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Nadja Kairies-Schwarz, Johanna Kokot, Markus Vomhof, and Jens Wessling[1]

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Abstract

Recent health policy reforms try to increase consumer choice. We use a laboratory experiment to analyze consumers' tastes in typical contract attributes of health insurances and to investigate their relationship with individual risk preferences. First, subjects make consecutive insurance choices varying in the number and types of contracts offered. Then, we elicit individual risk preferences according to Cumulative Prospect Theory. Applying a latent class model to the choice data, reveals five classes of consumers with considerable heterogeneity in tastes for contract attributes. From this, we infer distinct behavioral strategies for each class. The majority of subjects use minimax strategies focusing on contract attributes rather than evaluating probabilities in order to maximize expected payoffs. Moreover, we show that using these strategies helps consumers to choose contracts, which are in line with their individual risk preferences. Our results reveal valuable insights for policy makers of how to achieve efficient consumer choice.

JEL Classification: C91, I13, D81

Keywords: Health insurance; risk preferences; heterogeneity; heuristics; laboratory experiment; cumulative prospect theory

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1. Introduction

Recent policy reforms in the U.S. and in Europe have been directed towards more consumer choice (Cronqvist and Thaler, 2004; Coughlin et al., 2008; Thomson et al., 2013). The underlying reason is that consumers can best express their needs and preferences via their own choices. In the market for health insurance, effective consumer choice is supposed to stimulate price competition among health insurers leading to lower prices and reduced health care expenditure as well as to improved quality. A current example for stimulating consumer choice is the mandatory introduction of health insurance exchanges at state level in the U.S. as a consequence of the Patient Protection and Affordable Care Act of 2010. In these health insurance exchanges individual consumers and small employers are given the opportunity to compare various different plans on an online insurance market platform. It is expected that 13 million people will use the exchanges for choosing health insurance by 2015.[1] Such a reform towards more consumer choice relies on the fact that consumers choose health insurance efficiently.

A similar and well-studied reform is the Medicare Part D Prescription Drug plan within the Medicare Modernization Act of 2003 in the U.S. Having started in 2006, it gives seniors eligible to this plan access to a federally subsidized market for private insurance contracts covering non-mandatory drug prescription. Results on the quality of choice from Medicare Part D show that many consumers seem to make suboptimal choices (Abaluck and Gruber, 2011; McWilliams et al., 2011; Heiss et al., 2013). This evidence is in contrast to the standard economic theory where offering more contracts and full information should not make consumers worse off. This distortion can be explained by the fact that health insurance choices are complex due to the variety of different contracts available. Evidence from laboratory experiments shows a negative relationship between the number of contracts offered and decision quality. Schram and Sonnemans (2011) and Besedeš et al. (2012a,b), for instance, show that the quality of choice decreases with an increasing number of health insurance contracts available. Similar results are found in other complex decision scenarios in the field (Iyengar and Kamenica, 2010; Sinaiko and Hirth, 2011). Nevertheless, simply reducing the number of contracts would possibly neglect the fact that consumers differ in their preferences for contract attributes (Besedeš et al., 2014). In addition, suboptimal choices may also arise from contract attributes, which are difficult to assess. The latter may be deductibles and complementary insurance. Johnson et al. (2013) show for health insurance exchanges that suboptimal choices even persist in a simplified scenario and consequently find that deviations from the optimal contract cannot solely depend on lacking financial literacy. However, the authors pay little attention to explaining this, e.g. by individual risk preferences.

First attempts to reduce complexity while accounting for heterogeneity in preferences have been made in the health insurance exchanges in the U.S. Here, consumers are first asked for individual characteristics and preferences for contract attributes like deductibles. Then they are presented an individual selection of contracts. Evidence from the laboratory and the field supports this approach by demonstrating that individuals themselves use tastes in attributes to

[1] Congressional Budget Office: Insurance Coverage Provisions of the Affordable Care Act - CBO's April 2014 Baseline.

reduce complexity. Besedeš et al. (2012a,b) and Ericson and Starc (2012) show that in complex health insurance choices, consumers focus on salient contract attributes and make use of heuristics like choosing the cheapest plan. This finding is in line with a growing body of theoretical and empirical research from behavioral economics, which proposes that when making complex decisions people act on heuristics (see, e.g., Gilovich, 2002, or Gigerenzer and Gaissmaier, 2011 for overviews). Asking consumers for preferences in attributes might thus be a good way to guide them in reducing complexity while accounting for individual preferences. However, the existing evidence cannot make statements about whether using these heuristics to reduce complexity actually helps people to find contracts which are in line with their individual risk preferences and thus cannot make statements about individual decision quality. While Ericson and Starc (2012) use field data from the Massachusetts health insurance exchanges and cannot account for individual risk preferences, Besedeš et al. (2012a,b) use a laboratory experiment, but do not elicit them. To make statements about the success of individual pre-selection mechanisms based on contract attributes, it is important to understand how well heuristics actually match individual preferences.

Our objective is to analyze individual behavior in complex health insurance choice decisions and to investigate its relationship with individual risk preferences. For this, we use a controlled laboratory experiment with a sequential design. In the first part of the experiment, similar to Schram and Sonnemans (2011), subjects have to choose insurance in 14 different decision scenarios varying in the number of contracts available. Contracts mirror classic features of health insurance, such as deductibles and complementary insurance. Similar to Abdellaoui et al. (2007), Abdellaoui (2000), and Wakker and Deneffe (1996), we elicit individual choice preferences according to Cumulative Prospect Theory (CPT) in the second part of the experiment. In contrast to previous experimental studies, underlying assumptions of standard Expected Utility Theory (EUT) risk preferences (Schram and Sonnemanns, 2011; Besedeš et al., 2012 a), we explicitly elicit CPT preferences as they have shown to explain heterogeneity in decisions under risk particularly well. Bruhin et al. (2010), for example, demonstrate that only 20% of the population shows EUT preferences, while the majority demonstrates significant deviations from linear probability weighting which differ in strength and can be explained by Prospect Theory.[2]

Estimating a latent class model to account for heterogeneity in individual tastes for contract attributes reveals five classes. Based on this, we infer distinct behavioral strategies. Most subjects do not evaluate probabilities according to expected payoff maximization (EPM) but assume the worst case and then minimize their costs, i.e., they make use of minimax heuristics. Across classes, we find variations of this strategy differing in the evaluation of certain contract attributes, which are either important to the class members or which they neglect. We can thus give valuable insights into the heterogeneity of tastes in contract attributes. Investigating the relationship between the strategies and individual risk preferences, we find that strategies seem to help consumers to choose contracts, which approximate individual risk preferences.[3] Our

[2] See also Conte et al. (2011) finding heterogeneity in risk-aversion parameter and weighting function parameter for choices under risk. They also identify only 20 % of the observations being EUT types, while 80 % can be captured by Rank Dependent EUT.

[3] This complementary relationship between CPT and decision rules is also found by Suter et al. (2013).

results reveal valuable insights for policy makers of how to achieve efficient consumer choice.

The proceedings of the paper are as follows. In Section 2, we describe the experimental design. Section 3 describes the procedure. In Section 4, we report our results before we conclude in section 5.

2. Experimental Design

The experiment consists of two parts without any interaction between subjects. The first part of the experiment captures subjects' insurance choices in 14 individual decision situations varying in the degree of complexity. The second part serves to determine risk preferences according to CPT for each subject. It contains 72 lottery choices. The sequential design allows for two things. First, we can analyze health insurance choice behavior with a special focus on underlying heterogeneity in attribute tastes. Second, we can investigate the predictive power of individual CPT preferences for health insurance choices and the relationship to behavioral strategies.

2.1. Experimental Conditions

Health Insurance Choices

In each decision, subjects have to buy a health insurance contract. The decision framework and contract attributes are modeled similarly to Schram and Sonnemans (2011). Decisions vary in the complexity, that is the number of contracts available to choose from, ranging from 2 to 12. They occur in a sequence that is randomly determined and the same across all sessions. To buy a health insurance contract, subjects have to bear costs in form of a premium. In addition, depending on the characteristics of the chosen contract, treatment costs in case of illness are either paid by the subject, the health insurance or a combination of both. We abstract from other monetary and non-monetary costs that may go along with an illness, such as missing wages or pain.

Contracts vary in their attributes, i.e., their premium, complementary insurance for certain illnesses, and deductibles. In total, there are 5 illnesses A, B, C, D, and E, each of which can occur with a certain probability that remains unchanged across all decisions. Thus, individuals face risky decisions with potential losses.

Each health insurance contract consists of a basic and a complementary health insurance. While the basic insurance always covers treatment costs of illnesses A, B, and C, the complementary insurance can additionally cover treatment costs of illnesses D and E. Table 1 illustrates the contract attributes: the diseases covered by basic and complementary insurance, their probabilities of occurrence and their treatment costs without insurance. [4] Moreover, we introduce deductibles of 0, 10, or 30. In our scenario, a deductible refers to the three illnesses associated with the basic insurance. In case of occurrence of illness A, B, C, or a combination of them, a subject has to pay the accruing treatment costs up to the amount of the deductible; the health insurance pays the amount in excess. Depending on the contract, a subject has to pay the premium, the potential treatment costs up to the amount of the deductible under the basic insurance and the costs for the illnesses D and E if not covered by complementary insurance. For the full set of the instructions, see Appendix II.

[4] Values of contract attributes are measured in *Taler*, our laboratory currency.

Table 1: Basic Decision Situation

Disease	Probability of occurrence	Treatment costs without insurance
Basic insurance		
A	5%	60
B	20%	40
C	50%	20
Complementary insurance		
D	1%	2000
E	20%	50

By combining all attributes except for the premium, we obtain 12 unique health insurance contracts. For each of these 12 contracts, we calculate the fair premium. To induce a rank-ordering with respect to subjects' expected payoff value - for expected payoff maximizing (EPM) decision makers some contracts are preferred to others - we add a margin to the fair premium. We increase the variation in contracts by reproducing the 12 unique contracts to 48 contracts and add a different margin to each contract's fair premium. This way, we obtain a different rank ordering in each of the four sets and a total number of 48 distinct contracts. The contracts offered in a decision are randomly chosen from one of these four different sets. Contracts that are dominated in their cumulative prospect value and the EPM value are excluded.[5] For a detailed explanation of the contract design, see Appendix I.

Lotteries

In the second part of the experiment, subjects face 72 lottery decisions modeled according to Abdellaoui et al. (2007), Abdellaoui (2000), and Wakker and Deneffe (1996). In each of the decisions, subjects are presented with two alternatives from which they have to choose one. The two alternatives can either be two lotteries, or one lottery and one fixed payoff. The values of the payoffs can be either positive or negative. The first 24 payoffs are positive, the following 6 are mixed, and the last 42 are negative. This composition of lotteries allows us to determine individual parameters for the value and weighting function.[6]

Robustness Check

To make sure that results are not driven by framing effects, we also design a neutral experimental condition for the first part. The decision rounds are identical except for the wording. While the health framing condition contains health insurance contracts and treatment costs, the neutrally framed condition contains insurance contracts and costs in case of damage. Although framing should not make a difference for a rational decision maker, previous evidence has shown that there may be context dependency.

[5] To calculate ex-ante CPT values, we use the parameters form Tversky and Kahneman (1992).

[6] Note that as we aim at analyzing decisions over losses, we focus on the negative lotteries to benefit from more accuracy in the negative domain.

2.2. Payment

All monetary amounts in the experiment are indicated in the experimental currency *Taler*. 1 Taler equals *Euro* 0.50. In order to avoid wealth or averaging effects, we follow the standard of applying the random payment technique at the end of the experiment.[7]

Similar to previous studies dealing with losses, we endow each participant with an initial amount of money for each part. In experiments, this is a common approach to model losses. Etchart-Vincent and I'Haridon (2011) show that results do not differ essentially between bearing losses from an endowment and foregoing real losses. In particular, this means that participants integrate their endowment and evaluate costs as losses.

For the first part, one health insurance decision is randomly chosen to be payment-relevant. For each illness within this decision, it is then randomly determined whether a subject suffers from it or not. Subjects’ total costs in this part are detracted from the initial endowment of 2200 *Taler*. Afterwards, three decisions of the second part are randomly chosen to be payment-relevant. One of these is drawn from the positive, one from the mixed, and one from the negative lotteries. Realized losses from the lotteries are subtracted from the sum of realized gains and the initial endowment of 3500 *Taler*. Total earnings comprise subjects’ final payments for the randomly determined decisions in both parts of the experiment.

3. Experimental Procedure

The computerized experiment was programmed with z-Tree (Fischbacher, 2007) and conducted at *elfe*, the Essen Laboratory for Experimental Economics at the University of Duisburg-Essen, Germany in 2014. Overall 113 students from the University of Duisburg-Essen participated in five sessions (56 participants in the health treatment, 57 participants in the general treatment. Participants were recruited by the online recruiting system ORSEE (Greiner, 2004).

The procedure was as follows: Upon arrival, subjects were randomly allocated to their seats in the laboratory. They were given the corresponding instructions previous to each part of the experiment and were given time to read the instructions and to ask comprehension questions. The latter were answered in private by the same one experimenter across all treatments. To assure subjects' understanding of the decision task in each part, they had to answer a set of control questions. The experiment did not start unless all subjects had answered the control questions correctly. At the end of the experiment, subjects were asked to answer a short questionnaire including demographics and questions directly linked to their behavior in the previous decisions. In both parts subjects had access to calculators. In order to control for the use of them within the experiment, we asked about whether they had utilized them in the subsequent questionnaire. Sessions lasted for about 90 minutes. Subjects earned, on average, *Euro* 25.62.

[7] Various research studies confirm that the random payment technique does not dilute the power of the monetary incentives for non-complex choice tasks (Starmer and Sugden, 1991; Cubitt et al., 1998; Laury, 2006; Baltussen et al., 2012).

4. Results

4.1. Insurance Choice Behavior

Aggregate Behavior

For starters, we show descriptive statistics for health insurance choice behavior using the aggregated data. Specifically, we are interested in the contract attributes that are important for consumers when choosing health insurance. For this, we examine the potential losses of 2000 and 50 (illness D and E) as well as the deductibles of 0, 10, and 30 as representative of the basic insurance (illness A, B, and C). Table 2 summarizes the mean premium and shares of how often subjects choose these attributes across all decisions. Note that due to our contract design, in some decisions rounds all contracts are equal regarding a specific attribute. Therefore, we exclude these decisions and calculate means and standard deviations, provided that subjects were given the opportunity to decide on whether or not an attribute should be covered.

We observe that the coverage of the complementary insurance is high in actual chosen contracts and thus appears to be important for consumers; the attributes connected to the potential loss of 2000 and the potential loss of 50 are covered in 66% and 75% of all choices. Furthermore, we find a large percentage of actual choices including a deductible of 30 (52%). Fewer choices contain contracts including no deductible (26%) and a deductible of 10 (21%). However, the analysis based on averages of actual chosen attributes is rather limited since we expect heterogeneity in attribute tastes.

Table 2: Attribute means for actual choices

	Mean (Conditional decisions)
Premium	83.35 (34.52)
Complementary insurance	
Loss of 2000 [1%]	0.66 (0.47)
Loss of 50 [20%]	0.75 (0.43)
Deductibles	
Deductible 0	0.26 (0.44)
Deductible 10	0.21 (0.41)
Deductible 30	0.52 (0.5)

Standard deviations in parentheses. Probability of occurrence in square brackets

Latent Class Logit Model (LC-logit)

To investigate individual choice behavior and to assess heterogeneity in attribute tastes, we apply a model that is capable of providing insights in the underlying preference structure in our sample. The latent class logit (LC-logit) model allows us to identify differences in tastes across individuals. It is widely used in health economics applications to identify heterogeneity (Deb and Trivedi, 2002; Bago d'Uva, 2005, 2006; Bago d'Uva et al., 2009; Greene et al., 2014; Lagarde, 2013). The model estimates a probability of belonging to some (homogenous) class in the sample. These classes are generated endogenously based on underlying individual characteristics with the aim of achieving within-class homogeneity. In our case, the tastes in contract attributes - premium, insurance of the possible losses of 2000 and 50, and deductibles - are considered. Furthermore, we control for possible treatment effects by using a binary indicator of treatment.

Following Pacifico and Yoo (2012), we use the stata routine LC-logit to estimate the model. In this model, each of N respondents in the experiment faces J alternatives (contracts) in each of the D health insurance choice decisions. A binary choice indicator, y_{njd} is created, which becomes 1 if the respondent n chooses j in decision d. x_{njd} contains the contract specific attributes. Furthermore, respondents are characterized by z_n, which includes a constant and variables that are invariant across decisions for the respondents, e.g. the binary indicator for treatment.

As indicated, the model assumes that there is a number of classes C of different attribute tastes, $\beta = \beta_1, \beta_2 \dots \beta_C$. Under the condition that respondent n is in class c, the probability of n's choice sequence can be written as a product of conditional logit formulas.

$$P_n(\beta_c) = \prod_{d=1}^{D} \prod_{j=1}^{J} \left(\frac{\exp(\beta_c x_{njd})}{\sum_{k=1}^{J} \exp(\beta_c x_{nkd})} \right)^{y_{njd}}$$

As we do not know which class a respondent belongs to, we must specify the unconditional likelihood of respondent n's choices, i.e. the weighted average of the previous equation over all classes. The weight for a specific class c is the fraction of the population and modeled as fractional multinomial logit:

$$\pi_{cn}(\theta) = \frac{\exp(\theta_c z_n)}{1 + \sum_{l=1}^{C-1} \exp(\theta_l z_n)}$$

where $\theta = (\theta_1, \theta_2, \dots, \theta_{C-1})$ are class membership model parameters.[8] Summing up the log unconditional likelihood of each respondent yields the sample log likelihood.

$$\ln L(\beta, \theta) = \sum_{n=1}^{N} \ln \sum_{c=1}^{C} \pi_{cn}(\theta) P_n(\beta_c)$$

The optimal number of homogenous classes is identified by applying the Bayesian Information Criterion (BIC). In our analysis, the BIC suggests to define five groups. The LC-logit model

[8] θ_C is normalized to zero for identification.

estimates coefficients for each of the five classes. The coefficients can then be used to determine the average in-class willingness to pay (WTP) for certain attributes. Thus, the model allows us to analyze heterogeneity by considering distinct WTP-values for each single class, and hence to infer different behavioral types on basis of their attribute preferences, while not neglecting the complexity of the task itself.

Heterogeneity in Individual Insurance Choice Behavior

As previously indicated, classes are built based on underlying parameters. We include contract attributes and control for framing effects. Table 3 presents the estimation results.

Table 3: Latent Class Logit Model - Results

	Class 1	Class 2	Class 3	Class 4	Class 5
Premium	0.134***	0.044***	0.062***	0.029***	0.099***
	(0.019)	(0.004)	(0.008)	(0.004)	(0.011)
Loss of 2000 [1%]	-0.573	-3.905***	-2.177***	-2.645***	-1.681***
	(0.412)	(0.344)	(0.239)	(0.224)	(0.366)
Loss of 50 [20%]	-4.654***	-4.068***	-2.590***	-1.140***	-0.683***
	(0.705)	(0.570)	(0.257)	(0.268)	(0.345)
Deductible 10	-2.307***	-0.436***	-0.680***	0.049	-0.883***
	(0.462)	(0.204)	(0.228)	(0.204)	(0.340)
Deductible 30	-4.771***	-1.226***	-1.766***	-0.517***	-2.086***
	(0.870)	(0.224)	(0.366)	(0.232)	(0.437)
Health framing	-0.104	-0.233	0.597	-0.534	
	(0.892)	(0.682)	(0.795)	(0.783)	
Class share	0.097	0.361	0.196	0.231	0.116

Note: Latent class logit model estimated using Stata's lclogit command. N=10.170. Class 5 is assigned as reference group regarding health framing. Standard errors are calculated by gllamm and are provided in parentheses. *** p<0.01; ** p<0.05; * p<0.1.

The coefficients of health framing are not significantly different from zero. The LC-logit identifies five classes with different class sizes. Class 1 makes up 9.7% of all subjects, classes 2 to 5 include 36.1%, 19.6%, 23.1%, and 11.6% of all subjects, respectively. However, interpreting the results from the LC-logit model is tedious as we cannot directly quantify effects. Hence, we calculate the WTP, i.e. the amount (in *Taler*) a subject is willing to forgo to insure a certain attribute. In particular, the WTP is calculated for the attributes within each class by dividing each attribute's coefficient by the coefficient of the premium, i.e. $\widehat{WTP}_i = \frac{\widehat{\beta}_i}{\widehat{\beta}_{premium}}$. We find a considerable degree of heterogeneity as the WTP differs substantially across the five classes. Moreover, we observe that while some WTP values exceed the WTP value of a risk-neutral expected payoff maximizing decision maker (certainty equivalent, CE), others are substantially lower.

Exploiting heterogeneity in tastes for contract attributes, we investigate health insurance choice behavior on class level. For this, we account for the fact that health insurance choices in our scenario are difficult with respect to evaluating attributes like complementary insurance covering large losses occurring with small probabilities, or deductibles implying conditional probabilities. As previous evidence suggests that people use simplifying strategies, or heuristics, in such complex decision scenarios we account for behavioral strategies.[9]

For decisions under risk, two types of strategies seem reasonable, expected payoff maximization (EPM) and minimax. To distinguish between EPM and minimax we compare the WTP values with the certainty equivalent (CE). WTP values for each class and the CE are provided in Table 4. Individuals following EPM integrate probabilities and choose the contract that provides the highest expected payoff. WTP values for a class that behave according the EPM strategy should not substantially differ from the CE. Quite differently, the pure minimax players ignore information on all probabilities and choose a contract that induces the highest outcome in the worst situation, i.e. the lowest treatment costs in case of suffering from all illnesses. This strategy is widely found in the literature and is similar to the priority heuristic (Brandstätter et al., 2006) as well as to the minimax regret theory (Savage, 1954; Braun and Muermann, 2004; Hayashi, 2008).[10] Comparing WTP values with the CE reveals that there is only a small difference for class 5.[11] Thus, class 5 seems to integrate probabilities and can be classified as using an *EPM* strategy. All other classes differ in their WTP values from the CE for a majority of attributes and seem not to integrate probabilities.

Moreover, previous literature has shown that people focus on salient attributes (Tversky and Kahneman, 1973; Hensher, 2006). In our scenario, especially the attribute of potential loss of 2000 occurring with a 1% probability is a salient attribute, as it is by far the biggest stake. This might affect the minimax strategy in three ways. First, the combination of the potential loss of 2000 and the simplicity to evaluate it with 1% probability may make it more prone to being evaluated properly compared to other attributes. We might thus expect a minimax strategy where the 2000 is highly integrated. Furthermore, concerning this attribute, Tversky and Kahneman (1992) note that "… the (weighting) function is not well-behaved near the endpoints, and very small probabilities can be either greatly overweighted or neglected altogether" (p. 303). According to this, one could find WTP values for this attribute to be either extremely high, or extremely low. Extremely high WTP values would correspond to the pure minimax strategy where the probability of 1 % is greatly overweighted and thus, the attribute is covered in any case. The importance of this strategy is also underlined by the fact that on aggregate, 66% of subjects choose contracts covering the potential loss of 2000. In contrast, extremely low WTP values of the salient attribute would indicate that the probability of 1% is greatly underweighted and thus, the attribute is ignored and not part of outcome calculation. In a theoretical approach by Etner and Jeleva (2014) these types are called fatalists, as they would invest less in insurance than EPM types.

For class 1, we find that subjects do not integrate probabilities and ignore the salient attribute of potential loss of 2000 as the WTP is small and insignificant. Thus, class 1 follows a minimax strategy ignoring the potential loss of 2000 - the *fatalist minimax* strategy. This strategy highly relates to observations made by Kunreuther and Pauly (2014), who stress the tendency to ignore

[9] See, e.g. Gigerenzer and Gaissmaier (2011) for an overview.
[10] In general, the priority heuristic simplifies to minimax if no aspiration level is assumed and the preliminary step is omitted, where differences in the expected values are observed.
[11] The CE values are within the 5% confidence interval.

low-probability events with high-consequences in health insurance markets. We also find the opposite, respondents who overweight this small probability in classes 2 and 4, where the WTP values substantially exceed the CE. For class 2 all WTP values exceed the CE as participants use a minimax strategy that covers the potential loss of 2000 - *pure minimax* strategy. Class 4 differs from class 2 by ignoring the deductible of 10 -the *minimax ignoring deductible 10* strategy. Class 3 seems to be a hybrid class in the sense that participants seem to evaluate the salient attribute of 2000 properly but ignore all other probabilities - the *moderate minimax* strategy.

Table 4: WTP for Attributes by Class

	Class 1 N = 11	Class 2 N = 44	Class 3 N = 21	Class 4 N = 24	Class 5 N = 13	CE
Loss of 2000 [1%]	4.27 [-1.58, 10.13]	89.55 [78.14, 100.97]	35.16 [26.16, 44.16]	89.79 [68.92, 110.67]	17.07 [11.22, 22.92]	20
Loss of 50 [20%]	34.73 [29.38, 40.09]	93.29 [73.84, 112.73]	41.82 [32.50, 51.15]	38.69 [21.41, 55.98]	6.93 [0.79, 13.08]	10
Deductible 10	17.22 [10.78, 23.66]	9.99 [0.59, 19.39]	10.98 [3.16, 18.80]	-1.67 [-15.27, 11.94]	8.96 [2.27, 15.65]	6.2
Deductible 30	35.60 [28.60, 42.60]	28.11 [20.07, 36.15]	28.52 [20.72, 36.32]	17.55 [4.24, 30.87]	21.17 [14.32, 28.03]	14.8

Note: 5% significance intervals are provided in square brackets.

To quantify the predictive power of the five behavioral strategies, Table 5 shows the average fraction of observed choices in accordance with the strategies for the corresponding class over all decisions. Note that in some decisions, one contract may be favored by several strategies.[12] Table 5 shows that strategies have a high explanation power within their respective class.[13]

As types of minimax strategies are closely interrelated, we find similar fractions for some of them across the respective classes. In particular, following *minimax* or *minimax ignoring deductible 10* are closely related. Also, *fatalist minimax* and *moderate minimax* are related to each other and to the *EPM* strategy to some extent. Considering the whole sample, 53% of all choices can be explained by minimax heuristics. In comparison, 42% of all actual choices are in line with expected payoff maximization behavior.

[12] Double counting cannot be totally avoided a priori since strategies are inferred endogenously.
[13] In the vast majority off all decisions, a behavioral strategy predicts a unique contract. Just in two decisions, two strategies, moderate minimax and EPM, predict more than one single contract.

Table 5: Percentages of Choices in Accordance with Strategies

	Class 1 N = 11	Class 2 N = 44	Class 3 N = 21	Class 4 N = 24	Class 5 N = 13
	Fatalist minimax	Pure minimax	Moderate minimax	Minimax ignoring deductible 10	EPM
Fatalist minimax	**0.75**	0.24	0.50	0.19	0.40
Pure minimax	0.16	**0.79**	0.42	0.54	0.08
Moderate minimax	0.67	0.48	**0.62**	0.34	0.42
Minimax ignoring deductible 10	0.16	0.77	0.40	**0.57**	0.08
EPM	0.57	0.16	0.39	0.23	**0.79**

4.2. Individual Choice Behavior and CPT Risk Preferences

We now turn to investigating the relationship between individual choice behavior and Cumulative Prospect Theory (CPT). For this, we use the individual CPT risk preferences elicited in the lottery part of the experiment to calculate subjects' individual weighting and value functions. Based on these functions, we compute the individual CPT values for each available contract in the health insurance choice part. This allows an individual rank ordering of contracts with respect to each subject's CPT-values, whereby the individual contract with the highest CPT-value is captured by rank 1.[14] This rank order serves as a quality benchmark. The contract expected by CPT (rank 1) is chosen in 41.7% of all decisions. Participants opt for the best or the second best rank in the majority of all choices (71.9%). Thus, CPT preferences can explain individual health insurance choices to a substantial extent.

While CPT apparently has considerable predictive power for health insurance choices on its own, we aim at investigating the relationship between CPT-preferences, behavioral strategies, and complexity. Therefore, we use panel regression techniques to explain the rank of the chosen contract by the assigned behavioral strategies and the number of contracts on class level. We interpret the decision rounds as quasi panel and use individual fixed effects to account for decision-invariant individual heterogeneity. The strategies assigned to each class enter as dummy variable that equals 1 if the respondent chooses the contract expected by the assigned strategy. Table 6 reports the coefficients on the rank according to CPT.

[14] Note that the contract with the highest CPT-value may differ between subjects.

Table 6: Fixed Effects Model – Strategies and Complexity

	Class 1 N = 11	Class 2 N = 44	Class 3 N = 21	Class 4 N = 24	Class 5 N = 13
Number of contracts	0.206*** (0.0546)	0.129*** (0.0108)	0.168*** (0.0278)	0.186*** (0.0286)	0.101*** (0.0325)
Fatalist minimax	0.576 (0.421)				
Pure minimax		-0.919*** (0.202)			
Moderate minimax			-0.358 (0.214)		
Minimax ignoring deductible 10				-0.645*** (0.174)	
EPM					-0.721*** (0.216)
N	154	616	294	336	182
R^2	0.166	0.252	0.116	0.230	0.096

Standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.1.

We find that increasing the number of contracts has a highly significant positive effect on the rank across all classes, i.e., it increases deviation from the contract with the highest CPT value. This result confirms the expected negative relationship between number of contracts and decision quality. Acting on the assigned strategy has a negative coefficient, which translates into a decrease in deviation, except for class 1.[15] For class 3, the point estimate is negative and insignificant. That is, acting in line with strategies predominantly enables individuals to come closer to their CPT-optimal contract. Thus, behavioral strategies serve well as approximations of CPT behavior (or vice versa) in decision situations where certain attributes are difficult to evaluate.

4.3. Robustness Checks

Finally, we control for the robustness of our results with respect to the framing, gender and the use of a calculator using two-sided Mann Whitney tests. First, we test for differences in the distribution of actual choices between the health and the neutral experimental condition. In 12 of 14 decisions, we do not find any significant difference in choice making behavior ($p \geq 0.128$). In 2 decisions a weak significant difference is observed ($p \geq 0.077$). Furthermore, we control for differences in choice making behavior by gender and find no significant difference ($p \geq 0.157$). Last, we control for using a calculator. A two-sided Mann Whitney test reveals only in

[15] The effect of deciding on fatalist minimax is not significant at the 10% significance level.

2 of 14 decisions significant differences in choice making between subjects using a calculator and subjects that do not use one ($p \geq 0.03$).

5. Conclusion

In this study, we conduct a laboratory experiment with a sequential design to investigate the relationship between behavioral strategies and CPT risk preferences. Using a latent class model, we identify five classes demonstrating substantial heterogeneity in subjects' preferences for contract attributes. From this, we infer distinct behavioral strategies. In line with Bruhin et al. (2010), we find that a minority of subjects of about 15% are rational EPM decision makers while the majority show variations of minimax heuristics. Investigating the relationship of insurance choice behavior and CPT risk preferences, we find that individual CPT risk preferences perform well in predicting health insurance choices. In particular, CPT predicts the chosen contract for roughly 40%; considering first and second best contracts, CPT's predictive power even accounts to 70%. Analyzing the relationship between strategies and individual risk preferences shows that when increasing complexity, strategies help individuals to approximate their individual CPT preferences. Thus, we provide novel evidence to the strand of research of investigating individual health insurance choice behavior and heuristics, such as Ericson and Starc (2012), Besedeš et al. (2012a,b). However, we cannot say whether subjects were not able to optimize by maximizing expected payoffs due to a lack of knowledge, or whether they were simply unwilling to do so as they prefer heuristics. Future research should asses this.

Our results also give insights to policy makers for how to achieve efficient consumer choice. In the light of substantial heterogeneity in tastes for attributes, market places should acknowledge offering various contract options. While previous evidence has shown that increasing the number of health insurance contracts offered leads to worse decision quality (Schram and Sonnemans, 2011; Besedeš et al., 2012a,b), we find that individuals are heterogeneous in their tastes for contract attributes and apply simplifying strategies helping them to approximate their individual CPT risk preferences. Our results suggest that when setting rules in the insurance sector to decrease complexity, one should be careful not to restrict the number of contracts too much in order to account for the heterogeneity in tastes for contract attributes. Moreover, our results shed light on contract pre-selection mechanisms based on individual preferences for contract attributes as in the U.S. health insurance exchanges. According to our results, asking for preferences in certain contract attributes first, and then only showing an individual pre-selection, might be a successful way to balance complexity and heterogeneity in preferences and thus achieve efficient consumer choice. The latter can then stimulate competition among health insurance providers and reduce costs in the health care market.

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Appendix

Appendix I: Design of Contracts and Decisions

We generate four different sets of contracts (I, II, III, IV) which differ in rank ordering according to expected payoff maximization (EPM). This gives 48 possible contracts in total. Table 7 provides an overview of all possible contracts organized in the four sets. Set IV serves as control and is designed to have identical EPM values for each of the 12 contracts under consideration.[16] To avoid participants to remember contracts from the previous decision, all contracts offered in a decision round are selected from one of these sets; the actual set alternates between the decision rounds.

Table 8 provides an overview of all 14 decision situations ordered according to the number of available contracts to choose from. The table provides information about the contract characteristics of a decision situation. In addition, contracts predicted by the behavioral strategies and most frequently chosen contracts are provided. Furthermore, the most frequently predicted contracts based on individual Cumulative Prospect Theory (CPT) values elicited in the lottery part are presented. For a comparison CPT values from Tversky and Kahneman (1992) are given. Note that the labels of contracts refer to the columns in Table 7. For example, the most frequent chosen contract in the decision offering 9 available options refers to column 4 in Table 7.

[16] The EPM values are not strictly equal, since we round the premiums in order to generate integers.

Table 7: Contract Sets

	1	2	3	4	5	6	7	8	9	10	11	12
Premium I	111	161	149	100	135	55	62	29	105	84	35	50
Premium II	167	105	85	56	71	139	30	89	89	100	115	30
Premium III	159	81	157	120	95	75	90	49	25	36	83	106
Premium IV	91	85	81	76	75	71	66	65	61	56	55	46
A						0						
B						0						
C						0						
Deductible	0	10	0	30	10	0	30	10	0	30	10	30
D	0	0	0	0	0	2000	0	2000	2000	2000	2000	2000
E	0	0	50	0	50	0	50	0	50	0	50	50
EPM-Value I	-111	-167.2	-159	-114.8	-151.2	-75	-86.8	-55.2	-135	-118.8	-71.2	-94.8
EPM-Value II	-167	-111.2	-95	-70.8	-87.2	-159	-54.8	-115.2	-119	-134.8	-151.2	-74.8
EPM-Value III	-159	-87.2	-167	-134.8	-111.2	-95	-114.8	-75.2	-55	-70.8	-119.2	-150.8
EPM-Value IV	-91	-91.2	-91	-90.8	-91.2	-91	-90.8	-91.2	-91	-90.8	-91.2	-90.8
CPT-Value I	-141.928	-202.572	-197.609	-144.626	-188.083	-146.913	-114.705	-121.098	-217.679	-195.777	-142.503	-169.036
CPT-Value II	-203.317	-141.141	-126.713	-93.813	-116.525	-242.209	-76.324	-192.631	-199.803	-213.705	-234.258	-145.044
CPT-Value III	-194.721	-113.726	-206.196	-166.864	-143.935	-170.599	-146.714	-145.918	-123.658	-139.449	-198.754	-232.320
CPT-Value IV	-119.162	-118.353	-122.118	-117.290	-121.153	-165.928	-119.351	-164.971	-167.629	-163.491	-166.516	-164.318

Reference CPT-values are calculated based on Tversky and Kahneman (1992). Note, the EPM values in set IV are not strictly equal, since we round the premiums in order to generate integers.

Table 8: Contracts and Decisions

Set	II	I	III	I	IV	II	I	III	I	IV	II	III	I	II
Order of decision according to occurrence in the experiment	10	6	4	2	8	3	12	13	14	11	5	1	9	7
Number of available contracts	2	2	2	4	4	5	6	7	8	8	9	10	11	12
Number of contracts that cover the potential loss of 2000	1	1	1	1	2	5	3	1	4	4	4	5	6	6
Number of contracts that cover the potential loss of 50	2	0	1	2	2	2	3	4	4	4	4	5	5	6
Number of contracts with deductible 0	1	2	1	2	0	1	2	2	4	4	2	3	4	4
Number of contracts with deductible 10	0	0	1	0	0	2	1	3	1	4	4	3	3	4
Number of contracts with deductible 30	1	0	0	2	4	2	3	2	3	0	3	4	4	4
Contract predicted by fatalist minimax	10	9	6	10	9	4	10	8	6	6	4	8	6	4
Contract predicted by pure minimax	1	3	5	4	4	4	4	2	1	1	4	4	1	4
Contract predicted by moderate minimax	10	9	6	4	4 or 10	4	4	8	6	1 or 6	4	10	6	4
Contract predicted by minimax ignoring deductible 10	1	3	5	4	4	4	4	2	1	2	4	5	1	4
Contract predicted by EPM	10	9	6	12	all	7	12	9	6	all	4	10	11	7
Most frequently actual chosen contract	1	3	6	4	4	4	4	2	1	1	4	10	1	4
Most frequently expected contract according lottery part (individual CPT-values)	1	3	5	4	4	7	4	9	6	2	4	10	7	7
Expected contract by CPT assuming TK-values	1	3	5	4	4	7	4	2	1	2	4	10	7	7

Reference CPT-values (TK-values) are calculated based on Tversky and Kahneman (1992).

Appendix II: Instructions and Comprehension Questions

Note that instructions for the first part of the experiment are provided jointly for the non-health and the health framing. Words that differ in the health framing instructions are indicated in brackets.

Welcome to the Experiment!

Preliminary Remarks

You are participating in a study of choice behavior for the purposes of experimental economic research. During the experiment you and the other participants are asked to take decisions. In doing so, you can earn money. The resulting amount is depending on your decisions. After finishing the experiment, your total earnings will be converted into *Euro* and paid cash. For this experiment all amounts are designated as *Taler*, the laboratory currency, where 100 *Taler* translate to 0.50 *Euro*.

The experiment will take around 135 minutes and consists of two parts. Before each of the two parts, you will receive detailed instructions. Note, that neither your decisions made in part one nor the decisions made in part two will have an influence for the respective other part. Moreover, there are neither right nor wrong answers in any of the two parts.

Part I

Please read the following instructions carefully. Approximately five minutes after handing out the instructions, we will approach you to answer any unresolved issues. In case you have any questions along the experiment, please feel free to call attention for yourself by raising your hand. We will come to your seat to answer open questions. For this part you will be endowed with 2200 *Taler*.

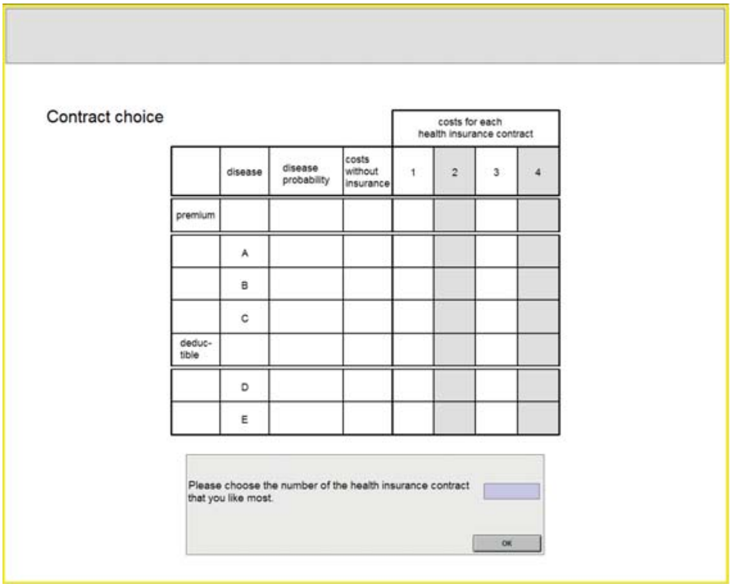
Description of Decision-Rounds

As a [health] insurance holder, you have to choose one [health] insurance contract in each of the 14 decision rounds. Depending on the round, the number of offered contracts may vary between 2 and 12. By purchasing a [health] insurance contract you have to pay a premium, for which you are entitled to receive [health] insurance benefits in case of [illness] damage. Further, [treatment] costs may be occasioned in case of [illness] damage. Depending on the benefits of the chosen contract, [treatment] costs are borne by either your [health] insurance or yourself.

[Health] Insurance Contracts

The [health] insurance contracts may differ in both, the height of the premium and the benefits, which you are entitled to receive from your insurance in case of [illness] damage. Thereby the premium corresponds to the price you pay for the respective [health] insurance contract. Each contract offers specific benefits, i.e. coverage of certain [treatment-] damage-costs in case of [illness] damage.

The different [health] insurance contracts from which you can choose are displayed in a table on your screen. The premiums for the particular contracts can be seen from the identically named row. An exemplary decision screen, without any entries, is depicted on the next page.



[Illnesses] Damages

In total [you can catch five illnesses] there are five possible damages, denoted A, B, C, D, and E. Each [disease] damage occurs with a probability, which is unchanged along the decision rounds. Whether [you catch the disease] a damage occurs in a round depends on these probabilities. From the respective columns on your screen, you can see both, the [illness] damage as well as the associated probability. It is possible [to catch] that none or even more than one [disease] damage occurs in a round.

After finishing the experiment one decision round is determined as being relevant for payment. Subsequently, a random number generator determines for each [disease] damage whether [you fall ill] it occurs in the round, which has been ascertained as being payment relevant priory. Therefore, the random number generator draws an equally probable number between 1 and 100 for each of the five [diseases] damages. If the drawn number is smaller or equal to the associated probability of [catching the disease] occurrence, [you fall ill] the damage occurs in this round. If the drawn number is larger than the associated probability of the [disease] damage, [you will not fall ill] it does not occur. Whether or not [you caught a disease] a damage occurs in the round, which is relevant for payment will be displayed on your screen after the second part of the experiment.

Benefits in Case of Damage [Illness]

When [you catch a disease] a damage occurs, it occasions [treatment] costs. As shown in the exemplary decision screen, [treatment] costs of the [diseases] damages in case of [illness] damage can be read off the column titled „Costs without Insurance". By paying your premium you are entitled to receive [health] insurance benefits in case of [illness] damage.

Each [health] insurance contract consists of a basic and a complementary insurance: [Diseases] Damages A, B and C are covered by basic insurance in all contracts. That is, [treatment] costs in case of [illness] damage are incurred by the health insurance. As complementary insurance, some contracts offer coverage of [treatment] costs for [diseases] damages D and E.

Additionally, some [health] insurance contracts include deductibles for the [treatment] costs from the [diseases] damages covered by basic insurance. A deductible means that you as an insurance holder have to bear the [treatment] costs for the basically insured [diseases] damages A, B and C up to the amount of the deductible in case of [illness] damage. If the sum of [treatment] costs for [diseases] damages A, B and C is larger than the amount of the deductible, you only have to pay treatment costs up to the amount of the deductible. If the sum of [treatment] costs is smaller than the deductible, you bear the complete costs. You find the deductible corresponding to the [health] insurance contract in the identically named row.

The total costs that you have to bear per decision round is determined as the sum of the premium of your chosen contract, possible deductibles and [treatment] costs for non-insured [diseases] damages in case of [illness] damage. The total costs for the round which is relevant for payment will be displayed on your screen after the second part of the experiment.

Earnings

After the experiment a random number generator draws one from the 14 decision rounds, which is relevant for payment. For this decision round you have to pay for the premium of your chosen contract, possible deductibles and [treatment] costs for non-insured [diseases] damages using your 2200 *Taler*. That is, all occurring costs of your chosen [health] insurance contract and [possibly caught diseases] possible damages of this round are added up. These total costs are then subtracted from your 2200 *Taler*. The residual will be paid to you cash after the experiment together with your earnings from the second part of the experiment.

Comprehension Questions

Prior to the decision rounds, we would like to ask you to answer six comprehension questions. These comprehension questions are intended to facilitate your familiarization with the decision situation. Please note that comprehension questions do not serve as guidance for the experiment. They are solely intended to sharpen your mind with respect to the decision situations which come up along the experiment. The entries that appear in the comprehensive questions are different from those in the experiment.

Part II

Please read the following instructions carefully. Approximately five minutes after handing out the instructions, we will approach you to answer any unresolved issues. In case you have any questions along the experiment, please feel free to call attention for yourself by raising your hand. We will come to your seat to answer open questions. For this part you will be endowed with 3500 *Taler*.

Description of Decision Rounds

In this part of the experiment, we ask you to participate in 72 decision rounds. In each of the 72 round, you will be shown two alternatives on your screen, alternative L on the left-hand side and alternative R on the right-hand side. Each time you must choose the one alternative that you prefer.

There are two possibilities of how the alternatives are designed:

- First, both alternatives are lotteries. A lottery consists of two payoffs, whereat one payoff is shaded red and the other payoff is shaded blue. Which one of the two payoffs is drawn depends on probabilities of occurrence, which are displayed on your screen.
- Second, one lottery and one safe payoff. A safe payoff is a single value, which occurs with 100% probability and is shaded gray.

The payoff values may be positive or negative for both, lotteries and safe payoffs. The first 24 decision rounds include only positive payoff values. The subsequent six decision rounds are mixed, i.e. they feature positive as well as negative payoff values. Afterwards, 42 decision rounds with only negative payoff values are shown. Positive values translate to gains while negative values stand for losses. The payoffs as well as the probabilities of occurrence may change along the rounds.

Probabilities of Occurrence

To convey a sense of the probabilities of occurrence, they are illustrated as pie chart between alternative L and alternative R on your screen. Thereby, the red area corresponds to the probability that the red payoff is drawn. Analogous, the probability for the blue payoff is depicted in the blue area. Additionally, the probabilities are given as number on the lines of the respective payoffs. Safe payoffs are safe and as such have a probability of 100%, if you choose this option.

Earnings

Subsequently to part two and after the draw for the payoffs in part I, a random number generator draws three of your chosen lotteries. These are relevant for payment. Thereby, one lottery is randomly drawn from the 24 positive decision rounds, one from the six mixed rounds and another one from the 42 negative decision rounds. If the drawn lottery is not a safe payoff, another random number generator determines for each lottery whether the red or the blue payoff occurs. These ascertained payoffs are subtracted from your 3500 *Taler*, if negative and added if positive. The result is your earning from part two.

Your total earnings from part one and part two of the experiment is the sum of your earnings from both parts and is paid to you in cash after the second part of the experiment.

Comprehension Questions

Prior to the decision rounds, we would like to ask you to answer two comprehension questions. These comprehension questions are intended to facilitate your familiarization with the decision situation. Please note that comprehension questions do not serve as a guidance for the experiment. They are solely intended to sharpen your mind with respect to the decision situations which come up along the experiment. The entries that appear in the comprehensive questions are different from those in the experiment.