Choosing health versus wealth: a laboratory survey

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Summary

This study uses a laboratory survey to estimate consumer preferences over stochastic health and stochastic wealth. A contingent-valuation method is used to estimate willingness to accept cash in lieu of a less-than-certain treatment for a hypothetical disease. In a series of scenarios, subjects choose either Policy T (full insurance covering an expensive treatment) or Policy C (large unfettered lump-sum cash indemnity paid upon diagnosis).

46 subjects together make 3,505 choices. They choose Policy T more often when the treatment is more efficacious; when choosing for loved ones rather than for themselves; when choosing for themselves rather than for anonymous strangers and when *ex post* regret over the choice is likeliest, even when no differences exist in efficacy.

The results suggest a low-cost methodology for estimating health-wealth tradeoffs and a potential means of inducing consumers to self-limit use of high-cost, low-benefit treatments. The study is a pilot for a later field experiment and suggests possible contract structures for circumventing the tradeoff between risk-bearing and moral hazard. Several puzzles concerning interpersonal utility emerge from the results.

Introduction and literature review

Motivation and description

How much are individuals willing to spend for medical treatments with a low probability of success? Is that willingness systematically related to the probability? Are they willing to spend more on loved ones than on themselves or total strangers? Does fear of regret play a role in such choices? With these questions in mind, this paper uses a laboratory survey to examine the monetary value that individuals place on a high-cost, low-benefit medical treatment.

We postulate a choice between two insurance policies, one offering a high-cost medical treatment (Policy T) and the other paying a large cash indemnity (Policy C). Aside from our principal questions, motives for our survey include developing a prototype for a field experiment and suggesting a possible structure for health insurance contracts.

Our methodology seeks a way to circumvent the well-known tradeoff between moral hazard and risk-bearing in health care markets. Hanson notes that in such markets, consumers may spend well beyond the point where marginal cost exceeds marginal benefit [1]. Insured consumers lack the motive to reveal or even assess such tradeoffs [2] and insurance pays for most medical expenses [3]. This poses obstacles to economic research and leads to economic inefficiency.

Contingent Valuation Methodology

We use a contingent valuation method to estimate individuals' willingness to accept cash in lieu of a treatment that has a low probability of success. Our payoff structure is such that patients bear the marginal cost of a high-cost treatment, but without bearing the associated catastrophic financial risk. We accomplish this by offering healthy individuals a choice of Policy T (full insurance coverage of an expensive treatment) or Policy C (a large, unfettered lump-sum cash indemnity upon diagnosis). For simplicity, we concern ourselves only with a single hypothetical medical contingency.

With Policy C, consumers bear the marginal cost of a high-cost treatment without suffering the risk of catastrophic financial loss. In our survey, the disease and policies were abstract and hypothetical and the sample of subjects relatively small. Nevertheless, the responses were strongly consistent internally and comported well with economic logic. While healthy, the subjects were capable of signaling the marginal value they placed on a small probability of life.

Our paper fits into the contingent valuation literature that is emerging in health economics. Olsen et al. [4] describe the increased popularity of willingness-to-pay (WTP) studies in health economics as a means of conducting cost-benefit analyses. Diener et al. [5] review the literature on contingent valuation methods in health economics. Most of the papers they considered used willingness-to-pay, and only a few used willingness-to-accept (WTA). They note that many papers have shown WTA to be higher than WTP in seemingly identical circumstances. These issues have also been covered in Coursey et al. [6], Hanemann [7], and Shogren et al. [8].

The best known examination of the WTP approach was the RAND Health Insurance Experiment. RAND Researchers randomly provided families with insurance policies featuring different deductible and co-payment structures. They found that if consumers bore more of the marginal cost of treatment, they consumed less health care [9] and that this marginal reduction in health care expenditures had little or no effect on patients' health [10].

We recognize that the WTP-WTA disparity can be problematic. We adopt the WTA approach because it is well-suited for future field experiments and is a plausible way to value contingent contracts. We suggest later that health insurance policies incorporating lump-sum indemnities (a WTA method) may even be a practical means of controlling health care expenditures on high-cost, low-benefit treatments. The WTA approach also makes sense if one assumes that employer-based policies will insure against a particular illness, the only question being the particular structure of the insurance benefit. Later in this paper, we mention an actual policy, offered by Trigon Blue Cross Blue Shield of Virginia, which incorporated such a WTA structure into its insurance against certain lung cancers. One other virtue of a WTA structure is that it offers a way to force patients to bear the marginal cost of an expensive treatment without forcing them to bear the risk of catastrophic financial losses.

Prior Expectations about Relationships

Prior to data collection, we had expectations about the signs on many of the parameters. On others, we suspected a relationship but were unsure of the likely sign. Most of these expectations were supported, usually strongly, by the data, though there were several surprises. Following were our prior expectations: Subjects would choose the treatment policy (T) over the cash policy (C) more often when the treatment provided a higher probability of cure (higher efficacy rate). They would more frequently choose T over C for loved ones than for themselves; we were not sure how they would choose for anonymous strangers. They might be influenced by the proportion of the population that would recover without treatment (natural recovery rate). They would be more likely to choose T when *ex post* regret was likely; this would occur when treatment either assured survival or provided the sole chance of survival.

We expected a correlation of policy choice with marital and parental status, though we were uncertain as to the signs of these correlations. People with spouses and children might be more likely to choose T because of the desire to live to enjoy their families; they might also choose Policy C because of a bequest motive. We expected those with higher incomes to choose Policy T more often. When the policy was chosen for a loved one, we anticipated correlations with the loved one's demographic characteristics. And we expected some relationship with age. The age relationship might not be monotonic; conventional wisdom might suggest that young adults and older adults would choose cash over treatment more often than those in the middle years.

Comprehensive Summary of Findings

This study was a pilot experiment with a relatively small sample of respondents. Nevertheless, the findings this paper reports were robust. Magnitudes and signs of parameters changed relatively little across a variety of models. Specifications included parsimonious, fixed effect, and, full-variable set specifications. Two variables were given in logs, but non-log versions gave similar results. The following results generally held across regressions: Choice of the treatment policy (T) was positively correlated with the efficacy rate. They were more likely to choose T over C for loved ones than for themselves; they were even less likely to choose T for strangers. When choosing for loved ones, the choice of T or C is more inelastic with respect to the efficacy rate than when choosing for self or stranger. Decisions did appear to be influenced by the prospect of regret; subjects were more likely to choose T in the treatment-assures-survival and neglect-assures-death scenarios; this contradicts a simple rationality model, since the prospect of regret is unrelated to the efficacy of the treatment. Subjects were not significantly influenced by the natural recovery rate, as a simple rationality model would suggest.

In some regressions, males choose T over C more frequently than females do. This runs counter to the “macho” stereotype, wherein males are more hesitant than females to seek treatment. Married people and people with children were more likely to choose treatment. Those with higher income were *less* likely to choose T over C than those with lower incomes. Also, older subjects were more likely to choose T over C; we suspect this may be a function of the relatively young age distribution of our sample. The age effect was miniscule.

Subjects were more likely to choose treatment for a male loved one than for a female loved one. Again, the choice of the treatment policy was positively correlated with age, though the parameter was small.

Indemnity Policies

We should mention that the idea behind Policy C is not entirely fictional. Most health insurance today pays for medical services upon treatment, but policies paying lump-sum indemnities upon diagnosis do exist and have existed in the past. Arrow [11] mentioned such policies, and Feigenbaum [12] argues that they were once the dominant form of health insurance. Other papers discussing indemnity-based policies Pauly [13], Pauly [14], Gianfrancesco [15], and Graboyes [16]. Disability insurance and personal accident insurance pay lump sum indemnities in response to medical contingencies, as do “dread disease” policies [17]. Trigon [18] and Journal of the National Cancer Institute [19] describe an experimental policy that offered some cancer patients a choice of reimbursement for chemotherapy or a cash indemnity.

Survey and data

Survey construction

In modern medicine, large costs often purchase small probabilities of medical benefit. Because insurers cover most large medical expenditures, markets may tell us little about the marginal value consumers place on high-cost, low-benefit treatments. This paper uses a laboratory survey to generate evidence of such tradeoffs.

We wished to develop a low-cost, flexible estimation technique. This survey is a prototype for field experiments using actual contracts, custom-designed for research. A secondary aim is to suggest how insurance policies could simultaneously guard against catastrophic financial loss and still provide incentives for self-control on large health care expenditures.

We recognize that this survey is a coarse approximation of preferences among the general population. Our survey sample was small and nonrandom. Most participants were well-educated, relatively affluent, and connected in some way with a university. They were younger on average than the general population. The objective here was to develop a methodology that can later be applied to larger, more representative samples. An important question was whether participants, asked to make dozens of hypothetical life-and-death choices in a short period, would do so consistently and rationally. In this case, they did so.

There were four cohorts on four different evenings. Each heard and read the quantitative characteristics of a hypothetical Disease X, said to be relatively rare, potentially fatal, and possibly treatable. In dozens of randomly ordered scenarios, subjects chose between two hypothetical contracts: Policy T covered 100% of the costs of a medical treatment that would otherwise cost patients $350,000. Policy C paid a $250,000 lump-sum indemnity upon diagnosis.

The price of the policies was set at zero. Since we were only interested in the relative values respondents placed on the policies' payouts, unequal prices for the two policies would have confounded the results. For simplicity, we set the hypothetical price of each policy at zero. We did not wish to offer them the possibility of purchasing no policy. Any positive price would have been merely a sunk cost. It is conceivable that a sunk cost would affect the choice of policy, but whether that is so is a question for another paper. In another sense, though, a price of zero may be realistic. In real life, the choice of Policy C vs. Policy T could constitute a carveout from a broader health insurance policy. An example is the Trigon policy described earlier. In that case, policyholders of a conventional health policy were allowed to accept cash in lieu of conventional coverage of medical expenses; this option applied only to a small subset of contingencies. At the moment the offer was made, the policyholder was, in effect, offered a choice of cash vs. treatment at a marginal price of zero.

Three variables defined the scenarios. First was the efficacy rate – the proportion of sufferers who recover if and only if treated for Disease X. Second was the natural recovery rate – the proportion of sufferers who would recover whether treated or not. Third was the identity of the insured party who, in roughly equal numbers of scenarios, was either the survey participant himself, a pre-designated loved one, or an anonymous stranger.

Cohort 1 parameters

15 Cohort 1 subjects received the following instructions: Subjects live in a state with 5,000,000 people. Of these, 1,000 (0.02%) will contract Disease X in the next year. Therefore, 4,999,000 (99.98%) will not fall ill. Subjects heard and saw parameters for 27 scenarios, each of which was asked twice, for a total of 54 measured scenarios.

The efficacy rate for Cohort 1 was B/1,000, where B was the number of patients who benefit from treatment. B could be 2, 20, and 200, yielding efficacy rates of 0.2%, 2%, and 20%, respectively. To reinforce comprehension, subjects were presented with raw numbers

(B) and the efficacy rates during the trials. Initially, and periodically thereafter, the figures were also presented as percentages or fractions of the 5,000,000 residents (0.00004%, 0.0004%, and 0.004% or 1/2,500,000, 1/250,000, 1/25,000). Thus, participants visualized the probabilities that the treatment would benefit them, both before any diagnosis and after being diagnosed as ill.

The motivation behind these multiple presentation formats appears in Gigerenzer and Hoffrage [20]. They cite an insight by Feynman [21] that "mathematically equivalent information formats need not be psychologically equivalent." Gigerenzer and Hoffrage find that decisions made with frequency formats appear to yield behavior more consistent with Bayesian models than do decisions made with probability or percentage formats. We thought it best to use both to reinforce the magnitudes. In the verbal presentation, the frequency format was cited with each quotation. For brevity, the percentage format was only said aloud every fourth or fifth scenario; the percentage format, though, was always visible on the projection screen.

The natural recovery rate for cohort 1 was R/1,000, where R was the number of patients who recover naturally, with or without treatment. R could take one of three functional forms (0,500-B/2, and 1000-B). R=0 meant that any patient not treated was certain to die, a situation we will refer to as the neglect-assures-death scenario. R=1,000-B meant that any patient who was treated is certain to live, a situation we refer to as the treatment-assures-survival scenario. We examined these two scenarios on the assumption that fear of regret may influence medical decisions. The logic behind this regret is explored in the Conclusions and Discussion section.

W could be one of three individuals. In some scenarios, the subject was insuring himself or herself against Disease X. In other scenarios, the policyholder was a predetermined loved one. In the remainder, the policyholder was an anonymous stranger.

To further reinforce magnitudes and their ramifications, subjects periodically viewed the values of several other functions of B and R. R+B is the maximum number of patients who can survive – the number who survive if all 1,000 patients are treated. 1,000-R-B is the minimum number of deaths – those who will die even if all 1,000 patients are treated. Periodically, the researchers queried subjects to assure that the meaning of the parameters was understood.

Each of the 27 possible B-R-W combinations was asked twice, yielding 54 recorded scenarios. For each pair, subjects made their choice once in private and once in public by standing. We had thought that subjects might be more inclined to choose the treatment policy during public decisions because they might wish to appear to be caring. The two modes of selecting made little difference in subjects' choices, so later cohorts heard each scenario only once and recorded their choices privately.

There is no private information in this model. The choice of insurance policy is made before anyone falls ill. No one knows beforehand whether or not any specific policyholder will contract Disease X. No one knows beforehand whether, if ill, a policyholder will be certain to recover, certain to recover if and only if treated, or certain to die whether treated or not. All patients know all of these parameters at the time they make the insurance decision. Only in a treatment-assures-survival scenario, when R=1,000-B, does a doomed patient know after-the-fact that treatment would certainly have saved him. Only in a neglect-assures-death scenario, when R=0 does a dying patient know (too late) that treatment would have provided his only chance of survival.

A simple model of rationality could suggest that the efficacy rate should matter, but that the natural recovery rate should not. Nevertheless, we thought that subjects might be more inclined to choose Policy T in the treatment-assures-survival and/or neglect-assures-death scenarios in order to minimize the possibility of *ex post* regret.

Cohort 2, 3, and 4 parameters

After reviewing the data from Cohort 1, we decided in future sessions to increase the variability of the efficacy and natural recovery rates. We wanted to measure choices when the efficacy rate was much lower, and we wanted to include intermediate rates for both variables. Cohorts 2, 3 and 4 included scenarios meeting these goals. Because the variables were rates, we could combine the data from all four cohorts. Instead of one state with 5,000,000 people, the base population was now a region with 50,000,000 people. Of these, 10,000 would contract Disease X in the next year (0.02%, as in Cohort 1). Again, 99.98% (now 49,990,000) would not fall ill. To help subjects visualize these magnitudes, we presented a map of Florida, Georgia, South Carolina, North Carolina, Virginia, Maryland, and the District of Columbia – a region with close to 50,000,000 residents. We noted that a soccer stadium (near the building where the survey was conducted) seats approximately 10,000.

For these three cohorts, the number of those who would survive if and only if treated, B, could equal 2, 10, 20, 100, 200, 1.000, or 2,000. These numbers were presented to subjects as raw numbers, as percentages of the 10,000 patients (0.02%, 0.1%, 0.2%, 1%, 2%, 10%, and 20%), and occasionally as percentages or fractions of the 50,000,000 population (0.000004%, 0.00002%, 0.00004%, 0.0002%, 0.0004%, 0.002%, and 0.004% or 1/25,000,000, 1/5,000,000, 1/2,500,000, 1/500,000, 1/250,000, 1/50,000, 1/25,000). Again, by stating rates per 10,000 and per 50,000,000, participants could visualize their chances both before any diagnosis and after having been diagnosed as ill.

The number who would survive either with or without treatment, R, was again stated as function of B: 0, 2,000-B/2, 5,000-B/2, 8,000-B/2, and 10,000-B. Once again, R=0 defined a neglect-assures-death scenario. Treatment-assures-survival scenarios shared the characteristic R=10,000-B. Again, subjects were presented with calculations for R+B (the maximum number of surviving patients) and 10,000-R-B (the minimum number of doomed patients). W could again represent self, loved one, or stranger. As noted previously, with the latter three cohorts, all decisions were made in private and the model contained no private information.

With the new parameters, 105 scenarios were possible (7 values of B x 5 functions R x 3 values of W). Because of time limitations, neither Cohort 2 nor Cohort 3 was presented with all 105. The 8 subjects in Cohort 2 responded to 70 scenarios. The 13 subjects in Cohort 3 responded to 71. Together, these two cohorts covered all 105 scenarios. Cohort 4 did make choices across all 105 scenarios and, in addition, repeated 5 scenarios, for a total of 110 choices. Table 1 shows five example scenarios, using Cohort 2, 3, and 4 parameters.

Note that scenario #1 is a neglect-assures-death scenario and that #2 is a treatment-assures-survival scenario.

[insert Table 1]

The Insurance Policies

To reiterate, each scenario is partly defined by whether the policyholder is the subject, the subject's pre-designated loved one, or an anonymous stranger. The researchers presumed the policyholder's identity might affect the subject's choice of Policy T (treatment) versus Policy C (cash). Each subject privately determined the loved one's identity before the rules or even the nature of the survey were introduced. Before any other business, the subject was asked to visualize a specific individual who was important to him or her – a spouse, a child, a parent, a friend, etc. Subjects were instructed not to divulge the identity of this loved one in order to avoid biasing the responses.

Policy T would pay the full cost of treating a patient with Disease X. Subjects knew beforehand that the treatment absorbs $250,000 of the insurer's resources, but would cost an uninsured patient $350,000 out of pocket. Policy C would pay a $250,000 lump-sum cash indemnity in the event that the insured party were diagnosed with Disease X. The patient with Policy C would not be treated unless he or she paid out of pocket. There were no limitations on how patients could use the proceeds from the indemnity. We mentioned to subjects that those receiving indemnities could use the funds for alternative treatments, hospice care, charity, bequests to family members, an around-the-world trip, a party, and so forth.

The $100,000 disparity was intentional. Without some disparity, subjects would have no motive to choose Policy T, since Policy C would always leave them with the option of full coverage of treatment. With the disparity, a patient with Policy C could still opt for treatment, but only by using the entire $250,000 indemnity, plus $100,000 in additional funds. We specified that no further medical information would become available upon diagnosis. That is, the post-diagnosis efficacy rate is identical to the pre-diagnosis efficacy rate, conditional on being diagnosed as having Disease X. The same is true with the natural recovery rate. Hence, in the absence of time inconsistency, no patient should purchase Policy T and then desire the cash indemnity upon diagnosis; no one should purchase Policy C and then wish treatment upon diagnosis. The second motive for the $100,000 disparity was to deny subjects any reason to focus on any concern other than their own private welfare (or on the loved one's or stranger's). We did not wish them to dwell on the welfare of the insurer, other policyholders, or society in general. Hence, we stated that the payouts on Policy C and on Policy T both cost the insurer $250,000. We requested that they not concern themselves with explaining the $100,000 discrepancy between the cost to the insurer and the uninsured, though several subjects noted that such disparities exist in today's insurance market. In all scenarios, the hypothetical policies were to be given free of charge to the survey subject. This construct was designed to minimize any consideration of premiums or other liquidity issues.

Summary measures

Choice of policy, efficacy, and identity of policyholder

The raw survey data suggest strong relationships between the choice of insurance policy and two independent variables: the efficacy rate and the identity of the policyholder. These relationships are visible in Figures 1. (The underlying data are in Appendix A, Table A1.) Later analysis will show that the choice of policy is not closely related to the natural recovery rate, though treatment-assures-survival and neglect-assures death scenarios do seem to matter.

[insert Figure 1]

The efficacy rate was defined earlier as the proportion of patients who will survive if and only if treated for Disease X. Figure 1 shows that the higher the efficacy rate, the more likely the subject was to choose the treatment policy over the cash policy. This relationship holds without exception across the full range of efficacy rates. The same relationship also holds without exception within the three subgroups of scenarios defined by policyholder's identity (self, loved one, anonymous stranger). Subjects are most likely to choose Policy T for loved ones, less likely to choose Policy T for themselves, and least likely to choose Policy T for strangers. These relationships hold without exception for all seven efficacy rates and all three identities. Given the identity of the policyholder, higher efficacy is always associated with higher likelihood of choosing the treatment policy. And given the efficacy rate, subjects are always likelier to choose the treatment policy for their loved ones than they are for themselves and likelier to choose the treatment policy for themselves than for strangers.

Choice of policy and other variables

Figures 1 suggests relationships between choice of policy, efficacy of treatment, and identity of the policyholder. Table 2 summarizes some additional evidence that differences exist between the conditions under which one chooses Policy C (cash) or Policy T (treatment).

[insert Table 2]

The members of the four cohorts together made 3,505 choices between the two policies. They choose Policy C 1,448 times (41%) and Policy T 2,057 times (59%). As Table 2 shows, there were differences, and they were often highly significant. For brevity, this section will refer to Set C (the 1,448 observations in which subjects chose Policy C) and Set T (the 2,057 observations in which they chose Policy T).

Table 2 shows t-tests for equality of means between Sets C and T. For Set T, the efficacy rate averaged around 8%, versus around 1.6% for Set C, and this difference was highly significant. The distribution of policyholders in the two sets differed at the 1% level, as well. In Set T, the policyholder was the stranger 29.3% of the time, self 31% of the time, and loved one 39.7% of the time; in Set C, the equivalent figures were 40.4%, 35.4%, and 24.2%.

We thought people might be more inclined to choose the treatment policy in treatment-assures-survival or neglect-assures-death scenarios. In Set T, 25.8% of the observations were treatment-assures-survival cases, versus only 21.6% in Set C, a highly significant difference. The neglect-assures-death cases were more prevalent in Set T than in Set C (25.9% vs. 24%), but this difference was not significant. We also suspected that scenarios with a high natural recovery rate might be higher in Set C than in Set T. This proved true (48.3% vs. 45.9%), but this relationship was only marginally significant.

Distribution by gender was not significantly different in the two sets. Set T had a higher proportion of married subjects (30.8%) than Set C (25.6%), and this difference was highly significant. The income distributions in the two sets were also different. Set C was split nearly evenly among those with income below $50,000 (34.3%), those with income between $50,000 and $100,000 (31.1%), and those with income greater than $100,000 (31.8%). Set T was skewed toward lower-income levels, with 45.7% below $50,000, 35% in the mid-range, and only 17.6% above $100,000. (These do not sum to 100% because one participant omitted income.) All of these differences were significant or highly significant. On average, Group T subjects were nearly 3 years older than Group C subjects, and this difference was highly significant.

To sum up Table 2: Neglect-assures-death scenarios and sex did not differ significantly between the two sets. Subjects were more likely to choose Policy T if the treatment were more efficacious, if the policyholder were a loved one versus oneself, if the policyholder were oneself versus a stranger, if treatment assures survival, if the natural recovery rate were lower, if one were married, if one's income were lower, and if one were older. All of these results except age matched our prior expectations. One might think that older participants would place less value on treatment, since they have fewer life-years to gain. Perhaps the relationship between age and choice is not monotonic. For example, this sample included a disproportionate number of people in their 20s, and perhaps that age group is less inclined to insure that those in their 30s or 40s. In a future experiment, a larger sample and wider age dispersion might help answer this question.

We offered subjects every possible combination of efficacy rate, natural recovery rate, and policyholder, and we offered each a similar number of times. This assured that the questions asked were uncorrelated with the other variables, meaning that correlations in the data must have come from the responses of subjects.

Regression Results

In a series of logistic regressions, the summary effects persisted strongly and consistently. In all cases, the dependent variable was the probability of choosing Policy T (the treatment policy) over Policy C (the cash policy). The regressions subjected the full data set plus three subsets to three specifications, for a total of twelve regressions. The three subsets were those observations in which the policyholder was the subject himself or herself, the pre-designated loved one, and the anonymous stranger; the full set, of course, combined all three subsets. The first specification was over a parsimonious set of independent variables. (see Appendix A, Table A2.) The second specification included fixed effects for each of the individuals participating in the survey. (see Appendix A, Table

A3. The third specification included the parsimonious regression variables plus six other variables (twelve in the case of observations where the loved one was the policyholder). For brevity, we will refer to the overall data set and the three subsets as ALL, SELF, LOVED, and STRANGER. We will also refer to the Parsimonious Model, Fixed Effects Model, and Full Variable Set Model.

Logistic Regressions, Full Variable Set Model

The full variable set model appears in the four regressions of Table 3. These results are similar in the regressions shown in Appendix A. In each logistic regression, the proportion choosing Policy T (treatment) is the dependent variable. In ALL, the log of the efficacy rate was highly significant, as were dummies for treatment-assures-survival, neglect-assures-death, and identity of the policyholder. Participants were most inclined to purchase Policy T for loved ones, less so for themselves, even less so for strangers. The log of the natural recovery rate was not significant.

[insert Table 3]

The results for the SELF, LOVED ONE, and STRANGER subsets were mostly consistent with those for ALL. The efficacy rate was highly significant in each subset. Treatment-insures-survival and neglect-assures-death were significant in some subsets; their signs and magnitudes were always consistent with the results from ALL.

The sensitivity of policy choice to efficacy is lower when the policyholder is the loved one. This is visible in Figure 1, where the slow of the Loved One curve is shallower than the others. The marginal effects can be interpreted as elasticities. So in ALL, a 1% increase in the log of the efficacy rate yields a 0.12% increase in the proportion choosing the treatment policy. In SELF and STRANGER, the elasticity is 0.15. But for LOVED ONE, it is 0.07. Not only are people more willing to treat loved ones than others, they are also less inclined to alter that decision in response to changes in the efficacy rate.

All four regressions are significant at well below the 1% level.

In the ALL data, five additional explanatory variables are highly significant. The likelihood of choosing Policy T is higher with those who are married, with those of lower income (2 ranges were considered), with those who are older, and with those who have children. As mentioned above, there are plausible explanations for the age result. At any rate, the effects here are small, albeit significant.

The income result is more perplexing. A chance at health seems naturally to be a normal good; higher income ought to imply a higher probability of choosing the treatment policy over incremental wealth. The opposite is true in these numbers. Several possible explanations come to mind: There could be a liquidity issue at work; perhaps wealthy participants saw the premiums coming from their own pockets, but treatments coming from the pockets of parents or other family members. There could be a wealth effect here; retirees in the survey may have low income, but high wealth. This anomaly is perplexing and a fit subject for further research.

Of the additional variables, only sex is not significant in the ALL data.

With only a few exceptions, the magnitudes, signs, and levels of significance in SELF, LOVED, and STRANGER are close to those in ALL. Among the significant parameters, there is only one anomalous sign change; in LOVED, the age parameter becomes negative. However, the marginal effect of this variable is miniscule.

In the regression on the LOVED data, we added an additional set of variables: sex, marital status, income, age, and children of the loved one, rather than of self. All were significant or highly significant, with the exception of marital status.

Other Regressions

We ran a number of other regressions, and most results were consistent with the results reported in the full-variable set model. Two other sets of regressions are shown in Appendix A, TablesA2 andA3. Table A2 shows a parsimonious model with only the first six independent variables shown in Table 3. Table A3 shows results from a fixed effects model. Explanatory variables included the six from Table A2, plus dummies for each participant in the survey. (Hausman tests showed the fixed effects model to have highly significant advantages over the parsimonious model.)

12 regressions appear in Tables 2, A2, and A3. We also ran equivalent regressions using the natural recovery rate and the efficacy rate, rather than the logs of the two rates. Again, the results were mostly consistent in sign, magnitude, and significance to the results shown in this paper.

Summary of regression results and additional details

We used three model specifications on the full data set and three subsets of the observations, for a total of twelve regressions. Results appeared strong and robust, with numerous significant or highly significant variables. Magnitudes, signs, and significance levels changed little across the twelve regressions. The signs were generally consistent with the researchers' preconceived notions. As mentioned, the signs on age and income were counterintuitive.

We collected, but did not use, data on several other variables: Is the subject a health care professional? How does the subject's current health compare with the average person of his or her age? What sort of health insurance does the subject have? What sort of financial impact would the subject's death have on the loved one determined at the start of the exercise? In several cases, there was little or no variation across subjects on these variables. In other cases, trial regressions indicated that the magnitudes of these parameters were small and the signs unstable. They added little or no explanatory power to the overall regressions.

Several observations were dropped because of missing data. One participant failed to register his or her age, so a dummy for "age missing" was added to the menu of independent variables. Several participants were dropped from the fixed effects regression because they always chose either Policy C or Policy T, rendering their data unusable in the regression.

Conclusions and Discussion

In this laboratory survey, subjects repeatedly chose between stochastic health and wealth. Most people have never been asked to make such a choice, given the prevalence of third-party payers in health care. The disease and policies were abstract and the sample of subjects relatively small. Nevertheless, the responses were surprisingly clear, internally consistent, and externally consistent with economic logic. While healthy, the subjects were capable of signaling the marginal value they placed on a probability of life.

The efficacy rate of the medical treatment mattered in their decisions, as economic logic would suggest. While we thought the natural recovery rate might influence their decisions, this did not appear to be the case; a simple rationality model would suggest that this rate ought to be irrelevant to the choice of policy, and the data seem to support this conclusion.

Subjects were more inclined to opt for a treatment policy in treatment-assures-survival and neglect-insures-death scenarios, irrespective of the efficacy rate. This finding is more consistent with behavioral economics models than with standard models of rationality. A likely explanation is that the possibility of regret matters in our choices. Consider the three scenarios shown in Table 4.

In all three scenarios, a person has a 1/5,000 chance of becoming ill. In all three scenarios, once he becomes ill, the treatment has a 2/10,000 chance of saving his life. Suppose all 10,000 choose the cash policy over the treatment policy. In Scenario 1, 9,998 people become wealthy and recover. 2 people become wealthy and then die, knowing their deaths were preventable with certainty. In Scenario 2, all 10,000 become wealthy and then die; none knows whether treatment would have saved him, but all know that they forfeited their only chance at life. In Scenario 3, 7,999 become wealthy and survive, and 2,001 become wealthy and die. They also know that treatment would only have conferred a 2/2,001 chance of survival and that even without treatment, they had a 7,999/10,000 chance of survival. We suspect that fear of future regret plays a role in medical choices. Scenarios 1 and 2 seem to provide grounds for regret. ("I could have survived" and "I threw away my only chance.") Scenario 3 does not impose any such certainties on the dying patient.

The results of this survey are broadly consistent with findings in behavioral economics. The prospect theory of Kahneman and Tversky [22] finds that people "underweight outcomes that are merely probable in comparison with outcomes that are obtained with certainty." Loomes and Sugden [23] adopt a regret theory approach assuming, "first, that many people experience the sensations we call regret and rejoicing; and second, that in making decisions under uncertainty, they try to anticipate and take account of these sensations." Both prospect and regret theory can yield results consistent with the responses this paper finds with respect to the treatment-assures-survival and neglect-insures-death scenarios.

Our regression results suggest that people are most likely to opt for the cash policy in Scenario 3, and less so in the other two. Since people are more likely to take the cash policy in Scenario 3 than in Scenario 1, this means people are more inclined to opt for the cash policy when they are less likely to survive to enjoy it. Unless one assumes a powerful bequest motive, this result is paradoxical.

For these subjects, the identity of the insured party mattered in the choice of policy. They were most likely to choose the treatment policy when insuring a loved one, less likely to do so when insuring themselves, and least likely to do so when insuring an anonymous stranger. This raises some interesting questions for future research. Most obvious is the question of why one would choose a different policy for a loved one than one would choose for oneself. Several possibilities come to mind, revealed most easily by imagining two spouses choosing for the two of them. Imagine the seeming inconsistency if each preferred Policy C for self and Policy T for spouse. One explanation would be altruism: I'm willing to die to enrich my spouse, but I wouldn't want my spouse to make the same sacrifice. Another explanation is selfishness: I don't want to go through the treatment, but I couldn't bear the guilt of leaving my spouse untreated or the pain of losing my spouse. Another explanation, to borrow an expression from the management literature, is that this might be an "Abilene paradox," as described by Harvey [24]; each spouse personally prefers the cash policy but genuinely presumes that the spouse would prefer the treatment policy. Subjects were least likely to choose the treatment policy for anonymous strangers. The explanation may lie in the realm of psychology or behavioral economics. This finding may be important in understanding how a public official's health care choices on behalf of his constituents may diverge from choices he makes on his own behalf. The same could hold true for those empowered to select health care insurance on behalf of employees.

Hanson [1] suggests that humans retain an ancient habit of providing medical care in order to "show that they care," i.e., to signal loyalty to associates. His model can integrate explanations of regulatory health paternalism, a low marginal health-value of medical care, and a strong social-status health-gradient. If men trying to convince their wives that they would not desert their children had the strongest need to signal loyalty, then married men with children would choose treatment the most often. Small and Loewenstein [25] find that experimental subjects more willingly compensate those who have lost money if the identity of the individual is already known – a phenomenon known as the "identifiable victim effect."

We collected no information on the following variables but might consider them in future research: religion, prior experience with serious illness, specific comorbidities, ethnic group, strength of belief in the prognosis, quality of life after treatment, specifics of the illness, discomfort of treatment, and presence or absence of a support structure of family or friends.

We see this survey as a prototype for field experiments involving actual health insurance policies, custom designed for research into health-wealth tradeoffs. Undoubtedly, the grandest effort at measuring that margin was the RAND Health Insurance Experiment, a massive, multiyear project costing tens of millions of dollars. The methodology we used here could be adapted to serve as quick, inexpensive "mini-RANDs." Theoretically, at least, insurers could agree to underwrite a pair of single-contingency contracts on some currently uninsured contingency. For example, one policy could promise full coverage of a currently experimental (and hence uninsured) treatment in the event the insured party is diagnosed with a specific illness. The second policy could promise a cash indemnity in the event of the same diagnosis. Subjects would choose Policy

C or Policy T in response to a menu of scenarios, having been told that there is one true scenario and that they will actually leave the room with the policy they selected in that particular scenario.

Finally, the cash-or-treatment option could conceivably be a tool of consumer-driven health care. Currently, Medical Savings Accounts and Health Savings Accounts seek to induce consumers to self-limit their use of low-cost, repetitive services. But much of the growth of U.S. health care expenditures is in high-cost, low-benefit treatments. There is currently no tool that forces consumers to consider the marginal benefit of such treatments and simultaneously protects them from catastrophic financial loss. The cash policy versus treatment policy could conceivably provide just such a vehicle.

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Appendix A: Tables and Figure

Table A1 shows the data that underlie Figure 1.

[insert Table A1]

Table A2 shows the regression results from a parsimonious set of independent variables, applied to all data, and then to the three subsets of data.

[Insert Table A2]

Table A3 shows the regression results from the parsimonious set of independent variables, plus fixed effects dummy variables for each individual participating in the survey.

[Insert Table A3]

Appendix B: Survey Caveats and Administration

This survey is a pilot for future experiments, and there are several caveats to keep in mind. The sample size is small, and the respondents were a nonrandom convenience sample. The results were statistically strong, and it will remain for future experiments to determine how well the findings could be generalized to broader populations. However, the results would still be important even if they were only indicative of a subset of the. Insurance markets are segmented, and it would be worthwhile to know more about the behavior of a large and important subset.

The test was given on four nights to cohorts of 15, 8, 13, and 10 individuals, respectively. After the first cohort was surveyed, several aspects of the treatment were altered in ways that kept the data compatible across cohorts. After the first cohort, public responses to questions were eliminated; this was because public vs. private responses differed little, but the dual public and private responses roughly cut in half the number of scenarios possible within our limited time frame. After the first cohort, the population parameters were scaled by a factor of 10 to allow more variation in scenarios. (A full description of these changes appears in the main text.)

The respondents were a convenience sample, primarily drawn from a university and its surrounding community in order to minimize costs. They were drawn from undergraduate students, MBA students, faculty members, and personal acquaintances from the community. They were recruited by word-of-mouth and by email routing lists. Members of the first cohort were paid $20 apiece to come, while members of the later three cohorts were paid $15 apiece.

Respondents were together in a college classroom and began the session by filling in a questionnaire on their individual demographic characteristics, including those of the loved one they would use for the survey. In the first cohort, each respondent had before him on paper the following description of the setup:

> 5,000,000 people live in the state
> 1,000 of these people will fall ill to Disease X in the next year
> Disease X is potentially fatal
> There is a treatment that will help some, but not all, of the sick people
> In each scenario, we know:
>   R: The number of people who will recover naturally, with or without treatment
>   B: The number of people who will recover ONLY if treated
>   R+B: The number of sick who will recover if all sick people are treated.
> No one knows who is who in advance
>
> Treatments for disease cost $250,000.
> But an uninsured person has to pay $350,000 for the treatment.
> Policy T (treatment) pays 100% of the medical bill
> Policy C (cash) pays YOU $250,000 in cash if you are diagnosed with Disease X
> Both policies are free, but you have to choose C or T.
>
> Scenario ________
> R: _______ people will recover with or without treatment
> B: _______ people will recover ONLY if treated
> R+B: ________ people will recover if all 1,000 sick people are treated.
> You are choosing the policy for _____________.

The respondents were read this setup, and the researcher answered questions. Once the survey began, respondents responded in writing and, in a duplicate set of scenarios, in writing and by standing up. At the beginning of each scenario, the variable names appeared onscreen, but no parameters were visible. As the scenario was read out loud, the parameters were simultaneously added to the screen. As each scenario was announced, the parameters were projected on a computer screen. These included the scenario number, R, B, R+B, and the identity of the loved one. R/10,000, B/10,000, and (R+B)/10,000 were also shown in percentage form. After respondents marked their choice of policy for a given scenario, the screen was cleared of parameters and the process was repeated.

The same procedures were followed with the second, third, and fourth cohorts. The difference was that the setup specified a region of 50,000,000 people, with 10,000 people falling ill. So the rates of illness, recovery, etc. were scaled by a factor of 10. To help participants envision a region of 50,000,000 people, a map of Maryland, the District of Columbia, Virginia, North Carolina, South Carolina, Georgia, and Florida was projected onscreen.

In all, each of the 15 members of the first cohort made 58 choices between Policy T and Policy C. The 8 members of cohort 2 made 70 choices, the 13 members of Cohort 3 made 75 choices, and the 10 members of Cohort 4 made 110 choices apiece. Out of 3,505 decisions, 2,057 were for the treatment policy T, and 1448 were for the cash policy C. The first three sessions lasted approximately two hours. The fourth session lasted approximately two-and-one-half hours.

References

1. Hanson R. Showing that you care: the evolution of health altruism. http://hanson.gmu.edu/showcare.pdf 2000 [27 June 2006].
2. Ubel PA. *Pricing Life: Why It's Time for Health Care Rationing*. MIT Press: Cambridge, MA, 2000.
3. Glied S. Health insurance and market failure since Arrow. *J Health Polit Policy Law* 2001; **26**: 957–965.
4. Olsen JA, Smith RD, and Harris A. Economic theory and the monetary valuation of health care. Working Paper 82, Center for Health Program Evaluation, Monash University, 1999.
5. Diener A, O'Brien B, Gafni A. Health care contingent valuation studies: a review and classification of the literature. *Health Econ* 1998; **7**: 313–326.
6. Coursey D, Hovis J, Shulze W. The disparity between WTA and WTP measures of value. *Q J Econ* 1987; **102**: 679–690.
7. Hanemann WM. willingness to pay and willingness to accept: how much can they differ? *Am Econ Rev* 1991; 81: 635–647.
8. Shogren JF, Shin SY, Hayes DJ, Kliebenstein JB. Resolving differences in willingness to pay and willingness to accept. *Am Econ Rev* 1994; **84**: 255–270.
9. Manning WG *et al*. Health insurance and the demand for medical care: evidence from a randomized experiment. *Am Econ Rev* 1987; **77**: 251ff.

10. Newhouse JP *et al*. *Free for All? Lessons from the RAND Health Insurance Experiment.* Harvard University Press: Cambridge, MA, 1993.
11. Arrow KJ. Uncertainty and the welfare economics of medical care. *Am Econ Rev* 1963; **53**: 941–973.
12. Feigenbaum S. ‘Body shop’ economics: what's good for our cars may be good for our health. *Regulation* 1992; **15**: 26-27.
13. Pauly MV. Indemnity insurance for health care efficiency. *Economic and Business Bulletin* 1971; **4**: 53–59.
14. Pauly MV. Taxation, health insurance, and market failure in the medical economy. *J Econ Lit* 1986; **24**: 629–675.
15. Gianfrancesco FD. A proposal for improving the efficiency of medical insurance. *J Health Econ* 1983; **2**: 175–184.
16. Graboyes RF. Our Money or Your Life: Indemnities vs. Deductibles in Health Insurance. Working Paper 00-4, Federal Reserve Bank of Richmond, 2000.
17. Panko R. Critical Competition. *Best's Review*. July 1999.
18. Trigon, Inc., Medical Research Foundation and Williamson Institute for Health Studies, Department of Health Administration, Virginia Commonwealth University. Effects of case management alternatives on the cost of care and quality of life for end stage non-small cell lung cancer patients. Williamson Institute for Health Studies, Richmond, VA, 1995.
19. Journal of the National Cancer Institute. New trial empowers patients in their end-of-life care. *J Natl Cancer Inst* (July 3) 1996; 88-13.

20. Gigerenzer G, Hoffrage U. How to improve Bayesian reasoning without instruction: frequency formats. Psychol Rev 1995; **102**: 684–704.

21. Feynman R. *The Character of Physical Law*. MIT Press: Cambridge, MA, 1967.

22. Kahneman D, Tversky A. Prospect theory: an analysis of decision under risk. *Econometrica* 1979; **47**: 263–290.

23. Loomes G, Sudgen R. Regret theory: an alternative theory of rational choice under uncertainty. *Econ J* 1982; **92**: 805–824.

24. Harvey JB. *The Abilene Paradox and Other Meditations on Management.* Jossey-Bass, Inc., San Francisco, 1996.

25. Small D, LoewensteinG. Helping *a* victim or *the* victim: altruism and identifiability. *Journal of Risk and Certainty* 2003; **26**: 5–16.

Table 1
Example Scenarios

Scenario #	R=number who recover with or without treatment			B = Number who survive if and only if treated			W=Identity of insured party
	R	Natural Recovery Rate 100%xR/ 10,000	100%xR/ 50,000,000	B	Efficacy Rate 100%xB/ 10,000	100%xB/ 50,000,000	W
1	0	0%	0%	2	0.02%	0.000004%	loved one
2	8,000	80%	0.016%	2,000	20%	0.004%	self
3	4,950	49.5%	0.0099%	100	1%	0.0002%	loved one
4	7,500	75%	0.015%	1,000	10%	0.002%	stranger
5	1,990	19.9%	0.00398%	20	0.2%	0.00004%	self

Table 2
Variation in Data

Choice of policy	sign	Cash N	Cash mean	Cash st. dev.	Treatment N	Treatment mean	Treatment st. dev.	All N	All mean	All st. dev.
Natural recovery rate	*	1448	0.483	0.369	2057	0.459	0.367	3505	0.469	0.368
Efficacy rate	***	1448	0.016	0.041	2057	0.080	0.085	3505	0.054	0.077
Treatment-assures-survival scenario (dummy)	***	1448	0.216	0.412	2057	0.258	0.438	3505	0.241	0.428
Neglect-assures-death scenario (dummy)		1448	0.24	0.427	2057	0.259	0.438	3505	0.251	0.434
Policyholder is self (dummy; anonymous stranger omitted)	***	1448	0.354	0.478	2057	0.31	0.463	3505	0.328	0.47
Policyholder is loved one (dummy; anonymous stranger omitted)	***	1448	0.242	0.428	2057	0.397	0.489	3505	0.333	0.471
Sex (1=female; 0=male)		1448	0.368	0.482	2057	0.355	0.479	3505		
Marital Status (1=married, 0=single; no widowed, divorced in sample)	***	1448	0.256	0.437	2057	0.308	0.462	3505	0.286	0.452
Income is below $50,000 (dummy; omitted)	***	1448	0.343	0.475	2057	0.457	0.498	3505		
Income is between $50,000 and $100,000 (dummy; <50,000 omitted)	**	1448	0.311	0.463	2057	0.35	0.477	3505	0.334	0.472
Income is above $100,000 (dummy; <50,000 omitted)	***	1448	0.318	0.466	2057	0.176	0.381	3505	0.235	0.424
Age by decade (e.g., 28-year old listed as 20)	***	1398	21.94	12.002	2032	24.803	12.428	3430	23.636	12.335
Has children (dummy)	***	1448	0.220	0.415	2057	0.319	0.466	3505	0.278	0.448

Significance indicates that means are significantly different between observations in Set C (observations in which subjects choose the cash policy) vs. Set T (observations in which subjects choose the treatment policy).
* = significant at the 10% level; ** = significant at the 5% level; *** = significant at the 1% level

Table 3
Logistic Regression of Probability of Choosing Treatment Policy over Cash Policy, Full Specification

Policy purchased for	All policyholders	Self	Loved one	Stranger
Constant	2.896 | 0.660 (0.042) ***	3.354 | 0.808 (0.076) ***	5.513 | 0.839 (0.066) ***	3.119 | 0.780 (0.080) ***
Natural recovery rate (log)	-0.161 | -0.037 (0.025)	-0.169 | -0.041 | (0.048)	-0.390 | -0.059 | (0.034) *	-0.037 ,-0.009 (0.047)
Efficacy rate (log)	0.574 | 0.131 (0.005) ***	0.628 | 0.151 (0.010) ***	0.578 | 0.088 (0.006) ***	0.611 | 0.153 (0.010) ***
Treatment-assures-survival scenario (dummy)	0.501 | 0.114 (0.032) ***	0.519 | 0.125 (0.060) **	0.422 | 0.064 (0.041)	0.686 | 0.171 (0.060) ***
Neglect-assures-death scenario (dummy)	0.429 | 0.098 (0.033) ***	0.404 | 0.097 (0.061)	0.570 | 0.087 (0.041) **	0.463 | 0.116 (0.061) *
Policyholder is self (dummy; anonymous stranger omitted)	0.366 | 0.083 (0.024) ***			
Policyholder is loved one (dummy; anonymous stranger omitted)	1.305 | 0.297 (0.025) ***			
Sex (1=female; 0=male)	-0.115 | -0.026 (0.021)	0.252 | 0.061 (0.039)	-0.443 | -0.067 (0.028) **	-0.483 | -0.121 (0.040) ***
Marital Status (1=married, 0=single; no widowed, divorced in sample)	0.295 | 0.067 (0.026) ***	0.142 | 0.034 (0.049)	0.025 | 0.004 (0.036)	0.401 | 0.100 (0.049) **
Income is between \$50,000 and \$100,000 (dummy; <50,000 omitted)	-0.722 | -0.164 (0.027) ***	-0.549 | -0.132 (0.050) ***	-0.824 | -0.125 (0.042) ***	-0.754 | -0.189 (0.050) ***
Income is above \$100,000 (dummy; <50,000 omitted)	-1.761 | -0.401 (0.028) ***	-1.972 | -0.475 (0.053) ***	-1.739, -0.265 (0.048) ***	-1.341 | -0.335 (0.052) ***
Age by decade (e.g., 28-year old listed as 20)	0.002 | 0.000 (0.000) ***	0.006 | 0.002 (0.001) ***	-0.002 | 0.000 (0.000) **	0.006 | 0.002 (0.001) **
Has children (dummy)	0.495 | 0.113 (0.024) ***	0.536 | 0.129 (0.045) ***	1.638, 0.249 (0.041) ***	0.135 | 0.034 (0.044)
Loved one's sex (1=female; 0=male)			-1.096 | -0.167 (0.031) ***	
Loved one's marital status (1=married, 0=single; no widowed, divorced in sample)			0.035 | 0.005 (0.031)	
Loved one's income is between \$50,000 and \$100,000 (dummy; <50,000 omitted)			0.213 | 0.032 (0.037)	
Loved one's income is above \$100,000 (dummy; <50,000 omitted)			-0.455 | -0.069 (0.045)	
Loved one's age by decade (e.g., 28-year old listed as 20)			-0.018 | -0.003 (0.001) ***	
Loved one has children (dummy)			-0.028 | -0.004 (0.036)	
N	3273	1087	1093	1093
Log-likelihood	-1590.561	-514.346	-456.578	-541.856
Restricted log-likelihood	-2198.146	-741.184	-646.162	-757.225
$\chi 2$	1215.170	453.675	379.168	430.738
Degrees of freedom	12	10	16	10
Significance level	0.00000000	0.00000000	0.00000000	0.00000000

Dependent Variable: 1=Chooses treatment policy; 0=Chooses cash policy. Independent variables: Six variables of interest plus shifters
Cell format: coefficient on variable | marginal effect (standard error of marginal effects)
Marginal effect can be interpreted as the elasticity of probability with respect to dependent variable
* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table 4
Examples of Treatment-assures-survival and Neglect-assures-death scenarios

		Probability of contracting Disease X	Efficacy rate	Natural recovery rate
Scenario 1	treatment-assures-survival	1/5,000	2/10,000	9,998/10,000
Scenario 2	neglect-assures-death	1/5,000	2/10,000	0/10,000
Scenario 3	ex post uncertainty	1/5,000	2/10,000	7,999/10,000

Table A1
Efficacy rate and Choice of Insurance Policy

Efficacy rate: Proportion of patients who survive only if treated	Number & proportion choosing Policy T (treatment). Scenarios where policy is chosen for:				Number & proportion choosing Policy C (cash). Scenarios where policy is chosen for:				Total number of choices made			
	All	Self	Loved one	Stranger	All	Self	Loved one	Stranger	All	Self	Loved one	Stranger
0.0002	123	32	67	24	312	112	80	120	435	144	147	144
	28.3%	22.2%	45.6%	16.7%	71.7%	77.8%	54.4%	83.3%				
0.001	110	28	56	26	200	72	49	79	310	100	105	105
	35.5%	28.0%	53.3%	24.8%	64.5%	72.0%	46.7%	75.2%				
0.002	290	92	129	69	437	162	110	165	727	254	239	234
	39.9%	36.2%	54.0%	29.5%	60.1%	63.8%	46.0%	70.5%				
0.01	189	61	83	45	139	44	40	55	328	105	123	100
	57.6%	58.1%	67.5%	45.0%	42.4%	41.9%	32.5%	55.0%				
0.02	440	137	164	139	260	87	60	113	700	224	224	252
	62.9%	61.2%	73.2%	55.2%	37.1%	38.8%	26.8%	44.8%				
0.1	288	87	100	101	45	13	5	27	333	100	105	128
	86.5%	87.0%	95.2%	78.9%	13.5%	13.0%	4.8%	21.1%				
0.2	617	201	218	198	55	23	6	26	672	224	224	224
	91.8%	89.7%	97.3%	88.4%	8.2%	10.3%	2.7%	11.6%				
TOTAL	2057	638	817	602	1448	513	350	585	3505	1151	1167	1187
	58.7%	55.4%	70.0%	50.7%	41.3%	44.6%	30.0%	49.3%				

Table A2
Logistic Regression of Probability of Choosing Treatment Policy over Cash Policy, Parsimonious Specification

Policy purchased for	All Policyholders	Self	Loved One	Stranger
Constant	2.003 | 0.473 (0.036) ***	2.439 | 0.594 (0.061) ***	2.721 | 0.517 (0.047) ***	2.217 | 0.554 (0.064) ***
Natural recovery rate	-0.150 | -0.035 (0.024)	-0.136 | -0.033 (0.043)	-0.310 | -0.059 (0.036)	-0.029 | -0.007 (0.043)
Efficacy Rate	0.488 | 0.115 (0.005) ***	0.508 | 0.124 (0.008) ***	0.422 | 0.080 (0.006) ***	0.532 | 0.133 (0.009) ***
Treatment-assures-survival scenario (dummy)	0.438 | 0.103 (0.031) ***	0.425 | 0.103 (0.055) *	0.294 | 0.056 (0.044)	0.593 | 0.148 (0.056) ***
Neglect-assures-death scenario (dummy)	0.376 | 0.089 (0.031) ***	0.331 | 0.081 (0.061)	0.410 | 0.078 (0.045) *	0.399 | 0.100 (0.057) *
Policyholder is self (dummy; anonymous stranger omitted)	0.315 | 0.074 (0.023) ***			
Policyholder is loved one (dummy; anonymous stranger omitted)	1.122 | 0.265 (0.024) ***			
N	3343	1111	1116	1116
Log-likelihood	-1814.222	-615.4602	-579.9383	-613.5507
Restricted log-likelihood	-2261.777	-761.3684	-674.9853	-773.5361
$\chi 2$	895.1082	291.8162	190.0940	319.9708
Degrees of freedom	6	4	4	4
Significance level	0.0000000	0.0000000	0.0000000	0.0000000

Dependent Variable: 1=Chooses treatment policy; 0=Chooses cash policy. Independent variables: Six variables of interest plus shifters
Cell format: coefficient on variable | marginal effect (standard error of marginal effects)
Marginal effect can be interpreted as the elasticity of probability with respect to dependent variable
* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table A3
Logistic Regression of Probability of Choosing Treatment Policy over Cash Policy, Fixed Effects Specification

Policy purchased for	All Policyholders	Self	Loved One	Stranger
Constant	4.956 | 1.063 (0.059) ***	4.380 | 1.006 (0.095) ***	9.376 | 0.734 (0.072) ***	4.700 | 1.173 (0.102) ***
Natural recovery rate	-0.146 | -0.031 (0.026)	-0.099 | -0.023 (0.048)	-0.284 | -0.022 (0.022)	-0.040 | -0.010 (0.050)
Efficacy Rate	0.704 | 0.151 (0.006) ***	0.740 | 0.170 (0.011) ***	0.889 | 0.070 (0.009) ***	0.724 | 0.181 (0.012) ***
Treatment-assures-survival scenario (dummy)	0.595 | 0.128 (0.034) ***	0.502 | 0.115 (0.062) *	0.576 | 0.045 (0.027) *	0.761 | 0.190 (0.066) ***
Neglect-assures-death scenario (dummy)	0.505 | 0.108 (0.034) ***	0.362 | 0.083 (0.063)	0.803 | 0.063 (0.028) **	0.497 | 0.124 (0.067) *
Policyholder is self (dummy; anonymous stranger omitted)	0.440 | 0.094 (0.025) ***			
Policyholder is loved one (dummy; anonymous stranger omitted)	1.605 | 0.344 (0.027) ***			
N	3273	1087	1093	1093
Log-likelihood	-1324.446	-444.614	-299.034	-468.702
Restricted log-likelihood	-2198.146	-741.184	-646.162	-757.225
$\chi2$	1747.399	593.139	694.256	577.046
Degrees of freedom	48	45	36	42
Significance level	0.00000000	0.00000000	0.00000000	0.00000000
Hausman test statistic (p-value): Tests for the existence of fixed effects vs. no error components relative to the Logistic Regression Model #1 (Table 3).	127.809 (0.000000)	43.807 (0.000000)	64.468 (0.000000)	38.377 (0.000000)

Dependent Variable: 1=Chooses treatment policy; 0=Chooses cash policy. Independent variables: Six variables of interest plus shifters
Cell format: coefficient on variable | marginal effect (standard error of marginal effects)
Marginal effect can be interpreted as the elasticity of probability with respect to dependent variable
* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

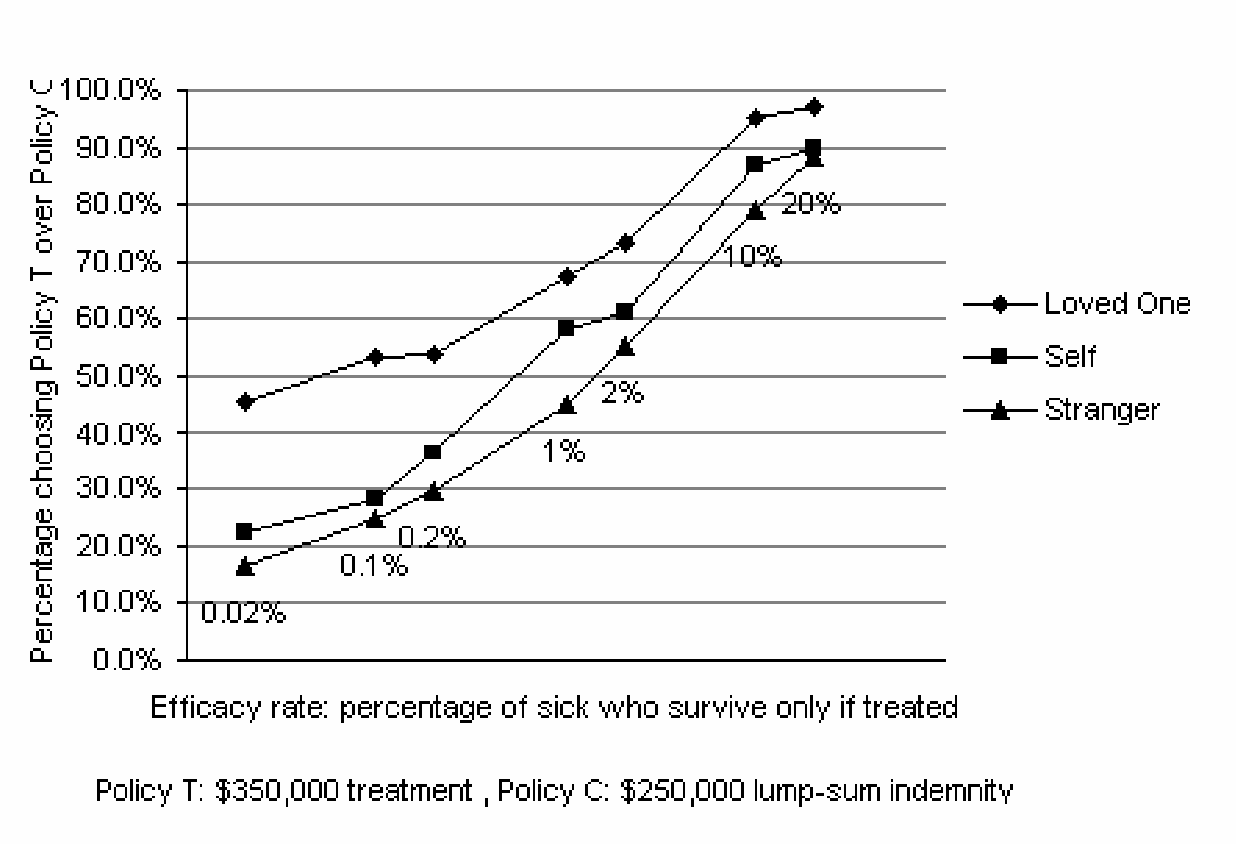

Figure 1: Choice of Policy as Function of Efficacy Rate