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Use of Insurance Against a Small Loss as an Incentive Strategy

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Abstract

The success of extended warranties and buyer protection plans suggests that insurance against a small loss has high decision utility. We explore whether the behavioral insight that people are highly averse to small chances of loss can be used to create a powerful incentive that has very low expected value. We compare decisions of individuals offered fixed payments for healthy choices to those offered insurance in exchange for healthy choices. We test the prediction that aversion to small losses will result in very high rates of health behavior uptake in exchange for insurance. Three hundred participants endowed with a \$2 bonus randomly received one of two incentives for completing a scheduled health risk assessment: (1) an insurance guarantee against the 1% risk of losing the \$2 bonus or (2) a fixed payment at the expected value of the insurance. Relative to the fixed payment condition, participants in the insurance intervention were 70% more likely to meet their health risk assessment appointment ($p < 0.01$). Fixed payments of \$2.59 were needed for every \$1 spent on insurance to achieve the same behavioral effect. Loss aversion, probability weighting, and the certainty effect may account for this result. Incentive design may benefit from utilizing an insurance paradigm.

Keywords

decision analysis; nonexpected utility; decision psychology; behavioral economics; incentives; insurance

1. Introduction: Insurance Against a Small Loss

People are willing to purchase insurance for inexpensive goods, where the insurance premiums are well in excess of the expected loss (Cutler and Zeckhauser 2004, Drèze 1981, Kunreuther and Pauly 2006, Pashigian et al. 1966, Sydnor 2010). An example is the extended warranty industry, which sold \$15 billion in product protection plans in 2004 (*Warranty Week* 2005). Profit margins are 50%–60% for warranties on home appliances and 15%–20% on electronics products (Struyk 2009, *Warranty Week* 2007). If consumers are finding these insurance products attractive, then it may be possible to design an incentive scheme for other desirable behaviors that corresponds to this real-world effect. Moreover, understanding the decision processes that make these products attractive is important to determine how best to engineer choices for policies involving incentives.

We designed an experiment where we endowed subjects with a reward and informed them that there was a small chance of losing this reward. Subjects were then randomized to one of two incentives for engaging in a desirable behavior. The first group was offered insurance against losing the reward as an incentive. The second group was offered the expected value of the insurance.

In this study the incentivized behavior was completing a health risk assessment form. We chose to study decision processes in health for two reasons. First, extended warranty plans are pervasive and often involve aggressive marketing. We wanted to avoid the use of this common framework for studying small losses, because respondents may have found these sales tactics objectionable, which could influence decision making. Second, incentivizing health behaviors is an active area of study with considerable applied value. More than two-thirds of employers with 50 or more employees use financial incentives to encourage uptake of health behaviors, and the most common type of incentive trigger is health risk assessment completion (Matke et al. 2013). Furthermore, lotteries that employ principles of decision under risk have been used as an incentive scheme in health risk assessment with initial success (Haisley et al. 2012). These features make health assessments an attractive behavioral target.

2. Theoretical Justification for a Small-Stakes Insurance Incentive Scheme

Several decision theories predict that insurance choices in small-stakes gambles will deviate from the optimal, rational choice given by expected utility, a theory that calculates the value of a risky choice as the sum of the product of the utility of each possible outcome multiplied by the probability of its occurrence. Expected utility theory over final wealth states does not predict insurance purchases for inexpensive items (Wakker 2010, p. 257, Example 9.3.2, and p. 74, Exercise 3.3.1; Rabin 2000, p. 1282). This has led to an alternative interpretation of expected utility, expected utility of income (Cox and Sadiraj 2006, Watt 2002), that considers changes in asset position from a given starting point.¹ Under expected utility theory, attitudes toward risk are modeled entirely through the curvature of the utility function. This severely constrains what choice behavior the theory can predict. Departures

¹For the purposes of this work, we follow the convention that “expected utility” is an evaluation of final wealth states. We include theories that address changes in assets as part of “nonexpected utility” theories.

of observed choices from expected utility have resulted in the conclusion that expected utility may not be the best choice when a descriptive model of behavior is needed (Kahneman and Tversky 1979). Behavioral decision theories have expanded the traditional model of risk to include an attitude toward chance (i.e., probability weighting, or “decision weights”) and reference dependence—a utility function that is different for losses and gains relative to some reference level and which includes loss aversion.

Most models of decision weights include a continuous probability weighting function (Prelec 1998) that assigns a weight to each real-valued probability. Some models of decision weights use interior linear weights but characterize them as discontinuous near 0 and 1 to accommodate “certainty effects” (Andreoni and Sprenger 2012). Both approaches explain attitudes toward chance reasonably well.

For a decision option that has two possible outcomes, a probability p of monetary outcome x_1 and a complementary choice with probability $1 - p$ of monetary outcome x_2 , *expected utility* holds if preferences over prospects $[x_1, p; x_2]$ can be represented by $p \cdot U(x_1) + (1 - p) \cdot U(x_2)$, where U is a utility function over these outcomes unique up to unit and location. For small-stakes outcomes over final wealth states, U must be linear (Rabin 2000), indicating that expected utility predicts that insurance and its expected value are equivalent. Expected utility predictions often act as a null hypothesis to be compared against models that capture irrational influences on decision making.

Several nonexpected utility models of decision making have been developed. For binary decisions within nonexpected utility theories, probability weights $w(p)$ and $1 - w(p)$ may be applied in evaluating the decision (see Wakker 2010, Observation 7.11.1). The probability weighting function captures the tendency to overweight the chance of a small probability, thus making insurance more valuable than its monetary expectation. The theory becomes more complex for n -ary outcomes and involves ranking outcomes and evaluating differences in transformed cumulative probability distributions (Diecidue and Wakker 2001, Quiggin 1982).

Prospect theory (Kahneman and Tversky 1979, Tversky and Kahneman 1992) posits a nonlinear probability weighting function. In addition, prospect theory assumes *sign dependence*: outcomes are perceived as gains and losses relative to a reference point. People are allowed to be more sensitive to losses than to gains (loss aversion). Loss aversion is often modeled exogenously through a slope parameter that increases the sensitivity of utility to losses. There is also separate probability weighting function for gains and for losses. More recent findings suggest that individuals respond to *expected* endowments as well as endowments that are already conferred; that is, a person’s reference level may be changed by expectations about the future (Ericson and Fuster 2011, K szegi and Rabin 2006). If people respond to expected endowments, then this change in reference level occurs prior to the resolution of risk or uncertainty. In this situation, purchasing protection against losing an expected asset position in the future may be attractive.

K szegi and Rabin (2006) proposed a theory of utility that specifies reference levels for expectations of future outcomes with the possibility that an individual may entertain degrees

of belief in two or more endowments. We call this *KR-Utility theory*. In KR-Utility theory, reference points are endogenous with respect to the choice of the decision maker. The theory treats the reference point as a probability measure that characterizes beliefs about outcomes. The utility of an outcome is both a function of consumption and a reference level. Similar to prospect theory, KR-Utility theory predicts aversion to losses. The KR-Utility theory framework is particularly relevant to the current study because if we observe loss aversion, it is on expected, rather than realized, endowments.

In sum, expected utility over final wealth states predicts equal preference between insurance against a small-stakes loss and a fixed payment in its expected value. Each additional component decision process is predicted to compound the effect of preference for insurance. For example, probability weighting predicts that the insurance value will exceed the expected value (EV) of insurance. Certainty effects predict that the elimination of risk will act as a particularly powerful incentive. Finally, loss aversion predicts the preference for insurance over a fixed payment in its expected value.

Taken together, these findings and theories suggest that one way to build an effective incentive scheme for desirable behaviors may be to endow people with an at-risk reward, then to allow them to insure the reward with the desired behavior. This work explores the application of nonexpected utility theories to incentive schemes for health behaviors.

3. Experiment

3.1. Subjects

Using Amazon's Mechanical Turk, a market for online tasks validated in economic studies (Horton et al. 2011), we recruited adult subjects (at least 18 years of age) from the United States. Three hundred participants were recruited for the main study. All study procedures were reviewed and approved by the University of Southern California's Institutional Review Board.

3.2. Design and Procedure

An experiment was designed to mimic the structure of insurance and warranty purchases described above; however, we substituted the cost of insurance with the completion of a health behavior task that is comparable to medication adherence or attendance of a convenient follow-up appointment. Figure 1 provides an overview of the financial consequences of the experiment. This experiment is represented by a decision tree. By folding back the tree, it is clear that the consequences of choices have the same expected monetary value.

All participants selecting our Amazon Mechanical Turk task completed a brief demographic survey before being offered a 99% chance of winning an additional \$2.00 and a 1% chance of no bonus payment, with a drawing to be held later in the week. Participants were randomized with equal probability to (1) a lottery insurance condition, where they could guarantee receipt of the \$2.00 bonus payment, or (2) a fixed payment condition. The fixed payment was set to the expected value of the insurance, 2¢. Insurance and fixed payments were contingent upon returning to the site at an appointed time to complete an online cardiac

risk assessment, which is the goal health behavior in this experiment. Appointment times were randomly assigned in 15-minute windows approximately 48 hours after the start of the task. We introduced this delay to increase the opportunity cost of participation and reduce the chance of ceiling rates of return by participants.

The task was listed on Mechanical Turk with a 50¢ payment and a potential bonus payment of \$2.00. The task listing was advertised in the following manner.

Title

Evaluate Appointment Incentives with possible \$2.00 bonuses (U.S. ONLY)

Description

\$0.50 payment for answering 6 demographic questions and for obtaining an online appointment time. Possible \$2.00 bonuses.

When potential subjects selected the task, they were directed to an instructions page:

Instructions

The purpose of this task is to evaluate incentives for participation in scheduled online health risk screening appointments.

To satisfactorily complete and receive payment for this task you will:

1. Complete a brief questionnaire;
2. Be given a URL, a code, and a 15 minute appointment window within the next 48 hours.

During your appointment window access the URL and enter your code to be eligible for a bonus.

START

After pressing “START” all subjects were asked basic demographic questions about age, race, ethnicity, gender, and income. After they had submitted these responses, subjects were randomized into two groups each to a different set of instructions.

Group 1 (Lottery Insurance)

You have been entered into a random drawing where you have a 99 in 100 chance of winning a \$2.00 bonus and a 1 in 100 chance of losing the drawing (winning nothing). You will be notified in 7 days about the results of this drawing.

However, your \$2.00 bonus is **guaranteed** if you access the URL listed during your appointment window and enter your code.

Group 2 (Fixed Payment)

You have been entered into a random drawing where you have a 99 in 100 chance of winning a \$2.00 bonus and a 1 in 100 chance of losing the drawing (winning nothing). You will be notified in 7 days about the results of this drawing.

In addition to this random draw, you can obtain a 2-cent bonus by accessing the URL listed during your appointment window and enter your code.

Each participant was assigned a 15-minute appointment, 46–50 hours into the future, with a URL linking to the health risk assessment form and a code to enter upon accessing that URL. If the user accessed the page prior to his or her appointment and entered the code, the user was reminded of his or her appointment. The code contained a check digit to prevent abuse or errors.

3.3. Statistical Analysis

The differences between the two groups on demographic characteristics were compared using a two-sample test of proportions; p -values were generated with z -tests when five or more observations in a demographic group were present, and Fisher's exact test was computed. Results for the main effects were analyzed using a two-sample χ^2 test for equality of proportions with a continuity correction.

These results can also be analyzed to assess the cost of a policy that uses an insurance incentive over a policy of offering fixed payments for the same behavior (the welfare impact). Because we conduct a randomized experiment with each arm constituting a binary choice between performing or not performing the health behavior, we do this in a standard fashion (Wilcox 2008) by forming a ratio of regressors, β_1/β_2 , within a simple binary logit discrete choice model: $\text{Prob}(y_i = 1) = 1/(1 + \exp\{-\beta_i x\})$, where $i = 1$ represents the “fixed payment” arm and $i = 2$ represents the “insurance” arm. We may solve for each of β_1 and β_2 simply by applying choice probabilities to the aforementioned equation.

4. Results

4.1. Response Rate

Of the 602 visitors to the task summary page, 300 users completed the demographic questionnaire. The task was terminated after 300 participants responded.

4.2. Participant Characteristics

The participant characteristics of the two study groups are presented in Table 1. Two participants were removed from the analysis as a result of self-reports that they were under 18 years of age, reducing the sample size to 298. There were no significant differences between study groups.

4.3. Main Effects

Participants offered lottery insurance were more likely to return for their appointment than those offered a fixed payment (39% versus 24% return rate; $\chi^2 = 8.56$, $p < 0.003$). The main effect was consistent across each demographic category using Bonferroni correction for multiple comparisons. The odds ratio for completing the assessment between the subjects

offered insurance versus those offered a fixed payment was 1.99 (1.21–3.28), or nearly double. Given rates of 24% of health behavior uptake in the fixed payment and 39% in the insurance arms, the marginal rate of substitution of a fixed payment for a lottery insurance policy under a standard logistic random utility model was \$2.59 to \$1 (95% confidence interval = \$1.41–\$6.51). That is, on average, \$2.59 had to be spent on fixed payments to achieve the same impact on behavior as \$1 spent on lottery insurance policies.

5. Discussion

With the increasing prevalence of workplace wellness programs and other public and private initiatives to promote health behavior, the results of this study are highly relevant to program design. This study demonstrates the efficacy of insurance for an at-risk reward as an incentive for engaging in health-promoting behaviors. Rational choice theory (expected utility) predicts that subjects would return to complete the health risk assessment in equal proportion in our two experimental groups (Arrow 1971). Expected utility over final wealth states cannot account for the observed risk aversion over such small amounts of money. Decision processes such as probability weighting and loss aversion may contribute to this effect. The high rate of choice of insurance over a fixed payment could mean that several of these processes are working together. There may be additional factors contributing to the psychological desirability of the insurance. For instance, having insurance may reduce anxiety about losing—or provide peace of mind by removing the annoyance of potentially losing—an earned reward that exceeds the very small monetary fixed payment.

Overall, the effect of insurance was large: \$2.59 had to be spent on fixed payments to achieve the same impact on behavior as \$1 spent on a lottery insurance policy. In the present experiment, this represents a 62% “behavioral discount.” However, it is too early to conclude that the proposed incentive device is cost saving; future work will have to study the benefits relative to that of the initial incentive. A comparison between the effect in this study to those of other recent studies that have evaluated pure gain lotteries—those that are likely influenced only by probability weighting—is difficult to make.

More recent studies have not delivered fixed payments, or if they have, they have not delivered them in the expected value of the gamble. For example, Volpp et al. (2008a) found that lotteries were an effective incentive to improve warfarin adherence but did not offer participants a fixed payment condition. Another study by this group compared lotteries to deposit contracts (which may be influenced by loss aversion), but not fixed payments (Volpp et al. 2008b). This study found that both pure gain lotteries (subject to probability weighting) and deposit contracts (subject to loss aversion) were comparably effective. In a study on health risk assessments, Haisley et al. (2012) found that pure gain lotteries were a more powerful incentive than fixed payments, though the lottery scheme did not guarantee the delivery of expected rewards at the rate of the fixed payment. A study by Halpern et al. (2011) compared lotteries to fixed payments in the expected value of the lottery but did not find differences when the fixed payments were delivered at the same time as the lottery payouts. By contrast, the present study finds a large effect under an insurance framework that may point to the power of loss aversion as an incentive.

There are limitations to this study that need to be addressed. First, the sample was a convenience sample drawn from Internet users. It is possible that these results may not generalize to other target populations. Although health risk assessments are a valid and important tool for all persons, adapting our method to a clinical population could produce different results. Targeted patient populations may have constraints that restrict their engagement in health behavior. Second, an online health risk assessment has a low opportunity cost, which could result in high participation rates in both experiment and control conditions. Although this does not threaten the validity of the study, the rates may not reflect what would be found in other domains of interest (e.g., exercise, weight loss). To counteract this, we made efforts to increase the opportunity cost by setting appointment times for visiting the health risk assessment site within short intervals determined by the experimenters, not by the participants. By doing this, the participants were inconvenienced and may have had to make special efforts to meet their appointment time and receive their reward.

There are several ways the results of this study can be used in the future. The results of the current study can likely be generalized to some health behaviors that require little effort, such as adhering to medication regimens, receiving vaccinations at the work-place, or calling for laboratory results. Future studies of this paradigm should evaluate the effectiveness of this type of intervention on real-world health behaviors, where opportunity costs and changes from the status quo behavior are greater than simply visiting a URL at an appointed time. Medication adherence and weight loss are two examples where more dynamic reward designs based on behavioral economics have been employed with greater success (Volpp et al. 2008a, b). Similarly, the insurance framework we used is most useful for dynamic decision making, where an at-risk incentive can be delivered at time n and an insurance incentive guaranteeing the reward can be delivered at time $n + 1$. Blood pressure monitoring among persons with hypertension, glucose monitoring among persons with diabetes, and weight monitoring are other examples where dynamic incentives are important and could be delivered using an insurance design for at-risk rewards.

In conclusion, the design of incentives for health-promoting behaviors may benefit from utilizing an insurance paradigm, particularly when the receipt of an attractive at-risk reward is contingent upon adhering to planned health behaviors. Insurance-based incentive designs may promote health behavior uptake by capitalizing on aversion to losing expected endowments. Future work should evaluate the persistence of such effects and the individual differences that may influence the magnitude of the effect.

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Figure 1.(Color online) Insurance Experiment, Given Expected Endowment (G)

Table 1

Participant Characteristics ($N = 298$)

Variable	N	%	Insurance condition (%)	Fixed payment condition (%)	z-Test p-value for group difference (Fisher's exact test)
<i>Female</i>	162	0.543	0.553	0.534	0.7358
<i>Latino</i>	29	0.097	0.08	0.12	0.3116
Race					
<i>White</i>	238	0.798	0.78	0.82	0.4204
<i>Black</i>	22	0.073	0.087	0.06	0.3951
<i>American Indian/Alaska Native</i>	3	0.010	0.007	0.014	0.5554 (0.62)
Nationality					
Asian	22	0.073	0.073	0.074	0.974
Other	13	0.044	0.053	0.034	0.4105
Education					
<i>High school</i>	36	0.121	0.127	0.115	0.7556
<i>Some college</i>	97	0.326	0.327	0.324	0.9657
<i>Associate's</i>	32	0.107	0.113	0.1	0.7394
<i>Bachelor's</i>	88	0.295	0.313	0.277	0.4938
<i>Master's</i>	32	0.107	0.08	0.14	0.1251
<i>Doctorate</i>	5	0.017	0.013	0.02	0.6424 (0.68)
<i>Professional</i>	8	0.027	0.027	0.027	0.9847 (1)
Income					
< \$25K	72	0.242	0.273	0.209	0.199
\$25K–\$49K	104	0.349	0.313	0.39	0.1948
\$50K–\$75K	52	0.174	0.16	0.189	0.5084
\$75K–\$99K	36	0.121	0.147	0.095	0.169
\$100K–\$124K	21	0.070	0.047	0.095	0.1067
> \$125K	13	0.044	0.06	0.027	0.1646
Age					
18–24	74	0.248	0.247	0.25	0.9471
25–29	71	0.238	0.273	0.203	0.1535
30–37	78	0.262	0.253	0.267	0.7405

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Variable	N	%	Insurance condition (%)	Fixed payment condition (%)	z-Test p-value for group difference (Fisher's exact test)
> 37	75	0.252	0.227	0.277	0.3182