How Individuals Choose Health Insurance:

An Experimental Analysis[+]

Arthur Schram*
Joep Sonnemans
CREED
Amsterdam School of Economics
University of Amsterdam
Roetersstraat 11
1018 WB Amsterdam
Email: USchram@uva.nl; J.H.Sonnemans@uva.nl
*corresponding author

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ABSTRACT

An individual choosing a health insurance policy faces a complex decision environment where a large set of alternatives differ on a variety of dimensions. There is uncertainty and the choice is repeated at least once a year. We study decisions and decision strategies in a laboratory experiment where we create a controlled environment that closely mirrors this setting. We use an electronic information board that allows to carefully monitor the individual's decision strategy. The number of alternatives, switching costs, and the speed at which health deteriorates are varied across treatments. We find that most subjects' search is based more on attributes than on policies. Moreover, we find that an increase in the number of alternatives increases decision-making time; makes subjects consider a lower fraction of the available information; makes it more likely that subjects will switch; and decreases the quality of their decisions. The introduction of positive costs of switching make people switch less often but improve the quality of their decisions. Finally, if health deteriorates only gradually, individuals tend to stick to their current policy too long.

1. Introduction

In 2006 the Dutch government introduced a completely renovated system of individual health care insurance. Before this reform, almost 2/3 of Dutch citizens were covered by a compulsory social insurance against most health risks whereas the remaining 1/3 where covered by voluntary private health insurance. The division was based on income. This was replaced by a uniform system for the entire population. This new system is characterized by an increased market competition combined with mandatory basic coverage of essential health care.[1] A major goal of the reform is the creation of a competitive and efficient market in health insurances where consumer demand is intended to play a major role.

A necessary condition for the new system to yield the benefits attributed to it is that the demand side of the market for insurance policies is well developed. For example, consumers must be able and willing to choose a policy based on quality and price, *e.g.*, the price elasticity must be large enough. Though estimates indicate that the short-run price elasticity is higher in the Netherlands than in other countries (Schut and Hansink 2002) the demand for health insurance is still price-inelastic and the long-run price elasticity is not even significantly different from zero in the Netherlands (Schut *et al*. 2002).[2] Aside from these estimated elasticities, very little is known about how consumers choose a health insurance policy (henceforth, policy). This study aims at narrowing this gap in our knowledge by carefully investigating how individuals in a controlled laboratory environment choose in an environment that is carefully set to have essential characteristic in common with the environment in which customers choose a health insurance.[3]

For our research questions, there are several advantages of using the control offered by the laboratory environment. First, though field data may sometimes be the preferred method to analyze final choices, they give no information about the way in which consumers make their decisions (*i.e.*, the *decision strategy* of the decision maker). In contrast, we will

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[1] More specifically, each year the government determines a minimum 'package' of essential health care that must be covered by the policy. Insurers may compete by setting a price for this 'basic insurance'. They are obliged to accept anyone at this price. In addition, insurers may offer extended policies that cover risks not included in the package. For these, price discrimination and selection based on risks are allowed. For more information, see http://www.minvws.nl/en/themes/health-insurance-system/.

[2] Of course, this may be different in the new system, but at this stage there is insufficient information to estimate these elasticities. For estimates of the price elasticity of the demand for policies in Germany see Andersen and Schwarze (1998); for estimates for the United States see Short and Taylor (1989), Feldman *et al*. (1989), Barringer and Mitchell (1994), Cutler and Reber (1996), Royalty and Solomon (1999), Buchmueller (2000), or Strombom *et al*. (2002).

[3] In fact, the research reported here was commissioned by the Dutch Ministries of Economic Affairs and Health, Welfare and Sports. They were specifically interested in gathering information about the choice of health insurance. Governmental specialists appointed by the ministries advised us about specifics of the experimental design in order to maximize its external validity.

see that laboratory control allows us to unravel the decision strategy in detail. Second, the quality of policy choice decisions is hard to measure using field data because the preferences of the decision maker are not known. In contrast, these preferences are induced in the laboratory (Smith 1976) and therefore the relationship between decision and preference can be directly measured.[4] Finally, experiments allow us to systematically vary specific characteristics of the situation consumers face and to test the effects of certain changes in the environment under truly *ceteris paribus* conditions. In short, laboratory control offers an opportunity to obtain important insights. In this way our results complement the knowledge obtained from field data (*e.g.* Kerssen en Groenewegen 2005).

There are many elements of the decision-task under scrutiny that may affect the behavior of the health insurance consumer. In this study we focus on three aspects that, according to the ministries that contracted this research, are especially relevant for policy choice but are also interesting from a more theoretical point of view. These are the *number of alternatives* an individual has to choose from; the occurrence of *costs when an individual switches* from one policy to another; and the *stability of an individual's health profile*, i.e. her risks. These three aspects correspond to the three treatments in our experimental design, as will be explained below.

The remainder of this paper is organized as follows. In the following section, we present our experimental design and procedures. Based on the (limited) theoretical literature that can be applied to our case, section 3 discusses the effects one might expect to see. The actual results and their interpretation are presented in section 4, followed by a summary and concluding discussion in section 5.

2. Experimental design and procedures

The experiment consists of a computerized individual decision making task with no interaction between participants.[5] Earnings are in 'points', which are exchanged for euros –at the rate of 200 points=€ 1– at the end of the experiment. The 148 participants earned approximately 17 euros on average in 75 minutes.

It is important to realize that we focus only on the demand side of the market for insurance policies. In particular, we are interested in studying how this demand develops. Hence, the policies are exogenously given and we are not interested in the competition

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[4] Of course, one aspect of preferences is risk attitude. Though one can theoretically try to induce risk neutrality in the laboratory by using binary lottery payoffs, this method generally fails in practice (Selten *et al.* 1999).
[5] The experiment is available at http://www.creedexperiment.nl/zorg for demonstration purposes (in the original Dutch version as well as an English translation). The reader is invited to get a feeling for the experiment by playing a few periods.

between insurance companies (though this would certainly be an interesting avenue for future research). Moreover, according to Dutch law, health insurance is mandatory. Therefore, each participant in the experiment must always choose a policy.

First, the subjects read the computerized instructions (see appendix 1 for a translation) and answer a few questions to check understanding. After answering correctly they start with the first of 35 periods. In each period they receive a fixed income of 250 points and may *lose* points depending on the occurrence of *events* (analog to illness, accidents, etc.). Whether an event occurs, is determined by means of a lottery. Before the lotteries are played, the participant chooses an insurance *policy,* the cost of which is subtracted from the fixed income.
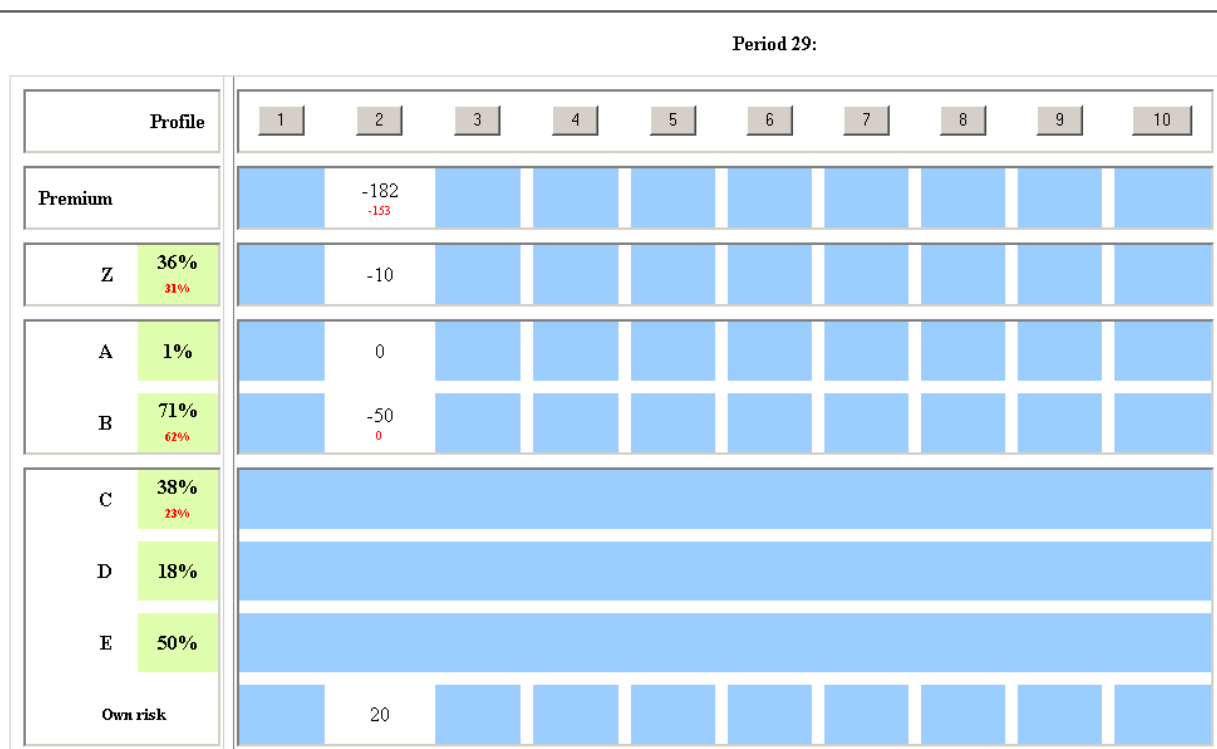
Events. There are 6 possible events, coded as A, B, C, D, E and Z. A is an event with a small probability but with severe consequences (-2000 points if not insured), B is an event with a higher probability but less severe consequences (-50 if not insured).[6] Events C (-40), D (-25) and E (-20) are covered by all insurance policies, but a deductible of 0, 20 or 50 may apply. Note the parallel with the reformed Dutch system: A and B are events not covered by the standardized package whereas C, D, and E are part of this package. Event Z is a quantification of qualitative aspects of a policy (how fast does the insurance company pay, service level, etc); possible values are 0, -10 and -20. The probability of event Z occurring is based on the probabilities of the other events (because the quality of service is only important in case of an accident or illness). Figure 1 shows the computer screen used. Events are represented in the rows of the table shown on the screen. We will explain the other parts of the table below.

Profiles. At the start of each period each participant observes her or his *health-profile,* which is a series of probabilities for the distinct events. These probabilities are shown in the second column of the table on the screen (figure 1). The word 'health' was not used in the experiment and we will use 'profile' in the remainder of this paper.[7] Profiles change across periods. As described in the introduction, we distinguish between two possible dynamics, to wit, gradually changing and suddenly deteriorating health. Figure 2 shows the development over time of the probabilities in these two profiles. Both profiles show an increasing

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[6] One can think of A as a catastrophic health event (*e.g.,* a specific kind of cancer). Though the standard treatment will be covered in the basic package by all policies, some additional insurance will cover, for example, treatment in specialized clinics abroad, which may significantly increase the chances of survival.
[7] An important disadvantage to using labels related to health is that they may add noise to the results (*e.g.,* because of uncontrolled individual responses to words like 'heath' or 'illness'), thereby decreasing their internal validity. We therefore follow the tradition in experimental economics and choose neutral labeling.

Figure 1: Computer Screen

Period 29:

| Profile	1	2	3	4	5	6	7	8	9	10
Premium		-182 / -153								
Z 36% / 31%		-10								
A 1%		0								
B 71% / 62%		-50 / 0								
C 38% / 23%										
D 18%										
E 50%										
Own risk		20								

Notes: this is an example of the screen seen by a participant in period 29. Rows represent events and columns represent policies. This participant had chosen policy 2 in period 28 and has not yet uncovered any information in period 29. Compared to period 28 the premium for policy 2 has increased from 153 to 182 and event B is no longer covered. As for health, compared to the previous period, the probabilities of events Z, B, and C have increased.

probability of events, analogous to a decreasing health over lifetime. In addition some small random noise is added, analogous to incidental fluctuations in health. Note that probabilities start at the same levels in both profiles and end at the same levels, save some random fluctuation.

Policies. Policies are represented by the columns in the table and denoted by numbers. Each policy is characterized by its premium (given in the second row) and by the financial consequences if events occur after that policy is chosen. For example, if a policy covers event A, the financial consequence of A occurring is 0. If it does not cover A, the consequence is –2000. For each policy the premium is determined as its expected value plus some random noise. Hence, the expected value of the policy including premium is on average zero. The number of policies is a treatment variable and is either 4 or 10. The 4 policies are a subset of the 10 policies.

Figure 2: Probabilities of Events

Gradual profile

Sudden profile
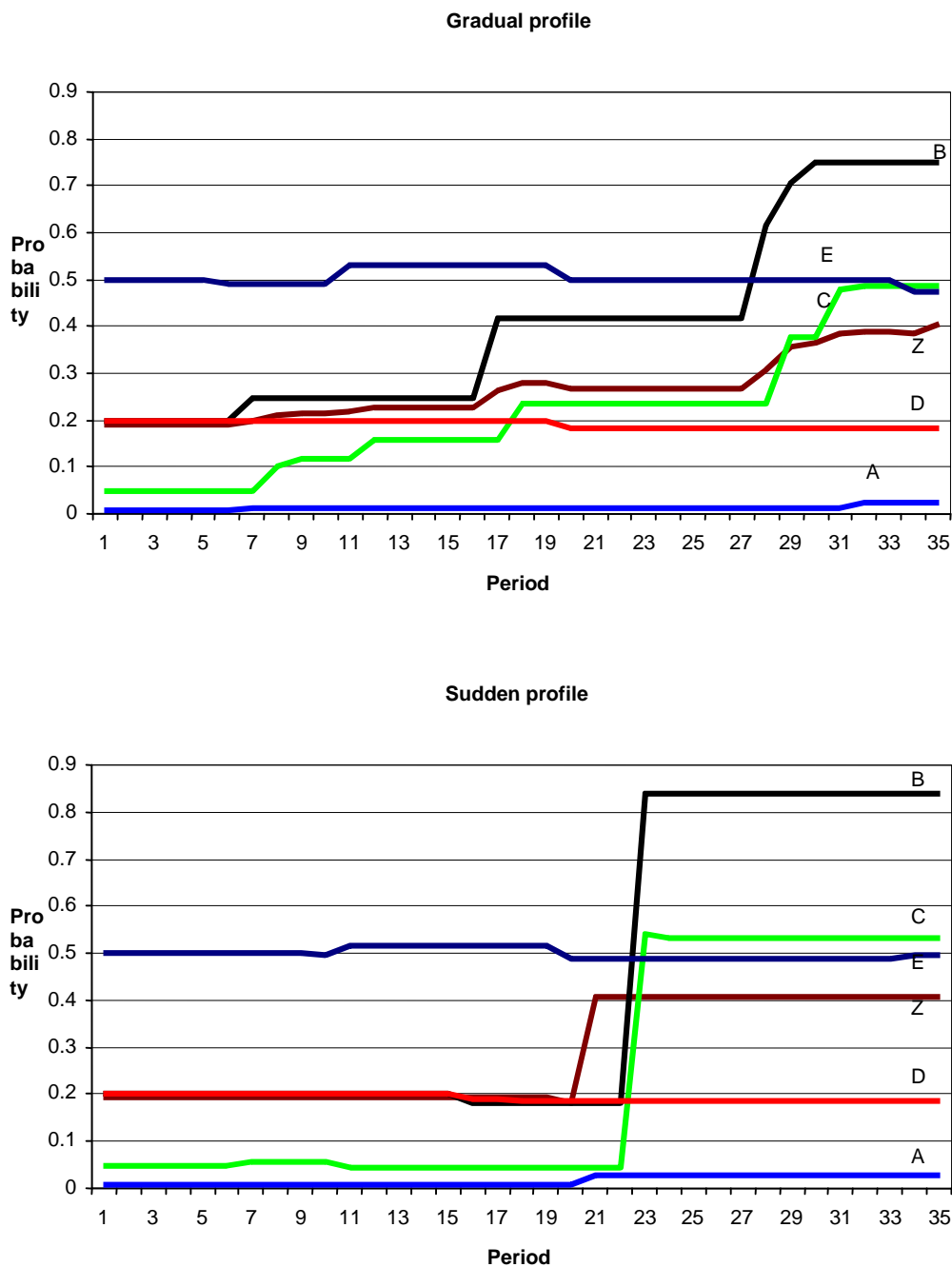
Notes: each line shows the probability of an event over time. Aside from minor random fluctuations all probabilities are non-decreasing. Increases are either gradual (upper panel) or sudden (lower panel).

Information and information board. Changes in the profile or current policy (compared to the previous period) are highlighted in red in the table shown to subjects (in figure 1 these may be recognized as numbers with a small font). The profile and policies do not change during the first 5 periods and participants know this. This allows a participant to get

acquainted with the task in these early periods. The method we use to collect information about individuals' strategies is an information board (for an overview of recent examples using this method see Crawford 2008). Clicking with the mouse on a table cell reveals information about the characteristics of the policies. Each click costs 0.25 points (0.00125 euro). Characteristics of the current policy are always displayed (without costs). This represents the fact that consumers typically have information about their current policy. The computer program saves all mouse clicks (enabling us to analyze the search behavior) and the total time used per decision (as in Rubinstein 2007). Our application of the information board differs from most previous studies in two ways, however. First, in other studies only one piece of information was displayed at a time (previous information disappears when a participant uncovers new information; for an example see Johnson *et al.* 2002) and making notes was not allowed. We thought this to be very unrealistic for our goal and not representative of the way people choose a policy. The second difference is that we charge a very small amount for each piece of information, in order to induce participants to only search for information that they expect to use, thus revealing their decision-making strategy to us.[8]

Switching costs. Choosing a policy is (implicitly) a recurring decision: in the Netherlands policies are one-year renewable contracts, hence, once a year the consumer has an opportunity to change to a new policy. If switching costs (*e.g.*, the time spent on investigating alternatives, the paperwork involved or the need to change the family doctor or hospital) are high enough it may never be profitable to switch (for discussions pertaining to the Netherlands, see, Kerssens *et al.* 2002 or Laske-Aldershof and Schut 2002). This type of extreme situation could easily be studied in an experiment, but the outcome is too predictable to be of any real interest. Even aside from such extreme costs, many policy makers seem to believe that lowering switching costs will *always* increase efficiency by increasing market competition (though there is no clear-cut empirical evidence supporting positive welfare effects of lowering switching costs). Switching costs is a treatment variable and is either 0 or 10 cents.

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[8] In a pilot-study without costs we found that some participants (about 40%) systematically clicked on all table cells and often decided almost immediately after observing the contents of the last cell, that is, without processing all that information. Obviously, information will only benefit the decision if it is used (Farley *et al.* 2002).

Risk preference. After the 35 periods of the insurance task are finished, participants' risk attitudes are measured by means of the Holt and Laury (2002) lottery task. In this task subjects choose 10 times between pairs of lotteries. One of their choices is played out for real money.

Treatments. A full 2x2x2 factorial between subjects design is applied. Switching costs are either 0 or 10, the number of policies is either 4 or 10 and the profile changes either gradually or suddenly. Because of no-shows, not all treatments have exactly the same number of participants (varying between 16 and 21).

Participants. The (148) participants were undergraduate students, predominantly in business (33%), economics (24%), psychology (12%) or medicine (12%).[9] 63% of the participants were male and the average age was 21.5 (varying between 18 and 28).

One natural question to ask at this stage is why this design represents the choice of a *health* insurance. One may consider the combination of profiles and policies to represent *any* type of insurance. Though we certainly believe that many of our results apply to insurance choice more generally, various aspects are specific to the health insurance environment (and were explicitly chosen in consultation with the Ministries). Such specific characteristics are, for example, (i) the increasing probabilities in the profiles (representing health deteriorating with age); (ii) the distinction between a mandatory 'basic' package and an additional voluntary insurance (mirroring the health insurance system introduced by the Dutch government); (iii) the system of deductibles (very common in Dutch health insurance policies); and (iv) the existence of 'qualitative aspects' such as freedom of doctor choice.

3. Expected Results

Standard economic theory does not straightforwardly provide predictions about behavior in our experiments. The reason is that these strongly depend on the various kinds of costs that an individual is confronted with while choosing. Aside from the costs that we explicitly impose –i.e., costs for searching information (clicking on cells) and switching to a new policy– there are costs of mental effort. Any prediction will depend on how such costs are

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[9] Of course, students do not form a representative sample of the population and may in some respects act differently than other groups. However, we will not focus on absolute measurements but on comparative statics across treatments. In general, most studies that compare populations across experiments find no differences between students and others in a qualitative sense (Schram 2005).

modeled. This does not mean that we cannot say anything about expected treatment effects, however. For each of our treatment variables, we therefore briefly summarize the more general conclusions that can be derived from an analysis of the decision making process involved.

First, the number of alternatives (4 or 10) may affect the *way* in which consumers choose and therefore the quality of their choice (as measured by its expected utility). Note that the traditional micro-economic model without search or decision costs predicts that the decision maker will choose the alternative with the highest expected utility. Adding options may add an alternative with a higher expected utility than previously available and may therefore increase the quality of the best available alternative. Following this traditional line of reasoning, an increase in the number of alternatives can only have a non-negative effect on decision quality. However, more alternatives will make the problem more difficult (and therefore more costly) for a boundedly rational decision maker.[10] There is abundant experimental evidence that with many alternatives, decision makers consider a smaller part of the available information and use elimination by aspects; a stepwise selection of alternatives based on their attributes (Tversky 1972). Elimination by aspects is a suboptimal strategy (for decision makers who have no search or decision costs) because there is no trade-off between aspects. Therefore the chosen alternative may deviate more from the optimum as the number of options increases. In addition, more alternatives will likely increase search costs. Finally, the ex-post satisfaction with decisions made tends to decrease with the number of options chosen from (Iyengar & Lepper 2000), Botti & Iyengar 2006). This suggests that more alternatives may increase (costly) switching behavior. Our design allows us to disentangle these distinct potential effects on the quality of decision making.

To do so, we distinguish between four potential effects of the number of policies on the quality of the decision, which we denote by I-IV.

I.   It may have a positive effect on the decision quality. With more alternatives to choose from, the best available policy will be at least as good as and often better than before.[11] In the experiment, the expected value of the optimal choice will be higher in this case.

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[10] Moreover, the costs for uncovering all information are higher when there are more alternatives. Though these costs are very low, this may affect the quantity of information considered.
[11] To guarantee this in the experiment, all policies of the 4-policies treatment were also included in the 10-policies treatment.

II.   There is a potential negative effect because it is more difficult to find the best policy when there are more alternatives. This means that participants may choose an option further from the optimum.

III.   Another negative effect occurs because the number of policies will affect decision costs. More policies imply higher search costs and information processing. For our subjects, this means that they may spend more on acquiring information.

IV.   A fourth negative effect is that more policies may lead to more (costly) switching. Participants have to pay the ten points switching costs more often.

Each of these effects will be directly measurable (as units of experimental currency) in our data. The net effect of the number of policies on the quality if the decision is the sum of these four effects. We expect that some, if not all of the positive effect of having more alternatives to choose from will be negatively compensated by the negative effects.

Second, consider the effect of switching costs. In theory, switching costs may influence the decision process at any specific point in time as well as the way in which decision makers learn over time. An example of the latter is that low switching costs decrease the direct costs of a trial-and-error strategy which may have a negative effect on the quality of the decision made. All in all, we expect that the effect of lower switching costs will not be as positive as the conventional wisdom of policy makers (that lower switching costs increase welfare) would have us believe. If the costs are too low, the changes in the process may even have negative consequences that completely override the positive effects. Our data will allow us to measure the net effect.

Third, we investigate the influence of the *stability* of the consumer's risk profile. The psychology literature shows that individuals often prefer stability to change. The 'Status Quo Bias' (a preference for the status quo) and the related 'Omission Bias' (a preference for inaction) are well-documented phenomena (Samuelson and Zeckhauser 1988, Spranca *et al.* 1991; for a recent overview see Anderson 2003) that may have a negative impact on switching behavior.[12] Intuitively, these effects will be stronger in a stable environment than in an environment where sudden changes take place. This is comparable to the 'boiling frog' anecdote: there seems to be a common (but biologically questionable) belief that a frog can be boiled alive even if it is capable of jumping out of a pan. The story goes that if a frog is placed in boiling water it will jump out, but if it is placed in cold water that is slowly heated it

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[12] Related phenomena that may negatively affect switching behavior are 'Inaction Inertia' (after forgoing a good opportunity, a decision maker prefers not to make any new decisions) and 'Choice Deferral' (a tendency to postpone decisions); for examples see Tversky and Shafir (1992) and Redelmeier and Shafir (1995).

will not. In our experiment we test the effect of changes in the environment by comparing groups of participants whose health-profile change gradually to those who experience sudden changes in this profile.

For each of these aspects, the *process* by which individuals make their choices, *i.e.*, their decision strategies, plays an important role. The type of multi-criteria decision-making concerned when individuals choose a policy has been extensively studied in the psychology literature, albeit that most studies do not consider choice sets where uncertainty plays a role.[13] From a methodological point of view, Payne *et al.* (1993) is a modern classic. In their framework a decision maker starts by choosing an information strategy. This describes what information will be gathered, in what order, and how it will be processed. They introduce the electronic information board (*mouselab*) as a method to uncover this strategy. The decision-maker (implicitly) compares costs and benefits of different strategies. Benefits are the expected improvement in the quality of the decision (accuracy), and costs are effort and other psychic costs.[14] Two different ways of information processing can be distinguished (Payne *et al.* 1993). In *alternative-based* search the decision maker studies all attributes of an alternative before considering another alternative. This corresponds to reading the complete prospectus of one policy before considering the next. In *attribute-based* search the decision maker first compares a set of alternatives based on a single attribute (*e.g.*, the premium); then forms a subset of alternatives based upon this attribute and considers a following attribute for this subset. This corresponds to, for example, first considering the premium offered by the various companies for their policies and then selecting a set of policies to consider more carefully. In the experiment alternative policies were in columns and attributes in rows. Note that alternative based search then implies that the participant searches down columns (*i.e.,* vertically) whereas attribute-based search implies searching across rows (horizontally). To investigate whether these search strategies are used, we consider the order of mouse clicks. A click in the same column (row) as the previous click is considered to indicate alternative-(attribute-) based search. Hibbard *et al.* (1997) predict that individuals in an environment like ours will use an information strategy that labeled "elimination by aspect" (Tversky 1972): first compare one characteristic across all available policies, then select a few policies, then

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[13] We will not try to provide a comprehensive overview of this literature but focus on the most relevant study instead. For additional references, see Payne *et al.* (1993). A related literature studies pension choice (see Huberman *et al.* 2006 and references therein). The problems in that choice (*e.g.*, time horizon) are very different than for insurance choice, however.

[14] The decision strategy chosen will depend on personal style, characteristics of the problem and context. The effort needed for a specific strategy depends on the number of elementary information processes (EIP's, like comparing two numbers, adding, storing, etc) and will be traded off with accuracy. A strategy that is relatively efficient when the number of alternatives is low may be inefficient in case of many alternatives. When the complexity of the problem increases, it may not be efficient to compare all alternatives on all aspects.

compare the remaining policies based on a next characteristic, etc. This suggests dominance of attribute based search above alternative based search. Data collected through our information board will allow us to test whether elimination by aspect is indeed a widely used strategy by our subjects.

4. Results

In presenting the results, we will first discuss the role of risk aversion. We then continue with a discussion of the determinants of the quality of decisions. After presenting our results on switching behavior, this section concludes with an analysis of the decision-making process itself. Because profiles and policies remained constant in the first 5 periods (and the participants knew this), these initial periods are not included in the analyses (but our conclusions are robust to their inclusion). Unless otherwise mentioned, all tests are non-parametric Mann Whitney or Wilcoxon tests with the decision-maker as unit of observation.

4.1 Risk attitude

We measured subjects' risk attitudes using the standard Holt and Laury (2002) test. Participants are asked to make ten choices between paired lotteries, denoted by option A and option B. In each of these pairs A is less risky than B. Each lottery consists of a high payoff and a low payoff. The high (low) payoff is €2.00 (€1.60) for option A and €3.85 (€0.10) for B. The probability of winning the high payoff is the same in each pair and increases from 1/10 to 10/10. Hence, only an extremely risk seeking subject will choose B in the first pair while in the tenth pair B (a certain €3.85) will be preferred over A (a certain €2.00) irrespective of risk attitude. Going from the first to the tenth pair, the individual's risk attitude determines when the crossover from A to B will be made (i.e., the pair in which it is made is a measure for the individual's attitude towards risk).

We can use the individually estimated risk attitude to determine the individual utility-of-wealth function with constant relative risk aversion:

$$U(x) = \frac{x^{1-r}}{1-r},$$

where r is the estimated relative risk aversion. Because there are nine pairs where a subject may have switched to option B, our subjects preferences for monetary outcomes may be represented by one of nine possible utility functions. For each of these utility functions, we calculated the expected utility of each insurance policy in every round. Hence, for any subject

in any round, we know which policy maximizes her or his (estimated) expected utility, for the chosen parameterization. The utility function with $r=0$ describes risk neutral preferences, for which utility is maximized by choosing the policy with the highest expected value.[15]

Of our 148 subjects, 8 were inconsistent in their responses to the measurement (switching more than once). We categorized these subjects as risk neutral ($-0.15<r<0.15$).[16] In aggregate, 43 subjects (29%) were categorized as risk neutral. 32% of our subjects were estimated to have a negative value of r (indicating a preference for risk-taking) whereas 39% had a positive value (indicating a preference for risk-avoidance).

For the insurance policies used in our experiments, it does not matter much whether we rank them according to expected value or expected utility. The optimal policy according to expected value is the same as the optimal policy according to the expected utility in more than 90% of all periods. Comparing the average ranks of a chosen policy according to expected value and expected utility at the individual level, the correlation coefficient is 0.90. At the choice level, the rank of the chosen policy in expected utility correlates with the rank in expected value with a coefficient of 0.88.

Because of this, we will use expected value as the measuring rod in the remainder of this paper. This has the advantage of providing an easily interpretable unit of measurement (money) without need for further assumptions (such as the parameterization of the utility function). Details about a similar analysis in terms of expected utility is available upon request.
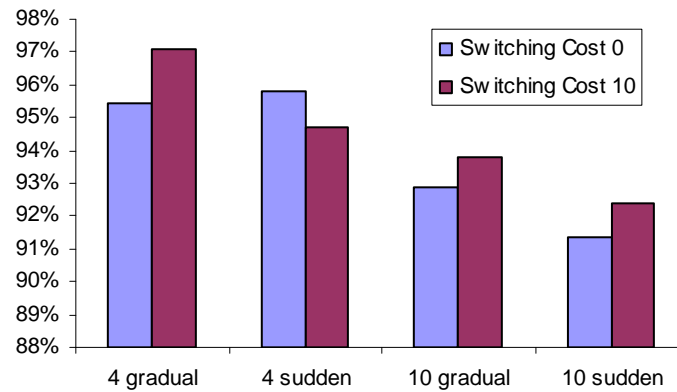
4.2 Quality of decisions

Because we know all probabilities and consequences, we can easily calculate the expected value of every policy in every period. Hence we know what the expected value maximizing choice is in every period. The first question we address is how the expected value of the policy chosen relates to this maximum. We call this the 'quality' of the policy chosen by the subject. This is one of the areas in which laboratory control provides unique opportunities. It is virtually impossible to study the quality of policy choices using field data. First of all, specific individual health profiles are not directly observable in the field, so one needs to resort to survey questions that allow one to derive indirect information about them. Second, individual preferences are not known in the field (*e.g.*, the extent to which a decrease in

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[15] A constant relative risk aversion (*r*) equal to zero is the estimate for any individual switching from option A to B between pair 4 (where the probability of a high prize is 0.4) and pair 5 (0.5).
[16] The results in this section are robust to excluding these subjects from further analysis.

health negatively impacts an individual's well-being). In contrast, we can precisely compute the expected value of each and every policy in the experiment. Figure 3 shows the quality of the decision by relating the expected value of the chosen policy to the maximally available expected value.

Figure 3: Decision Quality

Note: bars show the treatment average of the expected value of the decision divided by the optimal expected value.

We first consider the effect of the number of available policies on the quality of the choice. Recall that traditional micro-economic thinking without search and transaction costs would predict that the quality of the final choice is non-decreasing in the number of options. In contrast, our data show a statistically significant negative effect of the number of policies on the relative quality ($p<0.5$ in all treatment combinations). To better understand this result, we split the aggregate effect into the four categories distinguished in section 3. We do so in table 1, where we distinguish between periods in which the optimal policy of the 10-policies treatment is also contained in the 4-policies set and periods where this is not the case. Note that the only positive effect (I) is limited to the latter case. The second row of table 2 shows that in the experiment this positive effect is on average 7.87 for gradually changing profiles and 15.98 in the sudden treatment.[17] Next, we consider the negative effects II-IV. To determine the losses related to sub-optimality, rows 3 and 4 show the average difference between the expected value of the chosen policy and the expected value of the optimum available. On average, subjects lost between 3.91 and 15.28 points by not choosing optimally. They are typically further away from the optimum when there are ten policies than when

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[17] This positive effect occurs irrespective of the choices made by subjects. Effect II measures whether choices deviate more from the optimum in one case than in the other.

Table 1:Quality Effects of More Policies

	Policies	Gradual SC=0		Gradual SC=10		Suddenly SC=0		Suddenly SC=10	
		equal optimum	optimum 10 policies better	equal optimum	optimum 10 policies better	equal optimum	optimum 10 policies better	equal optimum	optimum 10 policies better
I: Expect value best policy in 10 minus best policy of 4		0.00	7.87	0.00	7.87	0.00	15.98	0.00	15.98
Expected value decision minus EV optimal policy	4	−6.05	−8.79	−3.91	−5.67	−7.98	−4.36	−9.44	−5.38
	10	−9.72	−11.31	−8.61	−9.80	−13.29	−11.63	−10.03	−15.28
II: Difference (4-10)		3.67	2.51	4.70	4.13	5.31	7.27	0.58	9.90
III: Extra cost info 10		0.60	0.78	0.71	0.47	0.52	0.52	0.74	1.10
IV: Extra cost switching 10				0.32	0.32			0.24	0.24
Aggregate effect (I–II–III–IV)		**−4.26**	**4.57**	**−5.74**	**2.95**	**−5.83**	**8.18**	**−1.56**	**4.74**
Overall expected effect		1.04		−0.53		2.52		2.22	

Notes: the table compares the quality of decisions with 4 or 10 policies and disaggregates the effect into categories I-IV as described in the main text. It distinguishes between periods in which the optimal policy of the 10-policy treatment was included in the 4-policy and periods in which a better optimum was available with 10 policies. Numbers represent per-period averages.

there are four. This difference, effect II, is given in the fifth row. The fact that the difference is positive in all circumstances confirms that on average the deviation from the optimum is larger with ten policies. The third effect (III) is measured by the additional costs for information acquisition when there are ten policies. The sixth row of table 2 gives the average increase in search costs observed for our 10-policies treatments compared to our 4-policies case. The last effect (IV) measures the average observed differences in switching costs paid in both treatments. Note that this difference is relatively small.

The aggregate effect of adding six policies (row 8) obviously depends on whether or not these include an improvement of the optimal choice. If they do, the positive effect (I) dominates and subjects earn on average about 3 to 8 points more per period. In periods where the same optimum can be obtained in both cases, there is no positive effect. Increased costs (II-IV) yield a loss of on average 1.5 to 6 points. Finally, given that in our design the optimal policy was the same in both sets in about 40% of the periods, we can calculate the aggregate expected effect of adding six policies. We find a small expected loss in the switching cost treatment where profiles change gradually, and expected gains from adding policies in the other treatments. Of course, these results may strongly depend on the precise parameters chosen. We will return to this issue in the concluding section.

Returning to Figure 3, switching costs appear to have a modest positive effect on the quality in three of the four treatment combinations, though this difference is only significant in the case where there are four policies and profiles change gradually ($p<.05$). Note that this is the counterintuitive result discussed in section 3: limiting the possibilities to choose by introducing switching costs improves the quality of the choice made (in at least one case). We will analyze the effects of switching costs in more detail, below.

The profile type (gradually versus suddenly deteriorating health) has no significant effect on the quality of the decisions. At first sight, this would mean that the boiling frog phenomenon is not observed in our data. We will see that some of our other results do provide support for this phenomenon, however.

As a final analysis of decision quality, we carry out a multivariate regression analysis to study the combined effect on the relative quality of the chosen policy of treatment variables, changes in the situation and personal characteristics. In addition, we control for differences in decision-making strategies as measured by the amount of time taken and the

15

type and quantity of information acquired.[18] Table 2 gives the results of a random effects Tobit regression explaining relative quality.

Table 2: Realized Fraction of Potential Earnings

	Variable	Gradual profile	Sudden profile
	Period	−0.007 (17.0)**	−0.014 (21.8)**
Treatment	Number policies	−0.007 (3.10)**	−0.025 (5.54)**
	Switching costs	0.005 (3.44)**	−0.003 (1.10)
Change in situation	Change in profile	−0.051 (6.64)**	0.052 (4.43)**
	Change in current policy	−0.043 (4.57)**	−0.077 (5.62)**
Personal characteristics	Inconsistent risk measurement	0.023 (0.49)	−0.177 (2.82)**
	Risk attitude	0.005 (1.07)	−0.022 (3.05)**
	Female	−0.019 (1.23)	−0.051 (1.74)
	Age	0.001 (0.31)	−0.002 (0.36)
	Studies economics	0.005 (0.26)	−0.002 (0.06)
	Studies business	−0.007 (0.33)	−0.019(0.54)
	Studies psychology	−0.016 (0.57)	−0.049 (1.11)
	Studies medicine	0.034 (1.39)	−0.002 (0.05)
Decision strategy	Decision time	0.000 (0.10)	0.000 (0.29)
	No information	0.029 (2.53)*	0.026 (1.38)
	# premium	0.009 (3.77)**	0.009 (2.39)*
	# Z	0.001 (0.11)	0.002 (0.74)
	# A	−0.009 (2.16)*	0.008 (1.68)
	# B	0.001 (0.30)	−0.002 (0.37)
	# deductibles	−0.001 (0.22)	−0.004 (0.81)
	Search direction	−0.001 (0.75)	0.000 (0.29)
	Constant	1.066 (15.8)**	1.521 (9.06)**
	ρ	0.067	0.121

Notes: The table presents the results of a random effects tobit regression where the dependent variable is the expected value realized by individual i in period t as a fraction of the optimal expected value. Formally, it gives the estimated coefficient vector β in $\pi_{it}=\sum_i X'_{it}\beta +\mu_i + \varepsilon_{it}$ if the RHS is <1 and $\pi_{it} = 1$, otherwise; where π_{it} gives the fraction described and X is the vector of independent variables described in the second column of the table. μ_i is a (white noise) individual-specific error term that corrects for the multiple observations we have for each i (ρ measures the fraction of total variance attributable to μ_i) and ε_{it} is a white noise error term. The independent variables are defined in Appendix 2 (note that to avoid a dummy trap students that study in a different field than the four distinguished here are absorbed in the constant term). Absolute z-values are in parentheses. *=statistically significant at 5%-level; **= statistically significant at 1%-level.

The results show strong treatment effects, confirming the conclusions drawn from figure 3. For both profiles, relative quality is lower when there are more policies, though the effect is much stronger with suddenly changing profiles than when they change only gradually (which confirms the aggregate numbers in table 1). Switching costs only have a significant (positive) effect on quality when the profile changes gradually.

Changes in the situation have significant effects on the quality of the chosen policy in all cases. Interestingly, a change in profile has a negative effect if profiles change only gradually

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[18] We will analyze these decision-making strategies in more detail in section 4.4.

but significantly improves the decision if changes are sudden. This is empirical support for the boiling frog phenomenon. Subjects improve their decision after a sudden change but let it deteriorate after a gradual change. Changes in the current policy reduce the realized earnings in both cases. Personal characteristics have little effect on the quality of the decision. Finally, a number of interesting patterns appear when analyzing the effect of decision strategy on quality. Although the time spent on making a decision does not affect realized earnings, the type of information considered does. Subjects who gather more information about the premium make better decisions, whereas (for gradually changing profiles) searching for information about the low-probability/high-consequence event decreases earnings. People who do the latter appear to overweight the importance of unlikely events. Finally, the variable 'search direction' concerns the search strategy used and will be discussed below. Note here that it does not appear to have an effect on the quality of the chosen policy.

4.3 Switching behavior

Using the expected value of every policy in any period we can determine whether or not a (risk neutral) consumer should switch. The optimal number of switches in 35 periods varies (depending on the treatment) between 6 and 11. For each treatment, figure 4 displays the average number of switches per participant together with the optimal number.

Figure 4: Switch Frequency
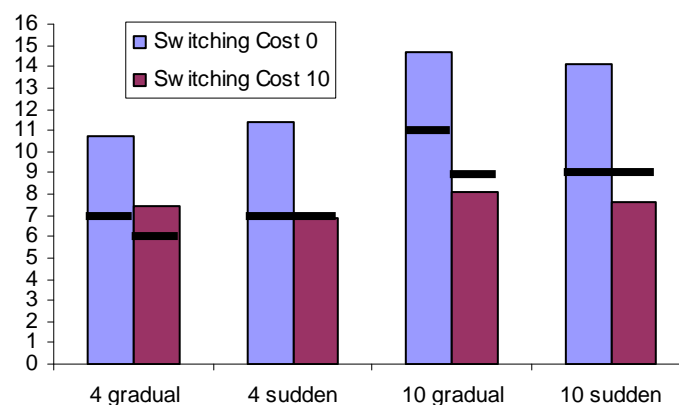
Note: bars depict the observed average number of switches per subject; the black lines indicate the expected value maximizing number of switches for each treatment.

A first thing to observe is that there are more switches when there are ten policies than when there are four. This difference is statistically significant when there are no switching costs

(p<.05). We also find that the introduction of (small) switching costs significantly decreases the number of switches (p<.01 in all four treatments). We conclude from the comparison with optimal behavior that there is a tendency to switch too often when there are no switching costs, whereas the number of switches is more or less in line with the optimal number when there are (small) switching costs. However, this does not mean that the participants always switch at the right moment and to the optimal policy. In many cases (10%-40% depending on the treatment) the new policy has a lower expected value than the previous one, as displayed in figure 5. Switches are more often an improvement in the 4-policies treatments than in the 10-policies cases (p<.01) and switching costs seem to improve the quality of the switches, though this latter effect is not statistically significant. Contrary to our initial expectations, we find no difference in switching behavior between the gradually and suddenly changing profiles. This holds for its frequency (figure 4) as well as the matter of whether it improves expected value (figure 5). We will see below that this last conclusion changes if we correct for other factors, however.

Figure 5: Quality Improving Switches
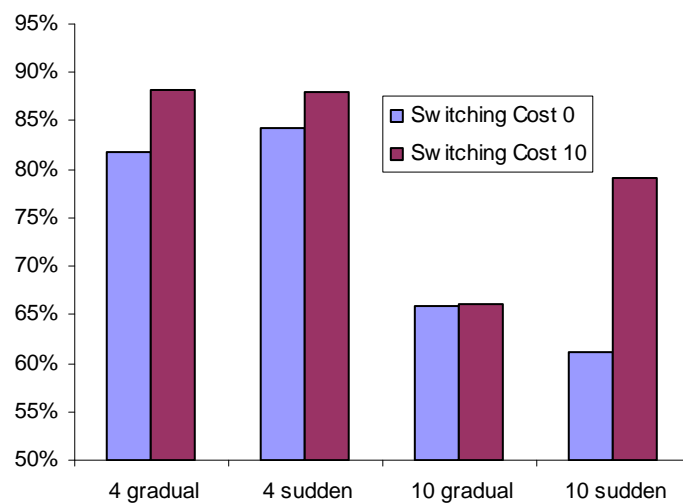
Note: bars show the percentage of switches where the expected value of the new policy is higher than the expected value of the previous one.

To correct for multiple factors influencing the decision to switch, we ran a (random effects) probit regression explaining this decision by our treatment variables and subject background characteristics (including risk aversion). We ran the regression separately for each of the two profiles. The results are presented in table 3. The note to the table provides details about the regression equation. The results confirm our conclusions about the treatments: subjects are

18

Table 3: Regression results Switching

Variable		Gradual profile	Sudden profile
	Period	0.003 (0.86)	0.006 (1.67)
Treatments	Number of policies	0.064 (3.42)**	0.058 (2.45)*
	Switching costs	-0.063 (5.73)**	-0.059 (4.55)**
Change in situation	Change in profile	0.013 (0.20)	0.211 (3.10)**
	Change in current policy	1.226 (16.6)**	1.307 (18.2)**
Personal characteristics	Inconsistent risk measurement	-0.265 (0.70)	-0.036 (0.11)
	Risk attitude	-0.063 (1.80)	-0.001 (0.03)
	Female	0.079 (0.63)	0.274 (1.74)
	Age	-0.025 (1.11)	-0.004 (0.15)
	Studies economics	0.148 (0.86)	-0.199 (0.97)
	Studies business	0.125 (0.79)	-0.147 (0.78)
	Studies psychology	0.475 (2.15)*	-0.082 (0.34)
	Studies medicine	-0.175 (0.90)	-0.048 (0.19)
	Constant	-0.284 (0.52)	-1.075 (1.57)
	ρ	0.098	0.173

Notes: the table presents the results of a random effects probit regression where the dependent variable is a dummy indicating whether or not individual *i* switched to a new policy in period *t* (=6,...,35). Formally, it gives the estimated coefficient vector β in $Pr_{it} = \Phi(\sum_i X'_{it}\beta + \mu_i)$ where Pr_{it} gives the probability that *i* switches in t. Φ denotes the cumulative normal distribution and *X* is the vector of independent variables described in the second column of the table. μ_i is a (white noise) individual-specific error that corrects for the multiple observations we have for each *i* (ρ measures the fraction of total variance attributable to μ_i). The independent variables are defined in Appendix 2 (note that to avoid a dummy trap students that study in a different field than the four distinguished here are absorbed in the constant term). Absolute z-values are in parentheses. *=statistically significant at 5%-level; **= statistically significant at 1%-level.

more likely to switch to a new policy if more policies are available and less likely to do so if switching costs are higher. This is confirmed for both profile types. In addition, the table shows that people react to changes in their environment. The largest effect observed is a strong increase in switching probability in response to a change in the current policy. Interestingly, a change in the profile has negligible effects if such changes occur gradually but now has a strong positive effect if changes are sudden.[19] This confirms the 'boiling frog' notion described in the introduction that people can be 'lulled to sleep' by introducing changes gradually as opposed to in large steps. Finally, personal characteristics −including the measured risk attitude− appear to have only limited influence on the decision to switch.

4.4 Decision-making process

Information acquisition and decision time

Figure 6 shows the average information acquisition across treatments (*i.e.*, the number of cells clicked to see the content). The left panel shows the number of units, the right panel

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[19] Changes are included as dummies in the regressions. Of course, a small change may be expected to have a smaller effect than a large (sudden) change, as observed. One would still expect the effect of small (gradual) changes to be statistically significant, however.

Figure 6: Information Acquisition
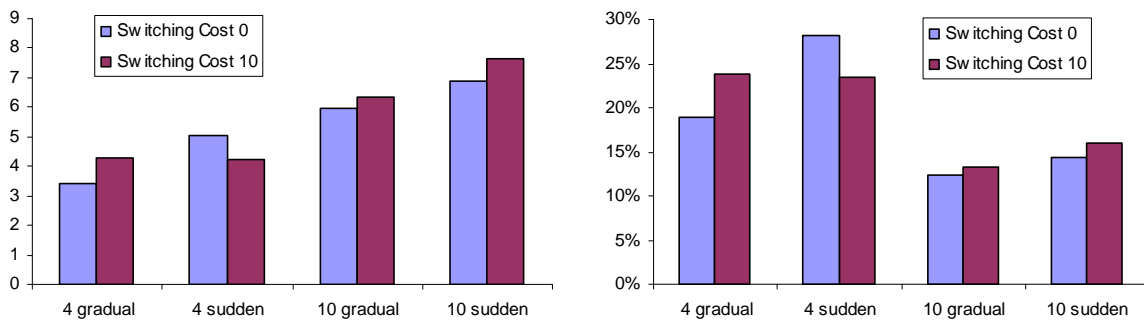
Note: the figure shows the number of cells clicked on to obtain the underlying information (left panel) and this number as percentage of possible clicks (right panel).

shows this number as percentage of the potential number of clicks (which is higher when there are 10 policies). The figure shows that more information is gathered when there are ten policies than when there are four (the difference is statistically significant; $p<.01$), but the percentage of cells clicked on (relative to the available cells) is lower with ten policies (also statistical significant; $p<.01$).

We also measured the number of seconds used by the subjects to make a decision. This is shown in figure 7.

Figure 7: Average Decision Time
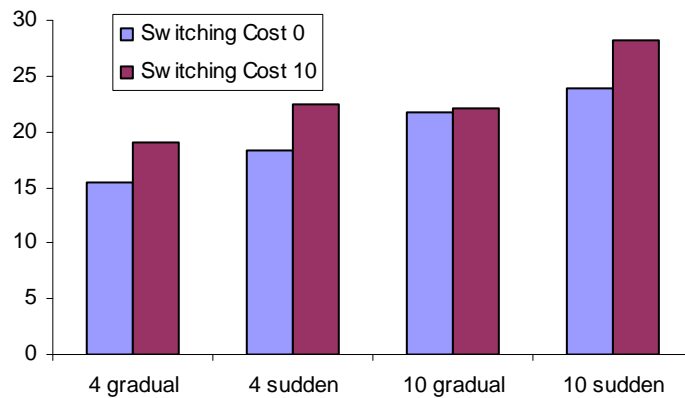
Note: bars measure the average number of seconds per period used to search information and make a decision

Not surprisingly, the number of policies has a significant (positive) effect: deciding with 10 policies takes about 15% more time ($p<.05$). Switching costs and profile have no significant effect on decision time.

20

All in all, subjects take more time to make a decision when there are more policies and look at more information in absolute terms but less information in relative terms.

Type of information

Participants could acquire information about the following characteristics: the premium, events A, B and Z and the level of deductibles. To analyze the type of information they chose to look at we consider the retrieval rate for each characteristic, defined as the number of cells clicked divided by the number of clickable cells. We can then rank these characteristics according to their retrieval rate. In doing so we use the notation $>_i$ if a difference is statistically significant at the i-percent level (i is 1 or 5) and ~ if the difference is statistically insignificant. Because switching costs and type of profile do not make a (statistically significant) difference, we pool all treatments with 4 or 10 policies. In the case of 4 policies the ranking we obtain is:

Premium (48.2%) $>_1$ B (24.4%) ~ deductibles (22.2%) ~ A (19.6%) ~ Z (19.5%),

where retrieval rates are given in parentheses. With 10 policies we observe:

Premium (29.1%) $>_1$ B (13.0%) ~ deductibles (13.0%) $>_5$ A (9.4%) $>_5$ Z (7.3%).

We conclude that −even though the retrieval rates differ− the ranking is the same for 4 and 10 policies. Most observed is the premium, followed by event B (which is the event that occurs with relatively high probability, but has limited consequences) and the level of deductibles. The priority given to the premium is likely related to the fact that it is the only event without uncertainty and thus most easily quantified.


Decision-making strategy

To investigate whether *attribute-based* or *alternative-based* search strategies are used (*cf.* section 3), we consider the order of mouse clicks. A click in the same column (row) as the previous click is considered to indicate alternative- (attribute-) based search. We therefore count the number of times successive clicks are in the same column or row. A click in a different row and column than the preceding one is not counted. Our results show statistically significantly more attribute based search than alternative based search ($p<.05$ for 4 policies and $p<.01$ for 10 policies).

The number of successive row clicks minus the number of successive column clicks is a measure for the relative importance of attribute-based search. If this difference is positive attribute-based search is relatively more important than alternative-based search. The reverse

holds for a negative difference. Figure 8 shows the value of this measure across treatments. In all cases except one, there are more successive row clicks than successive column clicks. This tendency for attribute-based search is clearly strongest in the 10 policies treatments (p<.001).[20]

Figure 8: Search Strategy
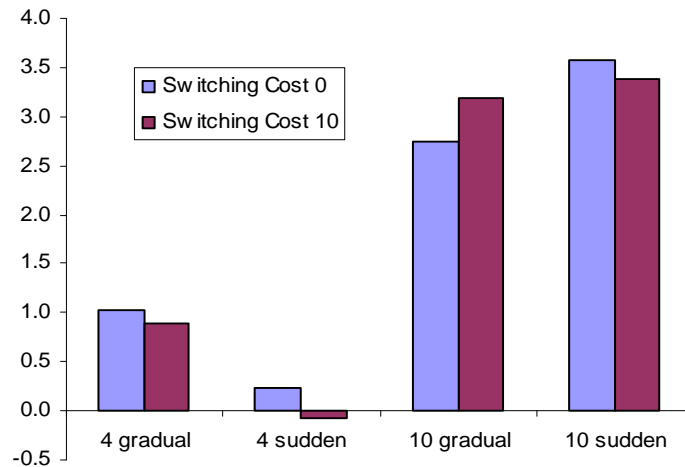
Note: bars represent average numbers of attributed-based searches (successive row clicks) minus number of alternative-based searches (successive column clicks).

5. Summary of results and concluding discussion

We start with a summary of our main treatment effects. First, the positive effect of having more alternatives to choose from (because the best available policy will be at least as good), is compensated by the negative effects of higher search costs, more switching costs and lower decision quality. The net effect is small or even negative (table 1). Even though in a relative sense *less* information is retrieved for 10 policies, in an absolute sense *more* information is used. This processing of more information leads to higher search costs and longer decision times. Moreover, subjects switch more often in the 10-policy treatments which is costly in the switching cost treatments. The main reason for our finding that the net effect is small is not the difference in search or switching costs, however, but the fact that subjects' choices

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[20] However, recall that more units of information are retrieved in the 10 policies treatment. To correct for this, we calculated a relative attribute search tendency, by dividing the attribute minus alternative variable by the number of information units used. We still find a difference between the 4 and 10 policies treatments, but a smaller one and only marginally significant (p=.09).

deviate more from the optimum when there are 10 policies. Note that as the number of alternatives increases, the processing effort (information search and finding the best alternative) increases at least linearly but the quality of the best decision will increase at a smaller order. It is therefore very likely that adding policies will at some point decrease welfare, as we observe.

Second, the introduction of switching costs has an interesting effect. When designing the experiment we followed the 'conventional wisdom of policy makers' in thinking that these would diminish the tendency to switch (*cf.* section 3); which could lead to less information retrieval, a slower adaptation to changing circumstances and a decreasing performance. Only the first part of this reasoning was confirmed: switching costs decrease switching. Switching costs did not decrease information retrieval, decision time or decision quality; on the contrary, these effects are opposite to what was expected (though sometimes statistically insignificant). A tentative explanation is that without switching costs some participants use a trial-and-error strategy. That strategy is too costly when there are switching costs, which lead to the use of qualitatively better strategies. Note that in the experiment we used relatively low switching costs. The effect of switching costs obviously depends on their level. In the extreme, if the switching costs were to be prohibitively high switching would be practically impossible and not adapting to changing circumstances (policies or health) would necessarily lead to very bad outcomes. We expect there to be some threshold level of costs for which it holds that increases lead to better decisions as long as costs remain below that threshold. This is a topic for future research, however. On average, participants indeed switch too often. This contradicts earlier findings in the literature on the status quo bias (and related biases). It is however in line with results in a completely different field, to wit, finance. Private investors have been shown to tend towards changing their portfolio of assets too often, decreasing their return by the transaction costs and an often-wrong timing (Odean 1999).

Third, the distinction between gradually and suddenly changing profiles provided some support for the boiling frog phenomenon. The following picture emerges. If profiles change gradually, subjects remain inactive and do not change to a new policy, even if this would improve their expected payoff (table 3). If, on the other hand, a sudden change in profile occurs, this increases the probability of a switch (table 3) which increases the realized earnings (table 2) because subjects think more carefully about their decisions.

As for the decision process, our subjects show a tendency towards attribute-based search and this tendency is stronger as the number of alternatives increases. This finding is in

line with previous results reported in the literature (Payne *et al.* 1993) and confirms Hibbard et al.'s (1997) prediction that subjects will use elimination by aspect in an environment like ours.

Finally, for all of these results, the use of laboratory control has proved to be of crucial importance. In field studies one can observe decisions, but not the decision strategy and the quality of the decision is hard to measure because preferences are not directly observable. Using an electronic information board in the experiment we were able to observe the strategy directly and by inducing preferences we can calculate the quality of the decision.

The outcome of any experiment depends on the parameters chosen (such as switching costs, search costs, attributes of policies, etc), however, and any generalization to the world outside of the laboratory is open to discussion. To support the external validity of this study, we chose the parameters after close consultation with governmental specialists in this field, who were appointed by the Dutch ministries that commissioned our research. Moreover, our conclusions are all based on comparative statics. For example, we show the effect of an increase in switching costs on the relative expected value of the chosen policy. We are not interested in the expected value *per se*. Future research should expand our experiments to include other subject pools, and to vary parameters, for example. As such research continues, our understanding of the way in which consumers choose insurance will increase.

Nevertheless, our results do point in the direction of a number of policy implications. We close with a brief summary of the most important of these. First, from a welfare perspective a limitation on the number of policies offered might sometimes be desirable. Second, switching costs are not always bad. There is no need to pursue reduction of these costs to zero. Finally, insurance companies might fare well by offering coverage of high-probability/low-cost events such as physical therapy.

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Appendix 1: Experimental Instructions

This appendix provides an English translation of the experimental instructions. The reader is invited to try the experiment online at http://www.creedexperiment.nl/zorg.

Introduction

Welcome to this decision-making experiment. In this experiment, you may earn points. These points are worth money. How many points (and therefore money) you make depends on your own decisions and on chance. Your decisions are anonymous. They will not be linked to your name.

General structure of the experiment

Today's experiment consists of 2 parts. The first part will take most of the time used. The second part will be explained after you finish the first part.

Today's experiment is individual choice and consists of **35 periods**. In every period you will receive a **fixed income** of 250 points. Moreover, you will lose points in every period. How many points you lose depends on your choice and on chance. In every period you will choose an **insurance policy**. Policies differ in premium and coverage. The premium of the policy you choose will be deducted from your earnings. In addition, you may lose points by **events** that are not or incompletely covered by your insurance.

How high the risk is that a specific event occurs depends on your **profile**. After you have chosen a policy, the computer will randomly determine for each of the events whether or not it occurs and your earnings for the period will be calculated.

We will now explain the experiment in more detail.

Profile

Your profile describes the probabilities that events "Z", "A", "B", "C", "D", and "E" will occur for you. Your profile will remain constant in the first 5 periods. Whenever the profile does change in later periods, this change will be clearly indicated on your computer screen.

Events

Your profile gives the probability of event **A** occurring. Whenever A does occur, the consequences are evaluated. If your policy covers this event, the occurrence of A has no consequences for you. If your policy does not cover A, points will be subtracted from your earnings.

Event **B** is comparable to A; however, the probability in your profile may be different than the probability for A and the consequences of B occurring (if your policy does not cover it) may be different.

Events **C**, **D**, and **E** are treated differently than A or B by the insurance policies. In this case, for each of the three events it is first determined whether it occurs and the consequences are added up. Only if these total costs are lower than or equal to the **deductibles** in your policy will they be subtracted from your points.

Finally, Event **Z**. The probability that this occurs is also given in your profile. The consequences of Z occurring differ across policies.

Two Examples

We start with a simple example.

Assume that your profile gives a probability 20% that B occurs.
- Insurance policy 1 does not cover this event; if B occurs it will cost you 50 points.
- Insurance policy 2 does cover this event and there are no financial consequences for you if B occurs.

After you have made your choice, the occurrence of all events is determined. The computer randomly draws a number between 1 and 100 for B. If the number is smaller than 20 (the probability of B in your profile), B occurs. Assume that the number 15 is drawn: you lose 50 points if you chose policy 1 and nothing if you chose policy 2.

An example concerning deductibles. Assume:
- Events C, D, and E cost 40, 25, and 20, respectively, if they occur.
- Your profile gives probabilities 5%, 20% and 50% of C, D, and E, respectively, occurring.

- Insurance policy 1 has 0 deductibles.
- Insurance policy 2 has deductibles equal to 50.

After you make your choice, the occurrence of all events is determined. Assume that the numbers 70, 7, and 34 are drawn for C, D, and E, respectively. Your profile then implies that C has not occurred but D and E have. If you chose policy 1, your deductibles are 0 and these occurrences have no consequences for you. If you chose policy 2, the total costs (25+20=45) are less than your deductibles and you lose 45 points.

Information

In every period you will see your profile. If something has changed in comparison to the previous round, this is indicated (by giving the previous numbers in small red font like here). You will not immediately see all of the characteristics of the policies. If, for example, you want to know the premium of policy 3, you move your cursor to the blue cell in the row "premium" of column "3". Your cursor will change into a little hand. If you click, you will see the information concerned.

Examples of such blue cells (click them!)

To try again, click the button *("hide info")*.

There are small costs related to retrieving information, to wit **0.25 points for each click** of the mouse in a blue cell.

After the first period, the information for your current policy (your previous choice) will be visible; hence, you do not need to click to get this information. If any of the characteristics of your current policy has changed, this is indicated (by giving the previous numbers in small red font).

Switching costs

If you choose a different policy than your current one (the one you chose in the previous period), one-time costs will apply. These costs are 10 points.

Making losses

It may happen that you lose more points in a period than your fixed income (250). In that case you will make a loss in that period, which will be subtracted from your aggregate points from previous periods.

Exchanging points for money

At the end of the experiment, points will be exchanged for euros, at a rate of 1 euro for every 200 points. The money you make will be paid to you personally and privately. We will ensure anonymity.

Screen examples

On the following pages, the experiment is illustrated further. You will see a (simplified) choice screen and the screen where earnings are determined. At the end we will ask you a few questions to make sure you understand everything. If there is anything you do not understand please raise your hand. One of the experimenters will then come to your table to answer your question.

Click here to continue

Choice Screen (reduced to two policies)

Profile		1	2
Premium			
Z	19%		
A	2%		
B	20%		
C	5%		
D	20%		
E	50%		
Deductibles			

This is an example of a choice screen with only two policies (there will be more policies in the experiment).
If you click in a blue cell in the "premium"-row of the table, you will see the premium (first row) of the insurance concerned (column).
If you click on one of the other blue cells, you will see the costs that occurrence of the event concerned (the row in the table) will yield if you choose the policy concerned.
Beware! For events C, D, and E you only observe one (broad) blue cell. The costs related to these events do not depend on the policy chosen. For these events, policies may only differ in the deductibles.
After you make your choice, click the button in the top row of the table.
In this example, you cannot make a choice.

Back   Continue

Example of a results screen

Profile		Choice	Result	Payoff
Premium		-148		**-148**
Z	19%	-10	14	-10
A	1%	-1000	08	0
B	20%	-50	62	0
C	5%	-40	71	0
D	20%	-25	97	0
E	50%	-20	61	0
Deductibles		25		0
Total				-158

This is an example of a results screen. The first column shows your profile and the second shows the characteristics of the policy you chose. For each of the events Z, A, B, C, D, and E lotteries are played. In each of these lotteries a number between 1 and 100 is randomly chosen (where 00 means 100). For example, an event with probability 19% will occur if the randomly chosen number is between 1 and 19. The random draws of numbers are independent (the draw for one event does not affect the draw for another event). Draws are conducted by the computer.

If you would like to see another draw, click [Draw Again]

(Of course, in the experiment you will not be able to ask for a new draw; there, you will have to accept whatever random draw you receive)

Finally, when you receive the results you will also receive information about the aggregate number of points you have earned.

Back   Continue

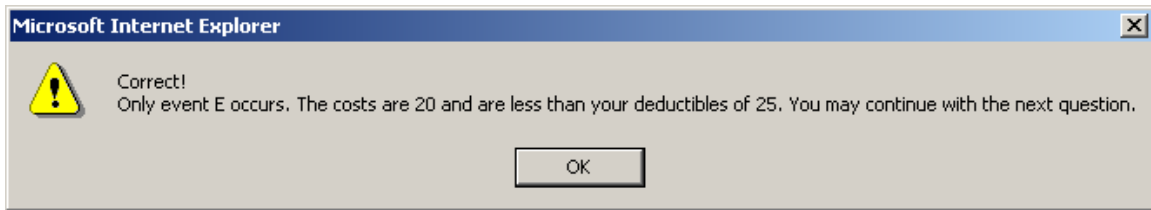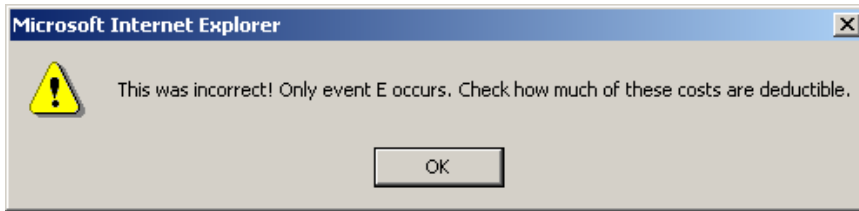|			
C	5%	-40	16
D	20%	-25	75
E	50%	-20	49
Deductibles		25	

We want to make sure that you understand the instructions. Therefore, we will ask you a few questions.

Question 1

The first question is about the **deductibles**. We therefore only consider events C, D, and E. Here you see the outcome of the random draws for C, D, and E (the computer drew numbers 16, 75, and 49, respectively). What are the consequences for your earnings?
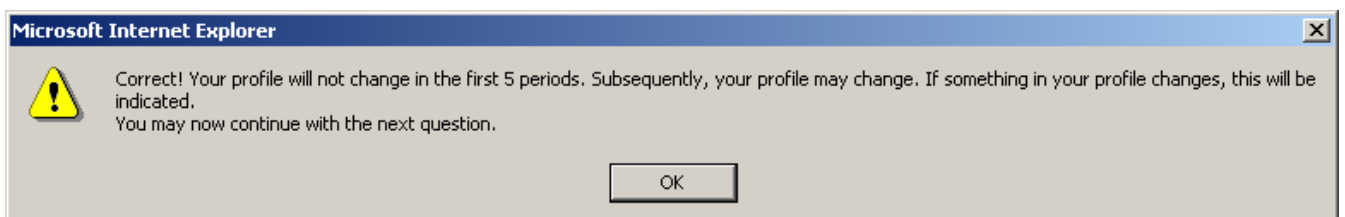
As a consequence I will lose: [   ]

[send]

Back

Microsoft Internet Explorer ✕

⚠ This was incorrect! Only event E occurs. Check how much of these costs are deductible.

[OK]

Microsoft Internet Explorer ✕

⚠ Correct!
Only event E occurs. The costs are 20 and are less than your deductibles of 25. You may continue with the next question.

[OK]

QUESTION 2

Is the following statement correct or incorrect?

My profile will remain constant for the whole experiment

○ Correct

○ Incorrect

[Send]

Microsoft Internet Explorer ✕

⚠ Your answer was incorrect! Your profile will not change in the first 5 periods. Subsequently, your profile may change. If something in your profile changes, this will be indicated.

[OK]

Microsoft Internet Explorer ✕

⚠ Correct! Your profile will not change in the first 5 periods. Subsequently, your profile may change. If something in your profile changes, this will be indicated.
You may now continue with the next question.
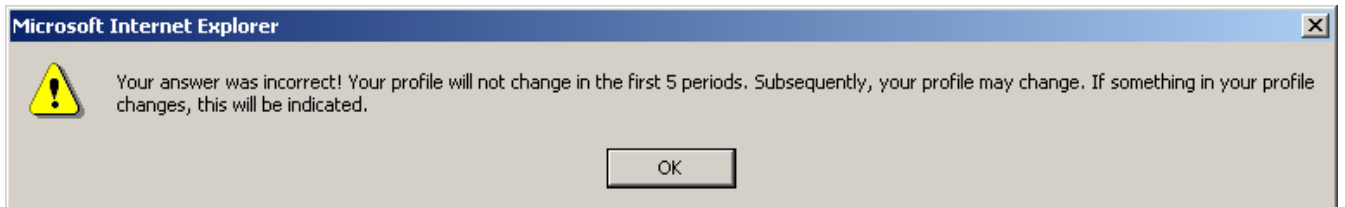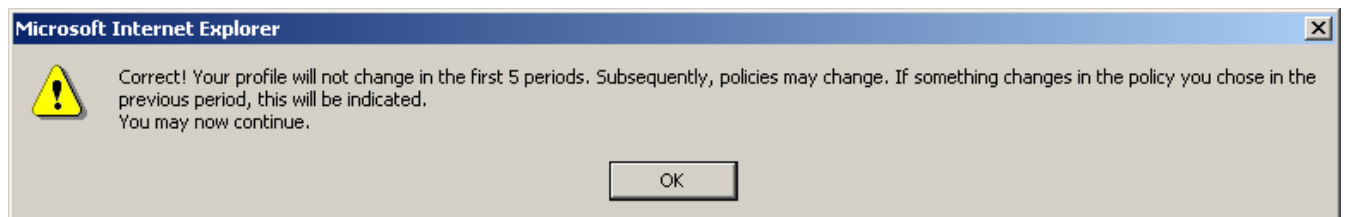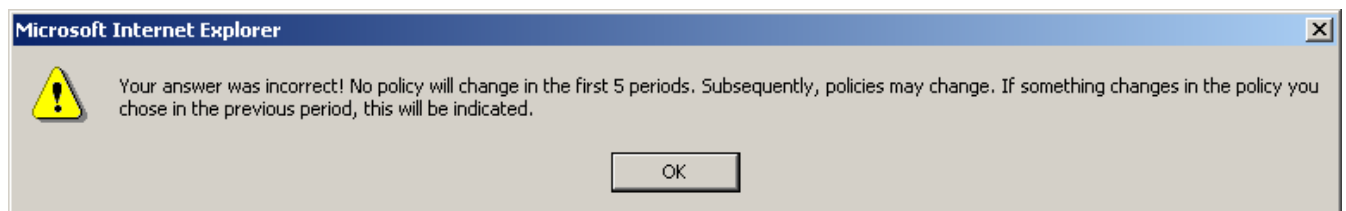
[OK]

QUESTION 3. INSURANCE POLICIES

Is the following statement correct or incorrect?

All policies will remain constant for the whole experiment

○ Correct
○ Incorrect

Send

Microsoft Internet Explorer ✕

⚠ Your answer was incorrect! No policy will change in the first 5 periods. Subsequently, policies may change. If something changes in the policy you chose in the previous period, this will be indicated.

OK

Microsoft Internet Explorer ✕

⚠ Correct! Your profile will not change in the first 5 periods. Subsequently, policies may change. If something changes in the policy you chose in the previous period, this will be indicated.
You may now continue.

OK

This is the end of the instructions. Please raise your hand if you have any questions.
One of the experimentors will come to you to answer your question.

If everything is clear, you may now start the experiment.
Start experiment

Appendix 2: Explanatory Variables

This appendix describes the explanatory variables uses in the regression equations underlying tables 1 and 3 in the main text.

Treatment	Number policies	The number of policies in the choice set (4 or 10)
	Switching costs	The costs incurred if a different policy than the previous is chosen (0 or 10)
Change in situation	Change in profile	Dummy variable equal to 1 if the policy changed compared to the previous period
	Change in current policy	Dummy variable equal to 1 if the previously chosen policy has changed
Personal characteristics	Inconsistent risk measurement	Dummy variable equal to 1 if the Holt/Laury measure of risk aversion is inconsistent
	Risk attitude	The Holt/Laury measure of risk aversion (if consistent)
	Female	Dummy variable equal to 1 if the participant is a female
	Age	Age of the participant
	Studies economics	Dummy variable equal to 1 if the participant studies economics
	Studies business	Dummy variable equal to 1 if the participant studies business
	Studies psychology	Dummy variable equal to 1 if the participant studies psychology
	Studies medicine	Dummy variable equal to 1 if the participant studies medicine
Decision strategy	Decision time	# seconds used to make a choice
	No information	# cells clicked to view information
	# premium	# cells about premium clicked
	# Z	# cells about event Z clicked
	# A	# cells about event A clicked
	# B	# cells about event B clicked
	# deductibles	# cells about deductibles clicked
	Search direction	# successive row clicks minus # successive column clicks