risk estimate of 27 chances in 100, andequals 0 or 1 as the condition in parentheses is false or true. Then the associated terms in equation (2) arewhen there is a family history andwhen there is no family history. If then a person with a family history increases the risk assessment, if and only if the prior assessment lies below overall objective risk. If then a person without a family history decreases the risk assessment, if and only if the prior assessment exceeds overall objective risk. In each case the absolute size of the update increases with the absolute size of the gap between the prior risk assessment and overall objective risk.

Table A-2-4. *Updates of Prior Risk Assessments: Ordered Probit Estimates*

|  |  |  |  |
| --- | --- | --- | --- |
|  | 100 x Effect on Probability that Revision is: | | |
| Information gap for: | Downward | Zero | Upward |
| Females | -0.024 | 0.004 | 0.020 |
|  | (0.096) | (0.015) | (0.080) |
| Males | -0.019 | 0.003 | 0.016 |
|  | (0.119) | (0.019) | (0.100) |
| Nonsmokers | 0.731\*\*\* | -0.118\*\* | -0.612\*\*\* |
|  | (0.189) | (0.052) | (0.161) |
| Smokers | 1.176\*\*\* | -0.190\*\* | -0.986\*\*\* |
|  | (0.225) | (0.077) | (0.193) |
| Do not have diabetes | -0.480\*\*\* | 0.078\*\* | 0.402\*\*\* |
|  | (0.105) | (0.033) | (0.090) |
| Have diabetes | -0.332\*\*\* | 0.054\* | 0.278\*\*\* |
|  | (0.124) | (0.028) | (0.105) |
| BMI < 25 | -1.194\*\*\* | 0.193\*\*\* | 1.001\*\*\* |
|  | (0.175) | (0.074) | (0.152) |
| 25 <= BMI < 30 | -0.972\*\*\* | 0.157\*\* | 0.815\*\*\* |
|  | (0.170) | (0.062) | (0.147) |
| 30 <= BMI | -0.830\*\*\* | 0.134\*\* | 0.695\*\*\* |
|  | (0.189) | (0.056) | (0.162) |
| Not told to lower blood pressure | -0.149\*\* | 0.024\* | 0.124\*\* |
| (0.072) | (0.014) | (0.060) |
| Told to lower blood pressure | -0.063 | 0.010 | 0.053 |
| (0.103) | (0.017) | (0.087) |
| Not told to lower cholesterol | 0.024 | -0.004 | -0.020 |
|  | (0.089) | (0.015) | (0.074) |
| Told to lower cholesterol | 0.036 | -0.006 | -0.030 |
| (0.129) | (0.021) | (0.107) |
| At least as much exercise as recommended | 0.062 | -0.010 | -0.052 |
| (0.076) | (0.013) | (0.063) |
| Less than recommended exercise | -0.383\*\* | 0.062\* | 0.321\*\* |
| (0.156) | (0.033) | (0.132) |
| At least as much fruit/veg as recommended | -0.125 | 0.020 | 0.105 |
| (0.076) | (0.014) | (0.064) |
| Less fruit/veg than recommended | -0.392\*\* | 0.063\* | 0.329\*\* |
| (0.163) | (0.034) | (0.138) |
| Healthy diet | -0.114 | 0.018 | 0.095 |
|  | (0.073) | (0.013) | (0.061) |
| Unhealthy diet | 0.135 | -0.022 | -0.113 |
|  | (0.300) | (0.050) | 0.251 |
| No family history | -0.138\* | 0.022 | 0.115\* |
|  | (0.075) | (0.014) | 0.062 |
| Family history | -0.334\*\* | 0.054\* | 0.280\*\* |
|  | (0.154) | (0.031) | 0.130 |
| Knows someone with heart disease | 1.785 | -0.234 | -1.551 |
| (1.821) | (0.209) | 1.633 |
| Has thought might get heart disease | -4.439\*\* | 0.927\* | 3.513\*\*\* |
| (1.797) | (0.512) | 1.351 |
| College graduate | 4.701\*\*\* | -0.686\*\* | -4.015\*\*\* |
|  | (1.516) | (0.340) | (1.329) |
| $60,000<= Household income <= $100,000 | 4.757\*\* | -0.978\*\* | -3.779\*\*\* |
| (1.851) | (0.526) | (1.405) |
| $100,000<Household income | 0.311 | -0.051 | -0.260 |
|  | (1.829) | (0.319) | (1.529) |
| Ethnicity black | -7.014\*\*\* | -0.487 | 7.501\*\* |
|  | (2.461) | (1.015) | (3.364) |
| Ethnicity Hispanic | -2.343 | 0.232 | 2.111 |
|  | (2.603) | (0.166) | (2.513) |
| Ethnicity other | 2.395 | -0.521 | -1.874 |
|  | (2.886) | (0.789) | (2.106) |
| Age > 43 years | -1.568 | 0.245 | 1.323 |
|  | (1.465) | (0.238) | (1.236) |
|  |  |  |  |
| Log-likelihood | -1809.786 |  |  |
| McFadden pseudo | 0.192 |  |  |

\*\*\*, \*\*, \* denote significance at the 1%, 5% and 10% level, respectively. Standard errors are presented in parenthesis.

**Appendix A-3**. *Theoretical model of MWTP to reduce heart disease risk.*

The one-period model follows Gerking et al. (2017). The representative person’s expected utility is given by wheredenotes posterior perceived risk of heart disease as a function of endogenous behaviors such as exercise and exogenous factorssuch as favorable family history withand wheredenotes income, andrespectively denote state-dependent utility functions if the individual is healthy (no heart disease) or sick (with heart disease). Total and marginal utility are greater when healthy than when sick for anyand the individual is not risk-loving in either health state.

Prior to the survey, the individual choseto maximize expected utility, implying that

The assumptions in the first paragraph of this appendix guarantee that second-order sufficient conditions for a maximum are satisfied and thus the optimal amount ofdenotedis a function ofand: Ifthen there is offsetting behavior: (see Liu and Nelson 2006). An additional technical assumption described by Liu and Nelson (2006; pp. 2068-2069) implies that the offsetting is partial in that an increase inreduces risk despite the offsetting change in

The individual’s optimal behavior prior to the survey implies that the MWTP to reduce heart disease risk equals the marginal cost of reducing perceived risk:

 (A.3-1)

where denotes the expected marginal utility of consumption at the maximum of expected utility. Following Gerking et al. (2017), whenandWhen an increase inreduces risk, these conditions are sufficient for MWTP to reduce risk to be larger when the level of risk faced is smaller, and the individual comes to the survey with a MWTP for risk reduction that is diminishing in the level of risk perceived.

The individual then is presented with the vaccine choice question in the survey. Her willingness to pay for the vaccine, denoted *WTP*, solves, wheredenotes the choice of with the vaccine, denotes the risk reduction offered by the vaccine, anddenotes maximum expected utility without the vaccine. Marginal willingness to pay to reduce risk based on the vaccine choice equalsObtaining this derivative atimplies that the individual’s MWTP to reduce risk of heart disease in the vaccine choice is given by

 (A.3-2)

which is equivalent to equation (A.3-1) and thus equal to

Therefore it remains true in the vaccine choice question that whenandimplying that if the individual experienced an increase in *G* prior to the survey, her MWTP to reduce risk in the vaccine choice would be larger. As long as an increase inreduces risk, her MWTP to reduce risk would be diminishing in the level of risk perceived. If on the other hand and the marginal utility of consumption is smaller when healthy than when sick, her MWTP to reduce risk would be increasing in risk. In either case, her valuation of reduced risk depends on the level of risk she perceives, and thus computing her MWTP at an objective risk level that differs from her perceived risk would misstate her valuation.

**Appendix A-4.** *Supplemental information and analysis: vaccine purchase intentions.*

Table A-4-1. Relative frequency of respondents who probably or definitely would purchase vaccine, by risk change and price

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Price (dollars per year) | | | | | |
| Proportionate Risk Change | 10 | 20 | 40 | 80 | 160 | All |
| 0.1 | 0.379 | 0.380 | 0.308 | 0.257 | 0.175 | 0.301 |
| 0.7 | 0.546 | 0.509 | 0.523 | 0.568 | 0.272 | 0.483 |
| All | 0.416 | 0.413 | 0.362 | 0.320 | 0.199 | 0.343 |

Table A-4-2. Vaccine purchase intentions. Probit Estimates treating all “Yes” response as indicating positive purchase intentions (including those who said they were uncertain about their intentions).

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Relationship of MWTP for 1/100 risk reduction to posterior risk: | | | | | |
| Covariate | Rectangular hyperbola | | |  | Linear | |
| Proportionate risk reduction | 0.009\*\*\* | |  |  | ---a |  |
| (0.001) | |  |  |  |  |
| Absolute risk reduction | ---a | |  |  | 0.051\*\*\* |  |
|  | |  |  | (0.007) |  |
| Vaccine price | -0.004\*\*\* | |  |  | -0.004\*\*\* |  |
| (0.001) | |  |  | (0.001) |  |
| Constant | -0.240\*\*\* | |  |  | -0.611\*\*\* |  |
|  | (0.048) | |  |  | (0.075) |  |
| Absolute risk reduction × Posterior risk | | | | | -0.001\*\*\* |  |
|  |  |  | |  | (0.0001) |  |
| Posterior risk | | | |  | 0.011\*\*\* |  |
|  |  |  | |  | (0.002) |  |
| Log-likelihood | -1357.535 | | |  | -1362.656 | |
| Likelihood ratio test statistic (df) | 120.630\*\*\* (2) | | |  | 228.210\*\*\* (4) | |
| Pseudo-R2 | 0.043 | | |  | 0.077 | |

a Denotes excluded variable.

\*\*\* Denotes significance at the 1% level.

Standard errors are presented in parenthesis.

**Appendix A-5** *Consistent estimation of marginal willingness to pay to reduce heart disease risk*

This appendix describes econometric methods used to estimate the marginal willingness to pay (MWTP) to reduce heart disease risk by 1 chance in 100 as a linear function of the level of posterior risk, as in column (3) of Table 3. Gerking *et al.* (2017) describe methods to estimate MWTP as a rectangular hyperbola in posterior risk, as in column (2) of Table 3. Whereas random assignment of percentage risk reductions and vaccine prices suggests that estimators of parameters in the specification of MWTP as a rectangular hyperbola are consistent, consistent estimation of the linear form is complicated by the endogeneity of posterior risk perceptions.

Stated willingness to pay for the vaccine is described by equation (4) in the text, reproduced here as equation (A.5-1) and written more compactly in equation (A.5-2).

 (A.5-1)

 (A.5-2)

where The observed dependent variable indicates only whether stated willingness to pay exceeds the price:

 (A.5-3)

Parameters of main interest in equation (A-2) areandbecause MWTP to reduce risk by 1 chance in 100 equals(see Cameron and James 1987).

The disturbance influencing the gap between stated and true willingness to pay for the vaccine,is assumed to be distributed independently ofandwith mean zero and variance Additionally, random assignment ofandsuggests that these variables are independent of individual characteristics includingandAdditionally, Thushas a standard normal distribution independent ofandButrepresenting tastes and opportunities for risk reduction, is likely correlated with posterior risk,Thus, using probit to estimatewill estimateinconsistently.

Nonetheless, probit will consistently estimate the MWTP to reduce risk by 1 chance in 100 if the distribution of conditional on posterior risk is normal, with a conditional mean that is linear in posterior risk. Under these assumptions, probit estimators ofandeach converge to the same constant multiple of the true values. (Estimators of do not converge to constant multiples of true values.) MWTP then is estimated consistently because it is a function of the ratiosand

The distribution of conditional onis the pertinent one to consider because In other words, conditional on the posterior risk, the disturbanceis independent ofandTo see this, begin with the conditional distribution ofgivenandUsingto represent a conditional probability density function and to represent a joint or marginal density or probability distribution function,



Because andare independent ofand Thus,andis conditionally independent of.

It follows that, conditional onis independent of functions of. Conditional on, and are functions ofTherefore,is conditionally independent ofso that This impliesIntegrating both sides of this equation overyields Dividing by the second conditional density on the right-hand side of the equation shows that

 (A.5-4)

According to equation (A.5-4), conditional on the posterior risk, the error component reflecting tastes and opportunities for risk reduction in equation (A.5-2) is distributed independently of the other covariates in the equation:

Now assume the dependence ofon posterior risk is linear with an independent normal disturbance:

 (A.5-5)

where is distributed asindependently ofdenotes the correlation betweenandandrespectively denote the mean and variance of posterior risk. The value of the intercept is determined by the assumption that the unconditional mean ofis zero (note there is a constant term in equations (A.5-1) and (A.5-2)). Under these assumptions,is normal with meanand variance

Substituting equation (A-5.5) into equation (A-5.2) yields

 (A.5-6)

whereis normally distributed independently of covariates in equation (A.5-6) with mean zero and variance Therefore the probability that an individual states that she will purchase the vaccine equals

 (A.5-7)

Under the assumptions of the model, equation (A.5-7) correctly represents the probability of a positive purchase decision. Therefore the probit ofonis expected to estimate parameters of equation (A.5-4) consistently under standard technical assumptions establishing consistency of maximum likelihood estimation (e.g., Wooldridge, 2002, *Econometric Analysis of Cross Section and Panel Data*, Massachusetts Institute of Technology, pp. 391-392). Usingto denote coefficients estimated by probit,where Thus the coefficients of absolute risk reduction and its interaction with posterior risk, and of the vaccine price, are underestimated (given) by the same proportion[[3]](#footnote-3). Consequently, and is estimated consistently.

Appendix A-6 reports results of a simulation study of the small sample performance of the probit estimator in equation (A.5-7). In summary, on average over 10,000 draws, estimates of MWTP to reduce risk by 1 chance in 100 at the mean of posterior risk are overestimated by between 4% and 6% of true values at a sample size of 2204, and by 1% of true values at a sample size of 10,000.

**Appendix A-6** *Supplemental information: Small-sample performance of probit estimator*

This appendix summarizes a simulation study of the small sample behavior and convergence of the probit estimator of parameters in equation (A.5-2) and the resulting estimated MWTP to reduce risk by 1 chance in 100. Additional details and a copy of the program used to run the simulations are provided in Appendix A-7. The simulation study involves seven steps.

1. Parameterize equation (A.5-2) by choosing “true” values of thecoefficients. Five different parameterizations are employed. One is based on estimates in Table 3, column 3. The other four are based on linear approximations to the functional form estimated in Table 3, column 2, taken at four different levels of posterior risk (33, 20, 50, and 67 chances in 100, approximately equal to the mean, first and second quartile, and twice the mean of posterior risk in the survey sample).
2. Generate samples of simulated data on covariates in equation (A.5-2) so as to approximate the distributions of covariates in the observed survey data. Two sample sizes are employed: *n*=2204 as in the survey sample, and *n*=10,000 to examine degree of convergence as sample size increases.
3. Generate data on disturbances consistent with the model in Appendix A-5. Generating the disturbancerequires assuming a value for, the correlation betweenand posterior risk. Various values ofranging from -0.9 to 0.9 are employed. The variance ofis set equal to unity for convenience, implying that
4. Using the data on covariates and disturbances and the assumed parameter values, generate data on stated purchase decisions according to equations (A.5-2) and (A.5-3).
5. Using the data on covariates and purchase decisions, estimate parameters of equation (A.5-2) by probit, and compute estimated MWTP to reduce risk by 1 chance in 100 at posterior risk levels of 0, 33, and 67 chances in 100.
6. For each parameterization of equation (A.5-2), each sample size, and each value of, repeat the process of generating simulated data and estimating the model and MWTP 10,000 times.
7. Report the average from 10,000 replications of the estimated parameters of equation (A.5-2) and the estimates of MWTP to reduce risk by 1 chance in 100.

Results are reported in Tables A-6-1 through A-6-5 below. The presentation is organized by parameterization, sample size, and assumed correlation between the disturbance and posterior risk. Thus Table A-6-1, for the first parameterization, presents for *n*=2204 and five values of, and then for *n*=10,000 and five values of. The same format then is used for the remaining four parameterizations in Tables A-6-2 through A-6-5. The tables below show results forThe simulation program, provided in Appendix A-7, simulates using values ofranging from -0.9 to 0.9 in increments of 0.15.

Each table shows the assumed values of the parameters in equation (A.5-2) and the “true” values of MWTP to reduce risk that are implied by the parameters. Then, for each assumed value ofthe tabulation shows (1) the probability limit of the probit estimator of the parameters of equation (A.5-2); (2) the average of 10,000 estimates of the parameters and of MWTP to reduce risk; and (3) the ratio of the average estimate to the “true” value of each parameter and of MWTP to reduce risk. Given thatthe probability limit of the ratio of estimated parameter to true value, for the coefficients of price, absolute risk reduction and its interaction with posterior risk, equals

Discussion here centers on estimates of MWTP to reduce risk, as the purpose of estimating the model for purchase intentions for the vaccine is to estimate this value at different levels of subjective risk. Simulation results indicate that at the sample size used in the paper, estimated MWTP to reduce risk is close to the true value at the mean of posterior risk, with larger errors for extreme values of posterior risk. For a sample size of 10,000, errors in estimating MWTP are modest over the entire range of posterior risk.

At the approximate mean of posterior risk of 33 chances in 100, the average estimate of MWTP exceeds the true value by 4% to 6% when *n*=2204, and by 1% when *n*=10,000, regardless of parameterization or the size of the correlation between posterior risk and the disturbance.

The divergence between average estimated MWTP and its true value is larger at extreme levels of posterior risk. At a posterior risk level equal to the lower bound of zero, average estimated MWTP differs from the true value by between -3% and +13% when *n*=2204, and by -2% to +3% when *n*=10,000. When posterior risk equals 67 chances in 100, in excess of the 90th percentile value, average estimated MWTP may differ from the true value by as much as -22% to +40% for the smaller sample size, and by -4% to +10% for the larger sample size.

**Table A-6-1. Coefficients set equal to estimates of functional form with MWTP to reduce risk as a linear function of posterior risk.**



**Table A-6-2. Coefficients based on linear approximation to functional form with MWTP to reduce risk as a rectangular hyperbola in posterior risk, at a risk level of 20 chances in 100.**

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**Table A-6-3. Coefficients based on linear approximation to functional form with MWTP to reduce risk as a rectangular hyperbola in posterior risk, at a risk level of 33 chances in 100.**

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**Table A-6-4. Coefficients based on linear approximation to functional form with MWTP to reduce risk as a rectangular hyperbola in posterior risk, at a risk level of 50 chances in 100.**

****

**Table A-6-5. Coefficients based on linear approximation to functional form with MWTP to reduce risk as a rectangular hyperbola in posterior risk, at a risk level of 67 chances in 100.**

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**Appendix A-7** *Supplemental information: Additional technical details for the simulation study.*

This appendix provides more details of the simulation study of the small sample behavior of the probit estimator of parameters in equation (A.5-2) and the resulting estimated MWTP to reduce risk by 1 chance in 100, as well as a copy of the LIMDEP program used to conduct the simulations.

In each simulation, 10,000 samples are drawn and the probit estimates computed along with the resulting MWTP estimates. The estimates are averaged over the 10,000 replications and compared to assumed true values of the parameters and to the probability limits obtained in Appendix A-5. Five different parameterizations of equation (A.5-2) are considered. For each parametrization, two sample sizes are considered: *n*=2204, as in the paper, and *n*=10,000. For each parameterization/sample size combination, different values of, the correlation betweenand are investigated. This appendix reports results for Results for other values of the correlation (ranging from -0.9 to +0.9 in increments of 0.15) can be computed by running the LIMDEP program included below.

*Coefficients.* The five parameterizations of equation (A.5-2) are constructed as follows. The first sets the parameters equal to the estimates presented in column 3 of Table 3. The other four are based on linear approximations to the functional form estimated in column 2 of Table 3, in which MWTP to reduce risk is a rectangular hyperbola in posterior risk. Consider first setting the key parameters of interest,As described by Gerking et al. (2017), the expectation of stated willingness to pay for the vaccine for the functional form estimated in Table 3, column 2 can be written as MWTP to reduce risk by 1 chance in 100 then equalsand In equation (A.5-2), MWTP to reduce risk equalsand Equating MWTP as well asbetween the two forms would imply thatandThe value of is assumed to be 2, based on results presented in Table 3, column 2:Next,is set equal to -0.004, because this is the estimated probit coefficient of price in both columns 2 and 3 of Table 3. The approximate values of the probit coefficients of absolute risk reduction and its interaction with posterior risk then are and These are the assumed true values in the simulations, where four different specifications arise from setting posterior riskequal to the values 33, 20, 50 and 67, corresponding roughly to the mean, first quartile, third quartile, and twice the mean of posterior risk in the survey sample.

The remaining coefficients in equation (A.5-2) are and The coefficient of posterior risk is set by re-writing the expectation of willingness to pay for the vaccine in the rectangular hyperbola for as, differentiating with respect to posterior risk and rescaling to obtainEquating this to the corresponding derivative of equation (A.5-2), assuming inserting the solutions from above forsolving forand then usingyieldsFinally,is set equal to -0.36, the estimated value in Table 3, column 2, for values of posterior risk equal to 33, 50, 67 chances in 100. For posterior risk equal to 20 chances in 100,  In this way the proportion of observations in the simulated samples for which  typically falls withinof the sample proportion in the paper, for each value of posterior risk considered.

*Covariates.* The data for explanatory variables is generated to be consistent with the data used in the sample analyzed in the paper. The vaccine price is drawn from a discrete uniform distribution with a probability of (1/5) for each of the five prices administered in the survey. The proportionate risk change is drawn from a discrete distribution to generate data consistent with the experimentally assigned frequencies of. The posterior risk is drawn from a normal distribution with mean 33 and standard deviation 19, the approximate sample mean and standard deviation in the survey sample. This variable is then censored to lie in the (0, 100) interval; typically about 4% of the observations in a given simulated sample are censored. The absolute risk reduction then is computed as the product of the proportionate reduction and the posterior risk.

*Disturbances.* The data for the disturbances in equation (A.5-2) is generated as follows. First,is drawn from a standard normal distribution as assumed in the model. Then,is generated using equation (A.5-5). Data on posterior risk in equation (A.5-5) are generated as described above; the values ofare determined by the assumed values ofand by the mean and standard deviation of the generated posterior risk variable. For simplicity,is drawn as standard normal, so that the conditional distribution ofis normal as assumed, and making the variance ofequal to 2. Thus the ratiosconverge in probability to

*Dependent variable.* The variableis generated according to equation (A.5-2), using the data generated on covariates and disturbances and the assumed parameter values for each specification of coefficients. The binary dependent variable indicating the purchase decision for the vaccine is generated using equation (A.5-3).

**LIMDEP** program to run the simulations.

/\*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\* This program conducts monte carlo simulations to examine \*

\* performance of probit estimation of equation for stated MWTP \*

\* for the vaccine to reduce posterior risk, when: \*

\* (1) MWTP for absolue recutions in risk is a linear function \*

\* of posterior risk; \*

\* (2) Posterior risk is endogenous; \*

\* (3) Proportionate risk change and vaccine prices are randomly \*

\* assigned. \*

\* The paramter "rojo" denotes the correlation between posterior \*

\* risk and the disturbance in the equation for stated MWTP vaccine\*

\* As written, values of the correlation range from -.9, to +0.9, \*

\* in increments of 0.15. These can be changed easily. \*

\* \*

\* Using LIMDEP (NLOGIT 6). \*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\*/

/\*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\* I. Initial set up: choose a sample size. \*

\* N=2204 is sample size in the paper. \*

\* N=10,000 shows effect of increasing sample size. \*

\* To use a large sample size like N=10,000 in my version of \*

\* LIMDEP requires re-setting the data area in "Settings" in the \*

\* Project menu. For example, 10,000,000 cells allows 11,111 \*

\* observations. \*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\*/

CALC; smalln=2204; bign=10000 $

SAMP; 1-smalln $

CALC; List; N$

/\*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\* II. Set assumed "true" values of coefficients of equation \*

\* describing MWTP for vaccine (=btrue). (Also initialize the \*

\* estimated values [=bavg] to zero.) \*

\* \*

\* Five different parameterizations \*

\* are used. Each one sets the coefficient of vaccine price as \*

\* -0.004. This is the estimated coefficient in both of the \*

\* functional forms used in the paper, the first of which (in which\*

\* MWTP to reduce risk is a rectangular hyperbola in posterior \*

\* risk) is presumed to be consistent. (Note it's the normalized \*

\* coefficients (b/sigmav) that are set.) \*

\* \*

\* The latent dependent variable is (stated MWTP for vaccine \*

\* less price of vaccine)/sigmaw, the std dev of disturbance. \*

\* The covariates in order are: \*

\* 1, dabs, vprice, dabsr1, risk1, where: dabs=absolute risk \*

\* risk reduction, vprice=vaccine price, dabsr1=dabs\*risk1, \*

\* risk1 = posterior risk. \*

\* \*

\* The first parameterization assumes the estimates obtained in \*

\* the paper (for the form in which MWTP to reduce risk is a linear\*

\* function of posterior risk) are the true values. The assumed \*

\* coefficients in order are: -0.7, 0.04, -0.004, -0.0005, 0.01. \*

\* \*

\* NOTE: Just comment out the \*

\* the parameterizations not being used, and un-comment the one \*

\* being used. \*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\*/

CALC; List; bstara=0.04; bstarp=-0.004; bstarar=-0.0005;

bstarr=0.01; bstar0=-0.7 $

/\*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\* Remaining parameterizations set the coefficints based on first- \*

\* order Taylor's series expansions of the functional form in \*

\* which MWTP is a rectangular hyperbola in posterior risk. \*

\* The Taylor's series are expanded around different values of \*

\* posterior risk of 33 (approx mean of risk1), 20 (approx 1st \*

\* quartile), 50 (approx 3rd quartile), and 67 (2x the mean). For \*

\* values of risk below 20 (chances in 100), the tangent to the \*

\* rectangular hyperbola is so steep that MWTP is predicted to \*

\* be negative at levels of risk below 50 in 100, so nothing \*

\* below 20 is shown here. Specifically, the coefficients of dabs \*

\* and dabs\*risk1 are set based on the Taylor's series; the \*

\* coefficient of vprice is left at -.004, and constant equals \*

\* estimated constant reported for the form in the paper, except \*

\* that in the form based on expanding around risk1=20, the \*

\* constant is adjusted. Then all forms generate data so that the \*

\* mean of the observed dependent variable (=proportion of sample \*

\* saying they would buy the vaccine that is within +/- 0.05 of \*

\* sample proportion. \*

\* So, the coefficients in the order described above are: \*

\* \*

\* risk1=33: -0.36, .048, -.004, -.000735, -.006. \*

\* risk1=20: -0.09, .080, -.004, -.0020, -.010. \*

\* risk1=50: -0.36, .032, -.004, -.00032, -.004 . \*

\* risk1=67: -0.36, .023, -.004, -.17821, -.0029. \*

\* \*

\* To set any of these up, set the scalar r0 to the desired \*

\* level of risk1 (33,20,50,67). \*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\*/

/\*

CALC; List; r0=20; bstar0=-0.09 $

CALC; List; r0=33; bstar0=-0.36 $

CALC; List; r0=50; bstar0=-0.36 $

CALC; List; r0=67; bstar0=-0.36 $

\*/

/\*

CALC; List; bstara=1.6/r0; bstarp=-0.004; bstarar=-0.8/(r0^2);

bstarr=-1/(5\*r0) $

\*/

MATR; List; bavg = Init(5,1,0.0);

btrue= [bstar0 / bstara / bstarp / bstarar / bstarr ] $

/\*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\* III. Compute "true" values of MWTP for reduced risk \*

\* (named mwtp-"risk level"-"tr" suffix), based on assumed true \*

\* values of the coefficients of the equation for MWTP for vaccine.\*

\* Also initialize estimated mwtp values to zero. \*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\*/

CALC; mwtp0=0; mwtp33=0; mwtp67=0; mwtp1=0;

List;

mwtp0tr =-1\*btrue(2)/btrue(3);

mwtp33tr =-1\*(btrue(2)+btrue(4)\*33)/btrue(3);

mwtp67tr =-1\*(btrue(2)+btrue(4)\*67)/btrue(3);

mwtp1tr =-1\*(btrue(2)+btrue(4)\*100)/btrue(3) $

/\*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\* IV. Set up procedure to run the simulations. \*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\* \*

\* First set up data: \*

\* vprice= Vaccine price, randomly drawn from 5 values with equal probability. \*

\* delta = Proporitonate risk change, randomly assigned. \*

\* risk1 = Posterior risk, constructed as normal based on sample mean & std dev, \*

\* then censored to [0,100]. About 4% of observations are censored \*

\* to zero, and fewer than 1% are censored to 100. \*

\* dabs = Absolute risk change = delta\*risk1 (chances in 100). \*

\* dabsr1= Interaction of absolute risk change and posterior risk. \*

\* v = Disturbance, theta0 + theta1\*risk1 + an independent standard normal \*

\* that is denoted "u" in the paper. \*

\* But for the minor censoring of risk1, v would be a linear combination \*

\* of normal r.v.'s. (This is "vstar" in notation in paper.) \*

\* rojo = rho(v,risk1), correlation of disturbance and posterior risk (assumed \*

\* value of rojo is set outside of the procedure). \*

\* theta1= dv/d(risk1), based on assumed value of rojo. \*

\* theta0= intercept, set so unconditional expectation of v is zero. \*

\* v = v-Xbr(v) mean-centers v so that empirically its mean is zero. (v has \*

\* a very small nonzero mean before centering.) Note there is a constant in \*

\* the estimating equation for MWTP for vaccine. \*

\* tau = v + an independent standard normal that is labeled "e" in the paper. \*

\* This is the disturbance in the equation for the latent variable that \*

\* leads ot the probit estimating equation for WTP for the vaccine. \*

\* x = Covariates in estimating equation. \*

\* ystar = Latent dependent variable (stated MWTP for vaccines less vaccine price, \*

\* all divided by standard deviation of w = sigmaw\*e. \*

\* y = Observed (0,1) dependent variable (0=not buy, 1=buy vaccine). \*

\* \*

\* Second, estimate equation for MWTP for vaccine by probit, compute average of \*

\* estimated coefficients over "nrep" reptions of the procedure. \*

\* \*

\* Third, update average estimated MWTP to reduce risk by 1 chance in 100, \*

\* based on estimated coefficients in each run: \*

\* mwtp0= MWTP to reduce risk at risk1=0. \*

\* mwtp33= MWTP to reduce risk at risk1=33 chances in 100 (approx mean of risk1). \*

\* mwtp67= MWTP to reduce risk at risk1=67 chances in 100 (2\*mean of risk1). \*

\* mwtp1 = MWTP to reduce risk at risk1=100 chances in 100. Usually, the "true" \*

\* MWTP here is negative based on the parameterization. \*

\* \*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\*/

PROC = probproc $

CREA;

unip = Rnd(5);

vprice= 10\*(unip=1)+20\*(unip=2)+40\*(unip=3)+80\*(unip=4)+160\*(unip=5);

unir = Rnd(4);

delta = 0.1\*(unir<4)+0.7\*(unir=4);

rsk = Rnn(33,19);

d0 = (rsk<0);

d1 = (rsk>100);

risk1 = d0\*0+d1\*100+(1-d0-d1)\*rsk;

dabs = delta\*risk1;

dabsr1= dabs\*risk1 $

CALC; theta1= rojo/(sqr(1-rojo^2)\*Sdv(risk1));

theta0= -1\*theta1\*Xbr(risk1) $

CALC; theta0m = theta0m + (1/nrep)\*theta0;

theta1m = theta1m + (1/nrep)\*theta1 $

CREA; v = theta0+theta1\*risk1+Rnn(0,1) $

CREA; v = v - Xbr(v);

tau = Rnn(0,1) + v $

CREA; tau = tau - Xbr(tau) $

NAME; x = one,dabs,vprice,dabsr1,risk1 $

MATR; ymat = x\*btrue $

CREA; ystar = ymat $

CREA; ystar = ystar + tau $

CREA; y = 0 + 1\*(ystar>0) $

PROB; Quiet; Lhs=y; Rhs=x $

MATR; bavg = bavg + {1/nrep}\*b $

CALC; mwtp0 = mwtp0 + (-1/nrep)\*(b(2)/b(3));

mwtp33= mwtp33 + (-1/nrep)\*(b(2)+b(4)\*33)/b(3);

mwtp67= mwtp67 + (-1/nrep)\*(b(2)+b(4)\*67)/b(3);

mwtp1 = mwtp1 + (-1/nrep)\*(b(2)+b(4)\*100)/b(3) $

CALC; rhov = rhov + (1/nrep)\*Cor(risk1,v) $

ENDPROC

/\*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\* V. Execute the procedure once to see what it does.\*

\* Here using zero correlation of risk1 & disturbance\*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\*/

CALC; rojo=0 $

CALC; rhov=0; theta1m=0; theta0m=0 $

CALC; Nrep=1 $

SILENT

EXEC; Proc=probproc; N=nrep $

NOSILENT

/\* Take a look at the data generated in one run. \*/

DSTA; Rhs=vprice,delta,rsk,d0,d1,risk1,dabs,dabsr1,v,tau,ystar,y $

/\* Comparing estimated to true values from one replication \*/

CALC; Nolist;

bplim1 = (btrue{1}+theta0m)/sqr(2);

bplim2 = btrue{2}/sqr(2);

bplim3 = btrue{3}/sqr(2);

bplim4 = btrue{4}/sqr(2);

bplim5 = (btrue{5}+theta1m)/sqr(2) $

CALC; Nolist;

brat1 = bavg{1} / btrue{1};

brat2 = bavg{2} / btrue{2};

brat3 = bavg{3} / btrue{3};

brat4 = bavg{4} / btrue{4};

brat5 = bavg{5} / btrue{5} $

MATR; List;

btrue; bavg;

bplim= [bplim1 / bplim2 / bplim3 / bplim4 / bplim5 ];

brat = [brat1 / brat2 / brat3 / brat4 / brat5 ] $

CALC; List; 1/sqr(2) $

CALC; List;

mwtp0; mwtp33; mwtp67; mwtp1;

mwtp0tr; mwtp33tr; mwtp67tr; mwtp1tr;

mwtp0-mwtp0tr; mwtp33-mwtp33tr; mwtp67-mwtp67tr; mwtp1-mwtp1tr $

CALC; List; rojo; theta1m; theta0m; rhov $

/\* Set up starting value for correlation so iterations compute the desired values. \*/

MATR; bavg = Init(5,1,0.0) $

CALC; mwtp0=0; mwtp33=0; mwtp67=0; mwtp1=0 $

CALC; rhov=0; theta0m=0; theta1m=0 $

CALC; rojo=-1.05 $

/\*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\* VI. Execute procedure "Nrep" times (here, 10,000). \*

\* Reset initial values, increment correlation, and execute. \*

\* \*

\* You can select all the code beginning with the next "MATR" \*

\* command, and then choose "Run multiple times" from the Run menu.\*

\* To use five values of disturbance/risk1 correlation considered \*

\* here, run the selection 5 times, etc. \*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\*/

MATR; bavg = Init(5,1,0.0) $

CALC; mwtp0=0; mwtp33=0; mwtp67=0; mwtp1=0 $

CALC; rhov=0; theta0m=0; theta1m=0 $

CALC; rojo=rojo+0.15 $

/\* Skip the zero correlation this time around. \*/

/\* CALC; If(rojo=0) rojo=rojo+0.25 $ \*/

CALC; Nrep=10000 $

SILENT

EXEC; Proc=probproc; N=nrep $

NOSILENT

/\*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\* VII. Report out results for each value of correlation. \*

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\*/

CALC; Nolist;

bplim1 = (btrue{1}+theta0m)/sqr(2);

bplim2 = btrue{2}/sqr(2);

bplim3 = btrue{3}/sqr(2);

bplim4 = btrue{4}/sqr(2);

bplim5 = (btrue{5}+theta1m)/sqr(2) $

CALC; Nolist;

brat1 = bavg{1} / btrue{1};

brat2 = bavg{2} / btrue{2};

brat3 = bavg{3} / btrue{3};

brat4 = bavg{4} / btrue{4};

brat5 = bavg{5} / btrue{5} $

TYPE; Results with rho= $

CALC; List; rojo; rhov $

TYPE; Results with theta1m= $

CALC; List; theta1 $

TYPE; Assumed true coefficient vector: $

MATR; List; btrue $

TYPE; Average of estimated coefficient vectors: $

MATR; List; bavg $

TYPE; Probability limit of estimator: $

MATR; List;

bplim= [bplim1 / bplim2 / bplim3 / bplim4 / bplim5 ] $

TYPE; Ratio, average estimated coefficients to true coefficients: $

MATR; List;

brat = [brat1 / brat2 / brat3 / brat4 / brat5 ] $

CALC; List; 1/sqr(2) $

TYPE; Average estimated MWTP to reduce risk by 1/100: $

CALC; List; mwtp0; mwtp33; mwtp67; mwtp1 $

TYPE; Assumed MWTP to reduce risk by 1/100: $

CALC; List; mwtp0tr; mwtp33tr; mwtp67tr; mwtp1tr $

TYPE; Difference, average estimated MWTP less true MWTP: $

CALC; List; abs0 =mwtp0-mwtp0tr; abs33=mwtp33-mwtp33tr;

abs67=mwtp67-mwtp67tr; abs1=mwtp1-mwtp1tr $

TYPE; Difference estimated less true as % of true: $

CALC; List; pct0 =100\*abs0/mwtp0tr; pct33=100\*abs33/mwtp33tr;

pct67=100\*abs67/mwtp67tr; pct1 =100\*abs1/mwtp1tr $

1. Adamowicz, W., M. Dickie, S. Gerking, M. Veronesi, and D. Zinner. 2014. Household decision making and valuation of environmental health risks to parents and their children. *Journal of the Association of Environmental and Resource Economists* 1: 481-519. [↑](#footnote-ref-1)
2. Pratt, J., H. Raiffa and R. Schlaifer. 1975. *Introduction to statistical decision theory*. NewYork: McGraw-Hill. [↑](#footnote-ref-2)
3. The estimated constant term in the probit model converges toand the estimated coefficient of posterior risk converges to [↑](#footnote-ref-3)