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Valuation of Cancer and Microbial Disease Risk Reductions in Municipal Drinking Water

An Analysis of Risk Context Using Multiple Valuation Methods

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RESOURCES FOR THE FUTURE

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Abstract

In this paper, we examine the value of health risk reductions to Canadians in the context of clean and safe drinking water. The health risks we examine pertain both to microbial illnesses and/or deaths and bladder cancer illnesses and/or deaths. The cancer risks arise because chlorine, the most common disinfectant used to remove microbial contaminants, has been implicated in the production of trihalomethanes (a disinfection by-product linked to increases in bladder cancer cases). Under these circumstances, public health agencies face issues of risk–benefit valuation as well as risk–risk assessment. To address this policy issue, we undertook a panel-based Internet survey of 1,600 Canadians conducted in the summer of 2004 and presented respondents with text and graphical information regarding risk changes. We employed two valuation formats (contingent valuation and attribute-based stated choice) to elicit consumer preferences for public programs to reduce health risks associated with improved tap water. We also used multiple analytical methods, including willingness-to-pay space models, and examine a host of comparisons between contingent valuation and attribute-based methods to assess the effect of risk context on value. Our analysis of the stated preferences of consumers reveals several types of values that are of interest to policymakers. These include the value of mortality risk reductions and the value of morbidity risk reductions for both microbial contaminants and cancer. In addition, the value of reducing cancer risks versus microbial risks in a public context is revealed. Our results suggest that reducing mortality risks from microbial illness has greater value than reducing mortality risks from cancer. Similarly, overall microbial risk-reductions programs (mortality and morbidity) have higher value than cancer risk-reduction programs in this context. In addition, we provide separate estimates of the value of statistical life associated with cancer and microbial risks, in a public context, and the value of statistical illness cases associated with these two risks.

Key Words: microbial risks, cancer risks, mortality risk, morbidity risk, risk context, public health risks, value of statistical life, municipal drinking water

JEL Classification Numbers: I18, Q51, Q58

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Introduction

Regulatory authorities in Canada and the United States are concerned with the levels of microbiological pathogens (here called microbes, e.g., E. coli, cryptosporidium, and giardia) and chemical contaminants in drinking water.[1] One such contaminant—a class of chemicals called trihalomethanes (THMs) that has been linked to bladder cancer—is of particular concern because it is formed from the chlorine used by most water treatment systems to kill microbes.[2] Techniques such as ozonation and ultraviolet are available to mitigate this trade-off, but they are more expensive than chlorination (U.S. EPA 1999). Hence, it is essential to understand public preferences for reducing health risks in drinking water in general, as well as the preferences involving the potential trade-off in reducing cancer versus microbial disease risks.

Using data from an Internet-based survey conducted across Canada during the summer of 2004, this paper presents the outcome of our efforts to elicit such preference information relating to reduced morbidity and mortality risks associated with two causes (cancer and microbes) with reference to the quality of publicly supplied water. We examine a variety of methodological issues surrounding this elicitation through use of both a contingent valuation method (CVM) survey and a nearly identical Attribute-Based Stated Choice Method (AB) survey (Adamowicz et al. 1998). Within the AB survey format, we also use different numbers of control options (one

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[1] The U.S. Environmenal Protection Agency sets standards for a wide variety of contaminants (U.S. EPA 2006). In Canada the federal government, in conjunction with provincial regulators, sets guidelines (Federal–Provincial–Territorial Committee on Drinking Water 2004).

[2] After reviewing the available evidence, an expert panel noted that five epidemiological studies show a statistically significant positive association of chlorinated by-product exposure with risk of bladder cancer (Mills et al. 1998). The experts concluded "… that it was possible (60% of the group) to probable (40%) that chlorination by-products pose a significant risk to the development of cancer, particularly bladder cancer." Furthermore, they stated that "… this is a moderately important public health problem."

versus two, plus the status quo). In addition, we apply a relatively new statistical approach to estimating AB values, the WTP space approach (Train and Weeks 2005), and contrast it with the conditional logit approach.

The next section discusses a number of methodological issues addressed in the survey. The third section describes the survey versions employed in this study, survey administration, and the resulting data. Econometric models are presented in the fourth section; the fifth section describes empirical results and statistical tests. A discussion of how these results can be useful in a policy context follows, and conclusions and suggestions for future research complete the paper.

Methodology

Elicitation Methods

We employ two nonmarket valuation methods for eliciting information about consumer preferences for avoiding public health risks from the public good "tap water": CVM and AB (Adamowicz et al. 1998; Holmes and Adamowicz 2003). CVM requires the researcher to describe in detail the characteristics of the good to be valued (scenario). Respondents then answer choice questions (we used a double-bounded dichotomous choice format) about whether they would be willing to pay for the described good at a stated price. The researcher estimates the willingness to pay (WTP) for the good, where the expressed WTP is for the good in its entirety as described in the scenario, from the pattern of responses. In the AB framework a good is described expressly as a bundle of characteristics or attributes. Each attribute provides valuable services to the consumer. While the individual attributes have value, they cannot be purchased separately but are acquired by the consumer at some stated price for the entire good. With this approach, then, the price paid for a particular bundle of characteristics becomes itself an attribute. In contrast to the CVM method, which provides an overall WTP for the bundle of attributes, the AB approach permits us to determine separate WTP values for each identified attribute as well as to examine trade-offs between individual attributes. For the purposes of this project, the relevant tap water attributes are household water costs and morbidity and mortality health risks from microbial and bladder cancer. Comparison of WTP estimates derived from the CVM and the AB enables us to examine the convergent validity of the stated-preference survey methods (Mitchell and Carson 1989).

Describing the Health Risks

In presenting the program choices to survey participants we provide information about the health effects, baseline risk levels, changes in risk levels, and costs of different programs.[3] Prior to seeing the preference elicitation questions the survey respondents are presented with three "screens" of health risk information.[4] The first screen describes symptoms of bladder cancer and clearly identifies the potential trade-off between the beneficial aspects of reducing microbial contaminants and the potential adverse effects in terms of enhanced risks of contracting bladder cancer. The second screen places the baseline microbial and cancer risks together and shows typical linkages between illnesses and deaths for each health outcome. In addition, it puts health risks from tap water consumption into a more general perspective. It is important to present the contextual setting to respondents so that tap water health problems are not viewed in isolation from other health risks. The third screen summarizes the baseline health risks from the four health outcomes: microbial illness, death from microbial illness, bladder cancer illness, and death from bladder cancer. Again, the magnitude of health risks from tap water consumption are contrasted with all health risks for each of these health outcomes.

After reviewing this background information, the survey respondent is presented with a discussion about changes to water disinfection methods that can alter health risks. The respondent is told that he/she will be faced with a series of choices regarding alternative municipal water treatment programs for his/her community. Each choice includes a status quo (do nothing) option and either one alternative program (CVM and AB) or two alternatives (AB).

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[3] Information describing symptoms of microbial and bladder cancer illnesses is readily available from several sources, including Health Canada and the U.S. Centers for Disease Control. Information on baseline risk levels and changes in risk levels resulting from policy interventions are more difficult to obtain. Recent work under the auspices of Health Canada reports on a study of individuals living around the Great Lakes. The research shows a link between the presence of THMs in drinking water and increased cases of bladder cancer. These results suggest that long-term exposure (on the order of 20–35 years or more) to THMs in water may cause between 14–16 percent of all bladder cancer cases in Canada (King and Marrett 1996). Similar numbers from the U.S. are between 2–17 percent (Mills et al. 1998). Cancer statistics are available on-line from Health Canada Cancer Surveillance (2003) by site. Status quo bladder cancer cases attributed to water consumption can be estimated by applying the attribution rates to all bladder cancer cases. Mortality rates are also presented on the Health Canada Cancer Surveillance web site. With baseline numbers established, we review the engineering and microbiological literature for estimates of anticipated reductions in microbes and/or THMs associated with improvements to water disinfection systems. Numbers from the U.S. EPA (1999), Havelaar et al. (2000), and Barbeau et al. (2000) form the basis for our estimates of changes in baseline risks presented to survey respondents. A range of reasonable program cost increases was estimated from information on alternative disinfection technologies (U.S. EPA 1999). These were presented as dollar increases per year in the household water bill effective January 2005, a date specified to be 6 months after respondents completed the survey.

[4] Since our survey was Internet-based survey respondents had to read through these screens in order to progress through the survey.

These programs lower the health risks and involve an annual increase in the existing water bill for the household; this increase is expressed as the equivalent monthly value.

To enable respondents to evaluate changes in health risks in a meaningful way, we adapt probability communication techniques from Krupnick et al. (2002) and present both numerical values and visual representations. Previous researchers have used visual aids such as graphs, pie charts, risk ladders, and tables (Jones-Lee et al. 1985; Hammitt 1990; Corso et al. 2001). After experimenting with a number of options we use what we call our “snake in the sand” design. This begins with a blue rectangle representing a population of 100,000. To this rectangle we add a yellow area representing individuals who get microbial illnesses from drinking tap water and a red area representing individuals who get bladder cancer from drinking tap water. We superimpose black squares onto either the red or yellow areas to illustrate the deaths arising from either microbial illnesses or cancer illnesses. An example of this graphic is shown in Figure 1 for a CVM format question. The AB choice task format is the same with two exceptions. The first is that the change in a household’s water bill is added as a row (as an additional attribute). The second is that the choice is elicited in the following way: “if there were a referendum, I would vote for …” and the choices are current situation and proposed program(s).

Private versus Public Risks

An issue arising from the approach adopted in this research is whether this particular problem should be treated as an individual (private) decision or a social (public) decision. The private decision context would readily yield individual specific measures of value (e.g., values of statistical life [VSLs]) that could be compared to other private good estimates (Krupnick et al. 2002). A public context, however, is more realistic in this setting since tap water is consumed by an individual at home as well as at other places (office, school, etc.), and most people view tap water treatment as a municipal or public responsibility. Therefore, the decision context chosen for this case is a public or social decision. Carson and Mitchell (2006) make the same choice in their open-ended CVM survey to obtain WTP for carbon filtration to reduce the risks associated with THMs. A potential drawback of this approach, however, is that the resulting estimates of the WTP for water quality improvement and for the specific attributes of reduced microbial and cancer risks may contain elements of altruism. While, in principle, we would like to have these "total social values" to make policy decisions, summing altruistic values from all individuals can introduce an unknown, possibly large degree of double-counting, as opposed to the summing of individuals' values for their own risk reductions. The latter provides, perhaps, a reasonable lower bound to social value. While this is a challenge, it may also provide us with important and interesting information. Since so many individuals in certain provinces and areas of Canada rely

solely on tap water substitutes, and thus may believe the benefits of such programs will be enjoyed wholly by others, we hope to be able to sort out altruistic and individual values. This is a topic addressed in Zhang et al. (2006).

Survey Administration and Data Description

Survey Administration

We employed Ipsos-Reid, a marketing and public research agency, to administer the survey and put it onto a secure on-line website. Respondents were solicited from among a panel of Internet users maintained by Ipsos-Reid.[5] The panel consists of over 100,000 members and reflects an accurate, balanced representation of Internet-enabled Canadians, recognizing that this does not necessarily mean that the panel is representative of all Canadians. These households have been recruited to the panel primarily over the telephone by using random-digit dialing. After focus groups and pilot testing to refine the survey, we implemented the final version during the summer of 2004. On our behalf Ipsos sent out 4,563 email invitations to its panel of Internet users, of whom 2,520 respondents began the survey. Of these, 1,633 completed the survey and 419 individuals quit the survey before completion. Additionally, 466 were dropped because they did not obtain any of their tap water from a local municipal water supplier. Finally, two responses were deleted after errors arose when the Ipsos server went down in the middle of completing a survey. Assuming that ineligibles are found in the same proportions to those contacted as to those responding (466/2,520 = 18.5 percent), the overall response rate is 46 percent (1,633/3,536). In this paper we discuss results relating to six of the eight versions of the survey; thus, the sample size is 1,219. Versions 1 and 2 (V1 and V2) used the CVM format, while the other four versions (V3 through V6) used the AB format.

Versions 1 and 2: Contingent Valuation Methodology Format

The CVM format (example shown in Figure 1) presents the respondent with the option to choose the status quo (no increase in water bill, no reduction in health risks) or a new municipal water treatment program (increase in water bill, reduction in some or all health risks). Regardless of the versions, each respondent was presented with three separate double-bounded dichotomous choice questions. For V1, when compared with the status quo, the first question presented a

[5] A publication by Statistics Canada (2004) noted that two thirds of Canada's 12.3 million households have at least one family member who regularly used the Internet in 2003.

reduction in bladder cancer illness (from 100 to 50) and a proportional reduction in the risk of death (from 20 to 10), holding constant microbial illness and death risks at their status quo levels. For the second question, respondents were asked to consider a reduction in microbial illnesses from 23,000 to 7,500 and a proportional reduction in the risk of death from 15 to 5, holding constant cancer illness and death risks at their status quo levels. For the third question, the reductions in health risks pertained to all four risks and were the same as those in questions one and two. The payment vehicle was additional costs to the household water bill. Payment levels ranged between $25 per year to $350 per year.[6] For V2 the ordering of the first and second WTP questions was reversed to enable clean comparisons of the WTP for cancer risk reductions and microbial risk reductions. The third question in V2 was identical to that in V1.

Versions 3 to 6: Attribute-Based Stated Choice Format

For each of the four choice tasks presented, the respondent compares a status quo option of no change in risks or household water bills with one alternative municipal water treatment program (V3 and V5), or two alternatives (V4 and V6), where attribute levels for these programs are varied systematically according to the experimental design. Programs describe three attributes: cancer cases, microbial cases, and household water bill. Cancer and microbial cases are each defined to have four levels of attributes, while household water bill has five levels (including a status quo level of zero increase in a water bill). These values are the same as those used in the CVM questions. Each combination of attributes/levels represents a unique bundle of the good to be valued (Cochran and Cox 1957). A modified fractional factorial experimental design procedure is used to identify those combinations that best reveal underlying consumer preferences (Louviere et al. 2000). We identify 32 combinations and divide these into eight blocks of four questions each. In order to avoid respondent fatigue, each respondent is randomly chosen to face a particular block of four choice tasks only.

V3 and V4 represent our proportional results. These versions maintain the fixed-proportions ratio between morbidity and mortality effects that is implicit in the CVM format. However, one problem with this assumption is that it does not permit us to disentangle the WTP for cancer or microbial morbidity risk reduction from that for cancer or microbial mortality risk reduction. While we could have created a large number of subsamples of CVM questions using varied proportions, this approach would have been costly since it would have required at least

[6] The typical range of annual household water bills in Canada is between $300 and $500.

100 respondents per sample in order to have confidence in the statistical properties of the estimates. Our solution is to employ a desirable feature of the AB format to obtain separate WTP values for each of the health risks of interest. Versions 5 and 6 (V5 and V6) are our nonproportional results versions, as they relax the assumption of proportionality between morbidity and mortality health effects.[7] This requires us to specify five attributes: cancer illnesses, cancer deaths, microbial illnesses, microbial deaths, and household water bill.

Data Description

Table 1 presents summary statistics from the data for all the variables used in this paper for two different samples: the full data set and data set that removes "yea-saying" observations (Kahneman and Knetsch 1992), because of the well-known problems with yea-saying in stated-preference studies. For the two CVM surveys we removed people who said that they would pay "anything" for health risk reductions and who answered Yes–Yes (YY) to all three dichotomous-choice questions with follow-up posed to them. This amounted to 44 respondents (11 percent of the sample of 407). Interestingly, 10 people who said they would pay "anything" actually did not answer YY to all three WTP questions. For the AB analysis, there is no equivalent to the YY condition. Even if we had identified those respondents choosing the alternative with the largest health improvement each time we would still not necessarily be removing yea-saying effects since attributes differ across programs. Thus, in very few cases are there clear and unambiguous "yea-saying" answers. Therefore, we removed those people who said they would pay "anything" for health risk reductions. This amounted to dropping 86 out of 812 respondents (10.6 percent) who answered one of the four AB surveys. The rest of the paper uses the truncated dataset.

Fortunately, this truncated dataset and the full dataset have very similar characteristics, as Table 1 shows, with the one main exception being the variable URBAN. The table shows that a higher percentage of the respondents who took V5 and V6 live in urban areas.

In addition, Table 1 compares the characteristics of the sample respondents to the Canadian population using 2001 Census statistics. For most characteristics, average values for survey respondents are virtually the same as those for Canada. The only sociodemographic

[7] Because the technologies reduce these substances at the source, mortality and morbidity effects should, logically, remain proportional. But to keep them proportional prevents us from estimating WTP for the separate effects. Hence we broke the proportionality in some surveys and then asked debriefing questions of all respondents getting this treatment about whether they realized we "broke" proportionality and whether they realized it was a logical feature of what we did. Few respondents identified this feature of the design. None of the respondents in the debriefing discussions identified a difficulty with the lack of proportionality.

characteristic that differs in any appreciable way from that of the general Canadian population is the percentage of individuals educated beyond high school. The 2001 Census estimate is 55 percent, while the corresponding value for our sample, collected in 2004, is 79.1 percent. A comparison of the 1996 and 2001 Census values shows that, over that 5-year period, the percentage of people educated beyond high school increased five points. So, the 2004 percentage is likely to exceed 55 percent.

Econometric Models

With respect to data from CVM respondents, we estimate a model described by equation (1). This defines *WTP**, the underlying WTP for a selected risk reduction, where S denotes explanatory variables; β is a vector of coefficients; and ε is an extreme value type I error term. Effectively, equation (1) describes a survival-time model based on the Weibull distribution.

$$\log WTP_i^* = S_i\beta + \varepsilon_i \tag{1}$$

The log-likelihood function for this model is shown in equation (2):

$$\log L = \sum_{i=1}^{n} \log\{F[(\log WTP_i^H - S_i\beta)/\sigma] - F[(\log WTP_i^L - S_i\beta)/\sigma]\} \tag{2}$$

where F is the type I extreme value distribution, $WTPi^H$ and $WTPi^L$ are upper and lower bounds for the payments as presented to respondents in the CVM questions, and S and β are as defined above. σ is the scale parameter of ε, as well as the reciprocal of the shape parameter of the Weibull distribution describing WTP. The scale parameter for the Weibull distribution is $\exp(S_i\beta)$. A similar model is estimated assuming preferences can be described instead by a lognormal distribution.

We adopt the random-utility approach to analyze responses from the AB surveys. This begins with the assumption that individual consumers choose alternatives that provide them with the greatest utility. The researcher defines a number of bundles of attributes and presents them to respondents in a series of choice tasks. The attributes of each alternative offered in a task comprise the Z vector and the sets of alternatives in each task comprise C, the choice set.[8] It is assumed that an individual's utility is composed of a deterministic component (V) and an

[8] Attribute levels for microbial illnesses were 7,500, 15,000, 23,000, and 30,000. Attribute levels for microbial deaths were 5, 10, 15, and 20. Attribute levels for cancer illnesses were 50, 75, 100, and 125. Attribute levels for cancer deaths were 10, 15, 20, and 25. All were defined for a population of 100,000 and over a 35-year period. Annual increases to household water bills ranged between $25 and $350.

unobservable or stochastic component (ε), where V is an indirect utility function. If the stochastic component or error term is a distributed extreme value, McFadden (1974) shows that the conditional choice probability of selecting alternative i is defined as in equation (3), where μ is a scale parameter that is confounded with the parameter vector β and normally set equal to 1.0.

$$\Pr ob(i) = \exp(\mu\beta_k Z_i) \Big/ \sum_{j \in C} \exp(\mu\beta_k Z_j) \tag{3}$$

Respondents answer four choice tasks in our survey. The resulting information is viewed as four individual choices from either a binary or a trinary universe. Maximization of the likelihood employing the probabilities derived from equation (3) provides estimates of the marginal utilities associated with attributes and allows for their use in welfare measures.

However, a simple conditional logit model like equation (3), while common in the literature, is not adequate for modeling our choice data for two reasons. Firstly, a simple logit model assumes choice decisions are independent across choices. Our data are a type of "panel" in that each respondent answers four choice questions. A better approach is to recognize the "panel" characteristics by allowing for fixed preferences in responses made by one respondent. Secondly, a simple logit model cannot capture preference heterogeneity, particularly unobserved heterogeneity.

One solution to both of these problems is to estimate a mixed logit (ML) model. However, problems may arise when calculating welfare estimates in some ML models. Specifically, when the welfare measure is the ratio of two random parameters, the estimator often has a large variance and may have unknown properties if both numerator and denominator are assumed to be normally distributed (Meijer and Rouwendal 2006). A common practice is to let the denominator (marginal utility of money) be a fixed parameter; however, this reintroduces the inefficiency an ML model tries to overcome. In addition, an ML model does not address the confounding discussed earlier between the estimated preference parameters and scale (of the type I extreme value error) parameters. This can prevent us from untangling the effects of preference heterogeneity from the effects of scale (heteroscedasticity) on welfare estimates.

Train and Weeks (2005) have proposed a WTP space model that directly estimates WTP, thereby avoiding the confounding issue. Rather than deriving welfare estimates indirectly as ratios of two estimated random parameters, a WTP space model derives the distribution of

welfare estimates directly. If utility is separable in price, *p*, and nonprice, *x*, attributes, equation (4) defines individual *n*'s utility for alternative *j* at choice task *t*.

$$U_{njt} = -(1/\sigma_n)\, p_{njt} + (\beta_n / \sigma_n)' x_{njt} + e_{jt} \quad (4)$$

In equation (4), β_n is the WTP for a unit change in the levels of an attribute and it varies randomly over decision-makers; σ_n is the individual specific inverse of the scale parameter, and e_{jt} is an independent and identically distributed error term. The variance of e_{jt} is a constant $(\pi^2/6)$ (Train and Weeks 2005). This is a random-parameters, multi-attribute generalization of the model introduced by Cameron (1988) for CVM responses. Because the estimation of a WTP space model involves making a distributional assumption on β_n and σ_n, the WTP estimates have known statistical properties by construct. Train and Weeks (2005) showed that preference parameters can be recovered as ratios between β_n and σ_n; they also found that the welfare estimates derived using a WTP space model generally have a smaller variance than those derived using an ML model. However, the converse is true for preference parameters—the estimated preference parameters have a larger variance using a WTP space model than an ML model. Since welfare estimates are more of our research interest, we derive welfare estimates based on the WTP space model, which can be compared to those derived by the simple conditional logit model.

In our estimation we assume that WTP (β_n) is lognormally distributed, implying that people are willing to pay a nonnegative amount to reduce a given level of health risk. The inverse of scale, σ_n, is also assumed to be lognormally distributed as it must be positive. While Train and Weeks (2005) employ Bayesian techniques to estimate the WTP space model, we use classical simulated maximum likelihood.

Empirical Results

The first set of results consider the WTP estimates from the CVM and AB models as described in Tables 2 and 5, respectively. Tables 3 and 6 present statistical tests associated with these results, respectively. Table 4 presents regression results for the AB dataset that are necessary to derive WTP estimates.

Contingent Valuation Methodology WTP Estimates

Mean and median WTP using the CVM data (V1 and V2) are presented in Table 2 for different combinations of cancer and microbial endpoints and two different assumptions (lognormal and Weibull) about the nature of the error distribution. Models are estimated without covariates and presented for both the full sample and the sample that removes yea-sayers. The

first six rows estimate the WTP models using data from V1 (or V2) separately for each of the questions. For example, WTP Cancer V1 uses responses from V1 only for the first question that involves a change in cancer risks alone, holding constant microbial risks. WTP Cancer V2, on the other hand, uses responses from V2 for the second question that involves only the change in cancer risks. These estimates can be examined for evidence of ordering effects. WTP Both Cancer and Microbial V1 uses responses to the third question in V1, which involves changes in both cancer and microbial risk. These estimates can be compared to responses from V2 (WTP Both Cancer and Microbial V2), which also uses responses to the third question involving changes in both risks. The risks changes are identical across versions but vary by cancer and microbial endpoint. Thus, the first value in the table, C$535 (2004 C$), represents the mean annual household WTP using all responses from V1. This WTP is for a reduction in 50 cancer cases of which 10 would have resulted in death (both over a 35-year period) in a community of 100,000. This WTP translates into a value per statistical case of C$14.4 million[9], where a case is the above mortality/morbidity combination. In contrast to the first six rows, the last three rows estimate the WTP models by pooling responses from the two versions. Thus, for example, WTP Cancer Pooled combines responses to the cancer risk change only question (question 1 in V1 and question 2 in V2).

Since the Weibull specification outperforms the lognormal distribution in a variety of ways and we believe the yea-saying observations should be removed, in Table 2 we highlight with grey shading the last two columns. The most reliable comparisons are for cancer asked first in Version 1 (Cancer V1), microbial asked first in Version 2 (Microbial V2), and Both Cancer and Microbial Pooled. The mean WTPs are C$182, C$200, and C$294, respectively. Using the pooled versions for added power, mean WTP for reductions in cancer cases is C$157 per household per year, while WTP for a reduced number of microbial cases is C$211. Finally, WTP for both types of reductions combined is C$294. Median WTP is about half that of the mean.

Table 3 presents results of Likelihood Ratio and Wald tests relating to potential differences in these estimated WTP values across versions and questions. We present results only for data samples from which the yea-sayers' responses have been removed and the Weibull error distribution adopted.[10] Both tests reveal that question order does not matter. Consequently, responses to questions from different versions can be pooled. Comparing WTP Cancer Pooled to

[9] $14.4 million = $535/50 cases*100,000*35 years/2.6 persons per household.

[10] Results for the full sample and/or using the lognormal distribution are very similar in pattern and outcome.

WTP Microbial Pooled we find that the Wald statistic is 3.685, slightly lower than the 95 percent Chi-squared statistic of 3.84. Thus, we barely reject the hypothesis that the microbial WTP is larger. An examination of tests of weak and strong adding up reveals that mean WTP for both risk reduction changes exceeds that for cancer alone when comparing Cancer Pooled to Both Pooled. However, comparing Microbial Pooled to Both Pooled, we reject this symmetric finding (barely). However, if we compare the more reliable WTP for microbial risk reduction (i.e., when it is the first question asked) to the WTP for the third question (Both) pooled, we find that the Wald statistic exceeds the target value and that therefore the WTP for both changes exceeds that for microbial risk reductions alone. As for the strong test, while it cannot be statistically rejected, the sum of mean WTPs for the individual risk reductions (C$157 + C$211) exceeds the WTP for both risk reductions (C$294), which is likely indicative of declining marginal utility for health improvements.

Attribute-Based WTP Results from Conditional Logit and WTP Space Models

AB-based WTP estimates must be derived from regression results. Thus we must present these results before presenting the WTP estimates. Table 4 presents estimates of four separate conditional logit AB models using data from V3 and V4 (assuming a proportional illness/death risk) and V5 and V6 (relaxing assumption of proportional risks).

The first results are for a pooled model that combines responses from V3 and V4 (Chi-squared test statistic is 3.95 and critical value is 11.07, indicating that pooling is appropriate). The next results are for V5 and V6 separately, since this pooling test is rejected (Chi-squared test statistic is 35.65 and critical value is 14.45). For comparison we report results using a pooled V5 and V6 data set. We find that all parameters in all models are significant and of the expected sign. The most significant difference between these versions can be seen in the size of the status quo effect. A much lower preference for the status quo arises in the two-alternative version (V5).[11]

[11] The reason for this difference is unclear, but shows up in other work by the authors and is a topic for further research.

Table 5 provides estimates of the WTP values obtained using parameter estimates from Table 4.[12] In order to facilitate a comparison with the CVM results in Table 2 we present AB results in rows 2 through 7 for the same "package" of risk reductions voted upon by respondents who did the CVM surveys.[13] The first three of these rows provide mean WTP estimates obtained when we use results from an AB model that includes a status quo effect, while the latter three rows use results from an AB model that excludes a status quo effect. When an AB model excludes the status quo effect this means that it relies only on the attributes of the model to capture the entire welfare change. When the status quo effect is included, changes from status quo are discounted by the amount of the status quo preference parameter. There is little guidance in the literature on how to treat this difference; however, the latter is the more conservative approach. We note that the WTP measures are significantly higher (on the order of 50 percent) when the status quo effect is excluded.

A noteworthy finding is that microbial risk-reduction programs appear to be more highly valued than the cancer programs. This is a finding similar to that obtained in the CVM responses. This policy-relevant result carries through many of our findings.

Table 6 provides Wald test statistics used to examine differences in the WTP from the AB conditional logit models in several different ways. The top panel tests differences between cancer and microbial values within versions. We find no significant difference between the cancer and microbial WTPs in V3 + V4 (proportional versions) and again for V6 alone ("Cancer vs. Microbial" column). However, using V5 data alone or combined with V6, we obtain significantly different WTP values. When we compare the WTP for reduced cancer risk to a combined WTP for reductions in both types of risk ("Cancer vs. Both" column), we find significant differences within versions regardless of whether we use proportional data (V3 + V4)

[12] While we do not report results from the full sample here, it is generally the case that removal of yea-sayers' responses reduces the WTP. For example, a reduction in microbial risks in the full-sample pooled model is valued at C$219; in the sample that removes yea-sayers' observations, this WTP is C$175. Overall, when we remove yea-sayers' observations the resulting WTPs are approximately 20 to 35 percent lower than in the comparable full sample.

[13] The CVM package consists of 50 fewer cancer cases, of which 10 would have resulted in death, and 15,500 fewer microbial cases, of which 10 would have resulted in death, all over a 35-year period in a community of 100,000. To obtain AB WTP values we multiply the marginal WTP per case (separately for cancer and microbial) obtained from the AB parameters by the number of cases. The difference between the proportional (V3 + V4) and nonproportional (V5, V6, and V5 + V6) version results arises from the fact that the former uses an estimate per case (mortality and morbidity risk together), whereas the latter provides separate estimates for mortality and morbidity risk reductions. Table 7 reports the individual per death and per illness values obtained from the AB conditional logit model in order to compare them with the AB WTP space model discussed in the next section.

or nonproportional data. Finally, a comparison of the WTP for reduced microbial risks and the WTP for reductions in both types of risk ("Microbial vs. Both" column) are generally not statistically different within versions; however, they are close to the critical value. The middle panel of Table 6 shows that there are no significant differences in values across versions. That is, the WTP values for either the cancer or the microbial risk reductions are not different across the proportional and the nonproportional versions. This powerful result suggests that these two different elicitation strategies do not generate significantly different WTP values. Finally, the bottom panel of Table 6 provides results relating to tests of the adding up of death and illness WTPs in the nonproportional versions (V5 + V6) (where these two effects are separated) against the WTP in the proportional version (V3 + V4). The null hypothesis of no significant differences is accepted in all cases, indicating that the response format does not significantly affect our ability to add up values.

In Table 7 we report estimates from the conditional logit models discussed above with estimates from comparable AB WTP space models.[14] We present mean[15] marginal WTP estimates for models using pooled V3 + V4, V5 alone, V6 alone, and pooled V5 + V6.[16] Since the data sample from V3 + V4 assumes proportionality between morbidity and mortality risks we can only obtain two different types of estimates: marginal value of combined microbial death and illness and marginal value of combined cancer death and illness.

Table 7 also compares WTP results from the conditional logit and WTP space models. The estimated marginal values for a reduction in risks of microbial cases (death and illness) using the pooled V3 + V4 data are larger than those for cancer case reductions (C$30.173 versus C$24.313 as estimated with the WTP space model and C$39.875 versus C$30.36 when estimated with the conditional logit model). When we examine the separate marginal WTP from V5, V6, and V5 + V6, we see that microbial risk reductions are still valued more highly than cancer risk reductions and that the marginal WTP for a cancer risk reduction is higher when estimated with

[14] The WTP space models outperform their conditional logit counterparts based on both the Akaike Information Criterion (AIC) and Bayes Information Criterion (BIC). This is not surprising since these WTP space models estimate individual specific preference parameters, so they incorporate preference heterogeneity. In the interests of space we do not report all goodness of fit statistics here; however, typically the AIC for V3 + V4 falls from 2278.70 to 2051.20 when the WTP space model is estimated. Similarly, the AIC for V5 falls from 1456.32 to 1249.12. Reductions in the size of the BIC are similar.

[15] We do not report median estimates; however, as expected they are smaller than the mean estimates since the median of a lognormal distribution is less influenced by large values in the extreme and is, therefore, more robust.

[16] A likelihood ratio test is conducted to test for equal preferences between versions 5 and 6. The hypothesis of equal preferences is rejected significantly at the 1% significance level.

the WTP space model, although the differences vary by sample. Comparing the mean WTP estimates generated by the WTP space models with those generated by the conditional logit models, the differences are not especially large; however, the mean estimates given by the WTP space models have much larger variances, probably resulting from incorporating heterogeneous preferences.

WTP Results for Deaths and Illness

With the nonproportional samples (V5, V6, and V5 + V6) we are able to separate out the marginal value of an illness and a death attributable either to cancer or microbial causes. Using the estimated mean WTP from Table 7, we report in Table 8 measures of VSL and the value of statistical illness (VSI) separately for cancer and microbial deaths and illnesses. In order to put these results into context, consider the results from Viscusi and Aldy (2003), who examine several studies that have produced estimates for the VSL. They report that the range of values is fairly broad, from US$3.9 million to US$21.7 million (2000US$). While our estimates fall within the range of these values, we must note that the majority of studies that calculate a VSL do so by using a WTP for a reduction in the risk of death to oneself (i.e., a private mortality risk). In contrast, our VSL estimates are based on the WTP to avoid public mortality risks. We would expect that altruistic WTP values might be higher than private WTP values since the former would include the WTP to avoid the deaths of members of one's community (including family members).

Table 8 reports results obtained from using the WTP space model estimates. Overall, the estimates are slightly larger than, but comparable to, the ones based on the conditional logit model. For example, using results from model estimates produced by V5, the VSL for microbial risk reduction is C$20 million and the VSL for cancer risk reduction is C$17 million. The microbial VSL is 1.2 times that of cancer. On the other hand, the VSI of cancer is C$3.2 million and the VSI of a microbial case is about C$33,000, suggesting that the cancer VSI is now 10 times that of the microbial VSI. Note that the variances of the values for VSIs are quite large, especially for microbial illness, perhaps illustrating the heterogeneity of respondents in dealing with probabilities and values at this scale.

It is also noteworthy that our estimates are for deaths from two specific causes. The fact that the VSL for deaths from microbial disease is somewhat greater than that for cancer is somewhat surprising given past research that supports a cancer premium (Hammitt and Liu 2004). This may be related to previous experience with contamination of municipal water systems in Walkerton, Ontario, and North Battleford, Saskatchewan, by microbial contaminants in 2000 and 2001, respectively. More research on this point is needed to verify if this is an

artifact of our survey or a true representation of preferences. While there are few other studies that estimate VSLs for public goods cases, those that do exist seem to provide results somewhat similar to ours. Strand (2004) finds VSLs for public cases to be US$3–$6 million, while private VSLs are US$1–$1.5 million. This corresponds to our finding of VSLs that appear to be two to three times that reported for private goods. Bosworth et al. (2005) describe differences in value across a variety of illnesses measured in a public good context. While we could not determine VSLs or values of statistical cases from their estimates, it is clear that their work provides evidence similar to that which we find here, including difference in risk context and evidence of diminishing marginal utility over health outcomes.

When we turn to estimates of VSI we find that the values relating to cancer fall between C$2.6 and C$4.3 million (2004C$) and range from 20 to 50 percent of the value of a cancer mortality reduction. Our estimates express values for cancer in welfare terms, which is an improvement over previous work that values cancer morbidity costs by using a cost of illness approach that is typically seen to be an underestimate. The value of a statistical case of microbial disease falls within a much lower range of values (C$18,000 to C$25,000). This is found as the product of an estimated WTP of $0.018 per case per household and 100,000 people (38,500 households) in the community over 35 years. The value per case appears to be quite high and in our view results from the inability of respondents to register preferences in a choice format that would lead to WTP estimates of a fraction of a cent.

Methodological Results

Results from statistical tests on selected WTP values from the AB and CVM versions of the survey are shown in Table 9. Two joint models (V3 + V4, which assumes fixed proportions of deaths to illnesses, and V5 + V6, which relaxes this assumption) are compared to the CVM WTP distributions (V1 + V2). The tests reject an hypothesis of equality for V3 + V4 with V1 + V2 except for the case of the microbial risk-reduction program and the status quo effect included. However, the values of the Wald tests are not that much above the critical value. The tests comparing V5 + V6 with V1 + V2 are accepted for cancer with the status quo effect excluded and rejected for all other cases. Recall that WTP measures with the status quo effect included are considerably lower than with the effect excluded. The WTP from the models with status quo effects included tended to be lower than the CVM values, while the WTP from the models with the status quo effects excluded tended to be higher than the CVM models. Thus, the AB results appear to bracket the CVM results by providing upper and lower bounds.

Conclusions and Future Directions

This paper presents findings from an Internet-based survey designed to elicit preferences relating to tap water quality and public health risks and address various methodological issues. This paper is novel because it presents new public values for cancer and microbial disease, which are, to the best of our knowledge, the first in the literature. It also provides a clean comparison of the AB and CVM approaches and tests a relatively new statistical method, the WTP space approach, to estimating WTP from AB data.

The values show that Canadians are willing to pay to reduce the public risks for several different water-related health conditions and that they may have a mild preference for reducing microbial contamination cases over cancer cases. The numbers pertaining to cancer appear reasonable and accord with prior work; however, there are no comparable estimates in the literature for microbial illnesses. We also estimate separate WTPs to prevent deaths and illnesses from the diseases that generally accord well with the small public goods literature and exceed, as expected, private values in the literature, recognizing that this literature for cancer specifically is very small, and nonexistent for microbial disease specifically.

The WTP estimates for a case integrate morbidity and mortality in one number and may prove even more useful for policy analysis than the VSLs or VSIs if the policy reduces the source of cases (such as a pollution reduction policy) rather than alters the ratio of illness to death (such as would occur with a health care policy) and the ratio of deaths to cases of morbidity is similar to ours.

We also find that the sum of WTP for cancer risk reduction and microbial risk reduction is greater than that for reducing both types of risks jointly, indicating that there may be diminishing returns to reducing different types of health risks.

One problem we noticed is that respondents appear to have trouble with the large number of illnesses presented in the microbial case. This results in small values per illness per respondent (C$0.02), but large values per illness when added up over the community. This is clearly an area requiring future study.

Our results for methodology imply that the AB approach may well produce WTP estimates that bracket those from the CVM approach, where the bracketing is caused by the treatment accorded the status quo variable (included or excluded). Excluding this variable pulls up WTP estimates. We also found that the conditional logit and WTP space approaches gave similar WTP estimates, although the latter were somewhat larger, but also had larger variances.

Future directions for this research include an examination of nonlinear indirect utility functions, additional analysis of choice format differences, and other specification issues. In addition, our results appear unreasonably large for the WTP to reduce microbial disease. This suggests that further work on different ways to communicate very small probability changes is needed. Finally, our study estimates values for reducing drinking water risks as a public good, yet we have made no attempt to distinguish private WTP values from altruistic values that underlie our estimated values, nor to distinguish among different types of altruism (paternalistic and nonpaternalistic), which would affect the welfare estimates. See Zhang et al. (2006) for attempts to make the first of these distinctions.

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Figures and Tables

Figure 1. Example of CVM Format Question

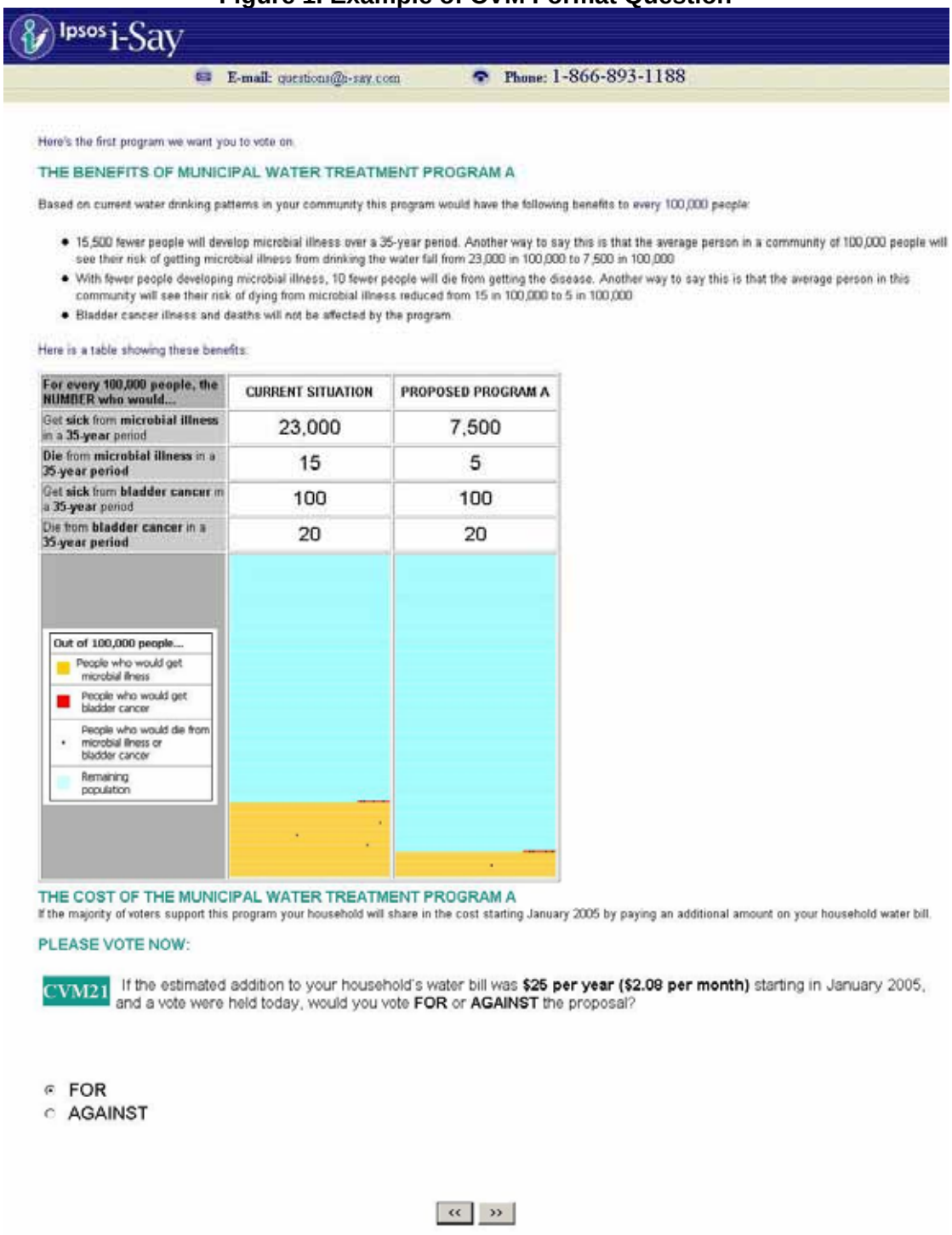

Table 1. Descriptive Statistics by Version and Subsample

		CVM		AB					
Variables	**Canadian Pop.**	**V1 + V2 Full Sample**	**V1 + V2 Yea-sayers removed[a]**	**V3 + V4 + V5 + V6 Full Sample**	**V3 + V4 + V5 + V6 Yea-sayers removed**	**V3 + V4 Yea-sayers removed**	**V5 Yea-sayers removed**	**V6 Yea-sayers removed**	**V5 + V6 Yea-sayers removed**
INCOME (per household)	**58360**	**58734.17[b]** (35562.79)	**58080.27** (35501.41)	**56819.12** (35699.68)	**56901.19** (35776.31)	**54743.30** (35012.21)	**57796.83** (35865.36)	**60289.60** (37069.08)	**59029.59** (36436.97)
MALE (% who are male)	**49.9%**	**54.55%** (0.50)	**54.96%** (0.50)	**51.85%** (0.50)	**51.72%** (0.50)	**49.86%** (0.50)	**50.81%** (0.50)	**56.35%** (0.49)	**53.55%** (0.50)
AGE (in years)	**45.8**	**44.93** (15.02)	**44.18** (15.25)	**47.36** (14.97)	**47.18** (14.94)	**47.58** (15.07)	**46.15** (15.30)	**47.42** (14.31)	**46.78** (14.81)
HHSIZE (# persons in household)	**2.6**	**2.63** (1.26)	**2.61** (1.26)	**2.57** (1.34)	**2.59** (1.33)	**2.65** (1.35)	**2.52** (1.37)	**2.53** (1.25)	**2.53** (1.31)
COLLEGE (% with more than high school education)	**55 %**	**61.18%** (0.49)	**62.04%** (0.49)	**62.07%** (0.49)	**62.86%** (0.48)	**61.77%** (0.49)	**64.86%** (0.48)	**62.98%** (0.49)	**63.93%** (0.48)
ENGLISH (% whose first language is English)	**73%**	**75.92%** (0.43)	**75.64%** (0.43)	**76.23%** (0.43)	**75.79%** (0.43)	**76.73%** (0.42)	**75.68%** (0.43)	**74.03%** (0.44)	**74.86%** (0.43)
URBAN (% living in city of more than 10,000)[c]	**80%**	**61.67%** (0.49)	**63.17%** (0.48)	**66.87%** (0.47)	**67.81%** (0.47)	**64.82%** (0.48)	**70.27%** (0.46)	**71.27%** (0.45)	**70.77%** (0.46)
BELIEFMS[d]	**na**	**73.96%** (0.44)	**71.39%** (0.45)	**75.25%** (0.43)	**74.00%** (0.44)	**72.85%** (0.45)	**80.00%** (0.40)	**70.17%** (0.46)	**75.14%** (0.43)
NOAVERT[e]	**na**	**45.95%** (0.50)	**46.46%** (0.50)	**45.07%** (0.50)	**44.98%** (0.50)	**42.38%** (0.49)	**49.19%** (0.5)	**45.86%** (0.50)	**47.54%** (0.50)
N		407	353	812	727	361	185	181	366

Notes:

[a] Yea-sayers are identified in CVM samples by answering YY for all three CVM questions and respondents indicate they are willing to pay anything for health risk reductions. It is identified in AB samples when the latter condition is true.

[b] Means are in bold and standard deviations are in parentheses.

[c] The Census definition is more encompassing than ours. It defines an urban area if the population is more than 1,000. We used 10,000 to better capture locations with municipally supplied water.

[d] Percentage of respondents who believe scientists are certain about microbial illnesses arising from drinking tap water. This is highly correlated with other belief variables relating to the certainty of the scientific community about risks associated with cancer and microbial deaths and cancer illnesses.

[e] Percentage of respondents who undertake no averting behavior (home filtering, bottled water purchases) against drinking water-related health risks.

Table 2. CVM Mean and Median WTP Estimates

	Lognormal				*Weibull*			
	Full Sample		*Yea-sayers Removed*		*Full Sample*		*Yea-sayers Removed*	
	Mean	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*
WTP Cancer V1[a]	**535**[b] (199)[c]	**110** (16)	**289** (82)	**84** (11)	**266** (46)	**119** (44)	**182** (27)	**91** (27)
WTP Cancer V2	**393** (149)	**72** (11)	**201** (55)	**55** (8)	**200** (33)	**79** (31)	**133** (19)	**60** (19)
WTP Microbial V1	**1075** (567)	**130** (22)	**532** (220)	**95** (15)	**332** (67)	**137** (61)	**226** (39)	**104** (38)
WTP Microbial V2	**552** (194)	**118** (17)	**344** (100)	**92** (13)	**265** (43)	**127** (43)	**200** (29)	**101** (30)
WTP Both Cancer and Microbial V1	**1187** (597)	**198** (35)	**667** (273)	**149** (24)	**404** (86)	**200** (82)	**293** (54)	**156** (55)
WTP Both Cancer and Microbial V2	**758** (278)	**179** (26)	**514** (162)	**143** (20)	**345** (60)	**186** (60)	**276** (44)	**153** (45)
WTP Cancer V1+V2	**464** (124)	**90** (9)	**244** (48)	**68** (7)	**232** (28)	**97** (27)	**157** (16)	**74** (16)
WTP Microbial V1+V2	**739** (223)	**123** (14)	**416** (101)	**94** (10)	**294** (37)	**132** (36)	**211** (24)	**103** (24)
WTP Both Cancer and Microbial V1+V2	**922** (277)	**187** (21)	**739** (223)	**123** (14)	**370** (50)	**192** (49)	**294** (37)	**132** (36)

Notes:

[a] V1 refers to Version 1 (CVM) and V2 refers to Version 2 (CVM). V1 asks questions in the following order: cancer change only, microbial change only, both changes. V2 asks questions in the following order: microbial change only, cancer change only, both changes.

[b] Values are in Canadian dollars (2004).

[c] Standard errors are in parentheses.

Table 3. Likelihood Ratio Tests and Wald Tests in CVM Model

	Mean	*Median*		*Mean*	*Median*
Likelihood Ratio Tests					
Cancer V1, V2 vs. Cancer Pooled	**4.663[a]***		**Related Tests**		
Microbial V1, V2 vs. Microbial Pooled	**0.294**		***Cancer V1 & Both V1***	**3.389**	**1.121**
Both V1, V2 vs. Both Pooled	**0.059**		***Cancer V2 & Both V2***	**9.032***	**3.635**
Wald Tests			***Cancer V1 & Both Pooled***	**5.879***	**0.803**
Cancer V1 vs. V2	**2.232**	**0.894**	***Microbial V1 & Both V1***	**1.001**	**0.605**
Microbial V1 vs. V2	**0.292**	**0.004**	***Microbial V2 & Both V2***	**2.086**	**0.927**
Both V1 vs. V2	**0.059**	**0.002**			
Cancer Pooled vs. Microbial Pooled	**3.685**	**0.964**			
Internal Consistency Tests			**External Scope Tests**		
Weak Adding-Up Test: Cancer Pooled vs. Both Pooled	**11.269***	**2.138**	***Cancer V1 & Both V2***	**3.355**	**1.372**
Weak Adding-Up Test: Microbial Pooled vs. Both Pooled	**3.453**	**0.465**	***Microbial V2 & Both V1***	**2.291**	**0.782**
Microbial V2 vs. Both	**3.897***	**0.434**			
Strong Adding-Up Test: (Cancer pooled + Microbial pooled) = Both Pooled	**2.507**	**0.971**			

Note:

[a] ***Means are significantly different from one another at the 1% level.

Table 4. AB Conditional Logit Model: Estimated Parameters Proportional Versions and Nonproportional Versions[a]

Variable[a]	*V3 + V4*	*V5*	*V6*	*V5 + V6*
Status Quo Constant	**0.759*** (.109)	**0.528*** (.127)	**1.132*** (.183)	**0.753*** (.102)
Microbial deaths (V3 + V4)[b]	**-0.163*** (.012)	**na**	**na**	**na**
Cancer deaths (V3 + V4)[b]	**-0.120*** (.011)	**na**	**na**	**na**
Microbial deaths (V5, V6)[c]	**na**	**-0.053*** (.011)	**-0.081*** (.018)	**-0.058*** (.009)
Microbial illness (V5, V6)[c]	**na**	**-7.552E-05*** (.000)	**-8.769E-05*** (.000)	**-7.974E-05*** (.000)
Cancer deaths (V5, V6)[c]	**na**	**-0.048*** (.011)	**-0.041*** (.016)	**-0.045*** (.009)
Cancer illness (V5, V6)[c]	**na**	**-0.008*** (.002)	**-0.020*** (.004)	**-0.010*** (.002)
Program cost	**-0.005*** (.001)	**-0.004*** (.001)	**-0.006*** (.001)	**-0.005*** (.001)
Observations (choice sets)	**1444**	**740**	**724**	**1464**
Log-likelihood	**-1131.35**	**-716.16**	**-398.46**	**-1130.95**

Notes:

[a] Results using data set with yea-sayers' observations removed.

[b] For V3 and V4 microbial deaths and illnesses are proportional; statistics are reported for deaths in the model. Similarly, cancer deaths and illnesses are proportional.

[c] For V5 and V6 microbial deaths and illnesses are not proportional.

[d] Standard errors in parentheses; * indicates significance at the 1% level.

Table 5. AB Conditional Logit Model: Estimated Mean WTP Values

	V3 + V4 [a]	***V5*** [a]	***V6*** [a]	***V5 + V6*** [a]
Including Status Quo Effect [b]				
Microbial deaths and illnesses	**175.400** (17.17)[c]	**288.190** (41.81)	**161.780** (31.36)	**237.190** (26.88)
Cancer deaths and illnesses	**88.427** (16.31)	**80.136** (38.35)	**43.977** (23.89)	**40.421** (24.30)
Microbial and cancer deaths and illnesses	**419.130** (36.612)	**501.150** (67.49)	**386.240** (49.83)	**447.040** (44.43)
Excluding Status Quo Effect [b]				
Microbial deaths and illnesses	**332.590** (38.44)	**426.580** (70.95)	**343.660** (58.59)	**404.610** (53.58)
Cancer deaths and illnesses	**244.150** (29.07)	**214.596** (47.99)	**226.663** (43.86)	**209.570** (33.82)
Microbial and cancer deaths and illnesses	**574.22** (65.40)	**641.176** (103.50)	**570.323** (94.22)	**614.180** (78.96)

Notes:

[a] Data set with yea-sayers' observations removed.

[b] Welfare measures are for 10 fewer cancer deaths, 10 fewer microbial deaths, 15,500 fewer microbial illnesses, and 50 fewer cancer illnesses. (2004C$)

[c] Standard errors in parentheses, based on Krinsky–Robb simulation using 1,000 draws.

Table 6. Wald Tests of Differences in Willingness to Pay in AB Conditional Logit Models

	Tests of Differences within Version[a]		
	Cancer vs. Microbial	***Cancer vs. Both***	***Microbial vs. Both***
V3 + V4	**3.367**	**34.924[b]****	**15.687****
V5 + V6	**9.47****	**22.19****	**4.82**
V5	**6.12****	**13.98****	**2.92**
V6	**2.55**	**10.93****	**4.17**
	Tests of Differences across Versions		
	V3 + V4 vs. V5 + V6	**V3 + V4 vs. V5**	**V3 + V4 vs. V6**
Cancer	**0.601**	**0.277**	**0.110**
Microbial	**1.193**	**1.357**	**0.025**
Both	**0.152**	**0.299**	**0.001**
	Test of Nonproportional Version Sum of Death and Illness vs. Proportional Effect		
	Including status quo effect	***Excluding status quo effect***	
Microbial	**3.751**	**1.193**	
Cancer	**2.691**	**0.601**	

Notes:
[a] Using WTP measures that remove yea-sayers' observations and exclude status quo effects.
[b] ** 5% level of significance.

Table 7. AB: Comparison of Estimated Marginal Willingness to Pay Space Models and Conditional Logit Models

	***Pooled V3 + V4*[a]**	***V5***	***V6***	***Pooled V5 + V6***
***WTP space*[b]**				
Marginal value of microbial death and illness	**30.173** (6.294)	**14.897**	**16.321**	**14.640**
Marginal value of cancer death and illness	**24.313** (18.598)	**14.831**	**11.762**	**14.502**
Marginal value of microbial death	[c]	**14.873** (28.379)	**16.307** (13.163)	**14.617** (33.149)
Marginal value of microbial illness	[c]	**0.024** (0.042)	**0.014** (0.001)	**0.023** (0.043)
Marginal value of cancer death	[c]	**12.399** (27.672)	**8.118** (3.883)	**11.446** (23.378)
Marginal value of cancer illness	[c]	**2.432** (13.228)	**3.644**	**3.056** (7.095)
Conditional Logit				
Marginal value of microbial death and illness	**39.875** (5.104)	**12.958**	**12.615**	**12.843**
Marginal value of cancer death and illness	**30.36** (3.881)	**13.627**	**9.524**	**12.187**
Marginal value of microbial death	[c]	**12.940** (3.32)	**12.601** (3.17)	**12.825** (2.50)
Marginal value of microbial illness	[c]	**0.018** (0.00)	**0.014** (0.00)	**0.018** (.002)
Marginal value of cancer death	[c]	**11.763** (2.86)	**6.354** (2.46)	**10.011** (2.06)
Marginal value of cancer illness	[c]	**1.864** (0.62)	**3.170** (0.68)	**2.176** (0.47)

Notes:

[a] Tests support pooling of V3 + V4; hence, only these results are reported.

[b] WTP space models are estimated using 300 Halton draws. Values are in Canadian dollars (2004).

[c] V3 + V4 only gives a combined marginal WTP for death and illness in fixed proportions. In order to compare results for V5 and V6 we add together the marginal WTP for cancer illness to the marginal WTP for cancer death and similarly for the microbial endpoints.

Table 8. Value of Statistical Life and Value of Statistical Illness Calculations

	Conditional Logit Models [a]			WTP Space Models [a]		
	V5	**V6**	**V5 + V6**	**V5**	**V6**	**V5 + V6**
Microbial death	**17,498,000** (4,510,100) [b]	**17,135,000** (4,333,800)	**17,634,000** (3,585,000)	**20,016,990** (4,988,558)	**21,953,310** (3,988,718)	**19,677,680** (5,206,360)
Microbial illness	**25,188** (4,291)	**18,591** (3,322)	**24,013** (3,124)	**34,269** (4,164,685)	**19,330** (3,867,622)	**31,248** (26,983)
Cancer death	**16,021,000** (4,057,400)	**8,538,000** (3,261,100)	**13,559,000** (2,785,800)	**16,691,720** (5,404,344)	**10,927,880** (4,331,812)	**15,408,610** (4,628,368)
Cancer illness	**2,539,900** (903,860)	**4,330,900** (943,830)	**2,952,400** (624,130)	**3,275,405** (5,978,036)	**4,908,321** (4,123,471)	**4,113,380** (4,685,878)

Notes:

[a] Results come from models that exclude the status quo effect and use data from which yea-sayers' observations have been removed.
[b] Standard deviations are in parentheses. Results are generated using 1,000 draws in a Krinsky–Robb procedure. Values are in Canadian dollars (2004).

Table 9. Wald Tests of Differences in Willingness to Pay

	Tests of Difference CVM versus AB [a, b]			
	V3 + V4 (Status quo excluded) vs. V1 + V2	***V3 + V4 (Status quo included) vs. V1 + V2***	***V5 + V6 (Status quo excluded) vs. V1 + V2***	***V5 + V6 (Status quo included) vs. V1 + V2***
Cancer	6.92	9.01	1.97	16.05
Microbial	7.20	1.45	10.87	14.45

Notes:

[a] All measures use data with yea-sayers' observations removed.

[b] V1 + V2 uses CVM format while V3 + V4 is proportional AB and V5 + V6 is nonproportional AB.