

Willingness to Pay for Public Health Policies to Treat Illnesses

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Keywords: public health policy; medical treatment; stated preference survey; conjoint analysis; willingness to pay; morbidity and mortality reduction; discounting

JEL Classifications: I12, J17, J28, Q51

* For their helpful comments on recent versions of this manuscript, we are very grateful to our discussants Richard Carson and Don Kenkel. We are also grateful for earlier comments from Maureen Cropper, Kerry Smith, Laura Taylor, Bill Harbaugh, Robin McKnight, Paul Slovic, Dan Burghart, and seminar participants at North Carolina State University, Virginia Tech, the University of Maryland-Baltimore County, the U.S. EPA, Utah State University, Research Triangle Institute, and the University of Oregon. The paper has been improved by feedback from session participants at the Third Biennial Conference of the American Society of Health Economists at Cornell in June 2010, the Annual Conference of the Society for Benefit-Cost Analysis in Washington, DC, in October 2010, and at the 12th Occasional California Workshop on Environmental and Resource Economics at UCSB in November 2010. This research has been supported by the US Environmental Protection Agency (R829485), Health Canada (Contract H5431-010041/001/SS), with additional support from the endowment of the Raymond F. Mikesell Chair at the University of Oregon. This work has not been formally reviewed by any of these entities. Any errors are our own.

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Abstract

As the U.S. pursues health care reform, it is important to understand the patterns in demand for, and opposition to, public provision of medical treatments. Using data from a nationally representative survey, we develop and estimate a utility-theoretic choice model to quantify demand for publicly provided medical treatment policies. We find diminishing marginal utility for increased recoveries and avoided premature deaths. We also show how the utility associated with different types of treatment policies varies with the socio-demographic group that would benefit (e.g., men, women, children, and seniors) and the program's duration and scope. Our model further permits utility, and hence willingness to pay, to vary with each respondent's own gender, age, race, income, community ethnic fractionalization and immigrant composition, as well as the respondent's expected private benefits from the policy and attitude towards government interventions and overall health care funding allocations. Self-interest is a prevailing finding.

Keywords: public health policies, treatment, individual discount rates, willingness to pay, distributional considerations, self interest

1 Introduction

The government bears a very large share of total spending on health services in the U.S.—about 45% of total direct health expenditures, increasing to 60% if one includes tax subsidies for private insurance and government purchases of private health insurance for public employees (Woolhandler and Himmelstein (2007)). Much of this spending goes toward treating specific illnesses that afflict specific subpopulations. To date, however, researchers lack a clear understanding of what types of government-funded medical treatments the average person most prefers (or most opposes) having to pay for. Nor is it well understood which factors best explain differences across people in preferences over publicly financed medical treatments. We address these knowledge gaps by characterizing peoples’ willingness to pay to support government-financed medical treatment programs.

A large and rich, but very different, literature concerns the value of a “statistical” life (VSL) and focuses on individuals’ willingness to pay to reduce their own small chances of contracting a fatal illness or suffering a fatal injury. Numerous VSL studies and several meta-analyses evaluate individuals’ preferences for *privately provided* risk reductions (i.e. Mrozek and Taylor (2002); Viscusi and Aldy (2003); Alberini (2005); Hammitt and Haninger (2010); Chestnut et al. (2012)). In contrast, we seek to identify individuals’ preferences for *publicly provided* policies that make treatments available to patients who are *already* sick or injured, where *other people* are the beneficiaries of these policies.¹

Such public policy preferences involve different considerations. First, the individual may be uncertain whether a particular government-funded treatment policy will ever directly benefit

¹ Some studies have explored population-level outcomes, focusing on risk-risk tradeoffs, such as Chilton et al. (2002); Cropper et al. (1994); Subramanian and Cropper (2000). Very few have explored individuals’ willingness to pay for public health risk reduction programs, as in Arana and Leon (2002). Some recent work by Lavetti et al. (2014) has considered individuals’ willingness to pay for health insurance coverage for others.

him or his family, so the preferences he expresses may be mostly other-regarding (e.g., altruistic or paternalistic) rather than self-regarding. Second, changes in the *risk* of illness or injury are not at issue, since all potential beneficiaries of the policy are already sick or injured. Third, different types of treatment programs may target different groups of beneficiaries (e.g., men, women, children, adults, seniors), and individuals may differentially value medical treatments for different types of people. Finally, government-funded treatment policies are typically financed through mandatory taxes, so attitudes toward taxation may matter.

Our analysis is based on more than 1,300 responses to a stated preference (SP) survey which uses discrete choice experiments to evaluate publicly funded medical treatments that increase the number of people who recover, and reduce the number who die prematurely, from specific illnesses or injuries. Within and across choice sets, we assess the effects of variations in the number of increased recoveries, the number of avoided premature deaths, the length of time the policy is in effect (i.e. the commitment period), the type of illness being treated, the size of the afflicted population, and one main experimental variation in choice-elicitation framing.

Our health-policy choices, used alone, do not permit robust estimation of discounting parameters. Thus we estimate jointly, with cross-equation parameter constraints, (1) a submodel to explain public health treatment policy preferences and (2) a submodel to explain choices between different ways of taking some hypothetical lottery winnings. Joint estimation allows us to identify individual-specific discount parameters assumed here to apply to future *utility* derived from any source. We allow the discounting parameter to vary with each individual's attributes, as numerous studies suggest (Warner and Pleeter (2001); Frederick et al. (2002); Harrison et al. (2002); Silverman (2003); Andersen et al. (2008)). There has, of course, been considerable discussion in the literature about whether people discount future health differently from future

money. We build enough utility-theoretic structure into our model so that we can discount the *utility* from future health and the *utility* from future money, while permitting the marginal utilities of health and money to differ.

We assume that a common preference function underlies both the policy choices and the lottery winnings disbursement choices in our study, which allows us to constrain time preferences and the parameters for the marginal utility of net income to be consistent across both types of choices. The estimated degree of risk aversion with respect to net income applies to both the public health policy context and the lottery winnings disbursement context. Ours appears to be the most general and comprehensive joint model, to date, that encompasses time preferences, risk preferences, and the demand for public health policies. We also illustrate the size of bias due to choice elicitation framing effects that occur for treatment programs if researchers choose to focus only on avoided premature deaths and neglect the number of recoveries associated with treatment policies.

Our model allows us to explore how these estimates of willingness to pay per recovery and avoided premature death vary with the age group of the patients who will benefit from specific kinds of treatment programs, and with the ethnic and immigrant composition of the community that will be served. The duration of commitment to each program and the program's geographic scope are permitted to have systematic effects on individual willingness to pay.

Our estimated model also enables us to characterize how demand varies systematically with the gender, age, race and income of the individual who is being asked to value these treatment policies. We can also control for individuals' own ratings of how much they themselves (or their families) might expect to benefit from each policy, their attitudes towards

the targeting of public health care expenditures in general, and their attitudes towards government regulation of environmental, health and safety risks overall.

Finally, some people are inclined to reject all publicly financed programs offered for their consideration. We specifically model how support for *any* of these tax-funded medical treatments, regardless of their costs or benefits, varies as a function of a broad range of individual characteristics.

The research upon which this paper is based involves many considerations beyond what can be covered within the page limits of a standard journal article. Throughout, we will refer to an accompanying online Appendix that contains comprehensive supporting information and alternative specifications, including many more tables and figures.²

2 Data and Survey Design

The data used for this analysis were gathered using survey instruments designed specifically to elicit individuals' willingness to pay for publicly provided health policies. The survey was administered in 2003 by Knowledge Networks Inc., an internet-based market research firm offering a representative panel of households in the U.S. who could complete surveys via a Web TV[®] or personal computer interface.³

² Fuller details of the two survey instruments are also available at http://www.uoregon.edu/~cameron/vsl/public_prevention_framed.pdf and http://www.uoregon.edu/~cameron/vsl/public_treatment_framed.pdf. For this paper, we use the “treatment” survey for the policy choices, but both surveys for the data on time preferences.

³ Marginal distributions of various socio-demographic variables for both our estimating sample and the U.S Census are provided in Bosworth et al. (2009). The response rate was 79% among invited participants from this consumer panel with excellent sampling properties. The online Appendix contain the details our models to explain the presence of individuals in the estimating sample relative to the 525,078 random-digit-dialed (RDD) initial contact attempts for recruitment to the contemporaneous Knowledge Networks panel from which individuals were invited to participate. Importantly, our selection models do not capture merely the process by which invited panelists decided to complete the survey. Our models go all the way back to the most “random” phase of RDD panel recruitment and reflect all levels of selection between that point and membership in our estimating samples for both portions of this joint model.

We have at our disposal a set of responses from 1,314 individuals who completed the Treatment Policy survey. At the core of this survey are five main choice sets, each offering the individual two prevention policies, Policy A and Policy B, that reduce future premature deaths and increase future recoveries, as well as a Neither Policy alternative (denoted N). We explain to individuals that they may find it appropriate to choose neither policy by pointing out several possible explanations why a reasonable person might choose neither policy in some cases.⁴ Respondents are asked to consider each choice separately, are reminded that the policies are not free, are asked to consider their budget constraint, and are reminded of people's propensities in survey settings not take these constraints adequately into account.⁵

In Figure 1, we show a single example of one of the 5,875 essentially unique (randomly generated) three-alternative "treatment" policy choice scenarios used in this study. Policy attributes are varied across individuals, across choice sets, and across proposed policies. The yearly policy cost to the respondent, explicitly via higher taxes, is randomly varied from \$60 to \$1200, and both this annual cost and the corresponding implied monthly cost of each policy are explicitly stated. The length of time the policy would be in effect is also randomly varied across policies within choice sets. Policies run for 2, 4, 5, 10, 15, 20, 25, or 30 years.⁶

Descriptive statistics for the randomized policy attributes for the 11,750 distinct policies (two per choice scenario) used in our policy choice analysis are presented in Table 1. This table

⁴ These reasons include that (1) they did not believe the policies would reduce health risks, (2) environmental problem does not cause illness, (3) they did not believe their community faced these health threats, (4) they could not afford either policy, and (5) they would rather spend the money on other things. If the individual chose "neither policy" (N) they were asked why (in a follow-up question). Reasons 1 and 3 indicate that the respondent did not fully accept the assumptions they had been urged to make with respect to the programs they were offered. However, excluding these choices has minimal qualitative impact on the estimation results, so we retain all choices.

⁵ Respondents were given a standard "cheap talk" script, as described in the online Appendix to this paper.

⁶ Had we been willing to assume linearity and additive separability of utility in all of its arguments, we could certainly have increased the efficiency of our estimates by limiting the number of levels for each of the up to nine attributes and pursuing an "efficient design" for the mix of attributes represented in each choice set. Nonlinearities are something we wished to identify as fully as possible, however, so we used a fully randomized design and rely upon our large sample and our structural model to reveal systematic differences in marginal utilities over different domains of the utility function.

also includes statistics for respondents' subjective ratings of their self-interest in each of these policies, elicited subsequent to each choice, a number of sociodemographic variables, and several attitudinal variables used in our specification.

The duration of the commitment represented by the treatment policy, and the policy's cost, are key attributes of the policies described in these choice sets. For example, alternative public health policies might involve a commitment of operating expenses for just a few years, or they may involve capital programs such as the construction of a specialized unit within a public hospital with useful life of twenty or thirty years. The range of treatment policies to be considered is very heterogeneous. These policies differ widely in terms of the numbers of potential increased recoveries as well as the number of potential avoided premature deaths. If the funding for diverse alternative policies such as these were to be raised through a bond issue on a referendum, citizens would have to make similar choices, but often with less structured comparisons than can be presented in a stated choice context.⁷

Our descriptions of alternative public health treatment policies also vary in terms of the demographic group that would most benefit from the policy (e.g. men, women, children, adults, seniors, or some combination of these groups) as well as the specific health threat addressed. For example, "Policy A treats children, adults, and seniors who have leukemia. Those helped will be 25% children, 25% adults, and 50% seniors (i.e. 25/25/50 mix).⁸ In the body of this paper, we do not focus on systematic variation in willingness to pay according to the *type* of illness addressed by each policy (e.g. leukemia). These illness labels were randomly assigned to each proposed

⁷ The voter pamphlet may include a statement from the legislative analyst on a bond referendum, or pro and con statements from advocacy groups on each side of the issue. But these statements are rarely distilled for the voter in side-by-side tabular comparisons.

⁸ For the treatment policies the list of specific health threats includes: prostate cancer and breast cancer (essentially gender-specific cancers), colon/bladder cancer, leukemia, lung cancer, skin cancer, asthma, heart attack, heart disease, stroke, respiratory disease, and traffic injuries.

policy so we could specifically inquire about the respondent's degree of self-interest in each policy. Fortunately, however, there should be little problem with omitted variables bias in the remaining coefficients. The explanatory variables are fully randomized, so they cannot be correlated with any of the respondent's observed or unobserved attributes.⁹

Table 2 shows the roughly equal proportions of respondents choosing Policy A, Policy B, or Neither Policy (overall, and separately for each of the five choice occasions in each survey). Policies A and B have attributes that have been randomized. There appears to be a narrow preference for Policy A on four of the five choice occasions in the survey, but Policy B is chosen slightly more often on the second choice occasion. In general, the mixes of attributes in our choice sets appear to have been reasonably well balanced.

Table 3 shows some simple partitions of the sample to reveal how the propensity to choose Neither Policy differs, pairwise, with the levels of some of the key explanatory variables to be used in our utility-theoretic model. Respondents are *more* likely to choose the Neither Policy option if they have no children living in the household, if they indicate that it would not be possible for them to improve their health by smoking less, if they are female, if their income is below the sample median, if they are white, and if they do not play the lottery. There appears to be no systematic preference for Neither Policy for seniors versus younger respondents, and

⁹ We have explored the effects of expanding our specifications in various ways to determine whether willingness to pay varies by type of illness. In Section 10 of the online Appendix, we report on a number of specifications that allow the main parameters to vary systematically by the type of health threat. In some of our other work, the distinct effects of illness labels, as opposed to illnesses prevented and premature deaths avoided, have been analyzed in detail in research based on the Prevention Survey sample described in Bosworth et al. (2009). At benchmark levels of other prevention policy attributes, for example, that study reveals considerable heterogeneity across types of cancers, and across other illnesses, in marginal WTP to reduce numbers of illnesses, and also considerable variation in marginal WTP to reduce the number of premature deaths from each type of health threat. No common "cancer premium" was detected, although there has been considerable policy interest in the possibility of a standard cancer premium in WTP. In the present study, there actually seems to be lower WTP to treat cancers than other illnesses. This may reflect the bleaker prognosis for many cancers, and may amount to a public goods analog to the "why bother" effect.

likewise for single versus non-single respondents, or those with just a high school education and those with higher education levels.

2.1 Time Preferences Survey Module

As part of the Treatment Survey described above, as well as the related Prevention Survey analyzed in Bosworth et al. (2009), individuals are queried about their preferences for receiving hypothetical lottery winnings. Many state-sponsored lotteries conclude their advertisements by noting that winners can opt to take their nominal winnings in annual disbursements, or they can opt to take a smaller total amount up front. Given this advertising, many of the survey's respondents may already have daydreamed about the happy dilemma of which payment schedule to choose.

Via their choices between a single large up-front lump sum and stream of smaller payments over time, individuals reveal information that allows us to estimate approximate individual-specific rates of time preference (impatience). Randomized yearly payments offered to respondents ranged from \$500 to \$240,000. These yearly payments were offered for 5, 10, 15, 20, 30, or 40 years. The 2,819 individuals who completed either the Treatment Survey or the analogous Prevention Survey can be used in this portion of the analysis.¹⁰

In the body of this paper, we concentrate on just the policy choices submodel, although it is estimated jointly with the discounting submodel. We have removed to our online Appendix the complete details for the discounting submodel, treating it as a necessary but incidental part of the specification. The online Appendix reproduces a sample choice page from the "lottery winnings" scenario used in both the Treatment Survey and Prevention Survey, and includes summary

¹⁰ Our usable sample size is 2,819, rather than 2,954 (the total number of respondents), because some questions were left unanswered by some respondents, depriving us of values for some of the variables used to explain individual-specific discount rates.

statistics for those variables which are relevant only to the discounting portion of our joint model.¹¹

3 Empirical Framework

3.1 Policy Choices

The sub-model used to analyze our stated choice data with respect to public health treatment policies invokes a utility-theoretic structure for preferences, using a simple present discounted utility framework. Let $recvr / yr_{ijt}$ represent the average number of increased recoveries in the community, per year, provided by policy j as described to person i over the duration of the policy, T_{ij} . Likewise, let dth / yr_{ijt} represent the average number of community premature deaths avoided due to policy j in year t .¹² Individual i 's indirect utility from policy j , in effect in year t , is assumed to be diminishing in the individual's income, Y_{it} , according to a function $f(Y_{it})$, and also diminishing in the average annual number of illnesses avoided in year t , and in the average annual number of premature deaths avoided in year t , according to functions $g(recvr / yr_{ijt})$ and $h(dth / yr_{ijt})$, where $g(0) = 0$ and $h(0) = 0$, and both g and h are increasing at a decreasing rate.

¹¹ We use a so-called "multiple-bounded" elicitation method like that of Welsh and Poe (1998), but we interpret the four-category ordered answers to each proposed lump sum as ordered-logit-type responses, as in Cameron et al. (2002).

¹² We assume that individuals interpret the avoided illnesses and premature deaths as being uniformly distributed across the years of the policy. It proved too difficult to convey, in the single screens for each choice set, differing time profiles for the pattern of avoided/recovered illnesses and avoided premature deaths.

In any comparison of policy j (involving an annual cost of c_{ijt}) to the status quo alternative (“neither policy,” alternative n , at an incremental cost of zero) the two utilities will be as follows:

$$\begin{aligned} V_{ijt} &= \beta f(Y_{it} - c_{ijt}) + \delta_1 g(\text{recvr} / yr_{ijt}) + \delta_2 h(dth / yr_{ijt}) + v_{ijt} \\ V_{int} &= \beta f(Y_{it}) + v_{int} \end{aligned} \quad (1)$$

Now let T_{ij} represent the duration of commitment to policy j , in years, described to respondent i . Our model requires the present discounted *utility* associated with the costs and benefits of each policy alternative. For conventional exponential discounting, the familiar formula is $d_{ij}(r_i | T_{ij}) = \sum_{t=0}^{T_{ij}-1} (1+r_i)^{-t}$. However, we find that a slightly better fit is provided by a generalization of the simple single-parameter hyperbolic discounting structure suggested by Harvey (1986), which employs $d_{ij}(b_i | T_{ij}) = \sum_{t=0}^{T_{ij}-1} (1+t)^{-b_i}$. We allow b_i to be a function of individual attributes rather than constant across all respondents.¹³

Using the cumulated discount factor, $d_{ij}(b_i | T_{ij})$, we can express the present discounted value of indirect utility over the period of commitment for policy j , normalizing on status quo utility, as:

$$\begin{aligned} PDV(V_{ij} - V_{in}) &= PDV(\Delta V_{ij}) = \beta_i \left[f(Y_{it} - c_{ijt}) - f(Y_{it}) \right] d_{ij}(b_i | T_{ij}) \\ &\quad + \delta_1 \left[g(\text{recvr} / yr_{ijt}) - 0 \right] d_{ij}(b_i | T_{ij}) \\ &\quad + \delta_2 \left[h(dth / yr_{ijt}) - 0 \right] d_{ij}(b_i | T_{ij}) + \varepsilon_{ij} \end{aligned} \quad (2)$$

¹³ The online Appendix compares both the exponential and the hyperbolic discounting specifications and their effects on the parameters of the policy choice submodel. We do not pursue a generalized two-parameter hyperbolic specification because the additional shape parameter makes it much more difficult for the algorithm to achieve convergence.

where $\varepsilon_{ij} = \eta_{ij} - \eta_{in}$, and its components $\eta_{ik} = d_{ik}(b_i | T_{ik})v_{ikt}$ are assumed to be conveniently distributed Gumbel (Type I Extreme Value).¹⁴

The different treatment policies described in the survey may also be more or less salient to different respondents. Willingness to pay for a public health treatment policy can be expected to reflect in part the individual's degree of perceived self-interest in each policy. In particular, after each policy choice task, the respondent is asked to rate "To what extent would each policy directly benefit you or your family." Each specific policy was reiterated (e.g. Policy A treats children and adults (30/70 mix) who have respiratory disease). Respondents then gave ratings ranging from 1 = "Very little" to 5 = "Greatly." These ratings are thus subjective policy attributes that we capture in our model with a set of four indicator variables: $1(\text{own benefit}_{ij} = 2)$ through $1(\text{own benefit}_{ij} = 5)$.

In the broader literature, for example Alesina et al. (1999), ethnic fractionalization has also been shown to explain popular support for public spending programs in some contexts. We need a proxy for the approximate mix of ethnicities (in the populations of either 100,000, 500,000, or 1,000,000 "people living around you" that respondents were asked to assume would be eligible to be helped by the treatment policies in our survey). For this, we construct a county-level ethnic fractionalization index.¹⁵

¹⁴ The assumed constancy over time in anticipated net incomes and anticipated annual recoveries and avoided premature deaths permits us to move the functions $f(\cdot)$, $g(\cdot)$ and $h(\cdot)$ outside the discounting operator, leaving just the cumulated discount factor, $d_{ij}(t | T_{ij})$, which is the sum of the period-specific discount factors from $t = 0$ to $T_{ij} - 1$.

¹⁵ We are grateful for the recommendation of an anonymous referee that we consider this issue. Access to each respondent's county characteristics was arranged after our survey took place. We were not permitted to know the respondent's county of residence at the time of our survey, so we needed to specify explicitly a size of the relevant population for the policy within our choice scenarios. The 100,000 group size was discontinued early, so the vast majority of respondents considered either 500,000 or one million potential beneficiaries.

Our index uses county-level data from the 2000 Census and distinguishes among seven mutually exclusive and exhaustive Census ethnic categories: White, Black, American Indian, Asian, Hawaiian/Pacific Islander, Other Race and Two or More Races. Let eth_{gi} be the fraction of the population belonging to ethnic group g in the county of residence of respondent i . Our index of ethnic fractionalization is then given by $(7/6) \sum_{g=1}^7 eth_{gi} (1 - eth_{gi})$. As the county approaches 100% in just one of the seven categories, the index goes to zero. A larger value of the ethnic fractionalization variable thus connotes a more equal distribution of the population across these seven categories, while smaller values imply greater concentrations in fewer groups, regardless of which groups these are.¹⁶

Community composition variables permit us to address the occasional expressions of public concern that the benefits of prospective taxpayer-funded health programs might go to undocumented aliens. We focus on the systematic effects of the proportions of immigrants in the respondent's community (measured along three different dimensions) on the respondent's estimated utility from "either policy," independent of its benefits. We also use the 2000 Census to calculate the proportions of the county population who (a.) do not speak English at home and also do not speak English well, (b.) are non-citizens, and (c.) were not living in the U.S. in 1995. However, it proves to be important to allow the estimated effects of these "immigrant proportion" variables to vary systematically with the degree of ethnic fractionalization in the respondent's county. Collectively, we will refer to these immigration-related county population

¹⁶ The decision about how many categories to use is arbitrary. Had our racial/ethnic data on each respondent matched these same census categories, we might have been able to control for a match between the respondent and the majority group in their county.

proportions and their interactions with the ethnic fractionalization index as “ethnic/immigrant composition of community” variables.¹⁷

We also allow the utility from any given treatment policy to be affected by community illness prevalence, as measured by $\#afflicted_{ij}$, independent of the number of increased recoveries or avoided premature deaths to be achieved via the program. Utility also differs from policy to policy according to the percent of those treated who are children, $\%children_{ij}$, and seniors, $\%seniors_{ij}$.

Finally, we introduce an alternative-specific constant, $either\ policy_j$, that is equal to 1 for either of the two public health treatment policy options and equal to 0 for the status quo (Neither Policy) option.

Our preliminary scoping analyses began with a simple version of equation (2) where the functions $f(\cdot)$, $g(\cdot)$, and $h(\cdot)$ were all linear. (See the online Appendix for a summary of preliminary models). However, the linear model is rejected in favor of a model with a Box-Cox transformation of net income, to allow for flexible curvature that captures risk aversion.¹⁸ Logarithmic-type transformations seem sufficient for increased recoveries and avoided premature deaths (as well as for the size of the afflicted group, another control variable that proves relevant). Our estimating specification becomes:

¹⁷ We have also explored other dimensions upon which fractionalization of the county population could matter: age, income, language, nativity, and mobility. However, the *ethnic* fractionalization measure, when interacted with language, noncitizen, and recent immigrant variables, seems to afford the greatest explanatory power.

¹⁸ The literature continues to evolve concerning the issues of the interaction between risk preferences and time preferences—for example, Epper et al. (2011)—and how to derive individual time preferences without specifying risk preference—for example Laury et al. (2012). It is an open question whether the results observed in experimental time horizons, or even in field experiments such as Andersen et al. (2008), extrapolate to the multi-year and sometimes multi-decade horizons relevant in this project.

$$\begin{aligned}
PDV(\Delta V_{ij}) = & \beta \left[\frac{(Y_{it} - c_{ijt})^\lambda - 1}{\lambda} - \frac{(Y_{it})^\lambda - 1}{\lambda} \right] d_{ij}(t | T_{ij}) \\
& + \delta_1 [\log(recyr_{ijt} + 1) - 0] d_{ij}(t | T_{ij}) + \delta_{2i} [\log(dthyr_{ijt} + 1) - 0] d_{ij}(t | T_{ij}) \\
& + \sum_{k=2}^5 \delta_{3k} 1(own\ benefit_{ij} = k) \\
& + \sum_{s=6}^{13} \delta_{3s} (community\ composition\ variables_i) \\
& + \delta_{4i} \log(\#afflicted_{ij}) \\
& + \delta_{5i} (\%children_{ij}) + \delta_6 (\%seniors_{ij}) + \theta_i (either\ policy_j) + \varepsilon_{ij}
\end{aligned} \tag{3}$$

Equation (3) represents the “index” portion of a three-alternative conditional logit submodel for policy preferences. Some of these basic utility parameters (β , δ_1 , δ_{2i} , $\delta_{32}, \dots, \delta_{35}, \delta_{36}, \dots, \delta_{3,13}$, δ_{4i} , δ_{5i} , δ_6 and θ_i) appear to be essentially common to all respondents, but others show evidence of being heterogeneous across individuals, differing as systematic functions of individual characteristics. Recall that the discounting parameters b_i also varies systematically across individuals.

The parameter θ_i deserves special attention. This parameter captures the average effect on utility of all unspecified policy attributes, other than those attributes—the cost, scope and effectiveness of the policy—explicitly included in our models. Empirically, θ_i is useful for summarizing individuals’ general inclination to choose any policy over the status quo, or vice versa, regardless of the other explicit attributes of the policies for which we control. The parameter θ_i represents the net impact of miscellaneous survey effects such as “payment vehicle effects”, “nay-saying,” “yea-saying”, or “scenario rejection,” among other behaviors that are

often found to contribute to a “status quo effect” or a systematic preference for or against *any* of the offered policies.¹⁹

If one were to assume an arbitrary common fixed value for the discounting parameters, as in the study of choices among prevention policies described in Bosworth et al. (2009)), and a fixed transformation for the net income variable, this choice model could be estimated using packaged econometric algorithms.²⁰ In this paper, however, we introduce additional information about each individual’s preferences that we use to help identify individual-specific time preferences that account for people’s choices when the policy options involve different durations of commitment. As a consequence, we must use general function-optimizing software to maximize the log-likelihood function for our joint model.²¹

3.2 Willingness to Pay

On one level, we can use our stated preference choice data to estimate the parameters of a continuous latent “propensity to support” function, with arguments that describe the attributes of a specified public health treatment policy and the characteristics of the individual. The estimated parameters reveal the extent to which public support for a proposed policy appears to vary systematically with policy attributes or respondent characteristics. However, when people make trade-offs between their net income and public goods in the course of expressing their policy

¹⁹ The choice of whether to include a dummy variable for the status quo (i.e. Neither Policy) option or its complement, an “either policy” dummy, is arbitrary because only utility differences matter. We choose the “either policy” dummy variable option (shared by Policy A and Policy B), but the estimates for the analogous parameters could be expected to be $-\theta_i$ if we had chosen instead to use a status quo dummy.

²⁰ For instance, Stata’s clogit algorithm, with or without fixed effects, could be used. The fixed effects tend to make a minimal difference because the policy attributes are all randomly assigned, and thus independent of any unobserved heterogeneity across individuals. Thus there is little scope for heterogeneity bias, a priori.

²¹ We use Matlab. See the online Appendix, Section 5, for the full log-likelihood function. Given that we pool the policy choice data with other data on each individual’s time preferences, we need to allow for the possibility of different error dispersions. We normalize to unity the dispersion parameter, κ^P , for the policy choices, and estimate the corresponding dispersion parameter for the time-preferences submodel, $\kappa^L = \exp(\kappa^{L*})$, as a multiple of the policy-choice dispersion parameter.

preferences, it is possible to solve for the policy cost that would make a given individual just indifferent between paying for the policy and receiving its benefits, or not paying for the policy and doing without its benefits.

With heterogeneous policies, this maximum willingness to pay (WTP) is likewise a formula that depends upon the amount of each policy attribute and the characteristics of the individual in question. WTP for a specified policy is calculated by setting the utility difference, relative to the status quo, equal to zero and solving for the implied maximum annual payment. Thus, we set the left-hand side of equation (3) equal to zero and solve for the policy cost, c_{ij}^* , that makes the equality true. This is the most that the individual would be willing to pay for the policy in question before he or she would be better off doing without the policy and keeping the money.²²

With all of our specific functional forms and parameter restrictions in place, the formula for c_{ij}^* becomes:

$$c_{ij}^* = Y_{it} - \left\{ Y_{it}^\lambda - \frac{\lambda}{\beta d_{ij}(b_i | T_{ij})} \left[\begin{aligned} &(\delta_1) \log(\text{recvr}/yr_{it} + 1) d_{ij}(b_i | T_{ij}) \\ &+ (\delta_2 X_{2i}) \log(\text{dth}/yr_{it} + 1) d_{ij}(b_i | T_{ij}) \\ &+ \sum_{k=2}^5 \delta_{3k} 1(\text{own benefit}_{ij} = k) \\ &+ \sum_{s=6}^{13} \delta_{3s} (\text{community composition variables}_i) \\ &+ (\delta_4 X_{4i}) \log(\# \text{afflicted}_{ij}) \\ &+ (\delta_5 X_{5i})(\% \text{children}_{ij}) + (\delta_6)(\% \text{seniors}_{ij}) \\ &+ (\theta Z_i)(1) + (\varepsilon_i) \end{aligned} \right] \right\}^{1/\lambda} \quad (4)$$

²² For all but the simplest linear functions for $f(\cdot)$, this expression will be a nonlinear function of the maximum likelihood parameter estimates. We constrain β to be strictly positive by estimating its logarithm. This prevents WTP from being undefined for zero values of β or from becoming large and negative for small negative values of the parameter. The systematically varying discounting parameter embodied in $d_i(b_i | T_i)$ is also constrained to be positive using the same device.

where *either* $policy_{ij} = 1$ in all WTP calculations because we are evaluating some policy, rather than the status quo. The discounting term, with individual heterogeneity that depends on a vector of characteristics W_i , expands to:

$$d_{ij}(b_i | T_{ij}) = d_{ij}(bW_i | T_{ij}) = \sum_{t=0}^{T_{ij}-1} (1+t)^{-bW_i}$$

This term, and the scalar parameters β and λ , are constrained to be identical across (a.) the policy choice submodel that is solved to yield this WTP measure and (b.) the discounting submodel that is reported in the online Appendix.

We can calculate a single point estimate of WTP corresponding to a given set of parameter estimates. It is, of course, necessary to specify the characteristics of the policy in question ($recvr/yr_{it}$, dth/yr_{it} , $\#afflicted_{ij}$, $\%children_{ij}$, $\%seniors_{ij}$ plus T_{ij} in the discounting formula) as well as the characteristics of the individual whose WTP we are considering (e.g. the characteristics X_{2i} , X_{4i} , X_{5i} , Z_i , plus W_i in the discounting formula, as well as the respondent's subjective extent to which each policy would benefit the individual or his/her family members, and the ethnic/immigrant composition of the community).²³

Equation (4) reveals that the “index” of the argument of the WTP expression is additively separable in the shifted log terms in number of recoveries and number of avoided premature deaths. However, the WTP expression itself is nonlinear in this index. As a result, if one were to calculate the WTP for just one increased recovery, and add it to the separately calculated WTP to reduce just one premature death, the result cannot be expected to be the same as the WTP for a single policy that simultaneously increases recoveries by one and reduces deaths by one.

²³ The normalized error term $\mathcal{E}_i$ is assumed to have a unit logistic distribution, but we employ its expected value, which is zero.

We repeat the calculation of c_{ij}^* for each of 1000 different random draws from the assumed asymptotically jointly normally distributed maximum likelihood parameters. This produces a “sampling distribution” for estimated WTP for a specified policy by a particular type of consumer. Summary statistics for these simulated distributions, such as the median simulated WTP and the 5th and 95th percentiles of the distribution, can then be used as approximate point and interval estimates of WTP under specified circumstances.

4 Empirical Results

Our structural specification needs several features: (a.) individual-specific discount rates estimated in a utility-theoretic framework, (b.) diminishing marginal utility of income, so that risk aversion can be accommodated, (c.) the same utility function applied to both the policy choices and the discounting choices, (d.) heterogeneity across individuals in the marginal utility of policy attributes as dictated by the data, and (e.) some basic corrections for systematic selection into the estimating sample from the original random-digit dialed panel recruitment at Knowledge Networks.

The discounting submodel is critical to estimation of the fitted discounting factor that is applied to the duration of each proposed public health treatment policy. Keep in mind, however, that the individual discount parameter “index” is not estimated freely using only the information in respondents’ choices about how they would prefer to take some lottery winnings. The discount parameter, as well as the two parameters related to the marginal utility of net income (β and the Box-Cox λ parameter) appear explicitly in both the policy choice submodel and the lottery winnings submodel, so the individual’s decisions in both of these arenas will influence our estimates for these shared parameters.

4.1 Policy Choice Model

We can now turn to Table 4, which presents parameter estimates for our preferred specification for the policy choice submodel. The policy choice portion of the joint model is based on equation (3) in Section 3. The discounting submodel is covered in the online Appendix. We reiterate that these two submodels are actually estimated simultaneously, with conforming utility functions and appropriate cross-equation parameter restrictions.

For the policy choices, indirect utility is initially assumed to be linear and additively separable in the *shifted logarithms* of additional recoveries per year and reduced premature deaths per year. Given the expectation that “psychophysical numbing” is likely to set in when large numbers of illnesses and premature deaths are involved, it is appropriate to use a specification that allows for diminishing marginal utility in these two types of policy benefits.²⁴

We also introduce an indicator to capture the consequences, for the coefficient on the term in the number of reduced premature deaths, when the respondent was *not* also told about the number of increased recoveries. Many studies consider only mortality risk reductions and not morbidity, so we are careful in this study to address the potential consequences of allowing a respondent merely to *infer* what might be going on with morbidity reductions, based solely on mortality information. Not surprisingly, the marginal utility associated with avoided premature deaths is exaggerated (i.e. the key coefficient is almost 60 percent larger) when no mention is made of increased recoveries due to the policy. The key coefficient on increased recoveries, however, is about 77 percent of the corresponding coefficient on avoided premature mortalities.

²⁴ These reductions in premature deaths are described as the number of people, afflicted by the disease in question, who would otherwise die over the duration of the policy. These people will avoid death during the specified period as a result of the treatment policy. We assume that these avoided premature deaths are equally distributed over the life of the policy and discount the avoided premature deaths in each future year. Recoveries are also given for the duration of the policy and are specifically described as “full recoveries” which presumably means no relapse for the duration of the treatment policy.

This is roughly consistent with the findings of Bosworth et al. (2009) in the case of preferences over prevention policies.

Some preliminary homogeneous-preferences specifications are reviewed in the online Appendix accompanying this paper. These models reveal intuitively plausible signs on the estimates for each of the main parameters in our model. Utility is lower for treatment policies that are more expensive and greater for policies which produce more recoveries and prevent more premature deaths. Utility is also greater for treatment policies which serve more sick people, and where a higher proportion of those who are treated are children. In contrast, there is evidence of aversion to policies for which a higher proportion of those who are treated are seniors, where this may reflect people's perceptions that Medicare is already available to seniors at public expense.

The indicator variable for "either policy" is profoundly important in preliminary homogeneous preferences models. A negative and significant coefficient on this indicator implies that regardless of any of the policy attributes we describe to respondents and explicitly include in the choice model, people associate a discrete lump of *negative* utility with any of the policy options, on average. There is something systematically undesirable about *all* of the proposed policies—one might suspect that this could be the fact that the payment vehicle is described as an increase in taxes—that is not fully captured by their cost to the individual, their effectiveness at achieving recoveries or reducing premature deaths, the number of people afflicted by the illness or injury in question, or the share of beneficiaries who will be children or seniors. Nevertheless, the positive marginal utility associated with the net income term confirms that people are more inclined to choose programs which are less expensive, and less inclined to prefer more-expensive programs, *ceteris paribus*.

As noted, we use a Box-Cox transformation to introduce an estimated amount of curvature into the preference function with respect to net income (consistent with constant relative risk aversion, CRRA). Our models produce a Box-Cox parameter on the order of 0.5, which corresponds roughly to a square-root transformation. This parameter is very precisely estimated and permits a roughly 200-point improvement in the maximized value of the log-likelihood function over a specification that is linear in net income, so this nonlinearity is extremely important.

When we allow for preference heterogeneity as we estimate our utility-theoretic joint model, Table 4 reveals a number of dimensions along which preferences over treatment policies differ systematically and robustly across people. There appears to be little systematic heterogeneity across sociodemographic groups in the marginal utility associated with increased recoveries. However, we find that respondents who identify themselves as black appear to derive less utility from additional avoided community premature deaths than do non-black respondents.²⁵

One of the most striking empirical results in this study is the large positive effects of the set of self-interest (i.e. anticipated private benefits) indicators. The large self-interest effects are evident in Figure 2, which shows the striking multi-modal marginal distribution of our point estimates of WTP across individuals (even in a simple preliminary ad hoc specification for just the policy choices). The five distinct levels of the self-interest variable are clearly discernible in this histogram. Total WTP is clearly dominated by this effect, which produces numerous large negative values for total WTP, as well as large positive values. A recent survey conducted on behalf of Stanford University et al. (2010) corroborates substantial heterogeneity in people's

²⁵ Only about 8.7% of our estimating sample (114 people) self-identify as black, so it is striking that the utility from avoided premature deaths should be strongly statistically significantly lower for this group. For other non-white groups, the differences were not statistically significant.

anticipated personal benefits from the health care law passed by the U.S. Congress in March of 2010—24% of the 1251 adults who responded to this survey believe that the new law will cause them, personally, to get either “a little better” or “a lot better” health care. However, 33% of the respondents believe it would cause them, personally, to get either “a little worse” or “a lot worse” health care (question WR1).

The characteristics of the community of likely beneficiaries of a treatment policy, regardless of the policy’s effectiveness, also influence support for any given policy. To review, we consider three variables that measure the proportions of immigrants in the respondent’s county: (a) the proportion who speak English “not well,” (b) the proportion of non-citizens, and (c) the proportion who resided outside the U.S. in 1995. Across respondents’ counties, these three dimensions of immigrant presence have considerable independent variation among themselves (in the upper portions of their domains) and relative to our ethnic fractionalization index. Of particular interest is the influence of the county’s ethnic fractionalization index on the estimated effects of the proportions of immigrants in a community.

Figure 5 illustrates that the effects of our different measures of immigrant shares vary systematically with the ethnic fractionalization of the community, where the cross-over values of the fractionalization index (the point at which the estimated effects of the immigrant variables change sign) tend to lie somewhere between 0.36 and 0.42 in our data (i.e. between the 50th and 58th percentiles of the distribution of the index among our respondents).

From Table 4, we see that the marginal utility of “Any Policy” varies statistically significantly with the baseline levels of each of the “immigration” variables (at the 1%, 5% and

10% levels). However, we cannot reject a zero effect for ethnic fractionalization in counties with zero immigrants, so we impose that restriction.²⁶

For counties with immigrant populations, however, ethnic fractionalization *does* influence the marginal utility of any public health treatment policy. If none of their neighbors have limited English skills or resided outside the US in 1995, ethnic fractionalization has a *positive* effect on the marginal utility of public health treatment policies when there are more noncitizens. This scenario could include counties with higher proportions of long-term resident aliens from Canada or the United Kingdom or other countries where English is at least a widespread second language. These individuals may tend to be higher-income workers, who came to the US for advanced training and stayed.

However, even if everyone in the respondent's county is actually a U.S. citizen, ethnic fractionalization can have a negative effect on the marginal utility of public health treatment policies if the immigrant population is less skilled in English or consists of more-recent immigrants. Xenophobia may account for resentments that permit ethnic fractionalization to decrease enthusiasm for public health treatment policies when more of the potential recipients are less fluent in the official language and more of them have recently arrived in the U.S.

Gender appears to differentiate the utility that respondents derive from certain types of policies. Men appear to be more willing to support a treatment policy that will deal with a more prevalent health problem (i.e. when more people are afflicted by the illness). Support by women, however, seem to be relatively unaffected by the numbers of patients/victims involved.

Some intriguing patterns also emerge with respect to the age distribution of the beneficiary group. People are more willing to support treatment policies that help children, but

²⁶ Compared to Model 4 in Table 6-1 in the online Appendix, a likelihood ratio test for the incremental contribution of the variables capturing the ethnic/immigrant composition of the community is 38.68 (whereas the critical value for a chi-squared test with seven degrees of freedom is only 14.07).

the extra utility associated with policies that benefit children declines with respondent age. Older respondents will be less likely still to have their own young children, and might be expected to be relatively more interested in supporting programs targeting adults or older beneficiaries.

We also control for an additional type of variable when we explore heterogeneity in policy support as a function of the proportion of children among the beneficiaries. At the end of the survey, respondents were posed some additional hypothetical policy questions. One of these was:

Our government has to make hard choices when it allocates money to prevent and treat illnesses. Imagine for a moment that you are the governor of your state. On behalf of your community, you have \$100 million to spend to improve the health of children, adults or seniors.

How would you divide that \$100 million over these groups of people? You can spend it all on one group or spread it out any way you think is right. (Remember it should add up to 100.)

Boxes were provided for “Adults,” “Children,” and “Senior citizens.” Not surprisingly, the greater the share of this hypothetical funding that the individual would prefer to devote to the treatment of children, the more a higher share of children among the beneficiaries of a policy positively affects the individual’s support for that policy.^{27, 28}

The “either policy” indicator captures the extent to which respondents dislike any policy, regardless of its specific cost or benefits.²⁹ Support for “either policy” varies systematically with age, reaching a minimum at about age 58. This may coincide with a point in the lifecycle of

²⁷ This type of systematic variation is commonly called “theoretical construct validity.” If estimated preference parameters behave as one would expect, in a manner consistent with other windows on the respondent’s preferences, then we can have more faith that the estimated choice model is reflecting those preferences.

²⁸ On average, the survey respondents are less willing to pay for programs where a larger share of beneficiaries consists of seniors. We expected to find a similar effect of the analogous follow-up question about the individual’s desired share of the million-dollar budget to senior citizens (based on the above question) on the effect of the “percent treated who are seniors” variable. However, this effect was not statistically significant.

²⁹ The “ethnic/immigrant composition of the community” variables discussed above are also implicitly interacted with this “either policy” indicator and thus could be discussed as part of this category as well. However, we discuss them along with the self-interest variables because they reflect the mix of beneficiaries for the policy in the community, beyond the respondent and his/her family.

many households where college costs for children have depleted people's savings, the current or future costs of caring for aging parents are a concern, and respondents are facing the prospect of their own impending retirement, so they may be less willing to incur additional tax obligations for any good cause.³⁰

Women appear to be systematically more inclined than men to support any of these publicly funded treatment policies. Respondents who identify themselves as black are more willing to support *any* type of treatment policy than are whites or other racial or ethnic groups. This “any policy” effect offsets the lesser influence for black respondents of the number of avoided premature deaths per year, described earlier. Perhaps minority groups and women are less likely to have high-quality health insurance and are therefore more likely to rely upon publicly provided treatment programs. Alternatively, they may be more sensitive to the fact that others in their community must do so.³¹

In the follow-up questions on the survey, respondents were asked their opinions about the role of government in the regulation of risks. This is not a question specifically about whether tax dollars should be used to provide health care, but it is likely to reveal attitudes towards government participation in healthcare provision:

People have different ideas about what their government should be doing. How involved do you feel the government should be in regulating environmental, health and safety hazards?

A rating scale of 1 through 7 was offered, with 1 being “minimally involved” and 7 being “heavily involved.” There is no statistically discernible difference across respondents with

³⁰ Stanford University et al. (2010) find that 52% of people believe that the new health care law will probably cause most people to pay more in taxes this year (question CST7B), and 72% believe most people will pay more in taxes five years from now (question CST7D).

³¹ Stanford University et al. (2010) find that 56% and 60% of people believe the new health care law will cause most black Americans and Hispanic Americans, respectively, to get better health care (questions WR6 and WR7). About 65% think it will cause most people with low incomes to get better health care (question WR8A), and about 58% think it will cause illegal immigrants to get more health care (question WR5).

ratings of 1 through 4 inclusive (where 4 was the implicit “moderate” (middle) category).³² For each of the three highest categories for levels of government involvement, however, we find that support for *any* type of treatment program, regardless of its cost or benefits, is statistically significantly higher and increasing with a stronger preference for government intervention.³³

The survey also asked a follow-up question about how, as governor, the respondent might choose to allocate \$100 million dollars to policies which improve health. One category was prevention for “at risk” individuals, another was reduction in exposure to risk, and a third was to provide treatment for those who are already ill or injured. We use this last share to assess the theoretical construct validity of our estimates with respect to the autonomous utility from “either policy.” Support for any type of publicly funded treatment program is greater if the individual would, as governor, devote a greater share of health care resources to treatment as opposed to different kinds of prevention.

Our final substantive variable is an indicator for whether the individual is a current smoker. In the policy choice model in Table 4, adding a smoking status variable has no discernible effect on policy preferences beyond what is already being captured by the self-interest variables which summarize the extent to which each type of treatment policy is likely to benefit the individual or their family members. In the online Appendix, however, we demonstrate that if the four self-interest dummy variables are suppressed, smokers are revealed to derive statistically significantly smaller utility from avoided premature deaths, but greater utility from *any* treatment policy, regardless of its specific attributes. In the *discounting* submodel that corresponds to the policy-choice model in Table 4 (where that policy-choice submodel includes

³² Only about 15 percent of the sample chooses a rating of 3 or less. Roughly 31 percent of the sample chooses a rating of 4 or less. About 21 percent choose a rating of 5, 20 percent choose 6, and 27 percent choose 7.

³³ Stanford University et al. (2010) find that 28% of respondents oppose the new U.S. health care law because they think “the federal government should not be involved in health care at all” (question HC1A). About 55% expressed a preference for a “small federal government providing few services” (question GV1).

the self-interest variables), the smoking status variable still has a statistically significant positive effect on the estimated discount parameter, which is estimated jointly from both the policy choices and the lottery-winnings choices.³⁴

Another incidental variable in the policy choice submodel is an indicator for the first choice among the five policy choices that each respondent was asked to consider. On the first choice occasion, perhaps because of the novelty of the choice task at that point, respondents were, on average, less likely to choose either policy, regardless of its attributes, confirming the slightly higher proportion in the simple marginal distribution of choices in Table 2. Subsequent choices, however, are not statistically different from each other in this regard.³⁵

Finally, our jointly estimated model also employs two types of incidental sample-selection variables. We use the fitted values from two prior selection models that explain presence of an observation in our estimating sample relative to the entire roughly half-million initial panel recruiting contacts by Knowledge Networks (one selection model applies to the policy choices, and another selection model applies to the larger number of discounting choices).³⁶ These comprehensive response/non-response models are designed to mitigate any systematic selection into the Knowledge Networks panel, as well as self-selection by invited

³⁴ These estimates appear in Table 1-2 in the online Appendix.

³⁵ The first choice different from the others in that the attributes of its alternatives, different for each respondent, were also used to populate the tutorial section for each respondent, where each attribute was described and explained carefully. In subsequent choices, there is also the difference that respondents learn the nature of the debriefing questions after the first choice, and may be induced to take these further considerations more into account as they contemplate the other choices. The debriefing questions after each choice included a rating of the difficulty of the choice, the question about direct benefits “to you or your family,” and (if the individual chose “neither policy”) the reminder of set of possible reasons why they might have done so and the invitation to indicate which reasons were most relevant for them.

³⁶ The two $\Pr(\text{selection})$ variables, and the two means from which they are deviated, are thus somewhat different (for the policy choice and discounting submodels). Missing data precludes estimation of the selection models in some cases, so we also include indicators for the availability of each type of selection variable. These are not the standard regression-type Heckman selection-correction procedures. These specifications only illustrate the extent to which systematic selection *could* influence key parameter estimates. Given the highly nonlinear and non-standard form of the log-likelihood function for our joint model, conventional packaged selectivity-correction approaches are inappropriate.

panelists into the final estimating sample.³⁷ We express these selection probabilities as deviations from the mean probability, such that counterfactual simulation of the mean probability for everyone corresponds to a zero value for this variable.

4.1.1 Willingness to Pay Estimates

The policy choice submodel in Table 4 can convey a great deal of information about the ways in which popular support for alternative public treatment policies might vary with the attributes of these policies and with the characteristics of the constituency. However, we have been careful to frame our models in such a fashion that we can also use them specifically to infer estimates of people’s willingness to swap other goods and services—i.e. their “willingness to pay” (WTP)—for the types of policies in question. Willingness to pay for a publicly funded health treatment policies will vary systematically with the attributes of the particular policy and the characteristics of the consumer in question. In Section 3.2 (and in the online Appendix), we explain the strategy for solving the formula implied by the estimates in Table 4 to yield the corresponding inverse demand function. Equation (4) involves the β parameter in the denominator. Further, the systematically varying hyperbolic discounting parameter b_i also enters the WTP equation in a highly nonlinear fashion because of the $d_{ij}(t | T_{ij})$ term. Thus we approximate the precision with which each WTP amount is estimated by making 1000 draws from the asymptotically normal joint distribution of the full set of maximum likelihood parameters. We calculate WTP for each draw and build up a sampling distribution for WTP

³⁷ These models use several classes of variables assigned via GIS matching of telephone exchanges to census tracts from the 2000 U.S. census. Of necessity, random-digit dialed households are assigned the characteristics of their census tracts, rather than the characteristics of the particular household, but this model reveals many dimensions of systematic selection into our estimating sample. Fortunately, these seem to be minimally related to treatment policy preferences or individual discount rates.

under the specified conditions. The precision of the parameter estimates reported in Table 4 is thus incorporated into the interval estimates for WTP reported in Table 5.

In this paper, we concentrate on the implications of our fitted model for the *marginal* willingness to pay (MWTP) for increased recoveries, avoided premature deaths, and the other explicit attributes of the treatment programs proposed to the survey's respondents. An infinite number of different policies could be considered, so we will convey the implications of our fitted model with a few selected illustrations. In these simulations of MWTP distributions, we will assume (unless otherwise specified) that all continuous variables involved are set to their sample means and all of the indicators for sociodemographic characteristics of the respondent are set to the omitted categories. Note, however, that not all of these variables enter into every MWTP formula. Only those individual characteristics which shift the discount factor or the specific marginal utilities involved in a particular MWTP calculation will have any influence on these simulated MWTP values.

We focus on various MWTP calculations for a baseline group defined as follows:

- Information about increased recoveries was provided, rather than suppressed
- Individual is male, non-black, non-Hispanic, and a non-smoker
- This is not the initial choice for a respondent, but a subsequent choice
- A fitted sample selection probability is available, but it coincides with the sample mean of fitted selection probabilities
- Education consists of high-school graduation through some college
- Policy duration is four years

Additional variables which enter our model have baseline categories and differentials which act to shift the coefficient on the indicator for "either policy." However, these variables will *not* be relevant to the calculation of MWTP amounts for the specific policy attributes of increased recoveries and avoided premature deaths. These other baseline categories are:

- "Very little" direct benefit to self or family is expected from the policy

- Individual believes government should be only moderately (or less) involved in reducing environmental, health and safety risks
- The eligible population is 1 million “people living around” the respondent

We note that the parameter estimates in Table 4 suggest that the marginal utility from avoided premature deaths is markedly smaller for blacks than for non-blacks. Also, the marginal utility from a policy that deals with an illness or injury with which more people are afflicted is much less for women than for men. In both cases, the differential is sufficient to overwhelm the baseline coefficient. This does not, however, imply that *total* WTP for any of the offered policies would be negative for these subgroups because blacks and females are willing to pay more for any policy, regardless of its attributes. This generally greater willingness to support any policy, in the case of blacks, is even sufficient to counteract the baseline status quo effect captured by the negative intercept term of the systematically varying θ parameter in Table 4.

Table 5 summarizes the results of a variety of simulations to illustrate the MWTP for different policy attributes. The online Appendix contains additional graphs of the age profiles for many of these MWTP estimates. In Simulation 1, we show that MWTP for the first avoided premature death is about \$20—greater than MWTP for the first increased recovery, which is about \$15. Simulation 2 shows that if we suppress the self-interest variables and permit smoking status to shift more of the marginal utility parameters, we find that non-smokers are more willing to pay to prevent community premature deaths than smokers (although smokers are more willing to pay for *any* public program to treat illnesses or injuries, regardless of the number of premature deaths that might be avoided).

Simulations 3 and 4 demonstrate our strong evidence for diminishing marginal willingness to pay for a policy as the number of recoveries and avoided premature deaths increases. MWTP drops from about \$15 for the first recovery to only about \$0.30 for the 100th

recovery. Likewise MWTP drops from about \$20 for the first avoided community premature death to about \$0.40 for the 100th avoided premature death. There is clearly diminishing marginal utility in premature deaths avoided via any single policy. This suggests that people are likely to derive greater utility if limited resources are spread across a diversity of smaller treatment policies, rather than being spent entirely on one large policy.

These results are provocative. Commonly used measures of the value of a “statistical” life (VSL) have been in the neighborhood of \$7 million, and readers will be inclined to wonder how our individual MWTP estimate of \$20 for the first avoided community premature death can be compared with standard VSL numbers. If we aggregate this \$20 amount across one million people living around the respondent, this would be \$20 million to avert one premature death in this community. VSL estimates, however, typically reflect the aggregate of individual willingness-to-pay amounts for tiny reductions in personal risks of death, aggregated across the risk reductions of a sufficient number of people to cumulate a 1.0 chance of somebody in that group dying. Our numbers, in contrast, refer to the certain death of one already-sick person in a relatively small group of patients localized within a community of 1 million or fewer people living around the respondent. We suspect that this enhances the “poster child” effect that is so successful in fund-raising ventures. People are more willing to pay to help specific, identifiable victims than they are willing to pay to help anonymous beneficiaries.

Simulations 5 and 6 show how willingness to pay depends on the age distribution of beneficiaries. WTP to help sick children decreases as people get older. While 30-year-olds have a MWTP per “proportion treated who are children” of about \$7, this amount falls to just \$4 for 70-year-olds. This striking pattern is also depicted in the graph in Figure 3. In contrast, if the

proportion treated who are seniors goes up, people are *less* willing to pay for a public program to treat illnesses or injuries, and this amount changes very little with the age of the respondent.

Simulation 7 demonstrates that the prevalence of the illness in question also matters to a certain extent. Consider each 1000 people in the community who are afflicted by the illness or injury in question. If 1000 more people are afflicted, respondents are willing to pay, on average, about \$0.08 more per year for the program, all else equal. This effect is very small, but still statistically significant.³⁸

Simulation 8 illustrates that attitudes about how government expenditures on health care should be allocated across age groups are strongly correlated with the effects of “the proportion treated who are children” on WTP for treatment policies. Figure 4 depicts graphically this strong evidence for theoretical construct validity of the MWTP estimates we derive from the survey respondents’ stated policy preferences.

Simulation 9 shows the influence of income on a variety of the MWTP estimates considered in the earlier simulations. Rather than median income (\$45,000), we assess MWTP for the first increased recovery, first avoided premature death, with respect to the proportions treated who are children or seniors, and per 1000 afflicted persons. We calculate these simulated MWTP amounts at the lower and upper quartiles of the *income* distribution and illustrate, for example, that MWTP for the first recovery at the first and third income quartiles is about \$10 and \$24, whereas MWTP for the first avoided premature death is about \$13 and \$31.³⁹

In Simulation 10 in Table 5 we show the effect of different policy durations. We replicate Simulations 5, 6, and 7 for a four-year policy commitment and for a twenty-year policy

³⁸ If a common illness like coronary heart disease affects, say 7% of the adult population, this would be about 70,000 people in a population of 1 million. If the same MWTP applied for all of these afflicted people, annual WTP would be on the order of \$5.60 per person per year for public treatment policies for this disease.

³⁹ This information is gleaned from the fitted profiles of MWTP documented in Figure 11-5 in the online Appendix.

commitment. Even controlling as much as possible for individual-specific discounting, as we do in this study, policies that involve longer time commitments are less desirable. For the selected cases in simulation 9, the longer time commitment appears to decrease annual WTP by about one-half, except for the MWTP for the first increased recovery or the first avoided premature death.⁴⁰

Figure 5 illustrates specifically the effects on WTP of the proportion of immigrants in the respondent's county, measured three different ways, and how these effects on WTP differ as a function of the ethnic fractionalization of the county.

5 Conclusions

There are several notable empirical results in this research. Our general population sample, with adjustments for sample selection, increases our confidence that these results are representative of the U.S. population. First, there appears to be substantial aversion to all types of publicly funded health treatment programs, regardless of their cost to the respondent or the specific public benefits the policies would provide. We impute that much of this “status quo” (or “either policy”) effect stems from the fact that the payment vehicle was described as an increase in taxes. If the same policy (at the same individual cost) could have been provided via some other payment mechanism, willingness to pay might have been different. This status quo bias against either policy in our choice scenarios is greatest for respondents in their late fifties or early sixties, depending upon the specification.

A second significant insight from this survey is that self-interest is a remarkably powerful determinant of individuals' willingness to pay for publicly funded health treatment policies.

⁴⁰ If the longer-running policies involved capital projects, of course, it may be that respondents anticipate up-front costs but benefits that would start later, when the capital project was completed. In this study, we must assume that people expected benefits of longer-term programs to begin at the same time as for policies that involve shorter commitments.

People are basically selfish. Our evidence suggests that they don't want to spend their tax dollars on policies that will only help people other than themselves or their families. Willingness to pay is unlikely to be greater than zero when a policy confers no anticipated private benefits.

However, when anticipated private benefits to the individual or his/her family are substantial, predicted willingness to pay for publicly funded treatment policies can be very, very high.

It is also notable that ethnic fractionalization in the community of beneficiaries, per se, does not have a uniformly negative effect on WTP, as some prior literature suggests for other types of public goods. Instead, the rate of English proficiency, the proportion of citizens versus non-citizens, and the proportion of recent immigrants all have a statistically significant effect on WTP for these policies. However, ethnic fractionalization determines the *signs* of the effects of these immigration-related variables. In ethnically *homogeneous* communities, people appear to be more willing to pay for public treatment policies when a larger share of their community has low proficiency in English or resided outside the U.S. in 1995, but they are less willing to pay when there are relatively more non-citizens in their community. Ethnically fractionalized communities do the opposite. Their willingness to pay for public treatment policies declines when the people around them have lower English proficiency or are recent immigrants to the U.S. However, they are more willing to pay for public treatment policies if relatively more people in their communities are non-citizens. A more thorough investigation of these observed regularities may require further research.

Aside from the dominant roles of status quo effects and self-interest in determining WTP for public health treatment policies, several of the specific attributes of public health policies described in each of our choice sets prove to make statistically significant contributions to people's WTP for these policies. Respondents can certainly discriminate readily between policies

with different scopes: numbers of increased recoveries and avoided premature deaths certainly matter. So do the numbers of people afflicted by the illness or injury, and the size of the population eligible to participate in the public treatment program in question.

The characteristics of the respondent matter to their support for publicly funded treatment policies. There is evidence to suggest that race, gender and age matter to the individual's level of support for these policies, and education and smoking status have additional effects via their influence on our estimates of individual time-preference parameters.

The types of beneficiaries also matter. The proportion treated who are children affects support for these policies—more so for people who would choose to target a greater share of state-level health-care expenditures towards children. However, there is lower support for public policies that help more seniors, perhaps reflecting a sentiment that seniors already benefit from Medicare.

The array of treatment policies we invite respondents to consider vary in the durations of commitment they would require. Even controlling for estimated and systematically varying individual differences in discounting behavior, as we do in this paper, we find that people are less willing to support long-term policy commitments than short-term commitments.

We have also indicated, in several footnotes to our paper, that the general tendencies we have identified in our utility-theoretic model used to estimate WTP for public health treatment policies appear to be supported by other empirical evidence. In particular, we cite the findings of an Associated Press survey by Stanford University et al. (2010) concerning the public's attitudes towards the health care reform law recently passed in the U.S.

Finally, any effort to assess willingness to pay for health-related policies will generate curiosity about how our dollar-denominated point estimates of willingness to pay for different

types of treatment policies might compare to current numbers adopted for the value of a “statistical” life (VSL) in formal benefit-cost analyses of public policies. Such a comparison is not really appropriate. Standard VSL numbers typically pertain to willingness to pay to reduce the risk of sudden death in the current period, commonly among healthy populations of workers, and pertaining to their own personal mortality *risk* levels. Our numbers are not conformable with VSL estimates because our estimates reflect the general population’s willingness to pay to improve the health outcomes of *other* people who are *already sick*. VSL estimates are also typically assumed to be proportional to the size of the risk reduction. In our model, willingness to pay is definitely *not* proportional to the number of increased recoveries or avoided premature deaths among these patients. This marked non-proportionality does, however, imply a strong demand for diversification in publicly funded medical treatments.

Overall, this study has explored a number of patterns in popular support, and thus willingness to pay, for publicly funded health care policies—a topic of considerable relevance in this era of debate over health care reform. If the public component of health care is to expand in the U.S., it will be important to understand, more fully, social preferences with respect to publicly provided health care. Given the tone of the recent health care debate in the U.S., it is unsurprising to find that there is considerable aversion, in the general population, to the prospect of “paying for socialized medicine.” The massive influence of self-interest in willingness to pay for alternative policies is also consistent with observed patterns of support for publicly versus privately provided health care in current healthcare debates.

Figure 1 – Sample Policy Choice Question

Recall that these two policies will be implemented for the 500,000 people living around you. Below we describe how many of these people get sick and die, with and without these policies.

Would you be most willing to pay for Policy A, Policy B, or neither of them?

	Policy A	Policy B
	treats children, adults, and seniors (25/25/50 mix) who have leukemia	treats seniors who have heart disease
How many Policy will affect, and when	700 will get sick over 30 years	10,000 will get sick over 4 years
Increased Recoveries	25 more full recoveries	50 more full recoveries
Deaths prevented	5 fewer deaths over 30 years	5,000 fewer deaths over 4 years
Cost to you	\$6 per month (= \$72 per year for 30 years)	\$35 per month (= \$420 per year for 4 years)
Your choice	☐ Policy A treats children, adults, and seniors (25/25/50 mix) who have leukemia	☐ Policy B treats seniors who have heart disease
	☐ Neither Policy	

Figure 2 –Fitted point estimates of WTP from preliminary ad hoc specification (note the strong dependence of WTP on the subjective self-interest ratings—the five levels of likely benefits of the policy to the individual or his/her family)

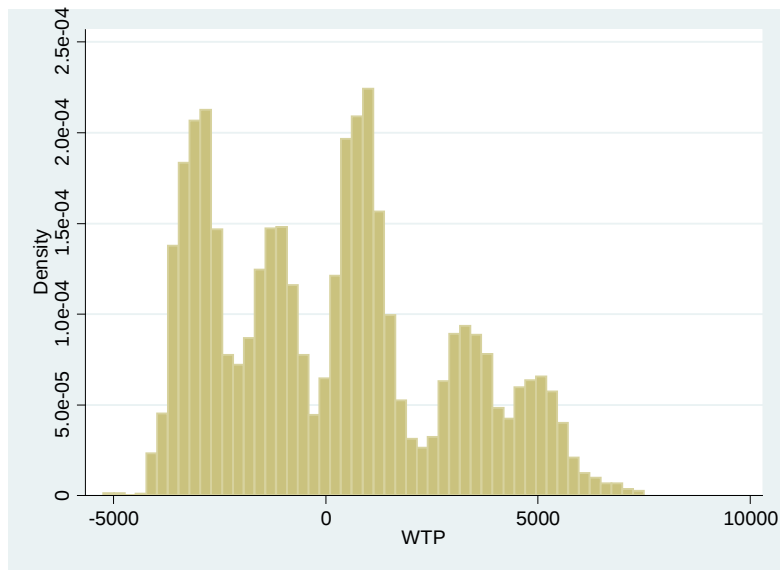


Figure 3 - MWTP as a function of respondent age
(Simulation 5 in Table 5)

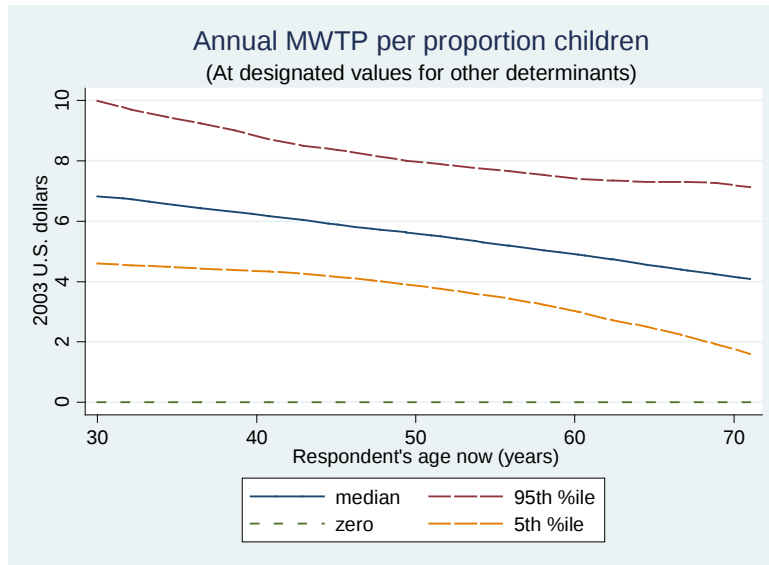


Figure 4 - Effect of proportion of \$100 million government expenditure preferred for children on MWTP for proportion of children helped (Simulation 8 in Table 5)

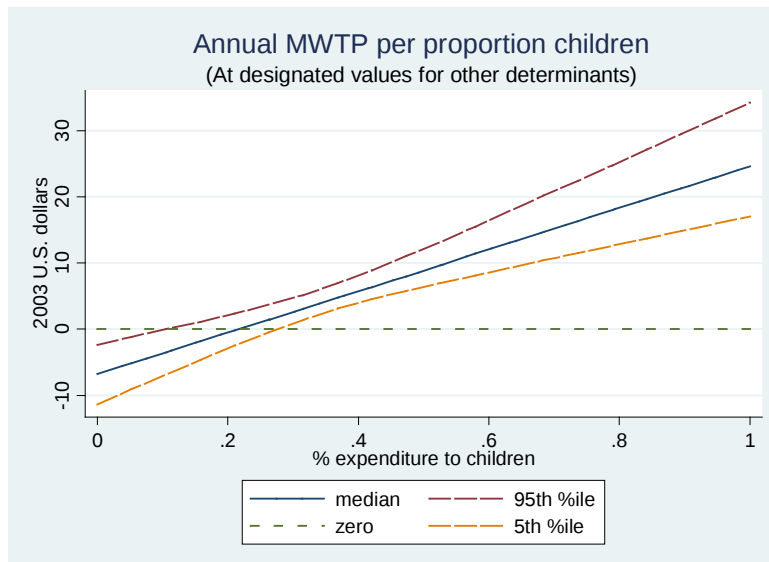


Figure 5 –Effects of ethnic fractionalization on the extent to which immigration-related variables influence TWTP.

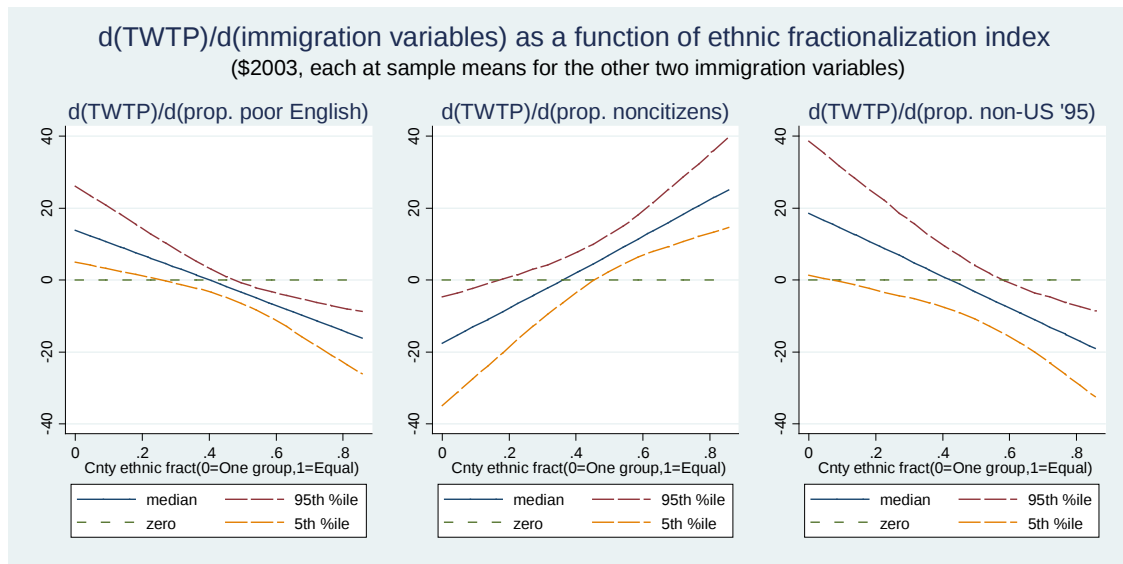


Table 1 - Descriptive statistics for policy choice submodel

Variable	Mean/prop	Std.dev.	Min	max
<i>Policy attributes (11,750 policies)</i>				
c_{ijt} = policy cost (\$2003, annual)	497	346	60	1200
c_{ijt} = policy cost (\$2003, monthly)	41.4	28.8	5	100
T_{ij} = policy duration (years)	13.8	9.71	2	30
$1(\text{no recovery info}_i)$	0.293			
$recyr_{ijt}$ = increased recoveries (per year) ^a	130	358	0	2500
$dthyr_{ijt}$ = avoided premature deaths (per year)	83.9	277	0	2500
$\#afflicted_{ij}$, ('000, over duration of policy)	8.55	6.91	0.1	20
$\%treated_{ij}$ = children	10.8	26.9	0	100
$\%treated_{ij}$ = seniors	45.3	42.0	0	100
$1(\text{population}_i = 500,000)$ (vs. 1 million)	0.492			
$1(\text{population}_i = 100,000)$ (vs. 1 million)	0.00357			
<i>Self-interest in policy</i>				
$1(\text{own benefit}_{ij} = 1)$ "very little" (omitted category)	0.323			
$1(\text{own benefit}_{ij} = 2)$	0.172			
$1(\text{own benefit}_{ij} = 3)$	0.291			
$1(\text{own benefit}_{ij} = 4)$	0.129			
$1(\text{own benefit}_{ij} = 5)$ "greatly"	0.085			
<i>Ethnic/immigrant composition of community (1315 respondents)</i>				
$1(\text{have county data}_i)$	0.924			
county ethnic fractionalization index _i ^b	0.387	0.218	0	0.856
county proportion speak English "not well" _i ^b	0.072	0.076	0	0.385
county proportion noncitizens _i ^b	0.058	0.061	0	0.272
county proportion non-U.S. in 1995 _i ^b	0.026	0.020	0	0.106
<i>Sociodemographic variables (1315 respondents)</i>				
Y_{it} = income _i (annual \$'000)	49.4	34.1	2.5	200
age _i (years)	49.7	15.5	24	93

$1(\text{female}_i)$	0.531			
$1(\text{black}_i)$	0.087			
<i>Attitudinal variables (1315 respondents)</i>				
$1(\text{govt}_i = 5)$	0.218			
$1(\text{govt}_i = 6)$	0.198			
$1(\text{govt}_i = 7)$: “heavily involved”	0.259			
%expenditure to children _i	0.398	0.138	0	1
%expenditure to treatment _i	0.351	0.151	0	1

^a Increased Recoveries summary statistics are reported for the randomly selected 71% of respondents (i.e. 8620 policies) where the number of avoided illnesses was shown in addition to the number of avoided premature deaths as part of an experimental framing treatment.

^bConditional on availability of county data (1215 respondents).

Table 2 - Alternatives chosen, overall and by choice set: counts and row percentages

	Policy A	Policy B	Neither Policy	Total
Overall	1,929 32.83 %	1,843 31.37 %	2,103 35.8 %	5,875 100 %
Choice Set 1	380 32.9 %	325 28.14 %	450 38.96 %	1,155 100 %
Choice Set 2	362 30.97 %	401 34.3 %	406 34.73 %	1,169 100 %
Choice Set 3	405 33.95 %	373 31.27 %	415 34.79 %	1,193 100 %
Choice Set 4	374 32.08 %	367 31.48 %	425 36.45 %	1,166 100 %
Choice Set 5	408 34.23 %	377 31.63 %	407 34.14 %	1,192 100 %

Table 3 - Percent choosing Neither Policy, with Pearson chi-squared test p-values

Variable	Category 1	Category 2	Pearson Chi-squared p-value
Presence of children	No children 36.90 %	With children 33.24 %	0.007**
Age	< 65 years 35.45 %	>= 65 years 37.40 %	0.233
Could improve health by smoking less?	No 36.85 %	Yes 33.55 %	0.014**
Gender	Male 33.69 %	Female 37.66 %	0.002**
Income	< 37,500 39.92 %	>=37,500 33.14 %	0.000**
Single	No 36.04 %	Yes 34.52 %	0.375
Education	<=high school 38.31 %	>high school 35.42 %	0.122
Nonwhite	No 37.19	Yes 30.41	0.000**
Play lotto?	No 40.21	Yes 33.69	0.000**

Table 4 – Estimation results for the policy choice submodel of the jointly estimated policy choice and discounting specification; Box-Cox specification; heterogeneous preferences (see online Appendix for discounting submodel)

Coefficient Name	Constructed Variable	Estimate (t-stat.)
<i>Net income terms</i> ^a		
$\log(\beta_{\text{Box-Cox}})$	$\left[\frac{\left(\frac{Y_{it} - c_{ijt}}{10000} \right)^\lambda - 1}{\lambda} - \frac{\left(\frac{Y_{it}}{10000} \right)^\lambda - 1}{\lambda} \right] d_{ij}(t T_{ij})$	0.82 (6.94)***
λ	Box-Cox parameter (in above transformation)	0.496 (27.98)***
<i>Increased recoveries and avoided premature deaths per year</i>		
δ_1	$\left[\frac{\log(\text{recyr}_{ijt} + 1) - \log(1)}{1000} \right] d_{ij}(t T_{ij})$	15.8 (4.87)***
δ_{2i}	$\left[\frac{\log(\text{dthyr}_{ijt} + 1) - \log(1)}{1000} \right] d_{ij}(t T_{ij})$	20.5 (5.42)***
	... $\times 1(\text{no recovery info}_i)$	12.2 (2.38)***
	... $\times 1(\text{black}_i)$	-38 (-3.19)***
<i>Self-interest indicators (nonzero/different only for the two programs, zero for the status quo)</i>		
δ_{32}	$1(\text{own benefit}_{ij} = 2)$	0.781 (9.85)***
δ_{33}	$1(\text{own benefit}_{ij} = 3)$	1.52 (22.13)***
δ_{34}	$1(\text{own benefit}_{ij} = 4)$	2.48 (30.12)***
δ_{35}	$1(\text{own benefit}_{ij} = 5)$	3.06 (29.26)***
<i>Ethnic/immigrant composition of community</i>		
δ_{36}	$1(\text{have county data}_i)$	-0.245 (-1.43)
δ_{37}	county proportion speak English "not well" _i	14.8 (2.45)***
δ_{38}	county proportion noncitizens _i	-19 (-2.03)**
δ_{39}	county proportion non-U.S. in 1995 _i	19.3 (1.65)*

$\delta_{3,10}$	<i>Ethnic fractionalization index_i</i>	0 ^b
$\delta_{3,11}$	$\dots \times \text{county proportion speak English "not well"}_i$	-36.9 (-3.12)***
$\delta_{3,12}$	$\dots \times \text{county proportion noncitizens}_i$	52.7 (3.07)***
$\delta_{3,13}$	$\dots \times \text{county proportion non-U.S. in 1995}_i$	-45.5 (-2.46)***

Number of people afflicted (nonzero only for the two programs, zero for the status quo)

δ_{4i}	$\left(\frac{\log(\# \text{afflicted}_{ij})}{100} \right)$	8.34 (3.06)***
	$\dots \times 1(\text{female}_i)$	-9.42 (-2.62)***

Beneficiary mix (nonzero only for the two programs, zero for the status quo)

δ_{5i}	$\left(\frac{\% \text{treated}_{ij} = \text{children}}{1000} \right)$	-3.25 (-0.89)
	$\dots \times (\text{age}_i / 100)$	-8.2 (-1.54)
	$\dots \times (\% \text{expenditure to children}_i)$	33 (5.43)***
δ_6	$\left(\frac{\% \text{treated}_{ij} = \text{seniors}}{1000} \right)$	-2.23 (-3.95)***

"Either policy" effect (complement of a status quo effect)

θ_i	$1(\text{either policy}_j)$	-0.82 (-1.86)*
	$\dots \times (\text{age}_i / 100)$	-4.2 (-3.27)***
	$\dots \times (\text{age}_i^2 / 10^4)$	3.57 (2.93)***
	$\dots \times 1(\text{female}_i)$	0.559 (1.79)*
	$\dots \times 1(\text{black}_i)$	1.05 (6.42)***
	$\dots \times 1(\text{govt}_i = 5)$	0.246 (2.95)***
	$\dots \times 1(\text{govt}_i = 6)$	0.338 (3.86)***
	$\dots \times 1(\text{govt}_i = 7)$	0.598 (7.10)***

$\dots \times 1(\text{population}_i = 500,000)^b$	-0.152 (-2.45)***
$\dots \times 1(\text{population}_i = 100,000)^b$	-0.751 (-1.35)
$\dots \times (\% \text{expenditure to treatment}_i)$	0.608 (2.95)***
$\dots \times 1(\text{choice number}_i = 1)$	-0.29 (-3.79)***
$\dots \times 1(\text{have selection prob}_i)_p$	-0.405 (-1.68)*
$\dots \times \left(\Pr(\text{selection}_i) - \overline{\Pr(\text{selection})} \right)_p$	-60.4 (-2.17)**

Hyperbolic discounting parameter b_i (where $d_{ij}(t | T_{ij}) = \sum_{t=0}^{T_{ij}-1} (1+t)^{-b_i}$ above):

See Appendix

Policy choice sets	5,717
Max LogL	-23050.090

^a These parameters are shared by both the policy choice and discounting submodels. Both submodels are estimated simultaneously in one maximum likelihood specification.

^b The coefficient on the fractionalization variable, if it is included in the specification, is -0.025 with an asymptotic t-test statistic of only -0.08, so we constrain this coefficient to zero.

^c These two attributes are actually unique to each choice set, not merely to each individual.

Table 5 – Summary of simulated WTP amounts (for 1000 random draws from joint distribution of MLE estimates, based on parameter point estimates and variance-covariance matrix)^a (See corresponding figures in the online Appendix.)

Simulation:	50 th (5 th to 95 th) percentiles of MWTP	Comments
1. Annual MWTP		
Per first increased recovery	\$15 (\$10 to \$24)	Minimal age profile based on discounting function
Per first avoided premature death	\$20 (\$14 to \$28)	
2. “Self-interest” indicators in Table 4 mask the effects of smoking status on MWTP. Alternative specification reported in the online Appendix drops the self-interest indicators. Smoking status then affects MWTP for avoided premature deaths. MWTP for smokers is lower, but they are willing to pay more for any treatment program, which offsets this effect.		
Per first avoided premature death	\$23 (\$14 to \$32)	For non-smokers
Per first avoided premature death	\$18 (\$12 to \$26)	For smokers
3. Declining MWTP <i>per additional recovery</i> at different baseline recoveries		
At 1 recovery	\$15 (\$10 to \$24)	Profile reflects best-fitting shifted logarithmic transformation
At 10 recoveries	\$2.90 (\$180 to \$4.20)	
At 100 recoveries	\$0.30 (\$0.20 to \$0.47)	
4. Declining MWTP <i>per additional avoided premature death</i> at different baseline numbers of premature deaths		
At 1 avoided premature death	\$20 (\$14 to \$28)	Profile reflects best-fitting shifted logarithmic transformation
At 10 avoided premature deaths	\$3.80 (\$2.50 to \$5.10)	
At 100 avoided premature deaths	\$0.40 (\$0.24 to \$0.58)	
5. Age dependence in MWTP for any policy with respect to <i>proportion treated who are children</i>		
At 30 years old	\$7 (\$5 to \$10)	(See Figure 3)
At 70 years old	\$4 (\$2 to \$7)	
6. MWTP for any policy with respect to <i>proportion treated who are seniors</i>		
	-\$ 2 (-\$3 to -\$1)	I.e. negative marginal value; Minimal decrease with age
7. MWTP according to prevalence of illness		
Per 1000 afflicted persons in eligible population	\$0.08 (\$0.04 to \$0.15)	Increases very slightly with age (by about \$0.01 between 30 and 70 years)
8. MWTP per proportion treated who are children as a function of “share of \$100 million for treatment” that respondent would allocate to children (follow-up question)		
If 0 %	-\$7 (-\$11 to -\$2)	Supports theoretical construct validity (See Figure 4)
If 100%	\$24 (\$17 to \$32)	

Table 5, continued

Simulation:	50 th (5 th to 95 th) percentiles of MWTP	Comments
9. MWTP with respect to policy attributes for <i>different income levels</i>		
Income level:	25 th %ile (\$27,500)	75 th %ile (\$67,500)
Per first increased recovery	\$10 (\$7 to \$15)	\$24 (\$15 to \$38)
Per first avoided premature death	\$13 (\$9 to \$18)	\$31 (\$21 to \$44)
Per proportion treated who are children		
At 30 years old	\$4.20 (\$3 to \$6.20)	\$10 (\$7 to \$16)
At 70 years old	\$2.80 (\$1 to \$4.50)	\$6 (\$3 to \$11)
Per proportion treated who are seniors		
At 30 years old	-\$1.30 (-\$2 to -\$.70)	-\$3 (-\$5 to -\$.170)
At 70 years old	-\$1.40 (-\$2.20 to -\$.75)	minimal change
Per 1000 afflicted persons in eligible population	\$.055 (\$.02 to \$.09)	\$.13 (\$.06 to \$.22)
10. MWTP with respect to policy attributes for <i>policies of different durations</i> ^b		
Commitment period:	4- year commitment	20-year commitment
Per first increased recovery	\$15 (\$10 to \$24)	minimal change
Per first avoided premature death	\$20 (\$14 to \$28)	minimal change
Per proportion treated who are children		
At 30 years old	\$7 (\$5 to \$10)	\$3.50 (\$2.25 to \$5.25)
At 70 years old	\$4 (\$2 to \$7)	\$2.25 (\$1.00 to \$4.00)
Per proportion treated who are seniors		
At 30 years old	-\$2 (-\$3 to -\$1)	-\$1.00 (-\$1.70 to -\$0.60)
At 70 years old	-\$2.1 (-\$3.30 to -\$1.20)	-\$1.20 (-\$2.00 to -\$0.70)
Per 1000 afflicted persons in eligible population	\$0.08 (\$0.04 to \$0.15)	\$0.05 (\$0.02 to \$0.08)
	slight increase w/ age	

^a Unless otherwise specified, MWTP amounts are calculated, for continuous determinants, at the sample means of income, afflicted persons, shares of \$100 million preferred for children and for treatment policies, but one extra recovery and one avoided premature death, only adults being helped and a four-year program. For discrete determinants, the settings are the zero values of all of the indicators, except for the indicator for the presence of the selection-correction fitted probability.

^b Policy attributes are modeled in terms of recoveries and premature deaths *per year*, but as simple functions of the proportions of those treated in each age group and per 1000 afflicted person.

REFERENCES

- Alberini, A., 2005. What is a life worth? Robustness of VSL values from contingent valuation surveys. *Risk Analysis* 25, 783-800.
- Alesina, A., Baqir, R., Easterly, W., 1999. Public goods and ethnic divisions. *Quarterly Journal of Economics* 114, 1243-1284.
- Andersen, S., Harrison, G.W., Lau, M.I., Rutstrom, E.E., 2008. Eliciting risk and time preferences. *Econometrica* 76, 583-618.
- Arana, J.E., Leon, C.J., 2002. Willingness to pay for health risk reduction in the context of altruism. *Health Economics* 11, 623-635.
- Bosworth, R., Cameron, T.A., DeShazo, J.R., 2009. Demand for environmental policies to improve health: Evaluating community-level policy scenarios. *Journal of Environmental Economics and Management* 57, 293-308.
- Cameron, T.A., Poe, G.L., Ethier, R.G., Schulze, W.D., 2002. Alternative non-market value-elicitation methods: Are the underlying preferences the same? *Journal of Environmental Economics and Management* 44, 391-425.
- Chestnut, L.G., Rowe, R.D., Breffle, W.S., 2012. Economic valuation of mortality-risk reduction: Stated preference estimates from the United States and Canada. *Contemporary Economic Policy* 30, 399-416.
- Chilton, S., Covey, J., Hopkins, L., Jones-Lee, M., Loomes, G., Pidgeon, N., Spencer, A., 2002. Public perceptions of risk and preference-based values of safety. *Journal of Risk and Uncertainty* 25, 211-232.
- Cropper, M.L., Aydede, S.K., Portney, P.R., 1994. Preferences for life saving programs - how the public discounts time and age. *Journal of Risk and Uncertainty* 8, 243-265.
- Epper, T., Fehr-Duda, H., Bruhin, A., 2011. Viewing the future through a warped lens: Why uncertainty generates hyperbolic discounting. *Journal of Risk and Uncertainty* 43, 169-203.
- Frederick, S., Loewenstein, G., O'Donoghue, T., 2002. Time discounting and time preference: A critical review. *Journal of Economic Literature* 40, 351-401.
- Hammitt, J.K., Haninger, K., 2010. Valuing fatal risks to children and adults: Effects of disease, latency, and risk aversion. *Journal of Risk and Uncertainty* 40, 57-83.
- Harrison, G.W., Lau, M.I., Williams, M.B., 2002. Estimating individual discount rates in denmark: A field experiment. *American Economic Review* 92, 1606-1617.
- Laury, S.K., McInnes, M.M., Swarthout, J.T., 2012. Avoiding the curves: Direct elicitation of time preferences. *Journal of Risk and Uncertainty* 44, 181-217.

- Lavetti, K., Simon, K., White, W.D., 2014. Taxpayer willingness to pay for health insurance reform: A contingent valuation analysis. *Economic Inquiry* 52, 994-1013.
- Mrozek, J.R., Taylor, L.O., 2002. What determines the value of life? A meta-analysis. *Journal of Policy Analysis and Management* 21, 253-270.
- Silverman, I., 2003. Gender differences in delay of gratifications: A meta-analysis. *Sex Roles* 49, 451-463.
- Stanford University, Robert Wood Johnson Foundation, Knowledge Networks, 2010. The associated press health care reform survey.
<http://surveys.ap.org/data/KnowledgeNetworks/Health%20Reform%20Topline%20for%20Posting.pdf>.
- Subramanian, U., Cropper, M., 2000. Public choices between life saving programs: The tradeoff between qualitative factors and lives saved. *Journal of Risk and Uncertainty* 21, 117-149.
- Viscusi, W.K., Aldy, J.E., 2003. The value of a statistical life: A critical review of market estimates throughout the world. *Journal of Risk and Uncertainty* 27, 5-76.
- Warner, J.T., Pleeter, S., 2001. The personal discount rate: Evidence from military downsizing programs. *American Economic Review* 91, 33-53.
- Welsh, M.P., Poe, G.L., 1998. Elicitation effects in contingent valuation: Comparisons to a multiple bounded discrete choice approach. *Journal of Environmental Economics and Management* 36, 170-185.
- Woolhandler, S., Himmelstein, D., 2007. Competition in a publicly funded healthcare system. *British Medical Journal* 335, 1126-1129.