WILLINGNESS TO PAY FOR HEALTH RISK REDUCTIONS: THE IMPORTANCE OF SCENARIO ADJUSTMENT, HOUSEHOLD STRUCTURE AND TYPE OF DISEASE

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Title: WILLINGNESS TO PAY FOR HEALTH RISK REDUCTIONS: THE IMPORTANCE OF SCENARIO ADJUSTMENT, HOUSEHOLD STRUCTURE AND TYPE OF DISEASE

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Environmental regulations are increasingly subjected to benefit-cost analysis as an aid to decision-making in policy. Economic benefits are most appropriately measured by the tradeoffs of other goods and services that people are willing to make to obtain reductions in risks to their lives and health. The measure of willingness to pay (*WTP*) allows for this comparison. These benefits from risk reductions are likely to vary systematically by characteristics of the individual, including the number and ages of children present in the household, and by the type of health threat under consideration.

In chapter one of this dissertation, I write a brief introduction. In the second chapter, I examine an important methodological issue—the extent of "scenario adjustment" in a Stated Preference (*SP*) conjoint choice experiment in the context of a household survey concerning health risk reductions. Scenario adjustment occurs when

respondents assume that a substantive alternative in a choice set, in their own particular case, will be different than the survey instrument describes. This is a potential source of bias in *SP* research similar to scenario rejection, but harder to detect. I analyze the impact of scenario adjustment on *WTP* and suggest a possible correction.

In the third chapter, I address the empirical question of patterns in adults' *WTP* for health risk reductions. I find that demand is influenced by the presence of children, the numbers of children in different age brackets currently in the household, and, for health risks with latency periods, by the prospect of children still being present when a parent's ill health begins or death occurs.

In chapter four, I find systematic differences in *WTP* for health risk reductions across different types of major health threats, such as Alzheimer's disease versus heart attacks. I also look for evidence of a cancer premium due to the dread factor associated with the prospect of cancer. The health threats considered include chronic heart disease, sudden heart attacks, five types of cancers, respiratory disease, stroke, diabetes, Alzheimer's disease and traffic accidents. In chapter five, I conclude.

This dissertation includes previously unpublished co-authored material.

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TABLE OF CONTENTS

LIST OF FIGURES

Figure Page

LIST OF TABLES

Table Page

CHAPTER I

INTRODUCTION

A main purpose of many environmental regulations, such as the Clean Air Act, the Clean Water Act, and the Safe Drinking Water Act, is to reduce human exposure to contaminants and improve human health. Air and water pollution can lead to increased risks of cancers, respiratory diseases and other adverse health impacts (EPA (2009)). Environmental policies that reduce air and water pollution can benefit humans by reducing the risks they face from these health threats. In this dissertation, I focus on the value of health risk reductions in an effort to quantify the benefits to society of human health related environmental policies.

Since it is probably costly to attempt to reduce pollution levels to zero, benefit-cost analyses are an important tool in deciding among policy alternatives. In 1993, the government mandated in Executive Order #12866 that any regulation with a predicted economic impact of $100 million or more must be subjected to benefit-cost analysis and consideration of alternatives (Robinson (2007)). Therefore, good information on both the costs and benefits of policies is extremely useful to regulatory agencies such as the U.S. Environmental Protection Agency (EPA). When done properly benefit-cost analysis is intended to be a neutral and objective tool to render decision making by regulators more transparent and methodical. The overall net benefit to society from a policy is determined by the value of the increase in well-being due to the policy minus the cost of the policy. Using this formula, an inexpensive policy that gives a minor

increase in well-being for a large number of people may have a larger net benefit than an expensive policy that significantly benefits only a few people. Since tax dollars to support environmental and health policies are limited, choices among alternative policies can be aided through the use of benefit-cost analyses.

One of the challenges in benefit-cost analyses is to figure out the benefits, in physical terms, from reducing health risks and then to quantify these benefits in dollar terms so that benefits can be aggregated and compared to the costs. For example, if a potential environmental policy is expected to have benefits due to a reduction in the probability of death due to colon cancer and is also expected to increase the amount of viable habitat for an endangered species, these incommensurate benefits will need to be aggregated in order to weigh the benefits against the costs. One feasible way to aggregate heterogeneous benefits is to convert them all into equivalent dollar values so they can be summed and compared against the costs. For economists, the ideal way to measure the value of a good is through individuals' willingness to pay (*WTP*) in the market. Since health improvements stemming from regulations are not conventional market goods, it can be difficult to measure an individual's *WTP* for these types of health risk reductions in dollar amounts.

Researchers have used many methods to estimate the value of human health benefits including Cost-of-Illness (*COI*), Quality Adjusted Life Years (*QALY*), and *WTP*, which is typically measured in terms of the value of a statistical life (*VSL*). The Cost-of-Illness approach uses medical expenditures and foregone earnings due to illness to estimate the value of health. This method is not grounded in economic theory,

however, and there is no particular reason why medical expenditures and foregone earnings should be equal to *WTP*. This method is convenient, however, since it makes use of information about the direct costs of illnesses and accidents that is usually readily available. COI estimates could be a lower bound on *WTP*, but they do not attempt to include any implicit costs of pain and suffering from the disease or injury, so *COI* is not necessarily a very good approximation of the true *WTP* for health risk reductions (Tolley et al. (1994)).

A second method of valuing health benefits, typically used in the health economics literature, is the Quality Adjusted Life Year. The *QALY* allows for a comparison of treatments or interventions by standardizing the health outcomes. Rather than comparing the lives saved from one intervention with the morbidity reduction from another intervention (like comparing apples and oranges), the *QALY* assigns a numerical value to each health outcomes which allows for easier comparison. The *QALY* is a product of two numbers, the increase in utility due to the intervention measured on a scale from zero (death) to one (full health) and the number of years a patient's life is extended with that utility gain. The gain in utility could be due to reduced morbidity, mortality or both.

The advantage of *QALY*s is that different health outcomes can easily be compared, but they also have several drawbacks. *QALY*s do not have strong theoretical underpinnings in economics as *WTP* measures do. *QALY*s necessarily give more weight to health improvements for younger people due to this method's emphasis on extended years of life—younger people have more potential life-years. The overall change

(increase) in utility due to an intervention is taken into consideration when estimating a QALY, but the original level of health of a patient is not taken into consideration. Several studies, described in Nord (1999) have shown that respondents in moderate health would prefer to forego medical treatment that would allow them to become fully healthy if that meant a severely sick person was allocated an intervention that allowed them to become only moderately sick (or in less pain). Thus, *QALY*s may not be representative of societal preferences concerning the allocation of health resources.

Since environmental policies take the form of regulations which impose costs on business or households, or represent public goods which are funded through tax dollars, these policies should reflect societal preferences. The ideal way of measuring benefits to human health would be to look at willingness to pay to avoid health risk reductions based on the types of choices individuals would make, were there a market for these risk reductions. This method is ideal since the values can be compared to other goods and services available for consumers to purchase. This captures the trade-offs that consumers are willing to make between their health and other market goods. *WTP* is based on a strong theoretical foundation because *WTP* is simply a measure of inverse demand, where demand is the outcome of consumer optimization constrained by income.

The difficulty in finding the *WTP* for health is that health is often not a conventional market good so we do not have good information in terms of competitive market clearing prices on how individuals make trade-offs between health and other goods and services. Outside of the market, however, individuals still regularly make

these kinds of trade-offs between health and other goods. For example, we sometimes drive faster to save time but, by doing so, increase our risk of suffering a traffic accident. People may choose to use their income to buy bottled water instead of drinking cheaper tap water if they think that bottled water has fewer health risks than tap water. Laborers may take a more dangerous job in return for hazard pay (a wage premium). Studying these related decisions that individuals actually make is one way that researchers can assess an individual's *WTP* for health and for health risk reductions.

A common way to represent this *WTP* for the reduction of health risks is through a measure known as the value of statistical life (*VSL*). Government agencies such as the EPA and the Department of Transportation use a *VSL* to convert the benefits for human health risk reductions from a particular policy into dollar terms. The *VSL* is based on a measure of average individual willingness to pay to achieve a tiny risk change (say 1 in 100,000). Then this *WTP* is normalized on a very large risk change of 1.0. It is tempting to interpret this risk reduction as "avoiding certain death" but no such extreme risk reduction is valued in any of the empirical data on *WTP* and no risk change as big as 1.00 is contemplated in any policy context where these values are used. A *VSL* is merely a scaled average *WTP* and is not intended to be equivalent to society's willingness to pay to save one particular human life with certainty (as that value would certainly be greater).[1]

[1] It would have been less controversial had early researchers decided instead on the convention to normalize *WTP* on, say, a 10^{-6} risk change (i.e a microrisk), where observed risk changes in empirical *WTP* contexts and those being considered in many policy cases would range from tens of hundreds of microrisk units.

The decrease in mortality risk used to estimate a *VSL* may come from many sources including wage trade-offs made for less risky jobs and *WTP* for increased access to medicines and disease prevention. Across studies, each empirical *VSL* estimate typically corresponds to a different-sized risk reduction, so it is not appropriate simply to average the *WTP* estimates from several studies. Thus, *WTP* estimates do need to be standardized on some common size of risk reduction before an average can be taken. The convention is to use the ratio of the marginal utility of a risk reduction to the marginal utility of income (a marginal rate of substitution), which is equivalent to scaling all of these tiny risk reductions and their corresponding *WTP* estimates to a vastly larger 1.00 risk change. In practice however, after averaging a variety of *WTP* estimates, the *VSL* is then scaled back down again to suit the relatively tiny risk changes at stake in a given policy context.

There are two general ways to estimate a *VSL*: revealed preference methods, most commonly from wage-risk studies, and stated preference methods, from contingent valuation and conjoint choice experiments. Typical *VSL* estimates from both of these methods range between about $1 million and $10 million (Viscusi and Aldy (2003)).

Wage-risk studies are the most common way of estimating a *VSL* using revealed preference (*RP*) data. This methodology employs a hedonic regression that explains wage variations using employee-specific characteristics, job characteristics and the actuarial job fatality risk as the explanatory variables. This method is described succinctly in Aldy and Viscusi (2007). The slope coefficient on the job fatality risk

leads to an estimate of the trade-off between risks and wages observed in the labor market and provides a *WTP* to reduce mortality risk. The average participant in wage-risk studies is a male who is about 36-37 years old and the health risk involved in this decision is typically a sudden, accidental death that occurs at the workplace (Robinson (2007)).

Although it is a common way to estimate a *VSL*, this wage-risk measure of a *VSL* may not be a good fit when it is "transferred" to the broader population affected by many environmental policies. The trade-offs between risk and income evidenced within the working-age population may not match the trade-offs willingly made by members of the groups most affected by impaired environmental quality. Groups who are not generally represented by a sample of individuals from the active labor force, such as children, the elderly and the infirm, are likely to enjoy a large share of the benefits from improved environmental quality. In addition to the differences between the relevant populations, the types of health risks from environmental exposures are different from risks faced in the labor market. Many types of risks from poor environmental quality do not cause sudden death, but instead involve a considerable latency period before an individual develops symptoms or dies.

Other contexts where researchers have derived estimates of the benefits using revealed preference (*RP*) data include health production functions (Dickie and Gerking (1991)), hedonic property values (Gayer et al. (2002)), individuals' willingness to exceed mandated speed limits, (Ashenfelter and Greenstone (2004)), and purchases of safety equipment (Hakes and Viscusi (2007) and Atkinson and Halvorsen (1990)).

Stated preference surveys are another tool for measuring *VSL*. Surveys can be targeted to represent the general population or a particular sub-population that is particularly affected by a specific health threat. There are different types of stated preference survey formats. In contingent valuation methods, preferences tend to be elicited for a particular program consisting of a fixed bundle of attributes at varying prices. In conjoint choice experiments, all specified attributes of the alternatives, including price, are varied independently. According to Krupnick (2007), a good stated preference study has a large sample size, passes both "scope" and "construct validity" tests and asks debriefing questions within the survey to identify potential problems such as scenario rejection. Some notable *SP* studies that estimate *VSL* include Alberini et al. (2004), Alberini et al. (1997), and Bhattacharya et al. (2007).

Although most researchers would prefer to use revealed preference data in assessments of willingness to pay, such preference data are not always available. In the health risk reduction context, it will typically be necessary to control for differences in disease latency (i.e. time-to-onset), the duration of the illness or injury, whether or not the affliction is fatal, and the number of life-years that may be lost as a result of having suffered from this illness or injury. The ability to control for these aspects is more easily done for *SP* than *RP* with respect to health. Although there are still potential problems with stated preference data from poorly designed surveys, many improvements in the methodology have been made in recent decades. In the second chapter of this dissertation, I contribute to the literature on methodological improvements by looking at subjective scenario adjustment by respondents in *SP* surveys.

Whether it is derived from RP or SP methods, the standard one-size-fits-all *VSL* for all people and all illnesses is imperfect for various reasons. It is a standardized measure of an inverse demand (a *WTP*) for health risk reductions, but a constant *VSL* implies that the demand does not vary with characteristics of the consumer as does the demand for most commodities. One particular drawback of the *VSL* is that it does not differ according to age—a standard *VSL* assigns the same value to one lost life-year as to eighty lost life-years. Therefore, a per-year measure called the Value of a Statistical Life-Year (*VSLY*) is used sometimes to quantify *WTP* in addition to (or in place of) the *VSL*. The *VSLY* is calculated by dividing the standard *VSL* by average remaining life expectancy. This method thus assumes that each year is equally valuable. Calculating a *VSL* on an annual basis and then multiplying by the number of life-years saved by a particular policy does not produce an ideal measure either. Younger people have more years to live, so the value of reducing risks to their health is higher using this measure. The approach is not based on economic theory, however, but on an arbitrary measure of life years left.

The standard *VSL* is simply a fixed value and does not vary with income, gender, age, household characteristics such as the presence of young children, or by the type of illness or accident for which a risk reduction is to occur. The same *VSL* estimate is typically used whether the program in question leads to a reduction in the risk of lung cancer, traffic accidents, or heart disease. Considerable empirical work has been done recently to show that the *VSL* does vary by individual characteristics, such as age, (e.g. Aldy and Viscusi (2007), Krupnick (2007), and Robinson (2007)). There is still much

research to be done to explain how *VSL* varies with income, age, life expectancy, and health status as outlined in Hammitt (2007).

Since the human health benefits of environmental, health or safety policy are unlikely to be uniform across the population, it is important to identify systematic heterogeneity in *WTP*. This knowledge will allow policy-makers to choose appropriate measures for the benefits from potential health risk reductions. In the third and fourth chapters, my dissertation adds to this body of knowledge. In Chapter III I analyze how *WTP* varies with household structure and in Chapter IV I look at how *WTP* varies by the type of disease or injury risk.

From a policy standpoint, it is important to have reliable measures for both the benefits and the costs of implementing a policy. *WTP* is the best measure to use since it has a strong theoretical motivation and captures the extent to which individuals are willing to tradeoff between health and other goods and services. (For this reason, *WTP* is preferable to the use of *QALY*s which only allow easy comparisons between different types of health interventions).

The risk reductions employed in the choice scenarios used in this dissertation involve a latency period. Therefore, the discount rate is an important issue. Since the choice contexts concern the individual's future health (rather than intergenerational choices), discounting is appropriate. I use a 5% discount rate throughout all chapters, but a sensitivity analysis using 3 and 7% rates is available in Cameron and DeShazo (2008). Future work using this data on health risk reductions will analyze individual discount rates.

A second challenge in evaluating people's preferences to avoid health risks is that conventional measures assume that people do not adjust and adapt to their changing health conditions. Research in psychology has shown that people are able to adapt their expectations and perceptions as their health conditions change, which is called "response shift" (Schwartz and Sprangers (2000)). For example, suppose a perfectly healthy adult is asked how much she would value life if she were in wheelchair. Research suggests that she will give a much more pessimistic response than she would if she actually was confined to a wheelchair and had experienced the opportunity to adapt to her new condition. Therefore, answers to how much a person would be *WTP* to avoid a health risk may be different ex ante, before the individual has a disease, and ex post, if the disease is already being experienced. The literature on response shift appears to only consider differences in individuals' responses to specified diseases over time rather than differences among different diseases. Many different diseases have been studied, but there seems to be no comparative assessment of heterogeneity in the extent of response shifts across different diseases.

A third issue that needs to be addressed regarding the estimation of benefits is the role that these preferences should play policy-making. The idea of "libertarian paternalism" includes both the notion that policymakers should respect consumer sovereignty, and the idea that some consumers may not always know what is best for them partly due to inaccurate or incomplete information. One example of libertarian paternalism is automatically signing up employees for a 401K plan and requiring them to opt out (as opposed to inviting them to opt in to the program). Another example is

the arrangement of foods at a school cafeteria so that children choose more of the foods that are good for them and fewer of the foods that are bad for them. This strategy may alter the transactions costs associated with choices. Thaler and Sunstein (2008) refer to policies like these as a "nudge" that helps people make better decisions. When people are left to make their own decisions, they sometimes do not choose wisely. This "nudge" does not mandate behavior, so people are still able to choose whichever option they want. However, the relative implicit prices of different options may have changed.

At the other extreme, benefit-cost analyses based on consumer preferences could potentially dictate policy based purely on whether, or by how much, the benefits of a policy outweigh the costs. Ultimately environmental policies influence the allocation of scarce resources, which should probably be used in a manner that will do the most good for society. The costs of policies are borne by consumers, workers, investors and taxpayers in the form of higher prices, lower wages, lower investment returns, or higher taxes. Thus, it seems reasonable that the preferences of the general population should be an important determinant of how these resources are used so that the greatest value to society is provided.

Policy should not, of course, be based solely on positive analysis of whether the benefits outweigh the costs, although benefit-cost analyses that take into account the societal preferences can be a valuable aid to decision-making. The final policy decision must carefully consider distributional consequences and may reflect considerable debate about what is fair and right.

In this dissertation, I explore some new dimensions of heterogeneity in *WTP* for health risk reductions. This information will be important in helping policymakers to make well-informed decisions about environmental and health policies. Policy-makers may find it expedient to use a *VSL* that is the same for everyone. However, this standard *VSL* may not represent the true preferences of the types of people receiving the benefits of a particular policy. Therefore, resources may not be allocated in the correct way. For example, using the same *VSL* for a 30-year-old (who may have a high *WTP*) and an 80-year-old (who may have a low *WTP*) could lead to a policy being implemented (and therefore valuable resources being spent). However, if most of the benefits accrue to the oldest seniors, and these individuals have a lower *WTP* the overall benefits may in fact not exceed the costs. These are distributional consequences, of course, but it is important that policy-makers have an accurate measurement of *WTP* for health risk reductions in order to indentify environmental policies that have benefits that outweigh the costs.

The data used throughout this dissertation are derived from a conjoint choice survey. Cameron and DeShazo (2008) use stated preference methods to elicit preferences for programs to reduce the risk of morbidity and mortality in a general population sample of adults 25 years and older in the United States. The survey was developed carefully using 36 detailed in-person cognitive interviews, three pretests and a large pilot study. Knowledge Networks, Inc. administered the survey to 2,439 of their panelists and achieved a respectable 79% response rate.

Extensive robustness and validity checks of the individuals' responses have been conducted to evaluate common problems in *SP* analyses. These include risk comprehension verification (where individuals are asked to rank the sizes of risk reductions), checks on the complexity of the choice sets (where individuals are asked to rate the difficulty of the choice sets), and a "cheap talk" reminder (so that individuals are careful to consider their budget constraints and not overstate their willingness to pay). A number of individuals and/or choice sets were dropped from the analysis according to minimal exclusion criteria. The exclusion criterion for risk rejection required that the respondent be able to rank successfully the sizes of the risk reductions associated with two risk mitigation programs. A total of 4,887 alternatives (1,629 choices) were excluded due to this risk comprehension criterion. The exclusion criterion for scenario rejection was that the respondent chose the "neither program" alternative and, in the follow-up question, chose only the answer "I did not believe the programs would work". A total of 6,708 alternatives (2,236 choices) were excluded due to scenario rejection. A further 996 alternatives (332 choices) were excluded due to a minor error in the randomized design. Order effects for the choice sets are considered and individuals are instructed to assume each choice set is independent of the other choice sets. Choices are readily demonstrated to be sensitive to the changes in the scope and central attributes—such as the cost of the program and the size of the risk reduction. Systematic sample selection effects are controlled for, with methods explained in detail in Cameron and DeShazo (2008).

Chapters II, III and IV are co-authored with Trudy Ann Cameron and J.R. DeShazo. Professors Cameron and DeShazo collected the stated preference data used in all chapters. I performed the majority of the econometric analyses using these data. I wrote and edited many drafts of these chapters, although my co-authors and dissertation committee members have of course provided valuable assistance towards polishing and refining the exposition.

The rest of this dissertation is as follows. In Chapter II, I consider whether respondents engage in scenario adjustment rather than taking the stated scenarios at face value (which the researcher typically assumes). In Chapter III, I discuss how *WTP* for health risk reductions varies by household structure such as the number and age of children in the household. In Chapter IV, I examine whether *WTP* varies for eleven different major health threats and check for evidence of a "cancer premium". Chapter V concludes.

CHAPTER II

WILLINGNESS TO PAY AND SCENARIO ADJUSTMENT

A version of this chapter is co-authored with Trudy Ann Cameron and J.R. DeShazo

1. Introduction

Researchers have long recognized that subjective beliefs are an important determinant of consumers' choices (Dominitz and Manski (2004); Manski (2004)). For example, individuals' beliefs about the timing of their own risks for particular illnesses may determine their willingness to pay to reduce these health risks (e.g., purchase organic foods), to measure their risks (e.g., purchase a new diagnostic test not currently covered by insurance), or to buy extra insurance against undesirable health risk outcomes (e.g., purchase medi-gap policies). As subjective beliefs change, individual behavior will probably change as well. All of this suggests that individual subjective beliefs are also likely to play an important role when research subjects answer questions in stated preference (*SP*) surveys used to value non-market goods.

An SP survey describes a scenario in which the respondent is offered a hypothetical opportunity to purchase one or more costly programs that yield particular sets of individual-specific consequences. When asked to make choices about health-related programs, individuals may hold strong prior beliefs about many aspects of the alternatives in the choice scenario, including their risks of particular illnesses, the time profile of those illness-specific risks over their lifetimes, the effectiveness of preventive

actions, the effectiveness of the probable treatments, etc. When respondents hold prior beliefs about any aspect of the scenario that diverge from the researcher-prescribed information, three possibilities arise. Respondents may replace their beliefs about aspects of the scenario with the information provided by the researcher. Alternatively, they may retain their beliefs and instead reject the choice scenario as irrelevant or unrealistic, often resulting in a protest response. Finally, they may accept the scenario but "adjust" some of its informational aspects to fit their own personal situation, history or context. Scenario adjustment occurs when respondents impute or modify some aspect of a given scenario based upon their personal beliefs.

This chapter concerns the identification of scenario adjustment and a strategy for its correction. When respondents engage in scenario adjustment, they assume a different choice set and thus answer a different choice question than is stated in the survey. This leads to potential bias in the resulting estimates of willingness to pay for the types of programs addressed in the survey. Using data from a stated preference survey on health risk reduction programs, we find evidence of scenario adjustment and then propose and illustrate a strategy to correct for this behavior. Corrections such as these have the potential to allow stated choice data to yield more-accurate estimates of willingness to pay (*WTP*).

The data are from an existing stated preference survey concerning prospective health risk reductions, described in Cameron and DeShazo (2008). This survey is designed to elicit choices that allow the researcher to infer willingness to pay for private programs which reduce the risk that respondents will experience specific illness profiles

over their remaining lifespan. An illness profile consists of a description of the sequence of health states associated with a major illness that a respondent may face in the future. The specific type of "scenario adjustment" problem we consider in this chapter has to do with each respondent's degree of acceptance of the stated latency of illness (i.e. the time until onset). Specific latencies are given for each illness profile described in the choice sets used in the survey.

Assessment of the consequences of scenario adjustment (and thus a potential correction strategy) is made possible because the respondents are asked debriefing questions after each stated choice question concerning alternative health risk reduction programs. These debriefing questions allow the researcher to distinguish between respondents who appear to accept the latency information given in the choice scenario (i.e. the ones who answer the choice question based on the latencies described in the choice scenario) from those who subjectively update the latency information in the scenario (and thus appear to have answered a somewhat different question). Some individuals underestimate the latency period before the tangible benefits of the program would begin. They express the opinion that the program's benefits, in their own case, would start sooner. Other individuals overestimate the latency period. If assumed latency affects *WTP*, then a respondent's latency perceptions can influence their estimated *WTP*.[2]

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[2] "Scenario adjustment" might occur as follows. Suppose a male respondent has a family history of heart disease at age fifty. In his copy of the survey, the stated choice scenario that involves heart disease may specify that this illness would lead to moderate and/or severe pain and disability starting at age seventy. However, given his private knowledge, he might answer the question as though the benefits of the proposed risk reduction program would begin at age fifty.

If scenario adjustment is ignored, it is possible that this behavior may cause the researcher to underestimate *WTP* for some respondents and overestimate *WTP* for others, to varying degrees. The opposing effects are unlikely to be exactly offsetting. Researchers should, whenever possible, calculate and compare estimates with and without corrections for scenario adjustment. As early as the process of survey design, researchers should try to anticipate the dimensions along which respondents may be inclined to adjust the stated choice scenario. Suitable debriefing questions should be included in the survey to allow a formal assessment of the extent of this behavior.

The researcher still faces the important question of whether these estimates *should* be adjusted. Correction of misalignments between what researchers assume when they ask a survey question, and what respondents assume when they answer it, may be considered an example of "libertarian paternalism" as discussed by Thaler and Sunstein (2003) and Smith (2007). "Libertarian paternalism" involves honoring consumer sovereignty to the greatest extent possible (the libertarian part), but intervening to override some aspects of behavior if the researcher believes they are mistakes (the paternalism part).

Which types of mistakes should be corrected ex post by researchers is still an open question. One class of argument for the correction of misalignments between researcher intentions and respondents' assumptions concerns incomplete information. If the mismatch stems from incomplete information, where respondents' choices (or the researcher's models) are based on objectively incorrect information, then researchers might want to undertake corrections if it is possible to simulate what would have been

each respondent's choice had they used complete and accurate information in making their decisions. In other cases, however, misalignments may stem from fundamental differences in individual attitudes or preferences—such as the case where respondents base their choices on their individual private discount rates and these discount rates do not adequately take into account the welfare of future generations.

The example of scenario adjustment considered in this chapter falls into the first category described above, namely that of incomplete information. If the researcher were to use the stated choice conditions from the survey instrument in an empirical model to explain respondents' choices, this would misrepresent the information actually being used by that respondent. If researchers have collected sufficient additional information from each respondent, there is a strong argument for considering ex post adjustments.

A final consideration when deciding whether scenario adjustment in stated preference studies should be corrected is the extent to which individuals tend to adjust analogous choice scenarios in real-life choice situations. If "scenario adjustment" happens with similar frequency in actual markets, then perhaps these misalignments are a part of how consumers truly behave in real markets. If a stated preference study is designed to predict future actual choice behavior, perhaps the *SP* choice models should allow people to make the same "mistakes" that they would make in real life. However, if the goal is welfare assessment based on *WTP* under conditions of full information, then perhaps corrections are more justified. Of course, if scenario adjustment is for some reason more pronounced in hypothetical choice scenarios, as opposed to real

market conditions, then perhaps the researcher should correct the misalignment in order to more accurately predict respondents' *WTP* under real conditions.

The empirical contribution of this chapter is to identify and illustrate one case of scenario adjustment by respondents to a stated preference survey, and to demonstrate the potential consequences of this behavior for the resulting estimates of *WTP*. The chapter proceeds as follows: Section 2 reviews in more detail the related literature on perceptions and *SP*. Section 3 briefly describes the survey data relevant to this chapter. Section 4 discusses the empirical specification and how to control for scenario adjustment. Section 5 conveys the empirical results and Section 6 concludes.

2. Related Literature

Researchers recognize that respondents bring their beliefs and perceptions about aspects of a choice scenario into a choice setting (Manski (2004)).[3] Researchers are also aware that the information provided in a choice scenario may conflict with respondents' beliefs and perceptions for several reasons. One common reason involves the random assignment of efficiently designed conjoint choice sets. This may result in some respondents being presented with scenarios containing unrealistic or irrelevant choice alternatives, given the individual's beliefs. A tension may thus arise between the efficient design of a choice set and respondents' expectations regarding which choice alternatives are realistic or relevant (Louviere et al. (2000); Louviere (2006)).

[3] For example Adamowicz et al. (1997) and Poor et al. (2001) compare *WTP* estimates from choice models that use both objectively measured and subjectively perceived levels of attributes. Experimental economists (e.g. Plott and Zeiler (2005)) have examined the role of subjective beliefs in explaining the gap between *WTP* and willingness to accept (*WTA*).

When confronted with unrealistic or irrelevant choice scenarios, respondents may issue protest responses. Scenario rejection may lead a respondent to state that they prefer the status quo alternative, but they do this for reasons that have nothing to do with their preferences or the constraints they face (or they may refuse to make any choice at all). This behavior may indicate merely that they doubt the viability of the hypothetical product or proposed program, rather than implying that they would not value it if it were guaranteed to be as advertised.[4] When some choices may be protest responses or belie some type of scenario rejection, then, it is important to distinguish these from "good" responses (although in practice it can be difficult to draw these distinctions).[5] Bateman et al. (2006) suggest several methods to identify these protest responses such as follow-up questions about why respondents answered the way they did. Strazzera et al. (2003) also offer possible corrections for selection bias caused by protest zeroes in contingent valuation studies.

Instead of outright scenario rejection, we address the phenomenon of scenario adjustment—where respondents find one or more of the attributes of the stated alternatives to be somewhat implausible but this problem does not derail the choice process entirely. Instead, the individuals may implicitly replace one or more of these implausible stated attributes with something that they deem more plausible and then

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[4] For a more detailed description of protest responses and protest bids, see Bateman et al. (2002) and Champ et al. (2003). Rejection of the proposed payment vehicle (e.g. a tax or a user fee) can be another form of protest.

[5] Even in real choice situations, a consumer may choose not to buy a product simply because the seller's claims about it seem "too good to be true." If the consumer could verify the product's qualities, however, they would actually make the purchase. This suggests that scenario rejection (and scenario adjustment) may thus be fairly common in real markets, too.

make their decisions based on these mental edits to the choice set. Outright scenario rejection may be difficult enough to detect, but scenario adjustment—which is a matter of degree, rather than an all-or-nothing proposition—may be more insidious and therefore even more difficult to detect. Debriefing questions asked after respondents make the key choice(s) can be invaluable for this purpose.

SP researchers have long realized the potential for debriefing questions to help them understand the perceptions of the respondent during the choice process. A handful of researchers have already used specific debriefing questions for *detection* of scenario adjustment. Carson et al. (1994) ask subjects whether they believed that the pollutants in question could actually cause the environmental problems stated in the choice scenario and whether they believed that natural processes would return things to normal within the stated number of years. When respondents said they did not believe the stated natural recovery time, they were asked if they thought the true recovery time was more or less than the stated time. In a similar vein, Viscusi and Huber (2006) ask their respondents for subjective assessments of the probability that the program in question will actually produce the advertised benefits.[6]

Researchers should put forth their best effort to make the choice scenarios in a stated preference survey as plausible as possible, for as many respondents as possible. Despite their best efforts, however, it may be impossible for researchers to fully anticipate the likely credibility of all dimensions of a randomized choice scenario from

[6] Burghart et al. (2007) extend a random utility model to include estimated scenario adjustment parameters that capture whether respondents appear to believe and/or pay attention to certain key attributes of alternatives in the choice set, conditional on the functional form of the choice model.

the perspective of every individual who might participate in the survey. The best strategy to deal with any residual scenario adjustments may be for researchers to anticipate that this behavior is inevitable in some proportion of cases and to plan for the option to assess and correct for it. This chapter illustrates how some carefully worded debriefing questions can be used to measure the approximate extent of one type of scenario adjustment. The econometric model controls for these scenario adjustments, and counterfactual simulations can then be used to infer what would be the estimated preferences (and hence *WTP*) had each individual in the sample fully accepted these key dimensions of the stated choice scenario.

3. Available Choice Data

Existing market-based data are not adequate to infer individuals' demands for risk reductions with respect to future time profiles of illness or injury. The revealed preference (RP) data which are most typically used concern tradeoffs between on-the-job fatality risks and wages. More-dangerous jobs tend to involve a wage premium, so workers' choices among jobs with different risk levels and different wages provide an indication of how much money those workers are willing to forego for risk reductions. There are dozens of empirical studies concerning the job choices of labor market participants. However, groups other than working-aged males may not be represented very well by these measures. This may be problematic because the amounts people are willing to pay for prospective risk reductions may vary considerably by gender, age, and labor market status. For example, stay-at-home mothers of young children may be

especially under-represented in wage-risk studies. For any group which is not in the labor market, stated preference (*SP*) data can be one of the few viable sources of rich information concerning willingness to pay for prospective health risk reductions.

Cameron and DeShazo (2008) use stated preference methods to elicit preferences for programs to reduce the risk of morbidity and mortality in a general population sample of adults in the United States. The survey was developed carefully using 36 detailed in-person cognitive interviews, three pretests and a large pilot study. Knowledge Networks, Inc. administered the survey to 2,439 of their panelists and achieved a respectable 79% response rate.[7] In brief, the survey consists of five modules. The first module asks respondents to rate their subjective risks, from low to high, of contracting each of a range of major illnesses or injuries. Individuals are also asked to think about how lifestyle changes would reduce their risks of these illnesses and how difficult it might be to implement these lifestyle changes.

The second module in the survey is a detailed tutorial that explains the concept of an "illness profile" to be summarized in the upcoming choice sets. An illness profile is a description of a sequence of future health states associated with a major illness or injury that the respondent may face over his or her remaining lifetime. The major and potentially life-threatening illnesses which are described in the survey are labeled as one of five specific types of cancer (breast cancer for women, prostate cancer for men, plus lung cancer, colon cancer, and skin cancer), heart attack, heart disease, stroke,

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[7]For more information on the survey instrument and the data, see Cameron and DeShazo (2008). For more detail on the survey, please see an annotated sample at: http://www.uoregon.edu/~cameron/vsl/Annotated_survey_DeShazo_Cameron.pdf .

respiratory illness, diabetes, traffic accident, or Alzheimer's disease. An illness profile includes the years before the individual becomes sick (i.e. the latency period), illness-years while the individual is sick, any recovered/remission years if the individual survives the illness or injury, and lost life-years if the individual dies earlier than he would have in the absence of the illness or injury. After the tutorial about illness profiles, the individual is informed that he or she might soon be able to purchase new programs that would reduce the risks of experiencing certain illness profiles. Each illness-related risk-reduction program described in the survey consists of a diagnostic blood test plus possible drug therapies and/or life-style changes, available at a specified overall cost that is not covered by insurance.[8]

The third, and key, module of each survey involves a set of five different three-alternative conjoint choice experiments where the individual is asked to choose between two possible health risk reducing programs and a status quo alternative. The part of the survey that is of interest here are the debriefing questions.

Each choice exercise is immediately followed by a set of debriefing questions designed to help the researcher understand the individual's reasons for their particular choice. Some debriefing questions depend on the alternative chosen by the respondent. For example, there are various perfectly legitimate economic reasons why individuals

[8] Early drafts of the survey made an effort to spell out that the quoted costs were intended to capture all of the monetized opportunity costs of participating in the program, but this additional material had to be cut to keep the survey within its length restrictions. An anonymous referee has suggested that we consider respondents' subjective perceptions about how easy it would be to improve their health habits. Respondents who would find it harder to make life-style changes have larger coefficients on their net income variable, which could be taking up the effect of what is instead just a larger value of perceived net income (i.e. smaller perceived program costs). Thus respondents do not, on average, appear to be imputing significantly larger full costs than are stated in the choice scenarios.

may prefer the status quo—including that they cannot afford either of the risk-reduction programs which are described, they would rather spend money on other things, or they believe they will be affected by another illness before they contract either illness stated in the scenario. If respondents choose the status quo, they are asked why "Neither Program" is their preferred alternative. Included among these possible reasons are some that reveal the presence of scenario rejection, such as "I did not believe the programs would work."

Other debriefing questions are asked regardless of which alternative the individual selects. One key question, shown in Figure 2, is "Around when do you think you would begin to value highly the risk reduction benefits of each program?" We interpret this question as being equivalent to the question "When do you think the program's benefits will start?" The benefit of the program is clearly defined on an earlier page of the survey as a reduction in the risk of suffering from the specified major illness or injury starting at the age stated in the scenario. This question is of great interest in this chapter since it essentially asks the individual about the latency period they used to answer the question. If the respondent fully accepts the stated scenario, then the age at which the scenario states the benefits start should probably match the age at which the respondent believes the benefits will start.

4. Empirical Specification

This empirical specification used in this dissertation builds off the model presented by Cameron and DeShazo (2008). In that paper, it is established that stated

choices in this general population sample appear to be best explained by a model that involves expected discounted utility stemming from durations in different adverse future health states. To permit systematically varying diminishing marginal utilities of net income, utility is not modeled simply as additively separable, but instead as quadratic, in present discounted expected net income.

To understand the basic model, consider just a pair-wise choice between Program A and the status-quo alternative (N).[9] If individual *i* chooses the status quo alternative, then let Π_i^{NS} be the probability of suffering a given adverse health profile (i.e. getting "sick"). The expected discounted utility is:

$$\text{PDV}\,(\text{E}\,[V_i^N]) = \text{PDV}\,(\Pi_i^{NS} V_i^{NS} + (1-\Pi_i^{NS}) V_i^{NH})$$

If the individual, *i*, chooses Program A, however, then the probability of suffering the adverse health profile is lower. Let Π_i^{AS} be the (reduced) probability of suffering this adverse health profile if Program A is chosen, and since $\Delta\Pi_i^{AS}$ is the risk *reduction* to be achieved by choosing Program A, $\Delta\Pi_i^{AS}$ is negative. Then we can write the expected utility from choosing Program A as:

$$\text{PDV}\,(\text{E}\,[V_i^A]) = \text{PDV}\,(\Pi_i^{AS} V_i^{AS} + (1-\Pi_i^{AS}) V_i^{AH})$$

The difference in the present discounted expected utility when an individual chooses Program A instead of the status quo is:

$$\Delta PDV[E_{S,H}(V_i^A)] = PDV[E_{S,H}(V_i^A)] - PDV[E_{S,H}(V_i^N)] \qquad (1)$$

[9] The model for a three-way choice between two alternative programs and the status quo is analogous.

The sequence of health states making up the illness profile to be addressed by Program A is captured by a set of mutually exclusive and exhaustive (0, 1) indicator variables associated with each future time period, t: $1(pre_{it}^{A})$ for pre-illness years, $1(ill_{it}^{A})$ for illness-years, $1(rcv_{it}^{A})$ for recovered or post-illness years, and $1(lyl_{it}^{A})$ for life-years lost. Individuals are modeled as expecting to pay the annual cost of the risk reduction program only during pre-illness and recovered years, but not if they are sick or dead.

Define the discount rate as r and let $\delta^{t} = (1+r)^{-t}$. The present discounted number of years making up the remainder of the individual's nominal life expectancy, T_i, is given by $pdvc_i^{A} = \sum_{t=1}^{T_i} \delta^{t}$. Future health states are discounted and summed from $t=1$ to $t=T_i$ and are denoted $pdve_i^{A} = \sum \delta^{t} 1(pre_{it}^{A})$, $pdvi_i^{A} = \sum \delta^{t} 1(ill_{it}^{A})$, $pdvr_i^{A} = \sum \delta^{t} 1(rcv_{it}^{A})$ and $pdvl_i^{A} = \sum \delta^{t} 1(lyl_{it}^{A})$. Since the different health states exhaust the individual's nominal life expectancy,

$pdve_i^{A} + pdvi_i^{A} + pdvr_i^{A} + pdvl_i^{A} = pdvc_i^{A}$.

To accommodate the assumption that each individual expects to pay program costs only during the pre-illness or recovered (post-illness) periods,

$pdvp_i^{A} = pdve_i^{A} + pdvr_i^{A}$ is the present discounted time over which payments must be made. This can be interpreted as the expected discounted duration of program costs, with the expectation taken across whether or not the individual gets sick.

To simplify notation we define $cterm_i^A = [(1-\Pi_i^{AS})pdvc_i^A + \Pi_i^{AS} pdvp_i^A]$, where $cterm_i^A$ can be intuitively explained as the expected number of present discounted years over which the program costs will be paid if the individual chooses Program A. We also define $yterm_i^A = [-pdvc_i^A + \Pi_i^{AS} pdvi_i^{AS} + \Pi_i^{NS} pdvl_i^A]$ even though $yterm_i^A$ does not have an easy intuitive explanation and we use it only to simplify the notation below. The expected utility-difference that drives the individual's choice between Program A and the status quo can then be defined as[10]:

$$\begin{aligned}\Delta PDV[E_{S,H}(V_i^A)] = {} & \beta_0\{(Y_i - c_i^A)cterm_i^A + Y_i yterm_i^A\} \\ & + \beta_1\{(Y_i - c_i^A)^2 cterm_i^A + Y_i^2 yterm_i^A\} \\ & + \alpha_1\{\Delta\Pi_i^{AS} pdvi_i^A\} + \alpha_2\{\Delta\Pi_i^{AS} pdvr_i^A\} + \alpha_3\{\Delta\Pi_i^{AS} pdvl_i^A\} + \varepsilon_i^A\end{aligned} \tag{2}$$

The terms in braces in equation (2) can be constructed from the data, given specific assumptions about the discount rate.[11]

In the sense of Graham (1981), the option price for a risk-reduction program is the maximum common certain payment that makes the individual just indifferent between paying for the program (and enjoying the risk reduction) and not paying for the

[10] Where there will be an analogous term for the utility difference between Program B and the status quo in our three-alternative model.

[11] In this paper, we assume a common discount rate of 5%. Cameron and DeShazo (2008) explore the consequences of assuming either a 3% discount rate or a 7% discount rate. Work in progress also involves the estimation of individual-specific discount rates simultaneously with these stated choices concerning health risk reduction programs, using additional data on intertemporal choices by a separate sample of respondents from the same population.

program (and not enjoying the risk reduction).[12] The annual option price $\hat{c}_i^A$ that makes the expression in equation (2) exactly zero can be calculated as:

$$\hat{c}_i^A = Y_i - f^{-1}\left(\frac{(\beta_0 + \beta_1 Y_i)yterm_i^A + pterm_i^A + \varepsilon_i^A}{-(\beta_0 + \beta_1 Y_i)cterm_i^A}\right) \tag{3}$$

Where $f(Y) = (\beta_0 + \beta_1 Y_i)Y_i = \beta_0 Y_i + \beta_1 Y_i^2$, so that $f^{-1}(\cdot)$ is the solution to a quadratic form, and $pterm_i^A = \Pi_i^{AS}\left[\alpha_1 pdvi_i^A + \alpha_2 pdvr_i^A + \alpha_3 pdvl_i^A\right]$ where $pterm_i^A$ is a combination of the present discounted health states in the illness profile.

The expected present value of this stream of payments must be calculated over the individual's remaining nominal lifespan:

$$E_{S,H}[PV(\hat{c}_i^A)] = cterm_i^A[\hat{c}_i^A] \tag{4}$$

To convert this expected present-value option price into a measure of the *WTP* for a microrisk reduction—a richer variant of the more-familiar "value of a statistical life" (*VSL*)—one can normalize arbitrarily on a one-in-one-million risk change by dividing this *WTP* by the absolute size of the risk reduction and scaling by .000001 to produce:

$$WTP = \frac{E_{S,H}[PV(\hat{c}_i^A)]}{\Delta\Pi_i^A} * 0.000001 \tag{5}$$

The *WTP* depends on the entire illness profile and upon all of the parameters in equation (2).

As described in Cameron and DeShazo (2008), the data suggest that the basic, homogeneous-preferences model given in equation (2) is dominated by a specification

[12] This notion of an option price differs from the sense in which is customarily used in the finance literature.

that is not merely linear in the terms involving present discounted health-state years. We can rewrite the terms in equation (2) that involve the α coefficients. Let j = *A, B, N*, and $pdvX_i^N = 0$ for $X = i, r, l$. Then:

$$\begin{aligned} &\alpha_1\{\Delta\Pi_i^{jS}\, pdvi_i^j\} + \alpha_2\{\Delta\Pi_i^{jS}\, pdvr_i^j\} + \alpha_3\{\Delta\Pi_i^{jS}\, pdvl_i^j\} \\ &= \Delta\Pi_i^{jS}[\alpha_1 pdvi_i^j + \alpha_2 pdvr_i^j + \alpha_3 pdvl_i^j] \end{aligned} \tag{6}$$

The simple linear specification fails to explain respondents' observed choices as well as a model that employs shifted *logarithms* of the $pdvX_i^j$ terms.

Starting from a form that is fully translog (including all squares and pairwise interaction terms for the three log terms), and retaining only those terms where the α coefficients are statistically significantly different from zero, equation (6) becomes:

$$\Delta\Pi_i^{AS}\left[\begin{array}{l} \alpha_1 \log\left(pdvi_i^A + 1\right) + \alpha_2 \log\left(pdvr_i^A + 1\right) + \alpha_3 \log\left(pdvl_i^A + 1\right) \\ +\alpha_4\left\{\log\left(pdvl_i^A + 1\right)\right\}^2 + \alpha_5\left\{\log\left(pdvi_i^A + 1\right)\log\left(pdvl_i^A + 1\right)\right\} \end{array}\right] \tag{7}$$

Finally, because the opportunity for longer durations in each health state is correlated with the youth of the respondent, the α coefficients must be allowed to differ systematically with the respondent's current age wherever this generalization is warranted by the data. This leads to a model where $\alpha_3 = \alpha_{30} + \alpha_{31} age_i + \alpha_{32} age_i^2$, and analogously for α_4 and α_5. This quadratic-in-age systematic variation in parameters permits non-constant age profiles for the model's *WTP* estimates, and this sample tends to produce the fairly typical higher values during middle age and lower values for younger and older respondents.

Since respondents choose between Program A, Program B, or neither program, the Random Utility Model (RUM) is the best theoretical framework to use. We assume that individuals will choose the option that gives them the most expected utility. Since we are analyzing risk reductions, we could choose to use a framework of prospect theory, which takes into account that individuals tend to overestimate the likelihood of very small probabilities and underestimate the likelihood of very large probabilities. Since the risk associated with our programs do not vary from 0 to 1, but instead are concentrated at the small end of the spectrum, we think using a random utility model is the preferred way to frame the model.

As noted in the description of the survey instrument, after each choice scenario, respondents are asked debriefing questions about when they believe that the benefits of each proposed program would begin, for them personally. Based on the answers to each of the questions in Figure 2, we define two variables. First, $1(never_i^j)$ is an indicator variable that takes a value of one if the individual responds by checking "Never (Program would not benefit me)." The second variable, $Bendiff_i^j$, is an approximately continuous variable defined as the "minimum overestimate of the latency," which measures the latency until the individual believes the benefits will begin.

The variable $Bendiff_i^j$ requires a more detailed explanation. If the interval checked in the question in Figure 2 contains the stated latency for the illness from the corresponding choice scenario, then $Bendiff_i^j = 0$. The relationship between the chosen interval and the stated latency is thus something like that shown in Part A of Figure 3.

In this case, the time when benefits begin (in the opinion of the respondent) is essentially the same as the latency stated in the choice scenario. In contrast, $Bendiff_i^j$ has a positive value equal to the difference between the lower bound of the checked time interval and the stated latency if that checked interval lies entirely above the stated latency for that illness in the choice scenario, like the outcome shown in Part B of Figure 3. $Bendiff_i^j$ has a negative value equal to the difference between the upper bound of the checked interval if the checked interval lies entirely below the stated latency, as illustrated in Part C of Figure 3. In Appendices B and C, the relationships between each of the two scenario adjustment variables are explored and an array of explanatory variables specific either to the individual or to the choice scenario.

The usual intent within a stated preference study is to induce individuals to accept the stated choice scenario as fully as possible and for them to respond conditional on that acceptance. If respondents selectively reinterpret the question (i.e. adjust the choice scenario) before they answer, then this violates an important maintained hypothesis behind the random utility model that produces the utility parameter estimates which are the foundation of most stated preference studies. We use the "observed" values of $1(never_i^j)$ and $Bendiff_i^j$ constructed from the debriefing questions associated with each of the 15,040 illness profiles presented to the respondents to control and correct for scenario adjustment with respect to the latency attribute. Descriptive statistics for the variables used in these models are presented in Table 1.

We accommodate scenario adjustment by allowing each of the utility parameters in the baseline model to differ systematically with individuals' responses to the debriefing questions about whether and when the benefits from each health risk reduction program are likely to be realized. The working version of the general model involves a total of fourteen parameters— β_0 and β_1 which capture the marginal utility of net income (i.e. expenditure on all other goods and services), the five basic α parameters ($\alpha_{10}, \alpha_{20}, \alpha_{30}, \alpha_{40}, \alpha_{50}$) appearing in the illness profile term in expression (7) above, plus the three pairs of coefficients on the age_i and age_i^2 terms that shift α_3, α_4 and α_5, and the single coefficient on the sample participation probability interaction term, α_{13}.

To effect corrections for scenario adjustment, the two scenario adjustment variables, $1(never_i^j)$ and $Bendiff_i^j$, are allowed to shift every one of these fourteen utility parameters. If each of these parameters is represented generically as θ, the new model substitutes a systematically varying parameter as follows: [13]

$$\theta = \theta_0 + \theta_1 1(never_i^j) + \theta_2 Bendiff_i^j \qquad (8)$$

for a total of 52 parameters in the fully generalized specification.[14]

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[13] In a set of preliminary models, both $1(never_i^j)$ and a pair of indicator variables for over- or underestimation (relative to none) to shift each of the α parameters in the general model are employed. The results were qualitatively similar to those reported here.

[14] Results for these fully generalized 52-parameter models are contained in Appendix C.

5. Empirical Results

In Table 2, however, we report results for a parsimonious version that retains only those shift variables which are individually statistically significant.[15] Model 1 in Table 2 gives the utility parameter estimates which result when the possibility of scenario adjustment is completely ignored during estimation. Model 2 in the same table (which spans columns 2 through 4) reveals the results when scenario adjustment is accommodated. The ideal situation (i.e. full acceptance of the stated latency of benefits) corresponds to $1(never_i^j) = 0$ and $Bendiff_i^j = 0$ for all respondents and all programs. Thus, we label the first column of parameters for Model 2 as "Corrected," since these are the estimated utility parameters which apply when both $1(never_i^j)$ and $Bendiff_i^j$ are equal to zero—i.e. when we simulate counterfactually the latency scenarios that the survey had intended each respondent to accept.

In Model 2, where we measure and correct for scenario adjustment, the magnitudes of some of the shift parameters are striking. The second column of results for Model 2 shows the significant shifts in each of these utility parameters when the respondent states that they will never benefit from the program in question. The third column shows the significant shifts in these parameters for a one-unit increase in $Bendiff_i^j$.

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[15] We acknowledge that these variables may be, to some extent, jointly endogenous with the underlying willingness to pay for health risk reductions because they are reported by the same individuals. In Appendix B, we note that despite the considerable number of statistically significant coefficients in the models to explain $Bendiff_i^j$, we are only able to explain (at best) about 35% of its variation across illness profiles using the large number of explanatory variables that are available.

The marginal utility of income from Model 2 serves as the denominator in the marginal rate of substitution (between each illness profile attribute and income) that gives the estimated marginal willingness to pay associated with each attribute. Overestimation of the latency appears to be associated with a higher estimated marginal utility of income, which means a lower *WTP*. The perception that a particular program will never benefit the respondent also appears to undo the evidence for a diminishing marginal utility of income. For these cases, *WTP* is no longer greater at higher incomes, whereas this appears to be the case when respondents fully accept the stated latencies.

There are also a number of important differences for "scenario adjusters" among the coefficients on the illness profile terms. In two cases (for the linear term in the shifted log of discounted sick years, and for the interaction term between the shifted logs of discounted sick-years and discounted lost life-years), the discrete shift in the parameter associated with the perception that the program will never provide any benefit is sufficient to completely change the sign of the effect. In two other cases, the sign of the coefficient remains the same but the coefficient more than doubles in size. Whenever the coefficients on the interaction terms involving $Bendiff_i^j$ are statistically significant, they bear a sign that is opposite to the baseline coefficient on the same term. Scenario adjustments can thus have a clearly discernible impact upon estimated marginal utilities.

The magnitudes of the shift parameters reported for Model 2 in Table 2 appear fairly large, but to appreciate the overall effects of these parameter changes on demand estimates, it is necessary to simulate distributions for the implied (normalized)

willingness-to-pay estimates. Bear in mind that the U.S. EPA, for example, relies upon an overall average value of a statistical life (a *VSL* associated with sudden death in the current period) of about $6 million, whereas for transportation policies, the *VSL* numbers typically used are closer to $3 million. In Table 3, we show selected *WTP* estimates for specified individuals and conditions. We consider, in succession, an individual who is 30, 45, or 60 years old. In all cases, the individual earns an income of $42,000 per year. The illness profiles involve shorter (and longer) illnesses with "recovery," shorter (and longer) illnesses followed by death, and sudden death with no preceding period of illness. The "sudden death" *WTP* estimates are most comparable to conventional *VSL* estimates.[16]

Scenario adjustment in this illustration concerns illness latency, so two different illness profiles are considered, one without latency and one with a latency period. We want to compare the *WTP* estimates that are corrected and uncorrected in each illness profile. Then we also want to compare the direction and magnitude of the differences between corrected and uncorrected between the two illness profiles. Since this scenario adjustment involves latency, there may be differences due to the length of the latency period.

In the first pair of columns in Table 3, we specify that each illness commences immediately (i.e. with no latency period). In the second pair, we specify a latency

[16] The illnesses described in the choice scenarios are all major illnesses, including most of the ailments from which people eventually die. It is clear from the analysis that people do not assume that their health status "after" one of these illnesses, should they recover, will be equivalent to their pre-illness state. Thus the value of avoiding a one-year major illness includes the value of avoiding the ensuing post-illness health state. It will not be the same as the value of avoiding *just* that year of illness, separate from any ensuing years in an incompletely recovered state.

period of twenty years. In each pair of columns, the initial uncorrected *WTP* estimates are calculated from the uncorrected parameters of Model 1 in Table 2. The corrected *WTP* numbers are calculated using the baseline coefficients from Model 2 in Table 2, which have been corrected for any scenario adjustments reported by respondents.

Table 3 shows that for the "No Latency" illness profiles, the corrected *WTP* estimates are mostly higher than those produced by the model that does not take scenario adjustment into account. The most dramatic differences are for longer and fatal illnesses for 60-year-olds, where the uncorrected model suggests a *WTP* of less than $1, whereas the corrected estimate is $6.93. The only exceptions (where the corrected estimates are lower than the uncorrected estimates) are for some of the illnesses which are not fatal. The difference in the corrected and uncorrected *WTP* estimates suggests that if scenario adjustment is not taken into account, willingness to pay estimates for many illness profiles of this type may be biased downward. This type of bias may result in the recommendation that some programs or policies that reduce illnesses and injuries with no latency (i.e. where benefits start immediately) should not be implemented when it may actually be welfare-increasing to put these measures into effect.

In contrast, the corrected estimates for illness profiles that have a latency of 20 years are almost all lower than the uncorrected estimates. The 90% simulated distributions for these *WTP* measures often include zero. The only two anomalies, where the corrected estimates are higher, are for the non-fatal illness profiles for 30-year-olds. This suggests that failure to take into account scenario adjustment could

cause some programs or policies that address long-latency health risks to be implemented when they are not actually welfare-enhancing from the current perspective of most age groups. These differences in the corrected and uncorrected *WTP* estimates show how important it may be to acknowledge and correct for scenario adjustments in stated preference research.

6. Conclusion

The absence of suitable market data sometimes forces researchers to use stated preference methods to assess demand for fundamentally non-market (or pre-test-market) goods or services. Given economists' skepticism about the reliability of stated preference data, researchers in fields where adequate market data tend to be scarce have systematically addressed many recognized problems with these alternative demand-measurement methodologies. One problem with *SP* research has been the occurrence of protest responses or scenario *rejection*, where respondents completely refuse to play along with the hypothetical choice exercise because they do not believe (or agree with) some aspect of the choice scenario. This chapter addresses the related but potentially more subtle problem of scenario *adjustment*. Respondents make the stated choices requested of them, but they first implicitly revise the choice scenario to better capture what would be the implications of each alternative in their own particular case.

Scenario adjustment may be more likely in situations where the alternatives involved in the choice problem are less easy to perceive and appreciate. For example, it may be possible to describe, unambiguously, the relevant attributes of alternative brands

of dishwashing soap, in which case scenario adjustment would be unlikely. In contrast, it may be very difficult to completely describe the relevant attributes of a program to enhance the survival of an endangered species, where even the experts cannot predict for certain whether the program will be effective. Choices that involve heterogeneous risks or uncertain outcomes, such as the reduction of health risks, may be the most vulnerable to scenario adjustment, since there is great variability in how different people perceive risks and uncertainty.

Assessment and correction for scenario adjustment is easier and can be more systematic if suitable debriefing questions about each key choice scenario are posed in the survey. The specific debriefing question used in the empirical illustration in this chapter is very useful, but it may still have been less than ideal. Carefully planned questions of this type, however, can help the researcher identify those individuals who acknowledge that they do not believe that the preceding choice scenario, exactly as stated, applies to them. Where possible, debriefing questions can also be used to quantify the likely *extent* to which individuals may have adjusted the scenario. With information about the extent of scenario adjustments, researchers can explicitly model the effects of scenario adjustment on the estimated utility parameters in their choice models. This allows counterfactual simulations of the individual's most likely response, had they answered the question exactly as it was asked. These types of simulations, with systematic correction for scenario adjustment, presumably permit more accurate estimates of demand.

In this chapter, using just one example of a debriefing question of this type in a stated preference survey concerning willingness to pay for privately provided health risk reduction programs, we construct two variables to quantify scenario adjustment. One is a binary variable that is equal to one if the respondent reports that the program in question will never benefit them. The second variable is a lower bound on how much the respondent may have overestimated (or underestimated) the latency period before the benefits of the program would begin to accrue (relative to the latency that is identified in the stated preference choice scenario). When both of these variables are zero, of course, scenario adjustment is implied *not* to be present.

The data used in this study suggest that some individuals may indeed update some aspects of choice scenarios so that these scenarios better apply to their own personal situations. We use an empirical choice model that allows the utility parameter estimates to differ systematically according to the respondent's reports of possible scenario adjustment with respect to latency periods. The estimation results show that the counterfactually simulated *WTP*-type benefits estimates—corrected for scenario adjustment—are often noticeably different from the uncorrected estimates. For example, the empirical estimates suggest that after correction for scenario adjustments, programs that benefit people *now* have mainly higher estimates, while programs that benefit people twenty years into the future have mainly lower estimates. These differences in estimated demands are big enough that they could potentially make the difference between enacting a policy that is warranted on a benefit-cost criterion and failing to enact it.

Given these findings and the differences in demand estimates (with and without correction) in this illustration, we infer that scenario adjustment is likely to be inevitable and potentially influential, in at least some proportion of cases, in many other applications as well. Debriefing questions to permit assessment and correction of scenario adjustment should probably be a regular feature of *SP* surveys. Likewise, formal modeling of scenario adjustment and its impact on the final estimates of interest should probably be a routine component of empirical work using stated preferences. Researchers should at least report sensitivity analyses for their main results with respect to this type of correction. Such information would allow the policy-makers to decide which types of "misalignments" between respondent and researcher information sets warrant correction, and therefore which demand estimates should be preferred.

In the next two chapters, we turn from methodological improvements toward looking at how *WTP* varies systematically. In the next chapter we examine differences by household structure. In Chapter IV, we examine differences in *WTP* by type of disease.

CHAPTER III

WILLINGNESS TO PAY AND HOUSEHOLD STRUCTURE

A version of this chapter is co-authored with Trudy Ann Cameron and J.R. DeShazo

1. Introduction

Parents can choose to invest in their own health and in the health of their children. Both market goods and parental attention are important for the health of the child. Therefore, these own-health investments that allow parents to work and care for their children may also be seen as investments in the health of the child. Jacobson (2000) developed a theoretical model of family-provided health to more fully explain the determinants and dynamics of health investments in adults and children. In her model, investments in each family member's health are jointly determined by the allocation of income and time made by other family members. We conduct an empirical test of the hypothesis that a family may change its investment in the health of a parent in order to benefit the children and we provide estimates of the willingness to pay to reduce risks and how they vary depending on household structure.

We further contribute to the literature on the family's role in the production of health by exploring several other questions which are raised, but not answered, by existing theoretical models. For example, we describe how the likely timing of a parents' future adverse health states, interacted with the anticipated timing of their children's departure from home, can affect the parents' current investments in mitigation of their own health risks. We also assess empirically how parents'

willingness to pay to reduce their own health risks will vary with the numbers of children in different age brackets in the household and across single-income and dual-income households.

Researchers have, of course, looked at many empirical aspects of child health more generally, and at parents' willingness to pay for improvements in the health of their children.[17] Numerous studies also explore a parent's propensity to invest in their children's health by reducing the child's risk of illness or death through improved access to medications and better safety measures. Among these, Liu et al. (2000) focus on Taiwanese mothers' willingness to pay to reduce the duration and severity of a cold for themselves and their children, and Jenkins et al. (2002) focus on parents' willingness to pay for safer bicycle helmets for their children.[18] Evans et al. (2006) examine how individual preferences for public policy changes are influenced by the time spent on the care of a dependent (e.g. an elderly parent or a child). Dockins et al. (2002) and Scapecchi (2006) both address the question of whether there are differences in willingness to pay to reduce health risks for children versus adults. Our work differs from these prior studies because we focus on adults' willingness to pay for health-risk reductions *for themselves* as a function of the presence of children of different ages.

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[17] Some examples from the child health literature are Currie and Hotz (2004), who find that a requirement of more education for day-care providers leads to fewer accidents involving the children in their care. Currie and Moretti (2003) find that an increase in a mother's education will, among other things, improve the health of her infants. Currie and Neidell (2005) and Chay and Greenstone (2003) look at the measurable negative effects of air pollution on infant health.

[18] Other examples include Agee and Crocker (1996); Barron et al. (2004); Chenevier and LeLorier (2005); Dickie (2005); Dickie and Gerking (2006); Dickie and Gerking (2007); Dickie and Messman (2004) and Maguire et al. (2004) .

Our analysis also contributes to the literature concerned with estimation of the "value of a statistical life" (*VSL*). Since not all readers may be familiar with the concept of a statistical life, we digress to explain this concept. A *VSL* is an average, scaled willingness to pay (*WTP*) to reduce mortality risk. Estimates of individuals' *WTP* are based on small reductions in mortality risks. The decrease in mortality risk may come from many sources including increased access to medicines and disease prevention. Each available estimate typically corresponds to a different-sized risk reduction, so it is not possible to average the underlying unscaled *WTP* estimates. Thus, *WTP* estimates need to be standardized on some common size of risk reduction before an average can be taken. The convention is to use the ratio of the marginal utility of a risk reduction to the marginal utility of income (a marginal rate of substitution), which is equivalent to scaling all of these tiny risk reductions and their corresponding *WTP* estimates to a vastly larger 1.00 risk change. (It is tempting to interpret this risk reduction as "avoiding certain death" but no such extreme risk reduction is valued in any of the empirical data on *WTP* and no risk change as big as 1.00 is contemplated in any policy context where these values are used.) The average of a set of scaled-up *WTP* estimates is termed the "value of a statistical life." For use in benefit-cost analyses, however, the *VSL* is scaled right back down to the very tiny individual risk reductions represented by most health, environmental, and safety regulations.

The U.S. EPA, for example, uses a *VSL* value of roughly $6-$7 million for a normalized risk change of 1.00. Viscusi and Aldy (2003) offer a meta-analysis of various *VSL* estimates found in the literature in the past thirty years and discuss how

estimates are used by governments to balance the costs and benefits of policies they may implement. Their meta-analysis reveals the extent of uncertainty in the accuracy of the point estimates, econometric problems, and variations in the estimates derived for different age groups. This literature, however, does not consider how the *VSL* of an adult may vary in the presence of children, so the main contribution of this chapter is to show how *WTP* varies along this dimension.

Using a model developed in Cameron and DeShazo (2008), we depart from a simple *VSL* and work with the more general concept of the willingness to pay for a microrisk reduction. Like the *VSL*, this *WTP* is constructed from a ratio of the marginal utility of a risk reduction to the marginal utility of income, but in our case, the marginal utility of a risk reduction is a much richer construct since we are able to capture differences in types of risk and differences stemming from heterogeneity in the demographics of the affected population. A methodological advantage of our approach is that we are able to estimate the adult's marginal utility of income as well as separate (and non-constant) marginal disutilities of future periods of illness and years of lost life. Given our utility-theoretic modeling framework, we are able to describe how each of these marginal utilities varies systematically for mothers and fathers with children in different age groups. We provide the first documentation of how adult willingness to pay to reduce the risk of adverse *health profiles* differs significantly for parents and non-parents. We show how estimates of the *WTP* differ for mothers and fathers. We illustrate how a mother's or a father's *WTP* varies systematically with the numbers of

children in different age groups presently in the household, and we show how *WTP* differs across single-income and dual-income households.

To preview briefly the survey data we use, we note here that our data are drawn from an extensive existing stated preference survey by Cameron and DeShazo (2008) that elicits individuals' demands for programs that reduce their risks of eleven different major health threats. The illnesses are described as a time sequence of health states that the individual has some risk of facing over their remaining lifetime. The risk-reducing intervention programs are described as an annual pin-prick diagnostic blood test and, if needed, associated drug therapies and life-style changes. The estimating sample consists of choices by over 1,800 individuals who are representative of the U.S. population in terms of standard demographic characteristics. In addition to thorough pre-testing of the survey, extensive robustness and validity checks of the individuals' responses have been conducted. These include risk comprehension verification and scope tests for *WTP* values. Individuals are given "cheap talk" reminders, where they are told to carefully consider their budget constraints, in order to mitigate hypothetical bias. Each choice set consists of a pair of risk reduction programs and a status quo alternative. Individuals are instructed to assume each choice set is independent of the other four choice sets they are asked to consider. We use these data to empirically test hypotheses about parents' investments in their own health.

Early theoretical models of the family, such as Becker and Tomes (1976) and Leibowitz (1974), focus on parents' investments in their children rather than in themselves. However, parents' investments in their own health may represent indirect

investments in the well-being of an individual's children. Jacobson (2000) recently developed a theoretical model of family-provided health to more fully explain determinants of health investments in both adults and children. By treating the family, instead of the individual, as the producer of health, she illustrates how investments in each family member's health are jointly determined by the allocation of income and time made by other family members.[19] The health of a child is determined both by the family's allocation of market goods to the child and by its allocation of health-denominated parental time to the child. Consequently, we would expect that utility-maximizing parents explicitly consider the role that their own health plays in determining the health and human capital development of their children. Jacobson also shows that parents do not have to be altruistic to invest. Even parents who are entirely selfish (e.g. those who do not appear to derive utility directly from the happiness of their child) will invest in the health of that child since failing to do so may have negative consequences for parents' incomes (e.g. a sick child may reduce the time a parent may allocate to the labor market or to consumption activities).

The model by Jacobson (2000) shows that family members, instead of equalizing health outcomes for each family member, equalize the marginal utility of lifetime health normalized by the price of health for that family member. It also shows that health influences income in two separate ways—good health allows a parent to work and good health increases the parent's wage rate. Since children require both income and time from a parent, we expect the presence of children to affect parental

[19] Jacobson extends Grossman (1972) who models the individual as the producer of health.

decisions in two ways. We expect children to increase a parent's marginal utility of income since the additional costs of caring for children will make the family budget tighter. We also expect children to increase a parent's marginal utility of healthy time since time spent in all pursuits becomes more valuable at the margin as the parent needs healthy time both to care for a child and to work. Thus, the model implies the following hypothesis:

> **Hypothesis 1:** Parents' marginal utilities from both income and healthy time are higher in the presence of children and may continue to increase with additional children.

Jacobson's model assumes that both parents have common preferences, but she admits that this assumption may not be realistic. Jacobson's model was extended by Bolin et al. (2001), Bolin et al. (2002a) and Bolin et al. (2002b) who hypothesize that a family's investments in the health of the mother, versus that of the father, will be different and will depend on their relative labor market opportunity costs, among other things. They highlight the way in which mothers' and fathers' investments in their own health can vary as a result of intra-household decision-making and Nash bargaining between husband and wife. To explain differences in men's and women's willingness to pay, these models illuminate the roles of several factors that may vary systematically across husbands and wives. Specifically, these factors include labor market opportunity

costs, the marginal utility of health improvement, and the marginal productivity of the parent's healthy time for the child's development.[20] This suggests the following:

> **Hypothesis 2**: If a woman earns a lower income and/or derives greater marginal utility from additional income and faces relatively lower (and longer-latency) health risks than her husband, she may be less willing to pay to reduce the risk of getting sick or dying in the near term.

If the inter-parent allocation process is an outcome of Nash bargaining, Bolin et al. (2002b) suggests each parent's *control* over family income may have an impact upon their own health investments. Each parent's degree of control over how income is allocated may depend in part upon both the share of total household income earned by that parent and the leverage generated from the threat of a possible exit from the household. (If the wife has her own income, for example, a husband's threat of exit from the marriage has smaller financial consequences for her.) This suggests the following hypothesis:

> **Hypothesis 3 (Second Income)**: Women who have independent incomes will be both more inclined and more able to invest in reducing their own health risks than will women who depend entirely upon their husbands' incomes.

We also expect willingness to pay for health-risk reductions to differ with changes in a parent's age. Although there is no definite consensus of how *VSL* changes with age, Viscusi and Aldy (2003) construct *VSL* estimates and find that *VSL* tends to

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[20] The child's health is also determined by efficiency parameters for both the mother and father. See equation (22) on p. 622 of Jacobson (2000).

increase with age until individuals reach their mid-50's and then tends to decrease.[21] In the context of our study, we control for the age of the adult when evaluating willingness to pay for health-risk reductions in order to distinguish between the effect of the parents' ages and the effects of parenthood status and the ages of children.

The next section briefly outlines the survey methods and the available data. The third section explains the structural model behind the empirical specifications. Sections 4 and 5 discuss the empirical estimation and simulated *WTP* results and Section 6 concludes.

2. Available Choice Data

Existing market-based data are not adequate to infer individuals' demands for risk reductions with respect to future time profiles of illness or injury. The revealed preference (RP) data that are typically available concern the tradeoff between risk levels and wages. Since more dangerous jobs are paid a wage premium, the choice between risk level and salary provides an indication of how much participants are willing to pay for risk reductions. Mrozek and Taylor (2002) complete a meta-analysis of studies that look at job choices of labor market participants. Groups other than working-aged males may not be represented well by these measures, which may be problematic because the amount people are willing to pay for prospective risk reductions may vary considerably by gender, age, and labor market status. For example, stay-at-home mothers of young

[21]Evans and Smith (2006), however, find an ambiguous relationship between VSL and age. Other researchers have tended to find that VSL and age have an inverted U-shape relationship.

children may be especially under-represented since they are out of the labor market. Stated preference (*SP*) data may be the only viable type of information concerning willingness to pay for groups which are not in the labor market.

Cameron and DeShazo (2008) use stated preference methods to elicit preferences for programs to reduce the risk of morbidity and mortality in a general population sample of adults in the United States. The survey was developed carefully using 36 detailed in-person cognitive interviews, three pretests and a large pilot study. Knowledge Networks, Inc. administered the survey to 2,439 of their panelists and achieved a respectable 79% response rate.[22] In brief, the survey consists of five modules. The first module asks respondents to rate their subjective risks, from low to high, of contracting each of a range of major illnesses or injuries. Individuals are also asked to think about how lifestyle changes would change their risks of these illnesses and how difficult it might be to implement these lifestyle changes.

The second module is a tutorial that explains the concept of an "illness profile." This is a description of a sequence of future health states associated with a major illness or injury that the respondent may face over his or her remaining lifetime (described as one of five specific types of cancer, heart attack, heart disease, stroke, respiratory illness, diabetes, traffic accident, or Alzheimer's disease). An illness profile includes the years before the individual becomes sick (i.e. the latency period), illness-years while the individual is sick, recovered/remission years after the individual more-or-less

[22]For more information on the survey instrument and the data, see Cameron and DeShazo (2008). For more detail on the survey, please see an annotated sample at: http://www.uoregon.edu/~cameron/vsl/Annotated_survey_DeShazo_Cameron.pdf .

recovers from the illness, and lost life-years if the individual dies earlier than he would have in the absence of the illness or injury. After the tutorial about illness profiles, the individual is informed that he might be able to purchase new programs that would reduce his risks of experiencing certain illness profiles. Each illness-related risk-reduction program described in the survey consists of a diagnostic blood test plus possible drug therapies and/or life-style changes, available at a specified overall cost that is not covered by insurance.

The third, and key, module of each survey involves a set of five different three-alternative conjoint choice experiments where the individual is asked to choose one of two possible health-risk reducing programs or a status quo alternative. Each program reduces the individual's risk of experiencing a specific illness profile. The illness profile is described in terms of its baseline probability, age at onset, duration, severity of symptoms and type of treatment, and eventual outcome (recovery or death). Each corresponding risk reduction program is defined in terms of the extent to which it can be expected to reduce this risk, as well as its monthly and annual cost. Figure 1 provides one randomized example of the type of a stated choice scenario posed to respondents.

Module 4 contains debriefing questions to cross-check the consistency of responses. Module 5 is collected separately from our survey and contains detailed socio-demographic data for the individual and the household, as well as responses to a battery of health-related questions (including any illnesses the individual has already faced).

Extensive robustness and validity checks of the individuals' responses have been conducted to evaluate common problems in *SP* analyses. These include risk comprehension verification where individuals are asked to rank the sizes of risk reductions, checks on the complexity of the choice sets where individuals are asked to rate the difficulty of the choice sets, and a "cheap talk" reminder so that individuals are careful to consider their budget constraints and not overstate their willingness to pay.[23] Order effects for the choice sets are considered and individuals are instructed to assume each choice set is independent of the other choice sets. Choices are readily demonstrated to be sensitive to the changes in the scope and central attributes, such as the cost of the program and the size of the risk reduction. Systematic sample selection effects are controlled for, with methods explained in detail in Cameron and DeShazo (2008).

Table 7 contains descriptive statistics for the variables used in the empirical models presented in this chapter. It summarizes only the subset of variables from the survey which are pertinent to the present analysis. These include attributes of the different illness profiles presented to respondents (latency, present discounted sick-years, recovered/post-illness years, and lost life-years). This information, combined with data on the numbers and ages of children currently in the family, allows us to

[23] A number of individuals and/or choice sets were dropped from the analysis according to minimal exclusion criteria. The exclusion criterion for risk rejection was the respondent needed to be able to rank successfully the sizes of the risk reductions associated with two risk mitigation programs. There were 4,887 alternatives (1,629 choices) that were excluded due to the risk comprehension criterion. The exclusion criterion for scenario rejection was that the respondent chose the "neither program" alternative and, in the follow-up question, chose only the answer "I did not believe the programs would work". There were 6,708 alternatives (2,236 choices) excluded due to scenario rejection. There were also 996 alternatives (332 choices) excluded due to an error in the randomized design.

determine whether the onset of the adverse health state will occur when there are likely to be children still under the age of eighteen present in the respondent's household. The variable list also includes attributes of the proposed risk reduction programs which are described as reducing the individual's chance of suffering from these adverse health states (including the cost of the program and the size of the risk reduction). Finally, there are a number of relevant characteristics of the respondent (age, gender, income, and whether there are two income-earners in the household).

3. A Random Utility Choice Model

The specification used to test the hypotheses outlined in the introduction builds upon the utility-theoretic model presented by Cameron and DeShazo (2008). The base model for his chapter uses the 13-parameter model from Cameron and DeShazo (2008) and the effects of "scenario adjustment" the includes $Bendiff_i^j$ and $1(Never_i^j)$ as described in Chapter II. We then focus on the consequences of introducing additional interaction terms that involve gender, the numbers of children in four distinct age groups, single- versus dual-income households, and whether children are likely still to be present in the household at the onset of each illness or injury as described in each illness profile.

4. Empirical Estimation

There is little theory to guide the functional form of exactly how household structure should enter into the empirical model. We considered five conditional logit

random utility models (*RUMs*) that were quadratic in discounted net income and employed translog-like transformations of terms in the numbers of sick-years, recovered (post-illness) years and lost life-years which make up each illness profile.[24] We considered heterogeneity with respect to household structure and found a parsimonious specification which appears to be warranted by the stated choices of these respondents. Our preferred specification is shown in Table 5, which displays all of the parameters in the model.

In Table 6, we summarize just the key results with respect to household structure for our preferred parsimonious model. Note that Table 6 describes just a single model. We have merely arranged the parameter estimates strategically to highlight the baseline coefficients (i.e. those which apply for males with no children) in column (1). The statistically significant coefficients on our interaction terms, reflecting systematic heterogeneity in preferences, are arrayed in columns (2) through (10) so that they line up with the baseline coefficients which they shift. Recall that the age of the respondent is extensively controlled for in the baseline specification (entering as it does, quadratically, as a shifter of three of the coefficients in the model). Without these respondent-age controls, there would be a much greater chance that the ages of children in the household also proxy for the age of the respondent.

The following discussion focuses on two classes of utility parameters, which are the two main ingredients used in the calculation of *WTP* for health-risk reductions: (a)

[24] Our models are estimated using a conventional conditional logit specification. In recent years, random parameter specifications have become increasingly popular. Explorations of random parameters models in simpler versions of models using these data have not yielded dramatically different results in terms of the expected values of the key parameters, so we continue to use the conditional logit specification.

the marginal utility of income, and (b) the marginal disutility from discounted future time in adverse health states. The *WTP* is constructed as the ratio of the estimated coefficients of these two classes of utility parameters. The presence of children of different ages in the household, as well as the other variables considered in this study, affect parameter estimates in both these classes of utility parameters and thus the estimated *WTP* for a particular respondent facing a specified illness profile.[25]

4.1 Family Structure and Differences in the Marginal Utility of Income

The first two rows of Table 6 reveal how the different dimensions of family structure—gender, the current presence of children, the structure of household income, and the likely presence of children at the onset of the prospective illness or injury—can affect the adult's marginal utility of net income. Net income measures the individual's consumption of all other goods and services aside from the risk-reduction programs in the stated preference choice scenarios. The marginal utility of income thus reflects marginal utility from other types of expenditures. The remaining rows in Table 6 show how the marginal utility of health state terms are affected by family structure and will be discussed in Section 4.2.

Our parsimonious fitted model in Table 6 offers support for the hypotheses made in the introduction. Row (1), column (2) shows a coefficient of 6.68 on the indicator variable for female which more than doubles the baseline coefficient of 4.7.

[25] In Dupont (2004), gender and parenthood indicators (and their interactions) enter directly into an atheoretic *WTP* function. Her model does not distinguish between marginal utilities of income and marginal utilities (or disutilities) from variations in environmental quality. Thus, only the net effects of these two influences can be discerned.

This suggests that the marginal utility of income is higher for women at all levels of income. These coefficients support Hypothesis 2, that if a woman earns a lower income than her partner, or if for any other reason she has a higher marginal utility of income, she may be willing to pay less for health-risk reductions.

Columns (3) through (9) in Table 6 show the influence of the numbers of children in different age groups on the marginal utility of income. The coefficient of about -2.3 on the interaction of the female indicator variable and the number of children ages 6-12, which is about half of the baseline coefficient, suggests that a mother's marginal utility of income is lower when children reach this age—which tends to coincide with the time when many mothers traditionally return to the labor market, and thus may experience an increase in their own incomes. As college costs and other expenses start looming in the presence of children age 13-17, we find that both males and females tend to exhibit higher marginal utilities of income, with a coefficient of about 2.2, which is an almost 50 percent increase over the baseline coefficient. Having teenagers, and a higher marginal utility of income, will tend to reduce both parents' demands for programs to reduce risks to their own health. Parents appear to be more willing to pay to reduce their own health risks when their children are younger.[26]

In column 8 of Table 6, we see that the presence of two incomes in the household, captured by the indicator variable $1(dualinc_i)$, produces a statistically significant effect on the marginal utility of income, but only for women. In the majority

[26] According to a report from the USDA's Center for Nutrition Policy and Promotion and data from the BLS Consumer Expenditures Data, families, on average, spend more money on teenagers (aged 12-17) than on younger children. See http://www.cnpp.usda.gov/Publications/CRC/crc2007.pdf.

of cases, the "second income" is likely to be the woman's own income. The coefficient of -2.1 provides support for Hypothesis 3, that a woman who has her own income (controlling for overall family income), may be more inclined to spend money on health-risk reductions for herself.[27]

The quadratic income term in row 2 represents the degree of financial risk aversion. A negative coefficient on the quadratic form in net income implies that the marginal utility of income declines as income increases. Men with no children appear to have roughly constant marginal utilities of income. The negative coefficient on the female indicator variable for the quadratic income term suggests that women are more risk-averse with respect to income changes than men (i.e. they exhibit diminishing marginal utilities of income, on average). Note, as shown in column (3) that both genders appear to be risk averse with respect to income when there are infants between the ages of 0 and 1 present in the household, as seen in the -.78 coefficient on the quadratic income term.

A higher marginal utility of income for women will tend to reduce the implied *WTP* for microrisk reductions, since this marginal utility enters via the denominator of the *WTP* formula. However, since the marginal utility of income declines more quickly for women as their incomes are higher, women's demands for health-risk reduction programs will increase more quickly as a function of income.

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[27] The Knowledge Networks Inc. panelist profile data contains detailed information on employment status (in nine discrete categories). In future work, we may consider systematic variation in demand for health risk reductions as a function not only of the number of workers in a household, but also the respondents' own employment status.

4.2 Family Structure and the Marginal Utility of Avoided Health Risks

The third through seventh rows of Table 6 reveal the sources of statistically significant heterogeneity in estimated (dis)utilities of discounted future time in different health states. Again, column 1 of Table 6 shows the baseline coefficient values (for males with no children). Column 2 shows that females with no children have positive coefficients that offset the baseline value. This shows that females derive substantially less disutility from the prospect of a discounted future sick-year than do males. The baseline coefficient is about -72, but this disutility is offset for females by a coefficient of about 28. Males also have somewhat more disutility from the prospect of a discounted lost life-year. The coefficient for males with no children is about -717 and the slight offset for females is about 25.

Columns 3 through 9, again, reveal the nature of heterogeneity due to the family structure and the numbers of children in different age groups. Column 4 reveals that males, in the presence of pre-school children (aged 2-5 years), seem to have a much lower disutility from sick-time than do childless males as shown by the positive coefficient of about 103, which more than offsets the baseline coefficient of about -71. Column 5 shows that women with children ages 2-5 have a substantially greater disutility for sick-time than childless males and certainly more than males with preschoolers. Perhaps children of this age are recognized to be exceptionally dependent upon their mother's care-giving, so mothers view their own healthy time as an essential input into their pre-school children's health.

While the presence of pre-school children may decrease fathers' disutility from sick-time, the presence of children in this age group appears to increase the disutility from present discounted lost life-years for both parents. The baseline coefficient, for males again, is -717 and the coefficient differential for each child aged 2-5 is about -41. These coefficients offer some support for Hypothesis 1, that a parent's marginal utility from healthy time is higher in the presence of children. The only coefficient that does not support this is the decrease in a father's disutility from sick time. Perhaps the reasoning for this is that being merely sick has the compensating benefit of an opportunity to be home with the family while the prospect of death does not have this compensating benefit.

One of the more provocative empirical results in this chapter is the finding that, in the presence of additional teenagers (i.e. children between the ages of 13 and 17), both males and females perceive lesser disutility from present discounted lost life-years. The baseline coefficient is, again, about -717 and the coefficient differential for each teenager is about 23. This may imply that parents view their own healthy time as a progressively less essential input into the child's wellbeing as the child gets older. However, a cynic might conclude that living with more teenagers makes the prospect of being dead start to look better and better. This lesser disutility of lost life-years, combined with the higher marginal utility of income with each teenager, produces a significant drop in parental willingness to pay for their own health-risk reductions during their children's teen years.

In column (9), we show the significant effects of the indicator variable, $1(dkidonset_i^j)$. This indicator captures any systematic effect caused by an illness profile for which the onset of the illness occurs when at least one child is still under 18 years of age. This is true for 3% of the 15,040 illness profiles used in the choices analyzed in this study (i.e. for about 430 profiles). The perceived disutility from sick-time is dramatically greater, for both genders, if the illness profile in question features an onset time when there will likely still be dependent children in the household as seen by the coefficient -114, which is greater than the baseline coefficient of -70. If a parent gets sick, the ailing parent may be less able to care for the child and any children in the household may have to bear part of the burden of caring for the sick parent.

The indicator $1(dkidonset_i^j)$ is a statistically significant shifter of the coefficients on each of the three variables involving interactions between discounted sick-years and discounted lost life-years. The coefficient of 482 on the interaction between sick years and lost-life years is dramatically larger than the baseline coefficient of 57. This suggests that the disutility of each discounted lost life-year is greatly lessened if it is preceded by an additional discounted sick-year. The interactions with age, however, suggest that this offsetting effect declines and then rises with the age of the respondent at the time of questioning.[28]

[28] The minimum occurs at about age 44 if a child is present at the onset of the disease. If none of the current children will be under 18 at the onset of the illness, the minimum *WTP* occurs at about 51 years of age.

5. Results for Simulated Distributions of Microrisk Reductions

The demand for health-risk reductions depends upon both the marginal utility of income and the disutility from the sick-time and lost life-years associated with the health risk in question. This demand can be summarized by the *WTP* for a microrisk reduction, which is a more-general analog of the value of a statistical life. Recall that *VSLs* tend to be viewed as one-size-fits-all measures of demand for *mortality* risk reductions, where the form of mortality is usually conceived as "sudden death now." Our measures incorporate both mortality and morbidity, as well as varying latencies and different durations of time in different adverse future health states.

Fitted *WTP* varies systematically with the individual's income and age, as well as with the exact nature of the illness profile under consideration. In Table 7, we display the results of some illustrative simulations of the distributions of *WTP* values implied by our fitted model. The top rows are for married individuals who are now 30 years of age, with differing numbers of pre-school children. The bottom rows are results for unmarried individuals of the same age. Table 8 displays the results for 45-year-olds with varying numbers of teenagers. For each age group, we calculate the simulated distribution of *WTP* for a microrisk reduction in two very simple illness profiles: (1) sudden death this year and (2) nine years in the future, the individual is sick for one year followed by death. Profile 1 is the closest our model can come to a *VSL*-type estimate if it were multiplied by 1 million, although our *WTP* estimates still depend fundamentally on age and income.

In the simulations for 30-year-olds, we consider persons in households with zero children, with one child between two and five years of age, and with two children between two and five years of age. For Illness Profile 2, sick for one year and then death with a nine-year latency, we assume that there will be at least one child present at the time of onset, so the $1(dkidonset_i^j)$ variable will be set equal to 1 in these simulations.

In the simulations for 45-year-olds, in Illness Profile 1 (risk of death this year), the youngest child currently in the thirteen- to seventeen-year-old interval will still be at home and the $1(dkidonset_i^j)$ variable will be set equal to 1 in these simulations. For Illness Profile 2 (with a nine year latency), the youngest child currently in the thirteen- to seventeen-year-old interval will be at least 22 years old at the time of onset, and thus relatively independent. The variable $1(dkidonset_i^j)$ is thus set equal to zero for all of these simulations.

In Tables 7 and 8, we show the medians as well as the 5^{th} and 95^{th} percentiles of the simulated distributions of *WTP* based on 1,000 random draws from the joint distribution of the maximum likelihood estimates of model parameters. For 30-year-old males with zero, one, or two children aged 2-5 years, willingness to pay for a microrisk reduction in the chance of sudden death is about \$7.90, \$10.40, and \$13.00. For 45-year-old males with zero, one, or two children aged 13-17 years, *WTP* for a microrisk reduction in sudden death is about \$8.70, \$5.30, and \$3.40.

5.1 Gender

Our *WTP* simulations suggest that women reveal a much lower willingness to pay for risk reductions than men under both illness profiles and for both age groups. This provides support for Hypothesis 2, that women may be less willing to pay to reduce health risks for themselves. The estimated differences in *WTP* between men and women control for household income levels, so this finding is not merely an artifact of the lower average incomes of women. Since both the numerator and denominator of the *WTP* are smaller, these two effects tend to offset one another in the overall *WTP* estimate.

5.2 Presence of Children

For 30-year-olds, the presence of each additional child aged two to five increases the *WTP* by about 25-35 percent for both males and females, which shows support for Hypothesis 1, that there is an increase in parents' marginal utility of healthy time in the presence of children. A 30-year-old female, having zero, one, or two children (ages 2-5), and facing an illness profile of sudden death this year is associated with a *WTP* for a microrisk reduction equal to $3.10, $4.20 and $5.30. That is a 36% increase for the first child and an additional 26% increase for the second child. Profile 2, sick for one year and then death after a latency period of 9 years, shows a similar increase in *WTP* with additional children. Both illness profiles for 30-year-olds exhibit a similar pattern in general which may be due to the fact that at least one child will be under the age of 18 when the illness strikes.

In contrast, for 45-year-olds, the *WTP* declines about 25-40 percent for each additional child age thirteen to seventeen years old. For example, being a 45-year-old female, having zero, one, or two children (ages 13-17), and facing sudden death this year is associated with a *WTP* of $3.40, $2.5 and $1.90. This decline is likely due to the fact that the presence of the teenagers seems to both increase the adults' marginal utility of income, and decrease their disutility from discounted lost life-years. We speculate that the growing need to provide for college expenses and the other costs associated with older children outweighs the adults' concerns about investing in their own future health. Furthermore, the growing independence of children this age means that the parent's own health is a less essential input into the child's well-being.

5.3 Presence of a Second Income

We simulate the *WTP* for women with and without two incomes in the household, while controlling for overall household income. We do this to evaluate Hypothesis 3, that women who have independent incomes will be more inclined and more able to invest in reducing their own health risks. For a 30-year-old woman with two children between the ages of two and five, a second income increases the *WTP* by $1.00, or by about 19 percent. For an illness profile of sick for one year and then death with a nine year latency, the *WTP* increases by $0.60—a 19 percent increase in the *WTP*. For a 45-year-old woman with two teenagers who is facing sudden death now, the *WTP* increases by 9 percent. These *WTP* estimates lend support to Hypothesis 3 that women's demands for health-risk reductions are sensitive to the proportion of

household income represented by their own earnings. For a 45-year-old woman with two teenagers who is facing illness and death in nine years, however, the *WTP* is much smaller, both with or without a second income. This may be partially due to the fact that a teenager will no longer be under the age of 18 when the illness strikes in ten years.

5.4 Differences Across Illness Profiles

For 30-year-olds, the *WTP* associated with the risk of death this year (Profile 1) versus a risk of illness and death in nine years (Profile 2) declines between about 26 and 45 percent depending upon the number of children present and the gender of the adult. For example, the decline for a female with no children is from $3.10 to $2.20, while the decline for a mother of two children (ages 2-5) is from $5.30 to $3.20.

These *WTP* differences across illness profiles are even larger for 45-year-olds. The *WTP* associated with the risk of death this year (Profile 1) versus a risk of illness and death in nine years (Profile 2) declines between about 47 and 65 percent depending upon the number of children present and the gender of the adult. For example, the decline for a childless female is from $3.40 to $1.70 (about 50 percent), while the decline for a mother of two teenagers is from $1.90 to approximately $0.70 (a decline of about 65 percent). These changes illuminate the differences in willingness to pay for health-risk reductions for sudden death this year versus illness and death with a latency period. The results also show differences in *WTP* for parents and non-parents across different illness profiles and how *WTP* varies in the presence of children of different ages.

6. Conclusion

As a result of the utility-theoretic basis for our model, there are two distinct opportunities for the effects of gender and parenthood variables to affect adult demands for health-risk reductions. On the one hand, the number of children in different age groups affects the adult's marginal utility of income (which reflects competing demands on the household's budget that may edge out expenditures on the adult's own health-risk reduction efforts). On the other hand, there is also evidence that the number of children in different age categories affects the adult's expected disutility from prospective sick-time and prospective lost life-years—especially when the illness profile in question will affect the adult while there are still likely to be children under the age of eighteen in the household.

We find the presence of children has significant effects on a parent's marginal utility of income even more broadly. Parents of infants are, on average, more risk-averse with respect to net income. Controlling for household income, women tend to have higher marginal utilities of income (perhaps because of their longer life expectancies). However, a mother's marginal utility of income is significantly lower in the presence of grade-school children—coinciding with the time that mothers traditionally return to the labor market, and thus experience an increase in their own incomes. When children reach their teenage years and the prospect of college starts to loom, we find that parents' marginal utilities of income are higher.

The marginal disutilities of adverse health states appear to differ systematically by family structure as well. We show that for each additional pre-school child, mothers

exhibit an increased marginal disutility of a sick-year—perhaps because they view their own healthy time as an essential input into their children's well-being at this age. However, for each additional pre-school child, fathers appear to exhibit an increased disutility of a lost life-year—perhaps because their continued income-earning power is viewed as essential to the child's future wellbeing (even though fathers are typically less involved in many child-rearing tasks than are mothers when children are very young). In contrast, in the presence of each additional teenager, both mothers and fathers reveal a *decrease* in their disutility of a lost life-year. This may be because parents, as their children grow older and more self-sufficient, view their own healthy time as a less essential input into the child's wellbeing. At the same time, with each additional teenager, the marginal utility of parents' income is greater (e.g. because income at this stage can be put to many other good uses, such as college expenses to enhance the child's human capital).

There appears to be some evidence that parents are much more concerned about preserving their future health if they will still have children at home, but their sense of urgency about their own health protection may decrease for illnesses or injuries that will not affect them until after their children are grown. Concern about the prospect of children still at home is most clearly expressed through differences in the substitutability between sick-years and lost life-years. This perceived substitutability differs with the age of the respondent (it tends to be quadratic in age, with a minimum during middle age), but it is much more pronounced if children are likely to be present at the onset of the illness.

Willingness to pay combines two components, the marginal disutility of adverse health states and the marginal utility of income, and varies systematically by household structure. For parents, we find that willingness to pay to avoid health risks varies systematically with the age of the parent as well as the numbers of children in each age group presently in the household. Simulations based on our estimated model reveal that, for younger adults, the presence of each additional preschool child increases the *WTP* by about 25-35 percent for both males and females. In contrast, for middle-aged adults, the *WTP* declines about 25-40 percent for each additional teenager in the household. Although fathers are willing to invest more in absolute terms to reduce their own health risks than are mothers, mothers exhibit a much higher percentage increase in *WTP* for health-risk reductions with the presence of children. We speculate that, controlling for income, the family may view the mother's health as a more essential input into the production of healthy children than a father's health, on average.

Finally, also controlling for overall household income, we find that women in households with two income-earners invest much more in their own health-risk reductions than do women in households with only one income-earner. Presumably, women with their own incomes find themselves both more inclined, and more able, to direct household resources towards their own health protection.

A few caveats need to be highlighted. The empirical results in this chapter reflect the assumption that individuals use a 5% discount rate. The issue of discounting is the subject of ongoing research, since, for the basic model in Cameron and DeShazo (2008), *WTP* estimates vary somewhat with the assumed rate of discount. Knowledge

Networks, Inc. report only the numbers of children in the respondent's household in each of four age categories. They do not report the genders of children in the survey and do not ask whether the adults who participated in the survey are actually the parents of these children. We refer in the chapter to "mothers" and "fathers," but we cannot be certain that these blood relationships exist. Finally, the illustrative examples concentrate upon illness profiles that involve sudden death now or sickness for a year at a point nine years in the future followed by death. Of course, the fitted model is general enough to admit for a wide variety of illness profiles, including non-fatal major illnesses and cases where long periods of morbidity may precede mortality.

Despite some limitations, we have described ways that willingness to pay for health-risk reductions appears to vary as household structure evolves over time. Willingness to pay for microrisk reductions is a more-general alternative to the *VSL* estimate. The *WTP* is more versatile and allows the willingness to pay estimates to vary fundamentally with income and age, as well as with attributes of the risk in question or the characteristics of the individual who is being asked to value the risk reduction.

The three main hypotheses tested in this research stem from theoretical models by Jacobson (2000), Bolin et al. (2001), Bolin et al. (2002a) and Bolin et al. (2002b), and we find that these three hypotheses are broadly supported by our empirical results. We find evidence that the presence of children affects the parents' marginal utilities of income and health, that women may be willing to pay less to reduce their own risks, and that women who have their own independent incomes may be willing to spend more on their own health risk reductions.

This research also complements other investigations concerning the willingness to pay by parents or society to reduce health risks faced by children. To the extent that the presence of children alters adults' willingness to pay for health-risk reductions for themselves, these changes in demand may reflect both parental altruistic motivation towards their children (i.e. parental concern for the value that their children place on their parents' health) and may also reflect the influence of competing demands on the household budget represented by the addition of financial responsibility for the care of children of different ages.

In the next chapter, we continue to look at aspects of heterogeneity in *WTP* estimates. We discuss how *WTP* varies by the type of disease in questions.

CHAPTER IV

WILLINGNESS TO PAY AND TYPE OF DISEASE

A version of this chapter is co-authored with Trudy Ann Cameron and J.R. DeShazo

1. Introduction

Government agencies such as the Environmental Protection Agency typically use a measure called the Value of a Statistical Life (*VSL*) to monetize the benefits for human health risk reductions from a particular policy. The *VSL* is an ex ante measure of individual willingness to pay (*WTP*) to achieve a tiny risk change, where this *WTP* has been scaled proportionately to a risk change of 1.0. Although it is tempting to interpret a *VSL* as society's willingness to pay to save one particular human life with certainty, this would be inappropriate. *VSL* estimates come from analyzing very small risk changes and are intended for policy use in contexts where similarly small risk changes are considered. Different environmental policies lead to different risk reductions, such as a reduction in the risk of lung cancer or heart disease. However, for all of these health threats, the same average *VSL* is commonly employed. This constrains the willingness to pay (*WTP*) for any given-sized risk reduction to be identical for all kinds of diseases and health threats. The contribution of this chapter is to demonstrate that *WTP* for health risk reductions varies systematically by disease type. This suggests the U.S. EPA and other government agencies should consider using different *WTP* values that are more closely tailored to particular diseases. This step

could more accurately represent the *WTP* of the particular population affected by a given policy.

In this chapter, we examine how individual willingness to pay (*WTP*) for health risk reductions varies systematically across different types of major health problems, including five types of cancers (breast cancer, prostate cancer, colon cancer, lung cancer, and skin cancer), chronic heart disease (as well as sudden heart attacks), respiratory disease, strokes, diabetes, Alzheimer's disease and traffic accidents. There are eleven different health threats in total, including one gender-specific cancer that is designated as breast cancer if the respondent is female, and prostate cancer if the respondent is male. In the conjoint choice study fielded by Cameron and DeShazo (2008), respondents are shown five sets of choice scenarios each involving three alternatives: two different risk-reduction programs and the status quo. For each respondent, ten of the eleven possible health threats for their gender were used (two in each of the five choice sets).

There are many reasons why people may be willing to pay different amounts to avoid different types of illness or injury. For example, there may be a "cancer premium" as noted in Savage (1993). Van Houtven et al. (2008) find strong evidence of a "cancer premium" and find that preferences differ with the length of the latency period. *WTP* by disease may also vary with the respondent's personal beliefs concerning their individual subjective risk of contracting a disease, their current health-related behaviors, and even with the extent to which they may feel that they have room

to improve their health-related behaviors in order to reduce the risks of different diseases.

Slovic (1987) explains that health risks may differ in terms of the degree of dread associated with them or with the perceived controllability of the risk. Tolley et al. (1994) finds that people, given a choice between saving 100 people from cancer, heart disease or motor vehicle accidents, found that most people choose to prevent deaths from cancer. Alberini et al. (2004) find that individuals who already have a disease appear not to have a lower overall *WTP* than others who have not had the disease. Savage (1993) finds that *WTP* differs across four specific causes of death: stomach cancer, plane crash, automobile crash and a home fire. In a random sample survey of approximately 800 people in Chicago, he finds that *WTP* is related to the perceived dread and the respondent's degree of familiarity with each cause of death. Respondents are first asked about their perception of their risk exposure for each cause of death. Then they are asked to allocate 100 dollars to reduce the risk of each of the four causes of death. Savage finds that *WTP* is positively related to the perceived risk of exposure and the extent to which they dread that particular cause of death and *WTP* is negatively related to the amount respondents know about a particular cause. He also finds that the *WTP* to reduce the risk of stomach cancer is more than double the *WTP* for other causes, which he attributes to the lack of familiarity with stomach cancer and the dread associated with it. Savage (1991) also finds similar responses in an earlier study about dreaded deaths due to nuclear power plant accidents.

Sunstein (1997) investigates people's assessments of *WTP* to avoid "bad deaths"—deaths that seem unusually horrible. There are many reasons that the cause of death may be perceived as "bad." For example, the cause of a particular type of death may seem less controllable, may affect certain demographic groups more than others, or may cause unusually long and severe amounts of suffering. In a study of 116 University of Chicago law students, Sunstein found that about 40% of respondents felt that an avoided death from cancer was worth more than an avoided death from a heart attack. Although respondents may harbor more dread concerning some diseases than others, Sunstein concludes that the major policy considerations should be the number of lives saved, the numbers of life-years saved, the quality of life during those saved years, and the cost-effectiveness of the programs. (I.e. he does not advocate than making policy simply based on the amount dread associated with a disease.)

Hammitt and Liu (2004) study systematic differences in *WTP* based on a latency period and the amount of dread associated with the disease. They find *WTP* estimates may vary greatly between *WTP* to avoid a fatal accident and *WTP* to avoid a disease that comes after a latency period or one that involves a large amount of dread. Since most illnesses and deaths due to environmental pollution come after a latency period, the work of Hammitt and Liu (2004) suggests an average *VSL* estimate that comes from a source such as a wage-risk study of sudden, job-related accidents, for example, may not be ideal for valuing the benefits due to environmental policies.

In this chapter, we contribute the literature by looking at systematic differences in *WTP* for measures to reduce an individual's risk of suffering from different specific

diseases. The chapter is structured as follows. Section 2 briefly describes the choice data and empirical specification. Section 3 discusses the empirical results and Section 4 concludes.

2. Choice Data and Empirical Specification

The stated preference dataset from Cameron and DeShazo (2008) provides sufficient information to permit an analysis of differences in *WTP* by type of disease. These data are explained in Chapter II and the descriptive statistics most pertinent to this chapter are shown in Table 8. The third module of the survey—where respondents choose between two different health risk reduction programs and the status quo—is the module of key importance in this chapter.

The empirical model used in this chapter is a generalization of the basic model, previously described in Chapter II of this dissertation. In this chapter, we generalize the basic 13-parameter utility-theoretic estimating specification for the three-alternative choice model to allow for systematic heterogeneity, by disease type, in the basic coefficients. Theory offers little guidance on how heterogeneity in preferences as a function of respondent characteristics and attitudes toward risk should enter into the systematically varying versions of the 13-parameter model (via interaction terms). Thus we allow data to dictate where the systematic differences appear to be present.

We explore a variety of alternate specifications when we add heterogeneity according to disease type. Initially we allow only the marginal utility of the log of discounted sick-years to vary by the type of disease, on the presumption that the nature

of the illness should affect the disutility of sick-years more than the disutility of lost life-years. Next, we introduce a new set of indicator variables associated with each program alternative (to capture the disease label attached to each stylized illness profile for which the respondent's risk is to be reduced). These indicators allow for a discrete "lump" of disutility to be associated with each disease label, independent of the illness profile specified in the choice scenario. Next we allow for heterogeneity in both places, simultaneously. Finally, we introduce systematic variation by disease in the disutility associated with lost life-years. This final model is potentially very large, and not all dimensions of heterogeneity have a statistically significant effect on every preference parameter. Thus we report, as our preferred model, a parsimonious specification with the persistently insignificant coefficients on the new interaction terms set to zero.

In the specifications we consider, note that we also allow for additional heterogeneity in parameters in each of these classes of respondent characteristics where we feel that failure to do so might contribute to omitted variables bias in our key coefficients of interest. In the following subsections, we discuss the rationale for each of these additional types of controls.

2.1 Confidence

"Confidence" is the respondent's answer, near the end of the survey, to the question "Imagine you experience one of the major illnesses described in this survey. How confident are you that your diagnosis and treatment by your current health care provider would be both timely and of high quality?" Possible responses include -1=

"not at all confident," 0= "somewhat confident," and "+1=highly confident." Intuitively, if a respondent does not have a high level of confidence that she would get timely and high quality treatment from her health care provider if she were to experience one of these diseases, she may be more willing to pay for a program to reduce the risk of getting the disease. Note that it might be preferable to represent this variable as a pair of indicator variables, but we utilize it as an approximately continuous variable due to the need to reduce the large number of parameters in the model.

2.2 Vulnerability

We allow the estimated marginal utilities associated with each of the health state terms to vary with "vulnerability." This is the respondent's answer to the question "What is the chance that you will experience, either for the first time or as a recurrence, one of the major illnesses discussed within the next 20 years?" The response options are coded as -2="very unlikely," -1="somewhat unlikely," 0="somewhat likely," and 1= "very likely." Intuitively, if a respondent feels they have a higher chance of experiencing one of these diseases in the next 20 years, they may have a higher *WTP* for health risk reduction programs. Again, we will normalize our estimates of fitted *WTP* on the "0" answer.

An additional normalization control is introduced via an interaction between the vulnerability variable described above and the respondent's age. We expect that older respondents are more likely to believe that they will face one of these diseases in the

next twenty years, so if "vulnerability" were used alone in the model as a control, it might pick up this additional age effect.

2.3 Controllability

We also allow for heterogeneity with respect to how easy the individual perceives it is to control the type of disease in question. "Controllability" is the respondent's answer to the question "How much do you think that improving your lifestyle or habits would reduce your risk of [each class of health risk]." Response options ranged from -2= "very little," to +2= "a lot." Again, the variable is treated as approximately continuous to limit the number of parameters, and we normalize on the zero value in calculating predicted estimates of *WTP*. A priori, the sign of the coefficient on this variable is actually uncertain. If respondents feel that a disease is more controllable, they might make program choices that suggest a higher *WTP* if this subjective controllability implies that they think the program being offered in the choice scenario is more likely to work. On the other hand, if they feel the disease is more controllable, perhaps their choices will imply a lower *WTP* if they feel they are able to control the disease on their own, without the intervention of the additional program offered in the choice scenario. We are only able to assess the net effect of these two countervailing possibilities.

2.4 Subjective Risk

We expect that individuals who feel more at risk for getting a *particular* disease would have a higher *WTP* for a risk reduction program for that disease, so the disutility associated with time in each adverse health state should be negative. "At risk" is the answer to the survey question "Think about your health, your family history, and hazards to which you are exposed. Which illnesses or injuries do you feel most at risk of experiencing over your lifetime?" Response options ranged from -2= "low risk," to +2= "high risk." We expect willingness to pay will be higher for a program that addresses the health threat that the respondent feels most likely to experience.

2.5 Smoker

We also control for whether individuals reveal that there is room for them to reduce their health risks by improving their lifestyle or habits if they quit smoking. We use this acknowledgement to differentiate between smokers and non-smokers. Then we allow for an interaction between current smoker and two of the health threats, respiratory disease and lung cancer. If the respondent could improve their health if they smoked less, which means they currently smoke, they may feel more vulnerable to experiencing respiratory disease and lung cancer. The descriptive statistics for all of these control variables are displayed in Table 9.

3. Empirical Results

Table 10 displays our first basic generalization by type of health risk which introduces an interaction term between sick years and the type of health threat. Intuitively, this means that the particular type of illness or injury may affect the amount of disutility associated with being sick. We use heart disease as the base case and all other marginal utilities are relative to the utility from reducing the risk of heart disease. The first column in Table 10 displays Model 1 which includes the coefficients from the basic 13-parameter model and introduces coefficients on the interactions of the sick-year term with the disease labels. What is most important is not whether these coefficients are significantly different from zero, but whether they are significantly different from each other.[29] Model 2 in Table 10 is a richer variation that estimates the disease label effects while controlling for heterogeneity in confidence, vulnerability, controllability, subjective risk, and whether the respondent is a smoker.

The next specification, in Table 11, has an indicator variable for each disease rather than allowing the coefficients on the sick-year terms to vary. In the real world, the health threat labels would have particular symptoms associated with them, so the attributes would be correlated with the labels. In Stated Preference research, we can randomly assign the labels to various illness profiles, as long as the label and the illness profile appear reasonable and credible to respondents (we did not allow for a recovery from Alzheimer's disease, for example). In this survey, it would be possible to see identical illness profiles associated with different illness labels. The advantage of

[29] Using a likelihood ratio test of the joint hypotheses, we tested pairs of coefficients and found that the parameters are significantly different from each other.

having the label and the illness profile randomized as much as possible is that it would be possible to estimate *WTP* for any major disease based on a particular illness profile.

As Table 11 shows, we find that the labels on the health threats have a certain meaning to respondents and thus have a lump of (dis)utility associated with them. A higher number, such as on diabetes, will increase the value on *WTP* for health risk reductions. Again we are concerned whether the parameters are significantly different from each other and we find that the parameters are significantly different from each other. The remaining columns in the table show additional interactions with sick-years and the disease labels, which allows for additional heterogeneity in the parameters.

Our empirical results suggest that the marginal (dis)utility from many diseases is very similar to the disutility associated with heart disease. We find that breast cancer has a lower marginal utility relative to heart disease and that colon cancer, skin cancer, respiratory disease and Alzheimer's disease have a relatively higher marginal utility relative to heart disease.

Table 12 incorporates heterogeneity in disease labels as well as in disease labels interacted with sick years. In this model, the estimates suggest that the greatest heterogeneity by illness type is in the constant terms. There is a lump sum of utility associated with the health threat label, rather than a difference in the utility of a sick year.

Table 13 is the most complete model and allows for heterogeneity by health threat in the constant term, the sick year term, and the lost-life year term. Again, most of the difference by health threat is seen in the difference in the constant term. There does

appear to be less disutility associated with sick years due to heart attacks, respiratory disease, and diabetes as compared to the disutility from heart disease. There appears to be more disutility from lost-life years due to breast cancer than due to heart disease.

All specifications considered have linear and quadratic marginal utility of net income terms. The linear term is expected to be positive and the quadratic term is expected to be negative to account for the diminishing marginal utility of income. We assume these are constant with the type of health threat considered in the illness profile. The income terms enter into the denominator of the *WTP* for health risk reductions. We assume that the marginal utility of net income is not influenced by the specific health threat considered. We interacted health threat with the income terms, but we did not find consistent evidence that the income terms vary by type of health threat. In the simple 5-parameter model, there is some evidence that the linear marginal utility of net income for respiratory disease may be lower than the other health threats, but this effect disappears in the 13-parameter model and there is significance on diabetes instead. Since there is not a consistent pattern to the significance, we have assumed the marginal utility of net income terms to be the same across all health threats.

The remaining marginal utilities displayed in the tables are for health state terms and enter in the numerator of the *WTP* for health risk reductions. These terms are allowed to vary by type of health threat.

The full model leads to a large number of coefficients, so the final specification is the parsimonious model that retains only the most statistically significant coefficients. Reducing the number of coefficients will reduce the effect of multicollinearity. The

parsimonious model is displayed in Table 14. We find, again, that most of the utility is a lump sum due to the illness label and not mainly due to utility differences in avoided sick years associated with a particular disease. We use this parsimonious model when simulating *WTP* values.

Table 15 shows the simulated *WTP* for 30-year-olds, 45-year-olds, and 60-year-olds. All three age groups have the *WTP* estimates for avoiding two different illness profiles. The first illness profile is sudden death now due to each of the health threats and the *WTP* estimates for avoiding this illness profile are shown in the third column. A *WTP* for an illness profile of sudden death now that is scaled for a risk change of 1.0 is the most similar to the conventional *VSL*. The second illness profile has a ten-year latency period before suffering from a particular health threat, then sick for 5 years, and then death. Including a latency period may be more accurately representing the scenario of avoidance of risk through increased environmental protection. The *WTP* estimates for avoiding this illness profile are shown in the fourth column of all three tables. Additionally, all of the attitudinal variables are zeroed out to get an estimate for the median respondent and a benchmark individual with an income of $42,000 is used.

For cancer risks, *WTP* is highest to avoid breast and prostate cancer. For non-cancer risks, *WTP* is highest to avoid heart disease and heart attacks. *WTP* to avoid a stroke is slightly lower varying from $6.4 for 30-year-olds down to $5.4 for 60-year-olds.

Most estimates are higher for avoiding sudden death now than for avoiding an illness profile with latency. The *WTP* to avoid sudden death now due to lung cancer and respiratory disease is much higher for smokers than for non-smokers, as expected.[30]

The *WTP* to avoid these health threats with a ten year latency period appears to decline with age. The 30-year-olds have the highest *WTP* values and the 60-year-olds have the lowest. The only exception is *WTP* to avoid Alzheimer's disease may increase slightly with age.

The *WTP* to reduce the risk of skin cancer is very low. We suspect that people find skin cancer to be the least bad option of these major diseases. Although some respondents chose the program to reduce the risk of skin cancer, fewer respondents chose these programs than the programs for the other health risks.[31]

WTP to avoid traffic accidents is very low. This may be due to the nature of the survey question since it is difficult to get the scenario for traffic accidents to conform to the other scenarios that pertain to diseases. Respondents were told that they could buy equipment for a new car or retrofit an older car. Many of the illness profiles happened more than seven years into the future and it is possible that respondents figured that they would have already purchased a new car by that time and, therefore, the safety devices considered in the illness profile would not help protect them. Also, people tend

[30] We also interact smokers with all health threats and smokers tend to have a lower *WTP* than non-smokers for health threats other than respiratory disease and lung cancer.

[31] There were 389 observations of choices of a program to reduce the risk of skin cancer. The next lowest number of observations for a choice was 486 for a program to reduce Alzheimer's disease. The largest number of observations was to avoid heart attacks and heart disease at 760.

to perceive that they are better than average drivers and are at relatively little risk of an auto accident.

4. Conclusion

Using a stated preference survey on willingness to pay for health risk reductions, we look at systematic differences by disease. We use a random utility model framework for this analysis and then allow the parameters to shift with disease labels in our empirical analysis. We find systematic differences due the disease labels and, to a lesser extent, in the marginal utilities of health states.

Reductions in the risk of breast and prostate cancers, especially in the near term, seem to be valued even somewhat above the *VSL* currently employed by the U.S. EPA. Values for colon cancer reductions are somewhat lower, but the range of *WTP* values includes the roughly $6-7 million *VSL* used by the EPA (if scaled for the 1.0 risk reduction). Reductions in lung cancer risks are of much lesser concern—except to smokers, where the *WTP* is on the order of $11 in the near term and even higher if some latency is involved. Non-smokers care relatively little about reducing lung cancer risks, and no respondents seem to be concerned about reducing skin cancer risks.

Willingness to pay to reduce risks from heart disease and heart attacks are very similar to each other (and to breast cancer and prostate cancer) suggesting *WTP* of $7 to $8, while strokes may be of somewhat lesser concern, perhaps similar to colon cancer (at least when some latency is involved) and in line with current EPA numbers.

Smokers appear to be as much concerned about reducing their risk of respiratory disease as men are about reducing prostate cancer risks if the risk involves some latency

(but somewhat less so in the case of sudden death in the current period). The *WTP* is $4 - $8. Non-smokers, however, have very little interest in paying to reduce their risks of respiratory disease.

Diabetes is more of a concern among the young than among older people, whereas the reverse is true for Alzheimer's disease. Traffic accidents are of surprisingly little concern among older people, perhaps because they see themselves to be less at risk because they spend less time on the road, or because they believe themselves to be safer drivers. Reports of traffic accidents for respondents themselves, or among their family and friends, seem to decline with age.

Concerning environmental threats to health, one might think first of respiratory disease and lung cancer from "criteria" pollutants and toxic air pollutants. Some portion of the population may also be aware of the role of air pollution in heart disease. Our results suggest that there may be a huge difference between the smoking and non-smoking populations in demands for health risk reductions via reductions in air pollution.

These differences in *WTP* estimates for different types of health threats suggest that models which constrain the estimated marginal utility parameters for different health states to be the same across all illnesses may be too restrictive. This restriction may cause the loss of information that may be very valuable from a policy perspective. The differences in *WTP* estimates suggest that respondents have different *WTP* values for avoiding different diseases. This suggests that the types of health threats targeted by a specific policy might be taken into consideration in benefit-cost analyses.

CHAPTER V

CONCLUSION

In this dissertation I explore heterogeneity in the *WTP* for health risk reductions. I first discuss a methodological improvement to stated preference research involving "scenario adjustment." Scenario adjustment occurs when respondents modify some aspect of a given scenario based upon their personal beliefs. For example, due to a family history of heart disease, a particular respondent might think a scenario that reduces heart disease for the average person in fifteen years is likely to affect them much earlier—say in only five years. This means the respondent answers a slightly different question than the researcher intended and give a *WTP* that does not exactly reflect the stated question. Through the use of debriefing questions, I find evidence of scenario adjustment in this choice experiment on health risk reductions. I also offer a possible counterfactual correction for scenario adjustment.

Next I examine empirical patterns in *WTP* by household structure. I find, through *WTP* simulations, that the presence of each additional preschool child increases the *WTP* for both males and females. I also find that, for middle-aged adults, the *WTP* declines for each additional teenager in the household. While controlling for overall household income, I find that women in households with two income-earners invest more in their own health-risk reductions than do women in households with only one

income-earner. Thus, household structure appears to affect *WTP* for health risk reductions.

Lastly, in Chapter Four, I discuss empirical evidence of systematic differences in *WTP* by type of health threat. Among cancers, I find that respondents have a higher *WTP* for breast and prostate cancers and a slightly lower *WTP* for colon cancer. I find that smokers have a dramatically higher *WTP* to avoid lung cancer and respiratory disease than non-smokers. Younger people have higher demands for risk reductions in diabetes than older people while older people have demands for risk reductions in Alzheimer's disease than younger people. Again, age and type of disease appear to influence *WTP* estimates.

Finally, I discuss the potential impact this research may have on benefit-cost analysis. I use a simplified example to show how the priority ranking of policies can differ when using *WTP* for health risk reductions that varies by individual and health threat characteristics discussed in this dissertation rather than the standard *VSL* estimate. In my example, I choose to use a simplified version of regulations rather than discuss all of the complexity and the many assumptions made in the actual benefit-cost analyses. I focus only on the benefits-side since dissertation concerns benefits estimation, but costs are also an extremely important part of the analysis. For simplicity, however, I will assume the costs of the policy are $10,000 for each policy and that costs are the same for all four of the policies.

I discuss five different policies that are all simplifications of actual regulations that have undergone benefit-cost analyses. Policy A is a regulation that will improve air

quality through a reduction of particulate matter and thereby reduce the risk of heart disease. Policy B regulates the use of disinfectants that can enter ground water and the drinking water system which can increase the risk of colon cancer. Policy C is a regulation that increases the stability of motor vehicles and decreases the likelihood of a fatal traffic accident. Policy D reduces exposure to hexavalent chromium which has been shown to increase the risk of lung cancer. Again, for simplicity, suppose each of the policies leads to a ten percent risk reduction in that specified health threat for a population of 100,000 people.

If the standard *VSL* estimate of $6.1 million (in 2003 dollars) is used, then the net benefits to society are $51,000. This number is calculated by first scaling the $6.1 million for the *VSL* down to a one in one million risk reduction to get $6.10. Then multiply 6.10 by the risk reduction of 10 percent per individual multiplied by the population of 100,000. Then the costs of the policy, $10,000, are subtracted to get the final net benefit estimate of $51,000. This is the estimate for all of the four policies due to my simplifying assumptions that allow me to focus on the benefits estimation. Since all the policies have the same estimate of net benefits, there is no priority ranking for the four policies in this simplified example.

If we use the *WTP* for a microrisk reduction where we consider the type of disease, however, we find different results. The estimated net benefits to society from Policy A, which reduces the risk of heart disease, are $73,700 (*WTP* = $8.37 multiplied by the ten percent risk multiplied by 100,000 in the population minus the costs of the policy of $10,000). Using the same methodology, but different *WTP* estimates as

discussed in Chapter Four, the estimated societal benefits from Policy B, which reduces the risk of colon cancer are $34,800. The estimated societal net benefits from Policy C, which reduces the risk of traffic accidents, are $-2,200. For Policy D, which reduces the risk of lung cancer, we need to make another assumption about the number of smokers in the population. On average, smokers appear to have a dramatically higher *WTP* to reduce the risk of lung cancer than non-smokers. The smoking rate has recently declined to less than 20% of the adult population (Benincasa (2009)). Therefore, in order to calculate an estimate the societal benefits, I assume that 20% of the population smokes and 80% does not. The estimated societal net benefits from Policy D are $19,860.

Given the different estimates of the net benefits to society, these policies can now be prioritized according to their net benefits to society. A comparison of the net benefits of these policies shows that, in this very simple example, society will rank Policy A with the highest priority followed by B, D and finally C. Thus, using *WTP* estimates that differ by type of disease (or by characteristics of individuals such as scenario adjustment and family structure) may provide policy-makers with a different priority ranking of regulations.

Given more assumptions and knowledge about the affected populations, this example could be expanded to reflect the findings in Chapters II and III as well. This quickly becomes extremely complicated, however, and does not offer the clear and concise demonstration of the importance of this research. Given this and other research,

however, the more specific information that is available will allow more accurate estimates of the benefits to society from particular policies.

These systematic differences in *WTP* are important for use in benefit-cost analyses for comparison of environmental regulations. Accurate estimates of the benefits of a potential policy will indicate whether society thinks the benefits are truly greater than the costs. This way, policy-makers can have a better idea of which environmental, health and safety regulations are highest priority for society.

Just as inverse demands for different individuals vary for goods and services in the market, we should also expect the inverse demands for risk reductions to differ. Using a standard *VSL* assumes that all individuals have the same inverse demands for these risk reductions and then societal benefits from a policy are estimated by multiplying the *VSL* by the expected risk reductions. In this dissertation, I discuss several dimensions along which these inverse demands vary by the individual and the health threat in question. *WTP* estimates that take into account the characteristics of the affected population as well as the type of health threat targeted by the policy will lead to more accurate estimates of the societal benefits from a particular policy.

APPENDIX A

FIGURES AND TABLES

Figure 1: One Example of a Randomized Choice Scenario

Choose the program that reduces the illness that you most want to avoid. But think carefully about whether the costs are too high for you. If both programs are too expensive, then choose Neither Program.

If you choose "neither program", remember that you could die early from a number of causes, including the ones described below.

	Program A for Heart Disease	**Program B for Colon Cancer**
Symptoms/ Treatment	Get sick when 71 years old 2 weeks of hospitalization No surgery Moderate pain for remaining life	Get sick when 68 years old 1 month of hospitalization Major surgery Severe pain for 18 months Moderate Pain for 2 years
Recovery/ Life expectancy	Chronic heart condition Die at 79	Recover at 71 Die of something else at 73
Risk Reduction	5% From 40 in 1,000 to 38 in 1,000	50% From 4 in 1,000 to 2 in 1,000
Costs to you	$15 per month [= $180 per year]	$4 per month [= $48 per year]
Your choice	☐ **Reduce my chance of heart disease**	☐ **Reduce my chance of colon cancer**

☐ **Neither Program**

Figure 2: Example of a Debriefing Question Used to Correct for Scenario Adjustment

You may have chosen Program A, Program B, or neither. Regardless of your choice, we would like to know when, over your lifetime, you think you would first need and benefit from the two programs (if at all).

Your answers below may depend upon the illness or injury in question, as well as your current age, health and family history.

Around when do you think you would begin to value highly the risk reduction benefits of each program?

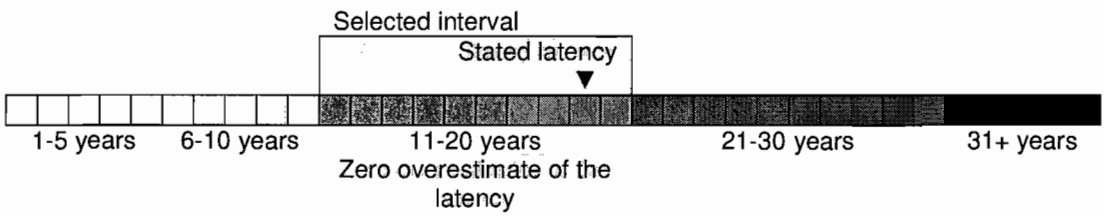
Select one answer from each column in the grid

	Program A to reduce my chance of diabetes	Program B to reduce my chance of heart attack
For me, benefits would start		
Immediately	☐	☐
1-5 years from now	☐	☐
6-10 years from now	☐	☐
11-20 years from now	☐	☐
21-30 years from now	☐	☐
31 or more years from now	☐	☐
Never (Program would not benefit me)	☐	☐

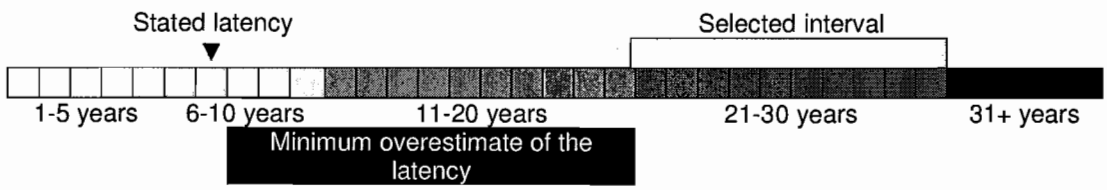
Figure 3: Examples of Benefits Differ Calculations

Different stated latencies, but respondent chooses "11-20 years" in the debriefing question

A. No "overestimate of latency" $(BenDiff_i^j = 0)$



B. "Overestimate of latency" is positive $(BenDiff_i^j > 0)$



C. "Overestimate of latency" is negative $(BenDiff_i^j < 0)$

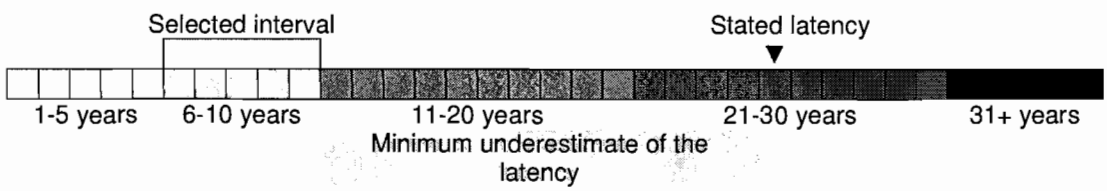


Table 1: Descriptive Statistics for Scenario Adjustment
(n = 15040 illness profiles and associated risk reduction programs)

	Mean	Std.dev.	Min.	Max.
Program attributes				
Monthly program cost ($)	29.9	28.7	2	140
$\Delta\Pi_i^j$ = Risk change achieved by program	-.00341	.00167	-.006	-.001
Stated Illness profiles				
Latency (in years, stated in scenario)	19.6	12.0	1	60
- $1(never_i^j)$ ("Program will never benefit me")	.0769			
- $Bendiff_i^j$ (minimum overest. of latency)	-7.47	12.0	-59	29
Sick years (undiscounted)	6.50	7.17	0	52
$pdvi_i^j$ = Present value of sick-years	2.21	2.51	0	16.3
Recovered years (undiscounted)	26.1	13.0	0	64
$pdvr_i^j$ = Present value of recovered years	.477	1.37	0	15.9
Lost life-years (undiscounted)	10.8	10.3	0	55
$pdvl_i^j$ = Present value of lost life-years	2.57	2.93	0	17.8
Attributes of individuals				
Annual income (in $10,000)	5.09	3.41	0.5	15.0
Age at time of choice	50.4	15.1	25	93
Systematic selection from RDD contacts				
$\hat{P}(sel_i) - \overline{\hat{P}}$ = Difference between fitted response/non-response and population average	.677	3.36	-.316	17.9

Table 2: Scenario Adjustment Model (Parsimonious; alternatives = 22560)

	Model 1	Model 2		
(Parameter) Variable	Uncorrected Coefficients	Corrected Coefficients	$\times 1(never_i^j)$	$\times Bendiff_i^j$
$(\beta_0 \times 10^5)$[first income term]	5.183 (8.30)***	8.071 (10.69)***	-	0.225 (5.14)***
$(\beta_1 \times 10^9)$[second income term]	-.1992 (4.22)***	-.2109 (4.15)***	.7656 (3.05)***	-
$(\alpha_{10})\Delta\Pi_i^{AS} \log(pdvi_i^A + 1)$	-47.89 (5.35)***	-57.32 (5.04)***	212.7 (3.91)***	7.083 (7.24)***
$(\alpha_{13})\left[P(sel_i) - \overline{P}\right]\Delta\Pi_i^{AS}\left[\log(pdvi_i^A + 1)\right]$	3.372 (2.34)**	3.853 (2.45)**	-	-
$(\alpha_{20})\Delta\Pi_i^{AS} \log(pdvr_i^A + 1)$	-16.49 (1.76)*	-57.93 (5.77)***	-	-
$(\alpha_{30})\Delta\Pi_i^{AS} \log(pdvl_i^A + 1)$	-580.1 (3.25)***	-858.3 (4.28)***	-	4.092 (3.26)***
$(\alpha_{31})age_{i0} \cdot \Delta\Pi_i^{AS} \log(pdvl_i^A + 1)$	20.46 (2.82)***	43.15 (5.41)***	-	-
$(\alpha_{32})age_{i0}^2 \cdot \Delta\Pi_i^{AS} \log(pdvl_i^A + 1)$	-0.1874 (2.70)***	-0.3719 (4.97)***	-	0.0064 (7.39)***
$(\alpha_{40})\Delta\Pi_i^{AS}\left[\log(pdvl_i^A + 1)\right]^2$	199.3 (2.41)**	281.8 (3.11)***	395.6 (4.51)***	-
$(\alpha_{41})age_{i0} \cdot \Delta\Pi_i^{AS}\left[\log(pdvl_i^A + 1)\right]^2$	-7.786 (2.32)**	-15.71 (4.31)***	-5.197 (3.69)***	-
$(\alpha_{42})age_{i0}^2 \cdot \Delta\Pi_i^{AS}\left[\log(pdvl_i^A + 1)\right]^2$	0.0739 (2.27)**	0.1365 (3.90)***	-	-0.0013 (3.12)***
$(\alpha_{50})\Delta\Pi_i^{AS}\left[\log(pdvi_i^A + 1)\right] \cdot \left[\log(pdvl_i^A + 1)\right]$	102.4 (1.40)	129.6 (1.62)	-348.0 (3.77)***	-4.301 (3.90)***
$(\alpha_{51})age_{i0} \cdot \Delta\Pi_i^{AS}\left[\log(pdvi_i^A + 1)\right] \cdot \left[\log(pdvl_i^A + 1)\right]$	-4.484 (1.57)	-6.680 (2.16)**	-	-
$(\alpha_{52})age_{i0}^2 \cdot \Delta\Pi_i^{AS}\left[\log(pdvi_i^A + 1)\right] \cdot \left[\log(pdvl_i^A + 1)\right]$	0.0561 (2.10)**	0.0624 (2.17)**	0.0752 (3.28)***	-
Log L	-11694.646	-10954.934		

[a] Corrected utility parameters are purged of scenario adjustment as captured by systematic differences in these parameters for alternatives where stated latency was not accepted by the respondent.

Table 3: Simulated *WTP* for a Microrisk Reduction with Scenario Adjustment Without and with correction for illness scenario adjustment in 2003 $US with Income = $42,000 (mean [5th, 95th percentiles][a])

		No latency[b]		Latency of 20 yrs	
Age	Illness profile	Uncorrected	Corrected	Uncorrected	Corrected
30	1 year sick, recover	$ 2.49 [1.3,3.94]	$ 3.20 [2.43,4.07]	$ 1.54 [0.77,2.49]	$ 1.94 [1.43,2.50]
	5 yrs sick, recover	3.75 [2.59,5.16]	3.94 [3.13,4.86]	2.32 [1.60,3.20]	2.35 [1.87,2.90]
	1 year sick, then die	4.14 [1.67,6.80]	6.52 [4.89,8.40]	4.42 [3.26,5.97]	1.67 [0.97,2.42]
	5 yrs sick, then die	4.19 [1.39,7.21]	7.02 [5.05,9.12]	4.57 [3.51,6.00]	1.99 [1.42,2.65]
	Sudden death	**4.26 [1.30,7.38]**	**5.74 [3.96,7.64]**	**4.35 [2.97,6.04]**	**1.42 [0.55,2.28]**
45	1 year sick, recover	2.33 [1.20,3.75]	2.68 [1.93,3.48]	1.33 [0.64,2.15]	1.27 [0.82,1.72]
	5 yrs sick, recover	3.56 [2.45,4.92]	3.47 [2.73,4.33]	2.08 [1.44,2.84]	1.68 [1.29,2.12]
	1 year sick, then die	4.59 [2.99,6.55]	7.61 [6.39,9.09]	2.53 [1.95,3.21]	-0.93[c] [-1.59,-0.37]
	5 yrs sick, then die	4.44 [2.73,6.66]	8.48 [7.04,10.14]	2.66 [2.16,3.32]	-0.39[c] [-0.89,0.04]
	Sudden death	**4.57 [2.88,6.58]**	**6.10 [4.88,7.39]**	**2.43 [1.71,3.19]**	**-1.37[c] [-2.15,-0.70]**
60	1 year sick, recover	2.21 [1.07,3.46]	2.04 [1.31,2.75]	1.11 [0.55,1.67]	0.30 [-0.08,0.63]
	5 yrs sick, recover	3.26 [2.19,4.5]	2.86 [2.19,3.62]	1.66 [1.22,2.11]	0.59 [0.27,0.87]
	1 year sick, then die	2.40 [0.98,4.03]	6.41 [5.26,7.82]	1.27 [0.57,1.91]	-2.76[c] [-3.79,-1.97]
	5 yrs sick, then die	0.92[b] [-0.6,2.58]	6.93 [5.65,8.48]	1.23 [0.67,1.78]	-1.85[c] [-2.63,-1.27]
	Sudden death	**3.46 [1.88,5.13]**	**4.97 [3.83,6.18]**	**1.39 [0.52,2.09]**	**-3.20[c] [-4.32,-2.33]**

[a] Based on random draws from the joint distribution of the estimated parameters.

Table 4: Descriptive Statistics for Household Structure
(7520 choice sets; 22560 alternatives; 15040 illness profiles; 1801 individuals)

Description	Mean	Std. Dev.	Min	Max
Illness Profiles				
Time until onset (years)	19.58	12.02	1	60
Present discounted sick-years	2.21	2.51	0	16.3
Present discounted recovered-years	0.474	1.36	0	15.9
Present discounted lost life-years	2.57	2.93	0	17.8
=1 if current child <18 at illness onset	.02859			
Risk-Reduction Programs				
Monthly cost	$29.87	28.71	2	140
Risk change	-.00341	.00167	-0.006	-0.001
Respondent Characteristics				
Income 2002 $ US	$50,771	33,966	5,000	150,000
Age in years at time of survey	50.30	15.21	25	93
=1 if female, = 0 if male	0.513			
=1 if married, = 0 if unmarried	0.688			
# children aged 0-1 yrs in hhld	.0161	.1352	0	2
# children aged 2-5 yrs in hhld	.1254	.3880	0	3
# children aged 6-12 yrs in hhld	.2143	.5737	0	5
# children aged 13-17 yrs in hhld	.1575	.4563	0	3
=1 if two incomes in household	.6356			
Illness Profile/Respondent Interactions				
=1 if the individual states that "the program will never benefit me"	0.385	.4865		
The individual's overestimate of the latency	-5.95	11.08	-59	29

Table 5: Parsimonious Household Structure Model
(n = 1801 individuals, 7520 choices, 22560 alternatives)

	Full Model
Linear net income term	
$(\beta_{00}\times 10^{5})$[linear net income term]	4.663
	(6.21)***
…* 1(female)	6.241
	(5.28)***
…* 1(female) * # kids 6-12 yrs	-2.266
	(2.02)**
…* # kids 13-17 yrs	2.143
	(2.31)**
… * 1(female) * 1(dual-income)	-0.165
	(1.59)
Quadratic net income term	
$(\beta_{10}\times 10^{9})$[quadratic net income term]	0
…* 1(female)	-.2835
	(3.89)***
…* # kids 0-1 yrs	-.762
	(2.41)**
Sick-years terms	
$(\alpha_{10})\Delta\Pi_i^{AS}\log\left(pdvi_i^{A}+1\right)$	-70.71
	(5.22)***
…* 1(female)	28.4
	(2.17)**
…* # kids 2-5 yrs	103.8
	(3.80)***
…* 1(female) * # kids 2-5 yrs	-68.52
	(2.11)**
…* 1(child at onset)	-116
	(3.07)***
Recovered-years terms	
$(\alpha_{20})\Delta\Pi_i^{AS}\log\left(pdvr_i^{A}+1\right)$	-58.54
	(5.78)***

Table 5, Continued

Lost life-years terms	
$(\alpha_{30})\Delta\Pi_i^{AS}\log\left(pdvl_i^A+1\right)$	-600.2
	(3.28)***
...* 1(female)	22.75
	(2.02)**
...* 1(married)	-34.54
	(3.09)***
...* # kids 2-5 yrs	-33.66
	(1.98)**
...* # kids 13-17 yrs	26.22
	(2.24)**
$(\alpha_{31})age_{i0}\cdot\Delta\Pi_i^{AS}\log\left(pdvl_i^A+1\right)$	33.66
	(4.67)***
$(\alpha_{32})age_{i0}^2\cdot\Delta\Pi_i^{AS}\log\left(pdvl_i^A+1\right)$	-0.285
	(4.23)***
Lost life-years squared terms	
$(\alpha_{40})\Delta\Pi_i^{AS}\left[\log\left(pdvl_i^A+1\right)\right]^2$	212.4
	(2.35)***
$(\alpha_{41})age_{i0}\cdot\Delta\Pi_i^{AS}\left[\log\left(pdvl_i^A+1\right)\right]^2$	-13.12
	(3.63)***
$(\alpha_{42})age_{i0}^2\cdot\Delta\Pi_i^{AS}\left[\log\left(pdvl_i^A+1\right)\right]^2$	0.113
	(3.28)***
Sick-years, Lost life-years interaction terms	
$(\alpha_{50})\Delta\Pi_i^{AS}\left[\log\left(pdvi_i^A+1\right)\right]\cdot\left[\log\left(pdvl_i^A+1\right)\right]$	-44.59
	(4.18)***
...* 1(child at onset)	555.5
	(2.39)**
$(\alpha_{51})age_{i0}\cdot\Delta\Pi_i^{AS}\left[\log\left(pdvi_i^A+1\right)\right]\cdot\left[\log\left(pdvl_i^A+1\right)\right]$	0
...* 1(child at onset)	-22.4
	(2.17)**
$(\alpha_{52})age_{i0}^2\cdot\Delta\Pi_i^{AS}\left[\log\left(pdvi_i^A+1\right)\right]\cdot\left[\log\left(pdvl_i^A+1\right)\right]$	0
...* 1(child at onset)	.2457
	(2.20)**

Table 5, Continued

Nuisance parameters	
- shift if respondent believes "will never benefit"	
$(\beta_{10}\times 10^{9})[\text{second income term}]\ *1(never_i^j)$	0.743 (2.97)***
$(\alpha_{10})\Delta\Pi_i^{AS}\log(pdvi_i^A+1)\ *1(never_i^j)$	206.8 (3.82)***
$(\alpha_{40})\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2\ *1(never_i^j)$	413.9 (4.69)***
$(\alpha_{41})age_{i0}\cdot\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2\ *1(never_i^j)$	-5.567 (3.93)***
$(\alpha_{50})\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]\cdot\left[\log(pdvl_i^A+1)\right]\ *1(never_i^j)$	-355.4 (3.84)***
$(\alpha_{52})age_{i0}^2\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]\cdot\left[\log(pdvl_i^A+1)\right]\ *1(never_i^j)$	0.08 (3.52)***
- shift with minimum overestimate of latency	
$(\beta_{00}\times 10^{5})[\text{first income term}]\ *bendiff_i^j$	0.233 (5.28)***
$(\alpha_{10})\Delta\Pi_i^{AS}\log(pdvi_i^A+1)\ *bendiff_i^j$	7.507 (7.55)***
$(\alpha_{30})\Delta\Pi_i^{AS}\log(pdvl_i^A+1)\ *bendiff_i^j$	4.266 (3.62)***
$(\alpha_{32})age_{i0}^2\cdot\Delta\Pi_i^{AS}\log(pdvl_i^A+1)\ *bendiff_i^j$	0.0063 (7.11)***
$(\alpha_{42})age_{i0}^2\cdot\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2\ *bendiff_i^j$	-0.0012 (2.98)***
$(\alpha_{50})\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]\cdot\left[\log(pdvl_i^A+1)\right]\ *bendiff_i^j$	-4.484 (4.03)***
- shift with difference from mean participation probability	
$(\alpha_{13})\left[P(sel_i)-\overline{P}\right]\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]$	3.784 (2.37)**
Observations	22560
Log L	-10901.417

Absolute value of z statistics in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Discernible Heterogeneity with Respect to Household Structure[a]
(n = 1801 individuals, 7520 choices, 22560 alternatives)

	Shifters for gender and household structure					
	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline: male, no kids	$*1(female_i)$	$*nkids01_i$	$*nkids25_i$	$*1(female_i)$ $*nkids25_i$	$*1(female_i)$ $*nkids612_i$
Marginal utility of net income:						
$(\beta_{00}\times 10^5)$[linear income term]	4.66 (6.21)[b]	6.24 (5.28)	0	0	0	-2.27 (2.02)
$(\beta_{10}\times 10^9)$[quadratic income term]	0	-.284 (3.89)	-.762 (2.41)	0	0	0
Marginal utility of health states:						
$(\alpha_{10})\Delta\Pi_i^{jS}\log(pdvi_i^j+1)$	-70.7 (5.22)	28.4 (2.17)	0	104. (3.80)	-68.5 (2.11)	0
$(\alpha_{30})\Delta\Pi_i^{jS}\log(pdvl_i^j+1)$	-600. (3.28)	22.8 (2.02)	0	-33.7 (1.98)	0	0
$(\alpha_{50})\Delta\Pi_i^{jS}\left[\log(pdvi_i^j+1)\right]\cdot\left[\log(pdvl_i^j+1)\right]$	-44.6 (4.18)	0	0	0	0	0
$(\alpha_{51})age_{i0}\cdot\Delta\Pi_i^{jS}\left[\log(pdvi_i^j+1)\right]\cdot\left[\log(pdvl_i^j+1)\right]$	0	0	0	0	0	0
$(\alpha_{52})age_{i0}^2\cdot\Delta\Pi_i^{jS}\left[\log(pdvi_i^j+1)\right]\cdot\left[\log(pdvl_i^j+1)\right]$	0	0	0	0	0	0

Table 6, Continued

	(1)	Cont…	(7)	(8)	(9)	(10)
	Baseline: male, no kids	…	$*nkids1317_i$	$*1(child\ at\ onset)$	$*1(female_i)$ $*1(dualinc_i)$	*1(married)
Marginal utility of net income:						
$(\beta_{00}\times 10^5)$[linear income term]	4.66	…	2.14	0	-1.65	0
	(6.21)[b]	…	(2.31)		(1.59)[c]	
$(\beta_{10}\times 10^9)$[quadratic income term]	0	…	0	0	0	0
Marginal utility of health states:						
$(\alpha_{10})\Delta\Pi_i^{jS}\log(pdvi_i^j+1)$	-70.7	…	0	-116	0	0
	(5.22)	…		(3.07)		
$(\alpha_{30})\Delta\Pi_i^{jS}\log(pdvl_i^j+1)$	-600.	…	26.2	0	0	-34.5
	(3.28)	…	(2.24)			(3.09)
$(\alpha_{50})\Delta\Pi_i^{jS}\left[\log(pdvi_i^j+1)\right]\cdot\left[\log(pdvl_i^j+1)\right]$	-44.6	…	0	556.	0	0
	(4.18)	…		(2.39)		
$(\alpha_{51})age_{i0}\cdot\Delta\Pi_i^{jS}\left[\log(pdvi_i^j+1)\right]\cdot\left[\log(pdvl_i^j+1)\right]$	0	…	0	-22.4	0	0
				(2.17)		
$(\alpha_{52})age_{i0}^2\cdot\Delta\Pi_i^{jS}\left[\log(pdvi_i^j+1)\right]\cdot\left[\log(pdvl_i^j+1)\right]$	0	…	0	.246	0	0
				(2.20)		
Log L	-10901.417					

Table 7: Simulated *WTP* for a Microrisk Reduction—Household Structure For specified individuals of age 30 with and without children and household income of $42,000 (2003 $US) (median, 5th and 95th percentiles)

Age = 30		Illness Profile #1 Sudden death this year		Illness Profile #2 In 9 years, sick 1 year then death	
Married	Children now	Male	Female	Male	Female
Married	0 children	$8.81 (6.01, 12.37)	$3.59 (2.46, 4.89)	$6.88 (5.01, 9.37)	$2.69 (1.98, 3.62)
	1 child 2-5 yrs	11.01 (7.52, 15.42)	4.50 (3.22, 6.13)	6.08 (3.96, 8.63)	2.64 (1.82, 3.69)
	2 children 2-5 yrs	13.16 (8.46, 19.14)	5.42 (3.55, 7.60)	6.88 (3.77, 10.52)	3.28 (2.01, 4.71)
	2 children 2-5 yrs, dual-income	-	6.26 (4.09, 8.85)	-	3.80 (2.32, 5.47)
Unmarried	0 children	6.56 (3.88, 9.62)	2.62 (1.55, 3.83)	5.05 (3.25, 7.00)	1.89 (1.21, 2.69)
	1 child 2-5 yrs	8.74 (5.53, 12.65)	3.55 (2.22, 5.05)	4.22 (2.04, 6.52)	1.87 (0.98, 2.74)
	2 children 2-5 yrs	10.91 (6.37, 16.37)	4.45 (2.57, 6.58)	4.98 (1.66, 8.30)	2.51 (1.10, 3.83)
	2 children 2-5 yrs, dual-income	-	5.14 (2.85, 7.67)	-	2.85 (1.23, 4.47)

Respondents were given no opportunity to express negative willingness to pay. Negative values for microrisk reductions (produced for some draws from the asymptotically joint normal distribution of the maximum likelihood parameters) can be interpreted as zero.

Table 8: Simulated *WTP* for a Microrisk Reduction—Household Structure
For specified individuals of age 45 with and without children and household income of $42,000 (2003 $US)
(median, 5th and 95th percentiles)

Age = 45		Illness Profile #1 Sudden death this year		Illness Profile #2 In 9 years, sick 1 year then death	
Married	Children now	Male	Female	Male	Female
Married	0 children	$9.56 (7.29, 13.03)	$3.96 (3.13, 4.99)	$5.22 (4.02, 7.04)	$2.07 (1.59, 2.61)
	1 child 13-17 yrs	5.61 (4.22, 7.60)	2.83 (2.15, 3.64)	2.79 (1.97, 3.76)	1.30 (0.87, 1.78)
	2 children 13-17 yrs	3.57 (2.26, 5.30)	2.01 (1.23, 2.89)	1.50 (0.48, 2.52)	0.77 (0.11, 1.35)
	2 children 13-17 yrs, dual-income	-	2.18 (1.28, 3.11)	-	0.81 (0.08, 1.47)
Unmarried	0 children	7.33 (5.31, 10.31)	3.04 (2.23, 3.94)	3.44 (2.33, 4.86)	1.29 (0.83, 1.80)
	1 child 13-17 yrs	4.09 (2.80, 5.84)	2.06 (1.37, 2.79)	1.55 (0.68, 2.46)	0.65 (0.17, 1.15)
	2 children 13-17 yrs	2.42 (1.06, 3.95)	1.34 (0.48, 2.17)	0.55 (-0.68, 1.54)	0.22 (-0.58, 0.82)
	2 children 13-17 yrs, dual-income	-	1.42 (0.46, 2.33)	-	0.20 (-0.65, 0.87)

Respondents were given no opportunity to express negative willingness to pay. Negative values for microrisk reductions (produced for some draws from the asymptotically joint normal distribution of the maximum likelihood parameters) can be interpreted as zero.

Table 9: Descriptive Statistics for Type of Disease

By Illness Profile: [a]	**Included in Illness Profile?**	**Controllability** -2 = very little +2 = a lot	**At Risk** -2 = low risk +2 high risk
Breast Cancer	0.0465	-0.2966	-0.0650
Prostate Cancer	0.0454	"	"
Lung Cancer	0.0912	"	"
Colon Cancer	0.0896	"	"
Skin Cancer	0.0906	"	"
Heart Disease	0.0938	0.2443	0.0057
Heart Attack	0.0933	"	"
Respiratory Disease	0.0891	-0.3881	-0.5481
Stroke	0.0943	-0.0520	-0.3576
Traffic Accident	0.0856	-1.1471	-0.3874
Diabetes	0.0902	-0.2488	-0.4349
Alzheimer's Disease	0.0906	-1.077	-0.9987

By Respondent:	**Mean (Std Dev)**
Age [b] (at time of survey)	50.296 (15.04)
Confidence [b] (in health care)	-.115 (.808)
Vulnerability [b] (in next 20 years)	0.159 (.667)
Could smoke less [c]	.963 (1.619)

[a] Sample Size is 13,696 illness profiles
[b] Sample Size is 1631respondents
[c] Sample Size is 1607 respondents

Table 10: Sick Year Shifters Only (Alternatives = 20,544)

Sick Year Terms:	**Model 1**	**Model 2**	*Confidence	*Vulnerability	*Age	*Vulnerability *Age	*At Risk	*Control
$(\alpha_{10})\Delta\Pi_i^{jS}\log(pdvi_i^j+1)$	-95.35	-191.7	-	-	-	-	-	-
	(7.45)***	(3.84)***						
* any cancer	-	-	-	-	-	-	-0.6119	-7.972
							-0.12	(1.29)
* breast cancer	-13.77	-137	-3.815	-89.64	4.236	1.085	-	-
	-0.6	-1.47	-0.12	-0.93	(2.62)***	-0.61		
* prostate cancer	1.983	123.3	21.88	-145.1	-0.504	2.492	-	-
	-0.09	-1.37	-0.68	-1.64	-0.31	-1.45		
* lung cancer	40.38	99.57	21.97	-34.34	0.9399	-0.3927	-	-
	(2.56)**	-1.61	-1.16	-0.59	-0.9	-0.34		
* colon cancer	21.72	150.6	35.38	-65.12	-0.5888	0.647	-	-
	-1.42	(2.49)**	(2.01)**	-1.15	-0.61	-0.6		
* skin cancer	110.1	191.6	-13.1	20.3	0.6026	-0.9654	-	-
	(6.56)***	(2.93)***	-0.65	-0.32	-0.55	-0.77		
* heart disease	-	-	-21.51	-151.4	2.077	2.155	4.237	-.488
			-1.26	(2.88)***	(2.24)**	(2.12)**	-0.7	(0.07)
* heart attack	14.22	129.8	10.82	-132.9	-0.3226	0.828	-	-
	-0.66	-1.49	-0.36	-1.42	-0.2	-0.46		
* respiratory disease	97.75	241.2	35.56	-78.59	-0.6714	0.09412	11.85	-.7585
	(5.49)***	(3.30)***	-1.59	-0.99	-0.55	-0.06	(2.44)**	(0.14)
* stroke	45.68	46.7	17.16	-188.4	1.747	1.756	5.56	-11.3
	(2.12)**	-0.5	-0.57	(1.76)*	-1.06	-0.88	-0.87	(1.62)
* traffic accidents	107.9	99.05	-13.63	51.94	2.679	-2.395	5.291	-6.988
	(4.80)***	-1.13	-0.42	-0.57	-1.6	-1.22	-0.98	(1.27)
* diabetes	67.22	61.45	-49.46	-101.1	2.345	0.5836	-8.056	-3.786

Table 10, continued

Sick Year Terms:	**Model 1**	**Model 2**	*Confidence	*Vulnerability	*Age	*Vulnerability *Age	*At Risk	*Control
	(3.77)***	-0.88	(2.14)**	-1.4	(1.91)*	-0.43	(1.70)*	(0.70)
* Alzheimer's disease	76.14	312.1	17.39	31.44	-2.241	-0.927	-1.943	15.01
	(4.20)***	(3.99)***	-0.76	-0.39	(1.76)*	-0.65	-0.34	(2.40)**
Observations	20544	20544						
LogL	-10610.6	-10537.1						

Additional parameters are included in the model and retain the same signs and significance levels as they display in Table 13. These parameters are the linear and quadratic income, recovered year, selection correction, interactions between age and interaction between sick years and lost life years, and higher order lost-life year and interaction terms.

Absolute value of z statistics in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

Table 11: Simple Disease Label Effects Only (Alternatives = 20,544)

		Shifters (0=neutral, except for age)				
Disease Labels:	Basic Terms	*Confidence	*Vulnerability	*Age	*Vulnerability *Age	*Smoke
breast cancer	1.463	-.08836	.5559	-.01756	-.003789	-
	(4.72)***	(0.71)	(1.53)	(2.93)***	(0.53)	
prostate cancer	.6704	-.06969	.9738	-.002084	-.01167	-
	(2.14)**	(0.54)	(2.65)***	(0.34)	(1.58)	
lung cancer	.1108	-.1194	.3749	-.004723	.0004623	.2952
	(0.43)	(1.21)	(1.31)	(0.98)	(0.08)	(7.91)***
colon cancer	.4528	-.007631	.4561	-.001773	-.002096	-
	(1.94)*	(0.08)	(1.64)	(0.40)	(0.38)	
skin cancer	.04743	-.008459	.3777	-.006317	-.00153	-
	(0.18)	(0.08)	(1.23)	(1.26)	(0.25)	
heart disease	-	-.0451	1.059	.01016	-.01329	-
		(0.49)	(3.88)***	(7.36)***	(2.50)**	
heart attack	.9605	.1938	.8664	-.006974	-.005922	-
	(4.00)***	(2.07)**	(3.09)***	(1.49)	(1.07)	
respiratory disease	-.04607	-.0806	.6294	-.004015	-.002302	.1804
	(0.17)	(0.78)	(2.02)**	(0.81)	(0.37)	(4.60)***
stroke	.731	.03887	.9462	-.00574	-.007716	-
	(3.09)***	(0.42)	(3.43)***	(1.25)	(1.42)	
traffic accident	.3349	.08645	.1857	-.01069	-.0004559	-
	(1.23)	(0.81)	(0.61)	(2.04)**	(0.07)	

Table 11, Continued

Disease Labels:	Basic Terms	*Confidence	*Vulnerability	*Age	*Vulnerability *Age	*Smoke
diabetes	1.159	.2556	1.039	-.0219	-.009477	-
	(4.65)***	(2.58)***	(3.45)***	(4.42)***	(1.57)	
Alzheimer's disease	-.0148	-.0333	.2189	.0003553	.0006567	-
	(0.06)	(0.34)	(0.76)	(0.08)	(0.12)	
Observations	20544					
LogL	-10370.799					

Additional parameters are included in the model and retain the same signs and significance levels as they display in Table 13. These parameters are the linear and quadratic income, recovered year, selection correction, interactions between age and interaction between sick years and lost life years, and higher order lost-life year and interaction terms.

Absolute value of z statistics in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

Table 12: Simple Disease Label Effects *and* Sick Year Shifters (Alternatives = 20,544)

		Shifters (0=neutral, except for age)						
Disease Labels:	Basic Terms	*Confidence	* Vulnerability	*Age	* Vulnerability *Age	*Smoke	*At Risk	*Control
breast cancer	1.645	-.3666	.2653	-.01894	.003763	-	-	-
	(3.31)***	(1.80)*	(0.44)	(1.94)*	(0.30)			
prostate cancer	1.201	-.05958	.8127	-.009229	-.004269	-	-	-
	(2.47)**	(0.29)	(1.38)	(0.96)	(0.35)			
lung cancer	.4581	-.2087	.564	-.01338	-.004338	.298	-	-
	(1.20)	(1.35)	(1.28)	(1.80)*	(0.48)	(7.91)***		
colon cancer	.8928	.3423	.02574	-.01174	.006426	-	-	-
	(2.54)**	(2.30)**	(0.06)	(1.71)*	(0.73)			
skin cancer	.2758	-.1693	.6447	-.01257	-.008539	-	-	-
	(0.69)	(0.98)	(1.38)	(1.58)	(0.90)			
heart disease	-	-.3143	1.056	.01409	-.01321	-	-	-
		(2.17)**	(2.49)**	(7.07)***	(1.54)			
heart attack	1.385	.2832	.8113	-.01311	-.005392	-	-	-
	(4.90)***	(2.65)***	(2.49)**	(2.36)**	(0.84)			
respiratory disease	.7035	.01013	1.189	-.01815	-.01191	.1833	-	-
	(1.81)*	(0.06)	(2.44)**	(2.41)**	(1.23)	(4.63)***		
Stroke	.9261	.07068	.9136	-.007343	-.007812	-	-	-
	(3.33)***	(0.66)	(2.89)***	(1.35)	(1.25)			

Table 12, Continued

Disease Labels:	Basic Terms	*Confidence	* Vulnerability	*Age	* Vulnerability *Age	*Smoke	*At Risk	*Control
traffic accident	.5665 (1.73)*	.06044 (0.48)	.3002 (0.85)	-.01432 (2.27)**	-.005281 (0.75)	-	-	-
diabetes	2.159 (5.36)***	.2876 (1.67)*	1.783 (3.40)***	-.04211 (5.19)***	-.02311 (2.12)**	-	-	-
Alzheimer's disease	.7238 (1.93)*	.05709 (0.36)	.5165 (1.13)	-.01478 (2.00)**	-.004757 (0.52)	-	-	-
Sick Year Terms:								
$(\alpha_{10})\Delta\Pi_i^{AS}\log(pdvi_i^A+1)$	-286.6 (5.57)***	-	-	-	-	-	-	-
* any cancer	-	-	-	-	-	-	-1.176 (0.23)	-8.361 (1.35)
* breast cancer	238.7 (1.69)*	-87.15 (1.71)*	-102 (0.64)	.8789 (0.35)	2.425 (0.80)	-	-	-
* prostate cancer	368.4 (2.73)***	12.41 (0.24)	-51.18 (0.36)	-1.359 (0.54)	2.157 (0.75)	-	-	-
* lung cancer	273.8 (3.12)***	-19.55 (0.64)	28.46 (0.31)	-.91 (0.58)	-.8605 (0.47)	-	-	-
* colon cancer	309.5 (3.67)***	87.15 (3.04)***	-125.8 (1.38)	-1.501 (1.05)	2.346 (1.32)	-	-	-

Table 12, Continued

Sick Year Terms:	Basic Terms	*Confidence	* Vulnerability	*Age	* Vulnerability *Age	*Smoke	*At Risk	*Control
* skin cancer	251.5	-34.6	49.71	-.4511	-1.49	-	-	-
	(2.77)***	(1.06)	(0.53)	(0.28)	(0.78)			
* heart disease	-	-72.6	-46.83	5.531	.5728	-	3.836	.2977
		(2.63)***	(0.56)	(5.47)***	(0.34)		(0.63)	(0.04)
* heart attack	361	64.32	-72	-1.117	.8381	-	-	-
	(3.54)***	(1.84)*	(0.68)	(0.60)	(0.40)			
* respiratory disease	409	30.79	157.7	-2.884	-2.66	-	12.83	4.302
	(3.91)***	(0.89)	(1.26)	(1.61)	(1.18)		(2.64)***	(0.78)
* stroke	212.5	21.86	-75.68	1.715	.781	-	4.883	-11.14
	(1.96)*	(0.62)	(0.63)	(0.90)	(0.34)		(0.77)	(1.60)
* traffic accidents	214.7	-11.23	43.9	1.154	-2.661	-	3.557	-8.583
	(2.10)**	(0.30)	(0.41)	(0.59)	(1.18)		(0.66)	(1.56)
* diabetes	457.9	10.34	194	-4.148	-3.517	-	-7.253	-6.465
	(4.42)***	(0.26)	(1.59)	(2.27)**	(1.49)		(1.52)	(1.19)*
Alzheimer's disease	394.3	25.77	69.95	-2.912	-1.257	-	-2.55	14.62
	(3.46)***	(0.69)	(0.54)	(1.53)	(0.54)		(0.45)	(2.33)**
Observations	20544							
LogL	-10296.213							

Additional parameters are included in the model and retain the same signs and significance levels as they display in Table 13. These parameters are the linear and quadratic income, recovered year, selection correction, interactions between age and interaction between sick years and lost life years, and higher order lost-life year and interaction terms. Absolute value of z statistics in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

Table 13: Full Model (Simple Disease Label Effects, Sick Year and Lost Life-year Shifters, Alternatives = 20,544)

		Shifters (0=neutral, except for age)						
	Basic Terms	*Confidence	*Vulnerability	*Age	*Vulnerability *Age	*Smoker	*Control	*At Risk
Disease Labels:								
breast cancer	1.133	-.467	.3414	-.0102	.00266	-	-	-
	(2.08)**	(2.10)**	(0.52)	(0.96)	(0.20)			
prostate cancer	1.242	-.192	.8572	-.009694	-.00599	-	-	-
	(2.44)**	(0.88)	(1.38)	(0.96)	(0.46)			
lung cancer	.5077	-.21	.5299	-.01453	-.002589	.3014	-	-
	(1.22)	(1.23)	(1.10)	(1.81)*	(0.26)	(7.95)***		
colon cancer	.9681	.3181	.03662	-.01346	.006045	-	-	-
	(2.54)**	(2.01)**	(0.08)	(1.81)*	(0.62)			
skin cancer	.4673	-.1569	.6625	-.01696	-.006844	-	-	-
	(1.07)	(0.84)	(1.29)	(1.97)**	(0.65)			
heart disease	-	-.2628	1.278	.01453	-.01906	-	-	-
		(1.70)*	(2.82)***	(6.91)***	(2.09)**			
heart attack	1.182	.1753	.7076	-.007819	-.003539	-	-	-
	(3.24)***	(1.10)	(1.55)	(1.08)	(0.39)			
respiratory disease	.7097	.04212	1.276	-.01883	-.01343	.1821	-	-
	(1.72)*	(0.25)	(2.37)**	(2.34)**	(1.25)	(4.59)***		
stroke	.8022	-.1859	1.263	-.004025	-.01792	-	-	-
	(2.23)**	(1.21)	(2.76)***	(0.57)	(1.95)*			
traffic accident	.6699	-.06071	-.087	-.01419	.003783	-	-	-
	(1.59)	(0.34)	(0.17)	(1.71)*	(0.36)			

Table 13, continued

Disease Labels:	Basic Terms	*Confidence	* Vulnerability	*Age	* Vulnerability *Age	*Smoker	*Control	*At Risk
diabetes	2.293	.224	2.144	-.04394	-.0306	-	-	-
	(5.21)***	(1.23)	(3.69)***	(4.90)***	(2.52)**			
Alzheimer's disease	1.025	-.08928	.6156	-.02042	-.006368	-	-	-
	(2.58)***	(0.52)	(1.24)	(2.59)***	(0.64)			
Sick Year Terms:								
$(\alpha_{10})\Delta\Pi_i^{AS}\log(pdvi_i^A+1)$	-273.2	-	-	-	-	-	-	-
	(4.39)***							
*any cancer	-	-	-	-	-	-	-8.089	3.37
							(1.20)	(0.59)
*breast cancer	380	-72.95	-93.52	-1.863	2.392	-	-	-
	(2.39)**	(1.31)	(0.55)	(0.69)	(0.75)			
*prostate cancer	352.2	53.26	-100.9	-1.497	3.315	-	-	-
	(2.17)**	(0.85)	(0.57)	(0.51)	(0.98)			
*lung cancer	250.3	-21.54	38.22	-.8414	-1.26	-	-	-
	(2.54)**	(0.68)	(0.39)	(0.51)	(0.64)			
*colon cancer	280.9	92.62	-136.1	-1.291	2.616	-	-	-
	(2.98)***	(3.03)***	(1.46)	(0.86)	(1.42)			
*skin cancer	202.5	-37.39	54.17	.1566	-2.01	-	-	-
	(1.99)**	(1.08)	(0.54)	(0.09)	(0.99)			
*heart disease	-	-75.95	-88.64	4.997	1.639	-	2.449	5.769
		(2.60)***	(0.99)	(4.10)***	(0.90)		(0.33)	(0.87)

Table 13, continued

Sick Year Terms:	Basic Terms	*Confidence	* Vulnerability	*Age	* Vulnerability *Age	*Smoker	*Control	*At Risk
*heart attack	341	59.19	-75.01	-1.178	.7862	-	-	-
	(3.13)***	(1.66)*	(0.70)	(0.62)	(0.37)			
*respiratory disease	412.1	23.98	144.5	-3.297	-2.528	-	-2.359	14.61
	(3.51)***	(0.64)	(1.10)	(1.72)*	(1.06)		(0.40)	(2.77)***
*stroke	185.4	12.53	-54.33	1.817	.2489	-	-6.593	1.023
	(1.60)	(0.35)	(0.44)	(0.93)	(0.11)		(0.87)	(0.15)
*traffic accident	208.8	-15.61	22.91	.8777	-2.232	-	-7.99	6.511
	(1.90)*	(0.41)	(0.21)	(0.44)	(0.97)		(1.33)	(1.11)
*diabetes	407.7	38.56	124.5	-4.163	-2.274	-	-3	-8.932
	(3.42)***	(0.82)	(0.94)	(2.11)**	(0.91)		(0.51)	(1.72)*
*Alzheimer's disease	273.2	73.93	11.61	-1.243	-.5095	-	13.17	-5.859
	(2.12)**	(1.77)*	(0.08)	(0.60)	(0.20)		(1.93)*	(0.95)
Lost Life-Year Terms:								
$(\alpha_{30})\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	-588.2	-	-	-	-	-	-	-
	(2.70)***							
*any cancer	-	-	-	-	-	-	-2.17	-11.07
							(0.35)	(2.09)**
*breast cancer	-245.9	-42.62	24.63	5.492	-.2938	-	-	-
	(1.70)*	(0.94)	(0.18)	(1.76)*	(0.11)			
*prostate cancer	72.63	-80.97	78.29		-2.013	-	-	-
	(0.52)	(1.67)*	(0.61)		(0.75)			

Table 13, continued

Lost Life-Year Terms:	Basic Terms	*Confidence	* Vulnerability	*Age	* Vulnerability *Age	*Smoker	*Control	*At Risk
*lung cancer	83.94	-.1182	-10.39	-.3346	.8254	-	-	-
	(0.70)	(0.00)	(0.10)	(0.12)	(0.40)			
*colon cancer	106.5	-14.24	33.45	-.9154	-.7189	-	-	-
	(0.88)	(0.43)	(0.33)	(0.33)	(0.34)			
*skin cancer	165.7	4.98	7.409	-2.116	1.044	-	-	-
	(1.33)	(0.16)	(0.07)	(0.76)	(0.45)			
*heart disease	-	26.59	177.3	1.758	-4.529	-	-3.476	-5.42
		(0.70)	(1.55)	(0.61)	(1.90)*		(0.47)	(0.87)
*heart attack	-5.615	-21.87	-23.12	1.826	.5835	-	-	-
	(0.05)	(0.84)	(0.29)	(0.69)	(0.36)			
*respiratory disease	27.96	23.01	52.7	.5354	-.6867	-	15.67	-3.674
	(0.21)	(0.57)	(0.40)	(0.18)	(0.26)		(2.85)***	(0.75)
*stroke	8.59	-62.23	98.15	1.564	-2.561	-	-12.8	8.593
	(0.07)	(2.29)**	(1.10)	(0.58)	(1.46)		(1.77)*	(1.32)
*traffic accident	66.42	-28.86	-82.59	.6184	2.181	-	-3.239	-7.596
	(0.57)	(0.98)	(0.99)	(0.23)	(1.22)		(0.57)	(1.38)
*diabetes	116.9	-41.31	155.9	-.2036	-2.992	-	-7.497	4.329
	(0.97)	(1.20)	(1.57)	(0.07)	(1.48)		(1.35)	(0.88)
*Alzheimer's disease	285.1	-101.7	116.3	-3.743	-1.677	-	6.899	7.343
	(2.00)**	(2.50)**	(0.87)	(1.24)	(0.69)		(1.08)	(1.23)
Observations	20544							
LogL	-10252.933							

Table 14: Parsimonious Model (Alternatives = 20,544)

		Shifters (0=neutral, except for age)						
	Basic Terms	*Confidence	*Vulnerability	* Age	*Vulnerability *Age	*Control	*At Risk	* Smoker
Disease Labels:								
breast cancer	.653 (5.22)***	-.3443 (1.95)*	.311 (3.06)***	-	-	-	-	-
prostate cancer	.6285 (4.66)***	-	.3988 (3.71)***	-	-	-	-	-
lung cancer	-.2941 (3.37)***	-	.3465 (4.21)***	-	-	-	-	.309 (8.44)***
colon cancer	.2128 (2.91)***	-	.3377 (4.28)***	-	-	-	-	-
skin cancer	-.4215 (5.27)***	-	.2669 (3.04)***	-	-	-	-	-
heart disease	-	-.1002 (0.70)	.7906 (3.00)***	-	-.008198 (1.60)	-	-	-
heart attack	.6626 (8.40)***	-	.536 (6.86)***	-	-	-	-	-
respiratory disease	-.4092 (4.63)***	-	.4802 (5.43)***	-	-	-	-	.1894 (4.92)***
stroke	.4475 (5.56)***	-.1737 (1.34)	.538 (6.82)***	-	-	-	-	-
traffic accident	-	-	-	-.005923 (3.91)***	-	-	-	-

Table 14, continued

	Basic Terms	*Confidence	*Vulnerability	* Age	*Vulnerability *Age	*Control	*At Risk	* Smoker
Diabetes	.8273 (3.60)***	-	.5445 (6.31)***	-.0179 (3.95)***	-	-	-	-
Alzheimer's disease	.4747 (1.44)	-	.2368 (2.82)***	-.01119 (1.74)*	-	-	-	-
Sick Year Terms:								
$(\alpha_{10})\Delta\Pi_i^{AS}\log\left(pdvi_i^A+1\right)$	-56.65 (4.88)***	-	-	-	-	-	-	-
*general cancer	-	-	-	-	-	-13.69 (2.72)***		
*breast cancer	-	-	-	1.205 (2.10)**	-	-	-	-
*prostate cancer	74.55 (2.19)**	-	-	-	-	-	-	-
*heart disease	-	-35.45 (1.34)	-	-.6759 (2.55)**	-	-	-	-
*heart attack	78.68 (3.24)***	-	-	-	-	-	-	-
*respiratory disease	-	-	-	-	-	-	12.13 (2.93)***	-
*stroke	76.24 (3.10)***	-	-	-	-	-	-	-
*traffic accident	-	-	-67.29 (2.64)***	-	-	-	-	-

Table 14, continued

	Basic Terms	*Confidence	*Vulnerability	* Age	*Vulnerability *Age	*Control	*At Risk	* Smoker
*diabetes	-	-	-	-	-	-	-8.164 (2.04)**	-
*Alzheimer's disease	-	82.32 (2.33)**	-	-	-	8.936 (1.68)*	-	-
Lost-life Year Terms:								
$(\alpha_{30})\Delta\Pi_i^{AS}\log\left(pdvl_i^A+1\right)$	-565.2 (3.22)***	-	-	-	-	-	-	-
*any cancer	-	-	-	-	-	-	-10.29 (2.32)**	-
*breast cancer	-	-69.27 (1.75)*	-	-	-	-	-	-
*respiratory disease	-	-	-	-	-	13.47 (3.13)***	-	-
*stroke	-	-53.49 (2.21)**	-	-	-	-13.3 (2.51)**	7.647 (1.59)	-
*diabetes	-	-47.46 (2.61)***	-	-	-	-6.506 (1.54)	-	-
*Alzheimer's disease	275.5 (2.73)***	-90.95 (2.46)**	-	-4.964 (2.75)***	-	-	-	-

Table 14, continued

Basic Model Terms:	**Basic Terms**	*Confidence	*Vulnerability	* Age	*Vulnerability *Age	*Control	*At Risk	* Smoker
$(\beta_{00}\times 10^{5})$[linear net income term]	5.369 (7.80)***	-	-	-	-	-	-	-
$(\beta_{10}\times 10^{9})$[quadratic net income term]	-.198 (3.90)***	-	-	-	-	-	-	-
$(\alpha_{20})\Delta\Pi_i^{AS}\log(pdvr_i^A+1)$	-17.42 (1.64)	-	-	-	-	-	-	-
$(\alpha_{13})\left[P(sel_i)-\overline{P}\right]\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]$	3.517 (2.35)**	-	-	-	-	-	-	-
$(\alpha_{31})age_{i0}\cdot\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	19.29 (2.73)***	-	-	-	-	-	-	-
$(\alpha_{32})age_{i0}^2\cdot\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	-.1614 (2.39)**	-	-	-	-	-	-	-
$(\alpha_{40})\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2$	221.5 (2.51)**	-	-	-	-	-	-	-
$(\alpha_{41})age_{i0}\cdot\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2$	-8.218 (2.29)**	-	-	-	-	-	-	-

Table 14, continued

Basic Model Terms:	**Basic Terms**	*Confidence	*Vulnerability	* Age	*Vulnerability *Age	*Control	*At Risk	* Smoker
$(\alpha_{42})age_{i0}^2 \cdot \Delta\Pi_i^{AS}\left[\log\left(pdvl_i^A+1\right)\right]^2$	.07364 (2.12)**	-	-	-	-	-	-	-
$(\alpha_{52})age_{i0}^2 \cdot$ $\Delta\Pi_i^{AS}\left[\log\left(pdvi_i^A+1\right)\right]\cdot\left[\log\left(pdvl_i^A+1\right)\right]$	.006295 (2.22)**	-	-	-	-	-	-	-
Observations	20544							
LogL	-10356.924							

Absolute value of z statistics in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

Table 15: Simulated *WTP* for a Microrisk Reduction, by health threat (two scenarios, income = $42,000) [a]						
Profile	**Sudden Death Now**			**10 year latency; sick 5 years, then death**		
Health Threat						
Age now	**30**	**45**	**60**	**30**	**45**	**60**
Breast Cancer	7.87 (4.65, 11.34)	8.39 (5.89, 11.25)	6.98 (4.56, 9.57)	8.66 (6.6, 11.04)	6.64 (4.08, 8.35)	4.44 (2.93, 6.03)
Prostate Cancer	7.38 (4.22, 10.74)	7.78 (5.29, 10.58)	6.4 (3.82, 9.08)	7.25 (5.26, 9.42)	5.65 (4.1, 7.44)	4.05 (2.62, 5.69)
Colon Cancer	4.46 (1.76, 7.32)	4.88 (3.09, 6.91)	3.47 (1.72, 5.35)	6.32 (4.67, 8.15)	4.76 (3.6, 6.03)	3.09 (2.03, 4.26)
Lung Cancer	.95 (-2.3, 3.14)	0.97 (-1.05, 2.74)	0.22 (-2.49, 1.29)	2.36 (0.8, 3.99)	0.78 (-0.53, 1.92)	0.04 (-2.34, .3)
...* smoker	10.59 (7.18, 14.26)	11.05 (8.32, 14.21)	9.62 (7, 12.79)	12.43 (9.75, 15.7)	10.93 (8.58, 13.59)	9.24 (7.22, 11.86)
Skin Cancer	0.43 (-3.28, 2.2)	0.36 (-1.98, 1.62)	0.04 (-3.49, 0.26)	1.37 (-0.01, 2.79)	0.16 (-1.55, 0.85)	0 (-3.49, -.67)
Heart Attack	8.22 (5.38, 11.5)	8.68 (6.58, 11.1)	7.29 (5.38, 9.61)	7.58 (5.76, 9.69)	6.09 (4.58, 7.84)	4.4 (3.01, 5.97)
Heart Disease	8.26 (5.38, 11.65)	8.73 (6.46, 11.35)	7.36 (5.24, 9.96)	9.05 (7.08, 11.32)	7.01 (5.59, 8.62)	4.82 (3.6, 6.26)
Stroke	6.37 (3.45, 9.4)	6.79 (4.85, 8.98)	5.4 (3.6, 7.53)	5.96 (4.17, 7.93)	4.33 (2.99, 5.87)	2.7 (1.29, 4.13)
Respiratory Disease	0.38 (-3.63, 2.12)	0.29 (-2.29, 1.56)	0.03 (-3.74, 0.08)	1.18 (-0.3, 2.81)	0.13 (-1.97, 0.85)	0 (-3.78, -0.69)
...* smoker	5.95 (2.96, 9.13)	6.34 (3.9, 8.99)	5.01 (2.65, 7.48)	7.81 (5.57, 10.51)	6.22 (4.29, 8.34)	4.62 (2.73, 6.72)

Table 15, continued

Profile	**Sudden Death Now**			**10 year latency; sick 5 years, then death**		
Health Threat						
Age now	**30**	**45**	**60**	**30**	**45**	**60**
Traffic Accident	1.11 (-1.72, 3.48)	0.82 (-1.03, 2.33)	0.07 (-3.2, 0.61)	2.69 (1.42, 4.08)	0.63 (-0.6, 1.64)	0.01 (-3.2, -0.12)
Diabetes	5.3 (2.32, 8.63)	3.36 (1.64, 5.23)	0.3 (-2.35, 1.57)	7.15 (5.1, 9.53)	3.24 (2.1, 4.45)	0.07 (-2.15, 0.47)
Alzheimer's Disease	0.2 (-10.19, 1.6)	0.85 (-3.25, 3.28)	2.24 (-0.5, 4.98)	0.73 (-4.06, 3.35)	0.91 (-1.31, 2.7)	1.03 (-0.55, 2.43)

[a] Cells describe simulated distribution of *WTP* (across 1000 random draws from the joint distribution of the estimated parameters). Since negative values are often an artifact of the functional form and there was no opportunity for any respondent to express a negative *WTP*, we convert negative simulated values to zero before calculating the mean (first entry in each cell). However, we also report the 5th and 95th percentiles of the distribution before negative values are converted to zero.

APPENDIX B

SCENARIO ADJUSTMENT INDICATORS

In this Appendix, we carefully consider the empirical correlates of the two scenario adjustment indicators. Table A-1 gives descriptive statistics for these variables and a set of regressors I used to explain systematic variations in their magnitudes. First, we use a simple binary logit model to examine how the value of the indicator variable $1(never_i^j)$ can be explained by a wide variety of (a.) characteristics of the respondent, and (b.) attributes of the health risk targeted by each program. Each respondent considers ten different health risk-reduction programs, in five sets of two, with each choice set including the status quo as a third alternative. In total, therefore, 15,040 substantive illness profiles and health risk reduction programs are considered in the 7,520 choice scenarios analyzed in this paper. For 1,156 (7.69%) of these illness profiles, respondents indicated their belief that they would never benefit from the risk-reduction program.

Models 1 and 2 in Table A-2 are ad hoc binary logit models to explain these 7.69% of cases where $1(never_i^j)=1$. Missing data for some of the explanatory variables used in these preliminary exploratory models accounts for the reduction of the number of illness profiles from 15,040 to 13,626. The logit specification suggests that people are more likely to say that a particular program will never benefit them if they are female, if they currently have a larger number of other illnesses, if they feel at greater

subjective risk for getting other illnesses, if they are a member of a larger household, or if they are a single parent. People are less likely to say the program will never benefit them if they are presented with an illness profile that includes long-term pain and/or disability, if they have not attended college, if they acknowledge a higher subjective risk of getting this disease, if they have (on average) more room to improve their health habits, and if they currently have children in their household.

Now we explore the determinants of the approximately continuous measure of how much the stated benefit and the perceived benefits differ, called $Bendiff_i^j$. This is a minimum overestimate of the latency, in this case using an ordinary least squares (OLS) model. The $Bendiff_i^j$ for a program is known only if the individual does not state that they expect never to benefit from the program (i.e. if $1(never_i^j) = 0$). Thus, we have a maximum of 15,040 – 1,156 = 13,884 potential observations on the $Bendiff_i^j$ variable. For many respondents and many programs, the interval during which the individual personally expects the benefits of the program to begin spans the onset time specified in the illness profile. For these individuals and programs, $Bendiff_i^j$ =0, signaling minimal scenario adjustment with respect to the latency period. This happens for 4,133 of the 13,884 programs for which $Bendiff_i^j$ information is available. Latency is overestimated to some degree for 1,542 programs, and underestimated for 8,209

programs. The mean value of $Bendiff_i^j$ is -7.57 (with a minimum of -59 and a maximum of 29).[32]

Models 1 through 5 in Table A-3 demonstrate the significant determinants of $Bendiff_i^j$ across a variety of alternative specifications. Missing data for some of the regressors again reduces the estimating sample, this time from 13,884 to 12,596 illness profiles. The coefficients on age and age-squared are highly significant in the first two models when latency variables for the specified illness profiles are left out of the model. When latency variables are included (as in Models 3 through 5), the coefficients on the age variables are no longer statistically significant. It is likely that latency effects are captured by the age variables in the first two models. The insignificant age terms are dropped from the specification in Model 4. Model 5 demonstrates the consequences of using an interval-data model rather than treating $Bendiff_i^j$ as an approximately continuous variable. As is clear from in Figure 2, respondents were asked to specify the future time interval when their benefits would start, and Model 5 more explicitly captures the interval nature of these data. However, the estimates produced by Models 4 and 5 are very similar. The only notable difference is that the estimated coefficient on the respondent's subjective risk of suffering other illnesses becomes statistically insignificant in Model 5 (although the point estimate remains similar).

[32] The scenario adjustment data with respect to latency thus suggests that underestimation predominates. This may reflect opinions that acute cases of major illness do not typically come as a complete surprise. They often occur after years of decline in the individual's general level of health.

Models 4 and 5 suggest that individuals are more likely to overestimate the latency period when they consider an illness profile with a longer period of pain or disability, if the illness profile has pain/disability lasting more than 60 months, if they feel at greater subjective risk for other illnesses, if they belong to a two-income household, or if they will have a child under the age of eighteen in the household at the time of the stated onset of the disease. Individuals are more likely to assume that the latency in their own case will be less than the stated latency in the survey if they have not attended college, if they already have the illness in question, if they have a larger number of other major illnesses, if they feel at a higher subjective risk for this illness, if they have (on average) more room to improve their health habits, or if they have children or are single parents. The length of the latency period stated in the illness profile is also an important determinant of $Bendiff_i^j$. Not surprisingly, a longer stated latency period in the scenario makes respondents more likely to underestimate the latency and vice versa.

Table B-1: Descriptive Statistics for Correlates of Scenario Adjustment Variables

Variable	Mean	Std. Dev.	Min	Max
Dependent Variables				
Will never benefit from program* $1(never_i^j)$	0.077			
Minimum overestimate of latency** $Bendiff_i^j$	-8.12	12.3	-58	29
Minimum overestimate if latency overestimated $Bendiff_i^j > 0$	7.72	6.45	1	29
Minimum overestimate if latency underestimated $Bendiff_i^j < 0$	-15.2	10.8	-58	-1
Attributes of stated illness profile				
Duration of pain/disability (months if less than 60)	35.8	38.0	0	192
1(Longterm pain/disability) (>60 months)	0.288	0.453		
Age/gender/income of respondent				
Age of respondent (years)	49.9	14.9	25	93
1(Female)	0.504			
Income ($10,000)	5.18	3.38	0.5	15.0
Educational attainment				
1(Less than HS)	0.104	0.305		
1(High School)	0.337	0.473		
1(Some College)	0.251	0.433		
Objective health status				
1(Have same illness)	0.040	0.195		
Count of other major illness	0.294	0.578		
Subjective health risks				
Subjective risk, same illness	-0.223	1.24		
Subjective risk, other illness	-0.242	0.861		
Avg room to improve health habits	3.446	0.831		

Table B-2, Continued

Respondent's household structure

Size of household	2.57	1.26
1(Have kids)	0.287	0.452
1(Single parent)	0.017	0.129
1(Dualinc-w/ or w/out kids)	0.647	0.478
1(Have kid at onset)	0.029	0.169
1(Single parent & kid at onset)	0.001	0.030
1(Dual-income & kid at onset)	0.023	0.150

* To conserve space, descriptive statistics are based on illness profiles with complete data for the model to explain $BenefitsDiffer_i^j$ (i.e. 12,596 observations). Proportion for variable *1(never)* is displayed for the 13,626 illness profiles with complete data when this is the dependent variable.

** 29.3% of the minimum overestimate of latency ($Bendiff_i^j$) observations are equal to zero. $Bendiff_i^j = 0$ if the respondent's subjective latency interval contains the latency stated in the survey.

Table B-2: Models to Explain "1(never)" (Program would not benefit me)

	1 - Binary Logit	2 - Binary Logit
Attributes of illness profile		
Duration of pain/disability	0.001	0.000
(months if less than 60)	(0.57)	(0.50)
1(Long term pain/disability > 60 months)	-0.157	-0.155
	(1.97)**	(1.95)*
Some demographic characteristics of respondents		
Age of respondent (years)	-0.006	-
	(0.45)	
$Age^2/100$	0.010	-
	(0.79)	
1(Female)	0.375	0.381
	(5.61)***	(5.71)***
Educational attainment		
1(Less than HS)	-0.254	-0.213
	(2.09)**	(1.77)*
1(High School)	-0.274	-0.246
	(3.27)***	(2.98)***
1(Some College)	-0.143	-0.136
	(1.64)	(1.57)
Health status and Risks		
1(Have same illness)	0.187	0.222
	(0.99)	(1.18)
Count of other major illness	0.116	0.146
	(1.99)**	(2.61)***
Subjective risk, same illness	-0.342	-0.343
	(10.15)***	(10.20)***
Subjective risk, other illness	0.152	0.147
	(3.23)***	(3.12)***
Avg. room to improve health habits	-0.081	-0.094
	(2.01)**	(2.36)**
Respondent's household structure		
Size of household	0.144	0.140
	(3.54)***	(3.70)***
1(Have kids)	-0.167	-0.219
	(1.42)	(1.96)*
1(Single parent)	0.578	0.564
	(2.48)**	(2.48)**
1(Dualinc-w/ or w/out kids)	0.017	-
	(0.22)	
1(Have kid at onset)	0.064	-
	(0.16)	
1(Dual-income & kid at onset)	-0.173	-
	(0.37)	
Constant	-2.720	-2.708
	(6.85)***	(15.76)***
Observations	13626	13626
Log L	-3550.8	-3552.8

Table B-3: Models to Explain How Perceived Benefits Differ ($Bendiff_i^j$)

	1 - OLS $Bendiff_i^j$	2 - OLS $Bendiff_i^j$	3 – OLS Latency $Bendiff_i^j$	4 –OLS Latency $Bendiff_i^j$	5 – OLS (Interval)* $Bendiff_i^j$
Attributes of illness profile					
Pain/disability (months if <60)	0.033	0.033	0.012	0.011	0.011
	(11.38)***	(11.37)***	(4.65)***	(4.31)***	(4.15)***
1(pain/disability) (>60 months)	0.502	0.499	0.578	0.574	0.578
	(2.07)**	(2.06)**	(2.76)***	(2.74)***	(2.61)***
Some demographic characteristics of respondents					
Age of respondent (years)	0.314	0.311	0.012	-	-
	(6.92)***	(6.87)***	(0.15)		
Age-squared (100s of years)	-0.116	-0.113	-0.078	-	-
	(2.70)***	(2.64)***	(1.10)		
1(Female)	-0.205	-	-	-	-
	(0.99)				
Educational attainment					
1(Less than HS)	-1.832	-1.876	-1.712	-1.813	-1.949
	(4.79)***	(4.93)***	(5.21)***	(5.52)***	(5.64)***
1(High School)	-0.673	-0.701	-0.559	-0.587	-0.516
	(2.56)**	(2.68)***	(2.47)**	(2.59)***	(2.15)**
1(Some College)	-0.239	-0.256	-0.375	-0.365	-0.405
	(0.86)	(0.92)	(1.56)	(1.52)	(1.59)
Objective health status					
1(Have same illness)	-2.554	-2.542	-2.125	-2.181	-2.118
	(4.70)***	(4.67)***	(4.52)***	(4.64)***	(4.29)***
Count of other major illnesses	-0.567	-0.555	-0.640	-0.704	-0.718
	(2.97)***	(2.90)***	(3.88)***	(4.28)***	(4.15)***
Subjective health risks					
Subjective risk, same illness	-1.115	-1.116	-1.411	-1.397	-1.471
	(10.54)***	(10.56)***	(15.42)***	(15.28)***	(15.20)***
Avg. subjective risk, other illness	-0.039	-0.043	0.269	0.272	0.202
	(0.25)	(0.28)	(2.01)**	(2.04)**	(1.43)
Avg. room to impr. health habits	-0.973	-0.974	-0.976	-0.935	-0.931
	(7.40)***	(7.41)***	(8.60)***	(8.27)***	(7.79)***
Latency Period					
Stated latency	-	-	-0.250	-0.204	-0.251
			(2.22)**	(3.09)***	(3.57)***
(Stated latency)^2	-	-	-0.001	-0.003	-0.004
			(0.78)	(3.97)***	(6.36)***

Table B-3, Continued

(Stated latency)*(Age)	-	-	-0.013	-0.008	-0.005
			(3.50)***	(3.42)***	(2.33)**
(Stated latency)*(Age^2)	-	-	0.000	0.000	-0.000
			(2.77)***	(0.58)	(0.82)
(Stated latency) *1(Female)	-	-	-0.025	-0.025	-0.019
			(3.25)***	(3.20)***	(2.30)**
Respondent's household structure					
Size of household	-0.118	-	-	-	-
	(0.88)				
1(Have kids)	-1.987	-2.208	-0.663	-0.673	-0.746
	(5.38)***	(8.27)***	(2.81)***	(2.86)***	(2.99)***
1(Single parent)	-1.858	-1.794	-2.058	-1.993	-1.979
	(2.20)**	(2.15)**	(2.85)***	(2.76)***	(2.60)***
1(Dualinc-w/ or w/out kids)	0.701	0.625	0.754	0.763	0.769
	(2.87)***	(2.74)***	(3.83)***	(3.88)***	(3.69)***
1(Have current kid at onset)	14.445	14.371	2.557	3.304	3.903
	(11.11)***	(11.07)***	(2.22)**	(2.91)***	(3.24)***
1(Dual-income & kid at onset)	-2.681	-2.601	-2.354	-2.394	-2.679
	(1.84)*	(1.78)*	(1.87)*	(1.90)*	(2.01)**
Constant	-17.957	-18.157	8.782	6.449	7.290
	(14.36)***	(14.64)***	(3.55)***	(12.29)***	(13.14)***
Observations	12596^	12596	12596	12596	12596
Log L					-33818.9
R-squared	0.12	0.12	0.35	0.35	

Absolute value of z statistics in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%.
^Sample size is smaller for models in Table B-3 than Table B-2 since they do not include those individuals who said the program would never benefit them.

* Interval-data model treats $Bendiff_i^j$ as an interval rather than as an approximately continuous variable. This is done using the upper and lower estimates of the stated latency of the benefits of the program and using the intreg command in Stata.

APPENDIX C

ALTERNATIVE SCENARIO ADJUSTMENT MODELS

Extensive, rather than parsimonious, version of main model

Table 5 in the main body of the paper gives parameter estimates from the model that corrects for scenario adjustment where all interaction terms with persistently insignificant coefficients have been dropped. Table C-1 in this Appendix provides the estimates for a model with the complete set of interactions.

Extensive and parsimonious versions of a "small" model

It may be important to demonstrate that the statistical significance of the interaction terms involving the two scenario adjustments variables in this study are not an artifact of the non-linear functional form of the specification in the main model. Tables C-2 and C-3 demonstrate that there are significant shifts in the estimated parameters even in simpler five-parameter versions of the specification for the program choice model.

Under- or over-estimate of latency (ordered discrete variable)

In addition to the interval-data model for the $Bendiff_i^j$ variable documented in Model 5 in Appendix C, Table C-3, we also considered a second specification for over- or under-estimating the latency. An ordered categorical variable $ordered\_latency_i^j$ is explored in the context of an ordered logit model. The variable $ordered\_latency_i^j$ is an ordered categorical variable that takes on the value 0 if the upper bound of the age interval

checked among the selections in Figure 2 is lower than the stated age of onset given in the choice scenario. It takes the value 1 if the age interval checked in Figure 2 contains the stated age of onset, and take a value of 2 if the lower bound of the age interval lies strictly above the stated age of onset in the choice scenario. In these data, latency is underestimated for about 54.6% of illness profiles, and it is overestimated for about 10.3% of profiles.

Results for this model are displayed in Table C-4. Individuals are more likely to overestimate the latency of the illness if they have finished only high school, have temporary or long-term pain described the illness profile stated in the scenario, or will likely have a current child still in their household at the stated onset of the disease. Individuals are more likely to underestimate the length of the latency if they have a lower income, have either this illness or another major illness, have a higher subjective risk for this illness, have children, or will likely have a current child still in their household at the stated onset of the disease.

Table C-1: Scenario Adjustment Model with All Interaction Terms (Alternatives = 22560)

	Model A1	Model A2		
(Parameter) Variable	Uncorrected	Corrected	$\times 1(never_i^j)$	$\times Bendiff_i^j$
$(\beta_0 \times 10^5)$[first income term]	8.387 (10.03)***	8.387 (10.03)***	-2.702 (0.76)	0.248 (4.11)***
$(\beta_1 \times 10^9)$[second income term]	-2.385 (3.86)***	-2.385 (3.86)***	10.235 (2.95)***	-0.027 (0.64)
$(\alpha_{10})\Delta\Pi_i^{AS}\log(pdvi_i^A+1)$	-58.359 (5.05)***	-58.359 (5.05)***	248.650 (3.87)***	7.233 (7.13)***
$(\alpha_{13})\left[P(sel_i)-\overline{P}\right]\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]$	3.892 (2.15)**	3.892 (2.15)**	6.055 (0.60)	0.012 (0.08)
$(\alpha_2)\Delta\Pi_i^{AS}\log(pdvr_i^A+1)$	-51.663 (4.52)***	-51.663 (4.52)***	-60.728 (1.12)	1.177 (1.00)
$(\alpha_{30})\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	-1019.412 (4.11)***	-1019.412 (4.11)***	499.341 (0.49)	5.900 (0.36)
$(\alpha_{31})age_{i0}\cdot\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	48.701 (4.80)***	48.701 (4.80)***	-19.464 (0.47)	-0.309 (0.41)
$(\alpha_{32})age_{i0}^2\cdot\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	-0.412 (4.24)***	-0.412 (4.24)***	0.144 (0.36)	0.012 (1.47)
$(\alpha_{40})\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2$	339.442 (3.13)***	339.442 (3.13)***	484.391 (0.81)	-3.979 (0.41)
$(\alpha_{41})age_{i0}\cdot\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2$	-17.555 (3.95)***	-17.555 (3.95)***	-7.705 (0.33)	0.308 (0.72)
$(\alpha_{42})age_{i0}^2\cdot\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2$	0.148 (3.44)***	0.148 (3.44)***	0.032 (0.15)	-0.006 (1.24)
$(\alpha_{50})\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]\cdot\left[\log(pdvl_i^A+1)\right]$	141.815 (1.55)	141.815 (1.55)	-416.324 (0.89)	-13.371 (1.42)
$(\alpha_{51})age_{i0}\cdot\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]\cdot\left[\log(pdvl_i^A+1)\right]$	-6.993 (1.95)*	-6.993 (1.95)*	-0.117 (0.01)	0.434 (1.07)
$(\alpha_{52})age_{i0}^2\cdot\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]\cdot\left[\log(pdvl_i^A+1)\right]$	0.063 (1.85)*	0.063 (1.85)*	0.101 (0.58)	-0.005 (1.20)
Log L	-11694.646	-10948.179		

Table C-2: Minimal Model (Alternatives = 22560)

	Model B1	Model B2		
(Parameter) Variable	Uncorrected	Corrected	$\times 1(never_i^j)$	$\times Bendiff_i^j$
$(\beta_0 \times 10^5)$[first income term]	5.342 (9.17)***	9.991 (12.98)***	-1.787 (0.54)	0.409 (7.40)***
$(\beta_1 \times 10^9)$[second income term]	-2.160 (4.61)***	-2.014 (3.33)***	9.731 (2.84)***	-0.026 (0.64)
$(\alpha_{10})\Delta\Pi_i^{AS}\log(pdvi_i^A+1)$	-27.053 (4.56)***	-37.493 (4.99)***	109.601 (2.75)***	5.348 (7.75)***
$(\alpha_{13})\left[P(sel_i)-\overline{P}\right]\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]$	3.297 (2.29)**	3.475 (1.90)*	5.121 (0.50)	-0.033 (0.23)
$(\alpha_2)\Delta\Pi_i^{AS}\log(pdvr_i^A+1)$	-21.870 (2.35)**	-37.893 (3.43)***	-60.407 (1.13)	0.993 (0.86)
$(\alpha_3)\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	-30.409 (5.97)***	-36.974 (5.89)***	190.347 (5.79)***	6.594 (11.12)***
Log L	-11726.31	-11073.051		

Table C-3: Parsimonious Minimal Model (Alternatives = 22560)

	Model B1'	Model B2'		
(Parameter) Variable	Uncorrected	Corrected	$\times 1(never_i^j)$	$\times Bendiff_i^j$
$(\beta_0 \times 10^5)$[first income term]	5.342 (9.17)***	9.816 (14.00)***	-1.900 (0.57)	0.387 (10.18)***
$(\beta_1 \times 10^9)$[second income term]	-2.160 (4.61)***	-1.800 (3.58)***	9.425 (2.76)***	-
$(\alpha_{10})\Delta\Pi_i^{AS}\log(pdvi_i^A+1)$	-27.053 (4.56)***	-37.184 (4.97)***	103.398 (2.72)***	5.398 (7.98)***
$(\alpha_{13})\left[P(sel_i)-\overline{P}\right]\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]$	3.297 (2.29)**	3.786 (2.39)**	-	-
$(\alpha_2)\Delta\Pi_i^{AS}\log(pdvr_i^A+1)$	-21.870 (2.35)**	-43.664 (4.45)***	-	-
$(\alpha_3)\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	-30.409 (5.97)***	-36.855 (5.89)***	188.932 (5.74)***	6.619 (11.22)***
Log L	-11726.31	-11074.305		

Table C-4: Correlates of $Bendiff_i^j$ as a Discrete Variable

	1 – Ordered logit $Bendiff_i^j$	2 – Ordered logit $Bendiff_i^j$	3 – Ordered logit $Bendiff_i^j$
Attributes of illness profile			
Duration of pain/disability (months if less than 60)	0.004	0.002	0.002
	(5.05)***	(1.93)*	(1.99)**
1(Longterm pain/disability) (>60 months)	0.064	0.094	0.095
	(0.93)	(1.30)	(1.32)
Some demographic characteristics of respondents			
Age of respondent (years)	0.036	0.000	-
	(2.72)***	(0.00)	
Age-squared (100s of years)	-0.029	0.003	-
	(2.34)**	(0.15)	
1(Female)	0.005	-	-
	(0.09)		
Educational attainment			
1(Less than HS)	-0.939	-0.940	-0.936
	(6.80)***	(6.68)***	(6.67)***
1(High School)	-0.040	-0.005	-0.007
	(0.57)	(0.07)	(0.10)
1(Some College)	-0.202	-0.207	-0.209
	(2.62)***	(2.57)**	(2.60)***
Objective health status			
1(Have same illness)	-0.679	-0.654	-0.651
	(3.20)***	(3.01)***	(3.00)***
Count of other major illness	-0.119	-0.137	-0.132
	(2.08)**	(2.28)**	(2.23)**
Subjective health risks			
Subjective risk, same illness	-0.132	-0.200	-0.201
	(4.38)***	(6.25)***	(6.28)***
Subjective risk, other illness	-0.081	-0.031	-0.028
	(1.86)*	(0.68)	(0.62)

Table C-4, Continued

Avg room to improve health habits	-0.155 (4.30)***	-0.174 (4.59)***	-0.178 (4.72)***
Latency Period			
Stated latency	-	0.013 (0.24)	0.010 (0.31)
Stated latency squared	-	-0.003 (6.86)***	-0.003 (7.70)***
Latency and age interaction	-	0.003 (1.35)	0.002 (1.86)*
Latency and age squared interaction	-	-0.000 (3.19)***	-0.000 (4.71)***
Respondent's household structure			
Size of household	-0.011 (0.29)	-	-
1(Have kids)	-0.284 (2.64)***	-0.097 (1.13)	-
1(Single parent)	-1.204 (2.80)***	-1.319 (3.06)***	-1.387 (3.25)***
1(Dualinc-w/ or w/out kids)	0.107 (1.55)	0.120 (1.82)*	0.107 (1.67)*
1(Have kid at onset)	1.809 (6.80)***	0.155 (1.03)	-
1(Dual-income & kid at onset)	-0.330 (1.13)	-	-
Observations	12596	12596	12596
Log L	-4259.161	-3697.929	-3698.915

Absolute value of z statistics in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%.

APPENDIX D

FULL HOUSEHOLD STRUCTURE MODEL

Table D-1: Full Household Structure Model
(n = 1801 individuals, 7520 choices, 22560 alternatives)

	Model 1	Model 2
Linear net income term		
$(\beta_{00} \times 10^5)$[linear net income term]	4.767	4.814
	(6.34)***	(6.40)***
…* 1(female)	6.718	6.668
	(5.71)***	(5.66)***
…* 1(female) * # kids 6-12 yrs	-2.398	-2.298
	(2.14)**	(2.04)**
…* # kids 13-17 yrs	2.139	2.022
	(2.31)**	(2.18)**
… * 1(female) * 1(dual-income)	-2.128	-2.073
	(2.07)**	(2.01)**
Quadratic net income term		
$(\beta_{10} \times 10^9)$[quadratic net income term]	-	-
…* 1(female)	-.2994	-.2987
	(4.11)***	(4.10)***
…* # kids 0-1 yrs	-.7802	-.7578
	(2.46)**	(2.39)**
Sick-years terms		
$(\alpha_{10})\Delta\Pi_i^{AS} \log(pdvi_i^A + 1)$	-70.14	-69.77
	(5.17)***	(5.14)***
…* 1(female)	28.13	27.41
	(2.15)**	(2.09)**
…* # kids 2-5 yrs	103	103.5
	(3.75)***	(3.75)***
…* 1(female) * # kids 2-5 yrs	-66.87	-68
	(2.06)**	(2.08)**
…* 1(single parent)		-1203
		(1.91)*
…* 1(kids in home at onset)	-111.6	-43.67
	(2.94)***	(0.80)
…* 1(kids in home at onset) * 1(dual-income)		-90.22
		(1.76)*

Table D-1 Continued

Recovered-years terms		
$(\alpha_{20})\Delta\Pi_i^{AS}\log(pdvr_i^A+1)$	-58.89 (5.81)***	-59.57 (5.88)***
Lost life-years terms		
$(\alpha_{30})\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	-830.5 (3.88)***	-804.2 (3.75)***
…* 1(female)	25.07 (2.24)**	25.62 (2.28)**
…* # kids 2-5 yrs	-41.51 (2.42)**	-41.74 (2.43)**
…* # kids 13-17 yrs	23.25 (1.99)**	22.91 (1.94)*
$(\alpha_{31})age_{i0}\cdot\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	41.77 (5.00)***	40.73 (4.87)***
…* 1(single parent)		32.34 (2.01)**
$(\alpha_{32})age_{i0}^2\cdot\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	-.3596 (4.65)***	-.3507 (4.52)***
Lost life-years squared terms		
$(\alpha_{40})\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2$	292.2 (3.06)***	279.6 (2.91)***
…* 1(single parent)		258.2 (1.76)*
$(\alpha_{41})age_{i0}\cdot\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2$	-16.03 (4.24)***	-15.53 (4.09)***
$(\alpha_{42})age_{i0}^2\cdot\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2$	.1377 (3.84)***	.1335 (3.72)***
…* 1(single parent)		-.1899 (2.14)**
Sick-years, Lost life-years interaction terms		
$(\alpha_{50})\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]\cdot\left[\log(pdvl_i^A+1)\right]$	67.84 (0.80)	71.03 (0.84)
…* 1(kids in home at onset)	473.5 (1.98)**	468.2 (1.97)**
$(\alpha_{51})age_{i0}\cdot\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]\cdot\left[\log(pdvl_i^A+1)\right]$	-4.772 (1.48)	-4.888 (1.51)
…* 1(kids in home at onset)	-19.36 (1.83)*	-18.89 (1.80)*
$(\alpha_{52})age_{i0}^2\cdot\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]\cdot\left[\log(pdvl_i^A+1)\right]$	.04655 (1.56)	.04756 (1.59)

Table D-1, Continued

…* 1(kids in home at onset)	.2186 (1.92)*	.2134 (1.89)*
Nuisance parameters		
- shift if respondent believes "will never benefit"		
$(\beta_{10}\times 10^{9})[\text{second income term}]\ ^{*}1(never_i^j)$	.745 (2.97)***	.7459 (2.97)***
$(\alpha_{10})\Delta\Pi_i^{AS}\log(pdvi_i^A+1)\ ^{*}1(never_i^j)$	205.8 (3.79)***	204.5 (3.76)***
$(\alpha_{40})\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2\ ^{*}1(never_i^j)$	397.5 (4.54)***	403.9 (4.55)***
$(\alpha_{41})age_{i0}\cdot\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2\ ^{*}1(never_i^j)$	-5.232 (3.72)***	-5.288 (3.72)***
$(\alpha_{50})\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]\cdot\left[\log(pdvl_i^A+1)\right]$ $^{*}1(never_i^j)$	-344.3 (3.72)***	-347.9 (3.74)***
$(\alpha_{52})age_{i0}^2\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]\cdot\left[\log(pdvl_i^A+1)\right]$ $^{*}1(never_i^j)$	.07632 (3.33)***	.07692 (3.33)***
- shift with minimum overestimate of latency		
$(\beta_{00}\times 10^{5})[\text{first income term}]\ ^{*}Bendiff_i^j$	.236 (5.33)***	.238 (5.37)***
$(\alpha_{10})\Delta\Pi_i^{AS}\log(pdvi_i^A+1)\ ^{*}Bendiff_i^j$	7.881 (7.76)***	7.881 (7.76)***
$(\alpha_{30})\Delta\Pi_i^{AS}\log(pdvl_i^A+1)\ ^{*}Bendiff_i^j$	-.1718 (0.07)	-.1813 (0.07)
$(\alpha_{32})age_{i0}^2\cdot\Delta\Pi_i^{AS}\log(pdvl_i^A+1)\ ^{*}Bendiff_i^j$	.007948 (6.39)***	.00794 (6.37)***
$(\alpha_{42})age_{i0}\cdot\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2\ ^{*}Bendiff_i^j$	.1381 (1.97)**	.1375 (1.96)*
$(\alpha_{42})age_{i0}^2\cdot\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2\ ^{*}Bendiff_i^j$	-.003806 (2.76)***	-.003795 (2.74)***
$(\alpha_{50})\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]\cdot\left[\log(pdvl_i^A+1)\right]$ $^{*}Bendiff_i^j$	-5.029 (4.37)***	-5.044 (4.38)***
- shift with difference from mean participation probability		
$(\alpha_{13})\left[P(sel_i)-\overline{P}\right]\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]$	3.786 (2.38)**	3.851 (2.42)**
Observations	22560	22560
Log L	-10903.222	-10898.947

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