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Heterogeneity in Health Insurance Choice: An Experimental Investigation of Consumer Choice and Feature Preferences

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Abstract:

We investigate heterogeneity in patterns of preferences for health insurance features using health insurance choice data from a controlled laboratory experiment. Within the experiment, participants make consecutive insurance choices based on choice sets that vary in composition and size. We keep the health risk constant and equal for everyone. In addition, we implement a treatment that entails a feature-based insurance filter, allowing us to validate feature preferences. We also account for individually elicited risk preferences. On aggregate, we find that there is considerable heterogeneity in consumer choice. Participants differ particularly (a) in their willingness to pay to insure themselves against illnesses that differ in terms of their probability of occurrence and the size of the losses to be covered and (b) in their preference to forgo deductibles. However, if we measure the quality of individuals' decisions based on risk preferences, the heterogeneity among participants disappears. Our results suggest that heterogeneity in health insurance choices is not reflected in decision quality when we assume a rank-dependent expected utility model of risk preferences.

Keywords: health insurance, consumer preferences, heterogeneity, laboratory experiment, risk preferences

JEL Classifications: C91, I13, D81, D83, G22

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1. INTRODUCTION

Based on the premise that consumers can best express their needs and preferences through their own choices, many of the recent policy reforms in the United States (US) and in Europe have aimed to facilitate more consumer choice (Cronqvist and Thaler, 2004; Coughlin et al., 2008; Thomson et al., 2013). Investigating consumers' preferences for health insurance plans from revealed choices relies on the assumption that choice sets can be observed (McFadden, 1974). In the US, consumers predominantly shop for health insurance through their employers or centralized choice platforms, such as Medicare Part D or health insurance exchanges, and the choice sets are known.[1] A large number of studies have investigated the rationality of health insurance choices in such settings, and their findings suggest that consumers often appear to make suboptimal decisions (see, e.g., Abaluck and Gruber, 2011, 2016; McWilliams et al., 2011; Handel, 2013; Heiss et al., 2013; Bhargava et al. 2017b, Liu and Sydnor, 2022). Less is known, however, about the heterogeneity of consumer preferences for certain features of health insurance plans and how consumers achieve their final choice set.[2] In the health insurance exchanges in the US, for instance, consumers are first asked for sociodemographic information and preferences for features like deductibles or supplementary insurance for various illnesses. Subsequently, they are presented with an individually tailored selection of plans. Knowing the feature preferences of consumers more precisely and how they use an insurance filter can help to understand better the heterogeneity of consumer preferences and differences in the quality of their decisions.

The aim of this study is therefore to investigate heterogeneity in consumers' preferences for certain features of health insurance contracts and to determine how the quality of their decisions is affected by these preferences. To do so, we use a framed laboratory experiment with a sequential design. The first part is inspired by Schram and Sonnemans (2011) and Kairies-Schwarz et al. (2017). In each round of the experiment, participants can acquire one or more of six different illnesses, each of which has a predetermined probability that is communicated to the participants. They have to decide on health insurance contracts in 12 varying choice sets, consisting of either six or 12 designed contracts. These differ with regard

[1] In contrast, in many countries, such as Germany, health insurance choice is still decentralized, and it is difficult to infer how consumers go shopping for it and the choice sets upon which they base their final decisions.

[2] Abaluck and Adams-Prassl (2021) propose a new approach using a discrete choice model to test choice data for full information and show that it identifies features that are not immediately visible to consumers in search results. While such approaches substantially improve our ability to infer preferences from observed data, as well as to account for missing choice sets and missing information on choice features, information about the search strategies themselves is missing.

to premium, deductible for the basic coverage of three illnesses, and additional coverage of three other illnesses. For roughly half of the participants, we introduce an ex-ante feature-based filter. The filter lets participants indicate their preferences for contract features and then uses this information to highlight contracts that include these features while preserving the entire set of choices. In the second part of the experiment, similar to Harrison and Ng (2016), Kairies-Schwarz et al. (2017), Jaspersen et al. (2022), and Harrison et al. (2023), we separately elicit individual risk preferences according to rank-dependent expected utility, thus addressing the fact that individuals are heterogeneous with respect to the value and weighting function of risk preferences (Payne et al., 1993).

The laboratory setting offers several advantages that facilitate the identification of an individual's preferences for contract features. First, we take advantage of the fact that we have a varying choice set, allowing the choices to change as the choice menu varies both in its degree of complexity and composition. We can determine a participant's valuation of the contract features (i.e., basic insurance, complementary insurance, and deductibles) by varying them and the cost across different rounds.[3] Based on the contract chosen, we can then provide evidence of an individual's willingness to pay for certain features and preferred insurance coverage.

Second, the laboratory setting allows us to control better for choice motives, which can be difficult to disentangle when using revealed choices from field data. A consumer may, for instance, choose a contract because he or she expects a claim to be more likely or because of risk aversion, either of which can be reflected in certain preferences for contract features such as low deductibles (Ericson et al., 2021). In our stylized decision situation, we assume identical probabilities of illness for each participant – i.e., the expected value of each contract could be calculated by the participants. Furthermore, we keep the probability of an illness occurring constant over time for all participants. In doing so, we can separate the effects of the expected risk of illness from those of preferences for a specific contract. Additionally, separately eliciting an individual's risk preferences enables us to characterize participants based on these, overcoming the issue of inferring risk preferences from insurance choices that may not always align with actual preferences (Bhargava et al., 2017b).

[3] We focus on repeated independent contract choices rather than on switching between contracts. This allows us to map a wider range of contracts and use the resulting information to determine preferences for contract features.

Moreover, the identified risk preferences allow us to evaluate insurance decisions.[4] Determining preferences based on field data depends on having sufficient variation in contracts. An important methodological contribution to solving this issue is the recent study by Ericson et al. (2021). They present a novel approach that identifies heterogeneity in risk perceptions and preferences using health insurance choice data from the Massachusetts Health Insurance Exchange. However, while their approach takes advantage of the differences in plans from which individuals can choose, it considers risk preferences and perceptions based only on the expected utility theory.

Third, when working with field data, it can be difficult to control for certain circumstances and external factors, making it challenging to infer preferences for contract features based on revealed decisions. For example, decisions may be influenced by inertia (e.g., Handel, 2013, Heiss et al., 2021), complexity or size of the choice set (Iyengar and Kamenica, 2010; Sinaiko and Hirth, 2011; Schram and Sonnemans, 2011; Besedeš et al., 2012a,b, Abaluck and Gruber, 2022; Biener and Zou, 2021), a lack of understanding of the decision situation (Bhargava et al., 2017a), or information on the financial consequences of various contracts (Samek and Sydnor, 2020). Further aspects, such as temporary liquidity constraints, are also difficult to control for due to a lack of information on individuals' financial circumstances. Finally, evidence has shown that consumers use simplified decision rules when making complex decisions (e.g., Kamenica, 2008; Ericson and Stark, 2012; Kairies-Schwarz et al., 2017). By using experimental data, we are able to control for the decision scenario – for example, by implementing ex-ante comprehension questions and by giving all participants the same financial endowments, which are sufficient to pay for health insurance contracts.

In this study, we classify individuals based on their preferences for different contract features using a latent class model and based on their contract choices. Similar to Kairies-Schwarz et al. (2017), we can then evaluate choices made in the different homogeneous groups based on the exogenous measure of risk preferences elicited in the experiment. The feature-based insurance filter enables us to validate which components are most important to participants in terms of contract composition. In doing so, we add to the literature on health economic experiments (Galizzi and Wiesen, 2017, 2018), particularly those involving health insurance (e.g., Schram and Sonnemans, 2011; Krieger and Felder, 2013; Kairies-Schwarz et

[4] One important contribution is the study by Barseghyan et al. (2021). They propose a method of discrete choice in which choice sets are unobserved and apply it to infer individual risk preferences from insurance choices in automobile collision insurance.

al., 2017; Mimra et al., 2020; Samek and Sydnor, 2020; Biener and Zou, 2021; Kairies-Schwarz et al., 2023, Harrison et al., 2023). The studies that are most closely related to ours are those by Schram and Sonnemans (2011) and Kairies-Schwarz et al. (2017). As in our study, Schram and Sonnemans (2011) investigate information acquisition in terms of the frequency with which participants seek information on contract features and the type of information they seek. They find that, irrespective of the choice set, individuals are most interested in the insurance premium, followed by the deductibles and complementary insurance. However, whereas they analyze aggregate choice behavior, we aim to identify preference heterogeneity among consumers.

To investigate how consumers choose insurance contracts, Kairies-Schwarz et al. (2017) use a measure of decision quality based on an exogenous measure of individual risk preferences elicited within an experiment.[5] However, they focus on decision quality at the aggregate level. In contrast, we investigate decision quality in the various homogeneous classes identified by our latent class model. As a treatment, our feature-based filter also relates to studies that explore the effects of decision support, such as those that show graphs of the financial consequences of different contracts to consumers (see, e.g., Samek and Sydnor, 2020; Biener and Zou, 2021) or those that give a curated selection of contracts (Gruber et al., 2021). In contrast to these studies, however, the purpose of our filter is not primarily to support decision-making (e.g., by reducing the size of the choice set) but to derive information about feature preferences independently of the contracts as a whole.

We find that our ex-ante insurance filter does not lead to differences in insurance choices compared to a scenario without the filter. We detect a high degree of heterogeneity in the decisions made by participants regardless of treatment (i.e., with and without the feature-based filter) and identify homogeneous classes of preferences. In particular, individuals differ (a) in their willingness to pay to insure themselves against different illnesses that vary in their probability of occurrence and cost in the event of a claim and (b) in their preference to forgo deductibles. Two different decision-making strategies can explain the extremes of these classes, whereas the classes in the middle are mostly combinations of these extremes. In the first strategy, the participants focus on the expected value of a contract, disregarding specific

[5] They also investigate whether participants use different simplifying heuristics that may lead to suboptimal choices. This approach is supported by evidence from the laboratory and the field demonstrating that individuals themselves use preferences in features to reduce complexity. Besedeš et al. (2012a,b) and Ericson and Starc (2012) show that in complex health insurance choices, consumers focus on salient contract features and make use of heuristics like choosing the cheapest plan.

features, and aim to minimize the expected medical costs. In the second strategy, the participants (a) opt for contracts that have higher expected value and (b) place greater emphasis on specific illnesses. Controlling for risk preferences reveals that decision quality does not differ substantially between the classes, indicating that differences in contract decisions can at least to some extent be attributed to variations in risk preferences. This suggests that even though some classes leave more money on the table than others when choosing health insurance, the quality of individual participants' decisions is comparable.

The remainder of this paper is as follows. Section 2 introduces our experimental design. Section 3 presents the results. Section 4 discusses the results and the limitations of our approach, and subsequently presents our conclusions.

2. EXPERIMENTAL DESIGN

Our experiment followed a sequential design consisting of two parts. In the first part, participants were presented with decision scenarios that required them to choose a health insurance contract from a menu of such contracts.[6] In the second part, they were presented with lottery choices to elicit their individual risk preferences. The instructions for participants are given in Appendix A.

2.1. Part 1 – Health insurance choice sets

Participants were provided with an initial endowment of 2300 talers, with 100 units of this lab currency equaling 0.50 euros. From this endowment, they could purchase health insurance to insure themselves against six possible illnesses (A, B, C, D, E, and F), each of which differed in its probability of occurrence and costs in the event of a claim. The costs in talers and the probabilities of occurrence are shown in Table 1. Other monetary and non-monetary costs that accompany an illness, such as lost wages or pain, are not considered here. The treatment costs and probabilities of each illness remained unchanged throughout the experiment.

The decision situation was as follows: Participants had to choose from menus of stylized health insurance contracts in 12 independent decision rounds.[7] The decision framework is

[6] We opted for health framing instead of neutral framing, as many studies have done before us. For an overview, see Galizzi and Wiesen (2017). In a setting similar to ours, Kairies-Schwarz et al. (2017) observed higher decision quality in health framing.
[7] We are aware that this design differs from the reality of knowing whether one has actually become ill, thus potentially reducing external validity. However, we expect that there are individual differences in the way participants react to an illness that they know they have acquired. In such cases, it would not be possible to

similar to that in Schram and Sonnemans (2011) and Kairies-Schwarz et al. (2017).[8] In each round, participants were presented with a different menu of choices. The first two choice sets were menus with six contracts. In the consecutive rounds, the menus alternated in their degree of complexity (six or 12 contracts). This was intended to jointly test the influence of menu size and feature complexity on the choice of contract. We also did this so as not to provoke a status quo bias. At the end of the experiment, one decision round was randomly determined to be relevant for payment. For this round, health status (i.e., whether a participant had one or more illnesses) was determined.

Table 1 Features of health insurance contracts

Insurance type	Basic			Complementary		
Deductible (in talers)	0, 10, 20, 30					
Illness	A	B	C	D	E	F
Treatment costs without coverage (in talers)	60	40	20	2000	70	40
Probability of illness occurrence	5%	20%	50%	1%	10%	30%

Contract design

The menu of health insurance contracts took the form of a table displaying contracts that varied along three dimensions: premium, deductible for basic insurance, and complementary insurance. Illnesses A, B, and C were covered by basic insurance, and D, E, and F could be covered by complementary insurance. Deductibles for illnesses covered by basic insurance started at 0 talers and went up to 30 talers in increments of 10. In case these illnesses or a combination of them occurred, the participant had to bear the treatment costs incurred up to the amount of the deductible, with health insurance paying the amount that exceeded this. In total, out of the initial endowment, a participant had to pay the premium, the potential treatment costs up to the amount of the deductible under basic insurance, and the potential costs of

distinguish between someone who chooses a contract because they prefer it and someone who chooses a contract because they suffered a loss (occurrence of illness) in the previous decision round. Therefore, we did not provide feedback after each decision. This means that our participants' health insurance choices are independent in the sense that they are made by participants given the same health status.

[8] Compared to Kairies-Schwarz et al. (2017), we increased the complexity of the decision scenario by adding an illness and offering more decision options. In addition, to allow for heterogeneity in the decisions, we adjusted the sets of contracts per decision in such a way that different preferences should lead to different choices of contracts. Regarding the possible preferences, we followed Kairies-Schwarz et al. (2017).

illnesses D, E, and F if not covered by complementary insurance. A sample screenshot of the decision scenario is provided in the participant instructions in Appendix A.

Without considering the premium, there were 32 ways to compose contracts differently with our six illnesses. A fair premium for illnesses D, E, and F and the deductibles was then calculated for each of these 32 variants. Another value was added to the premium to induce a ranking. The resulting order of contracts was basically determined randomly.[9] Ultimately, the 32 contracts differed in rank-ordering according to the expected value (EV).[10] We based our parameters on objective EV because it represents (a) the risk-neutral variant of expected utility theory and (b) a special case of the rank-dependent expected utility theory (RDEU) when the value function is linear and there is no probability weighting. Table A1 in the Appendix provides an overview of all contracts. All contracts offered in a decision round were selected from these 32 contracts and alternated between the decision rounds to prevent participants from remembering contracts from the previous decision. Table A2 in the Appendix provides an overview of all contracts in all choice sets.

Experimental conditions

To investigate initial preferences for contract features, we implemented two treatments: a baseline condition with insurance choice (IC) and a treatment variation with a feature-based filter (IC filter). The use of the filter was voluntary. This allows us to observe different types of users and their search behavior. With the filter, participants had the opportunity to indicate the characteristics of their preferred plan (i.e., their maximum deductible and the illnesses they desired to have covered by supplementary insurance) in each decision round. Contracts that matched the filter selection were highlighted in green, and the other contracts remained as a choice option.[11] Participants could change their feature selection as often as they wished during a decision round, with other contracts then being highlighted accordingly. There was also a possibility that no contract in the selection fulfilled all the conditions from the filter, resulting

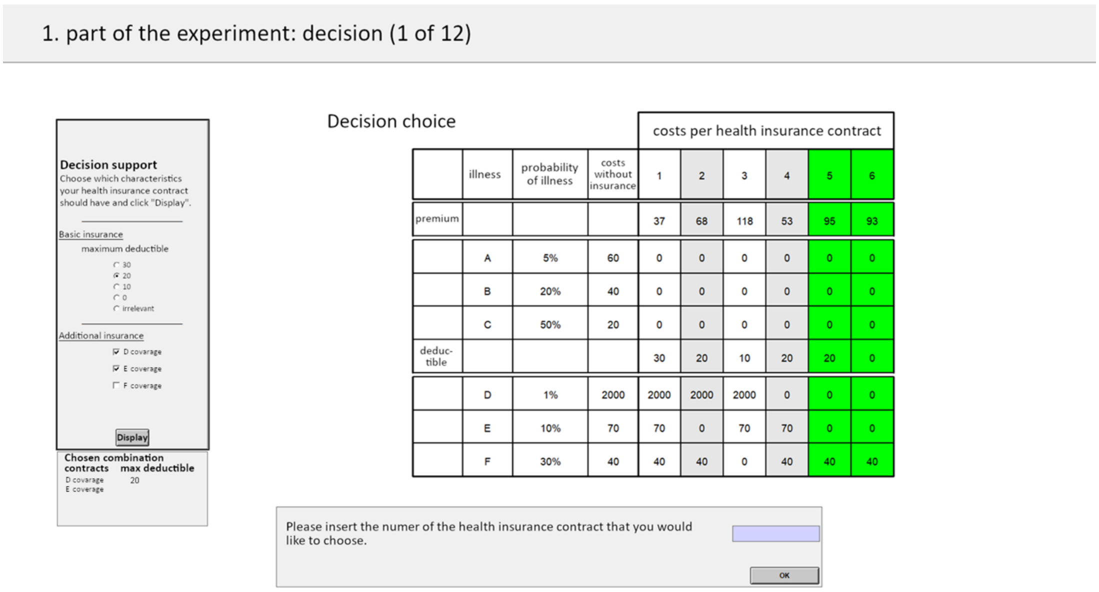
[9] However, the exception to this was that the 10 best contracts (by EV rank: 1 - 10) did not cover the 2000 taler treatment cost feature, whereas the 10 worst contracts (by EV rank: 23-32) did. This rule served to ensure that players had an actual trade-off in terms of rank-dependent expected utility (RDEU). For example, if the best EV contract covered the 2000 taler cost feature, this would be a dominant contract that would be easy for participants to identify.

[10] Note that we used EV as an objective measure to determine the rank-ordering of contracts because we did not have individual risk preference measures before the experiment. This also most likely resembles a realistic health insurance choice scenario in which the underlying choice set is the same for all individuals.

[11] We are aware that this scenario does not correspond to many real-world decision support tools for choosing health insurance, which reduce the number of alternatives within the choice set. However, by keeping all contracts within the menu, we can investigate whether participants ultimately choose the plan or plans that correspond to their indicated feature preferences. We are also able to compare insurance choices to the treatment with no filter.

in no contract being displayed in green. Figure 1 provides a screenshot of the decision situation with the feature-based filter. With the filter treatment, we can fill an information gap, i.e., we can identify preferences for contract features that cannot be clearly identified when using only revealed choices from field data. We can then infer the importance of the features based on the choice.

Figure 1 Screenshot of choice set with a feature-based filter



2.2. Part 2 - Risk elicitation and definition of decision quality

In Part 2 of the experiment, we elicited individual rank-dependent expected utility risk preferences in a manner similar to that used by Kairies-Schwarz et al. (2017). Our measurement of risk preferences is based on the concept of rank-dependent expected utility (RDEU) introduced by Quiggin (1982). Because the consequences of insurance contract choices in the experiment are framed as losses, we consider RDEU here as being defined only over losses. Considering a complete ranking of all (negative) outcomes of a prospect *f*, i.e., $0 \geq x_{\mathrm{j}} \geq \cdots \geq x_n$, and associated probabilities $p_1, \dots, p_n$ the prospect's value is calculated as:

$$RDEU(f) = \sum_{j=1}^{n} \pi_j(p) \cdot U(x_j)\,. \tag{1}$$

The utility function $U(x_j)$ is evaluated by a probability weighting function $\pi(x_j)$. The weighting function is strictly increasing in probabilities between [0,1], and $w(0) = 0$ and $=$

$w(1) = 1$ must hold. Equation 2 shows how we calculate decision weights while accounting for rank dependence[12]:

$$\pi_j(p) = w(p_j + \cdots + p_n) - \mathrm{w}(p_{j+1} + \cdots + p_n). \quad (2)$$

In the experiment, we applied the trade-off method (Wakker and Deneffe, 1996) and implemented a bisection procedure, which is similar to the approach taken by Abdellaoui (2000) and Abdellaoui et al. (2007), to facilitate the decision process. As previously mentioned, we focused only on the loss domain relevant to the choices of insurance in Part 1 of the experiment. We therefore did not need to elicit the degree of loss aversion in this setting. We scaled the lotteries to fit the decisions made in Part 1 and to ensure that scaling effects would not bias our results.

Participants had to choose between 70 pairs of lotteries, ensuring that our data would be rich in terms of quantity and quality. In 38 decision rounds, participants had the choice between two lotteries to calculate the value function parameters. In the remaining 32 decision rounds, they had the choice between a safe option and a lottery, allowing us to calculate the weighting function parameters. See Appendix D for a detailed example of the decision situation. Participants received an initial endowment of 4800 talers in part 2. One of the participants' decisions was selected randomly. According to a random selection process, the outcome of the decision was determined and subtracted from the initial endowment.

We use the risk preferences elicited from each participant and derive a rank-ordering of contracts for him or her in each decision. This notion of decision quality allows for interpersonal comparisons and, thus, aggregations. Doing so also allows us to investigate the influence of risk preferences on the final choice of health insurance contract without needing to account for the complexity of the decision situation or various biases.

2.3. Experimental procedure

The experiment was programmed with z-Tree (Fischbacher, 2007) and conducted through the Essen Laboratory for Experimental Economics (elfe) in 2016. It involved 253 individuals recruited from the general student population of the University of Duisburg-Essen using the Online Recruitment System for Economic Experiments (Greiner, 2015). In total, 117 individuals participated in the IC filter and 136 individuals participated in the IC treatment.

[12] Note that the weight is defined as $\pi_1(p) = w(1) - \mathrm{w}(p_{j+1} + \cdots + p_n)$ and $\pi_n(p) = w(p_n) - \mathrm{w}(0)$ for the largest and smallest outcome, respectively.

Overall, we conducted seven sessions at the laboratory, each lasting approximately 135 minutes, to collect data.

The experimental procedure in all sessions was as follows: Upon arrival, participants were randomly assigned to cubicles, where they were given printed instructions. After reading these, they had the opportunity to ask questions. In addition, to prepare participants for the complexity of contract composition, we asked them eight comprehension questions, each of which focused on the premium, the probabilities of an illness occurring, the total cost, the individual medical costs, or the amount of the deductible (see Appendix A for an overview of the specific questions). The experiment did not start until all participants had answered the comprehension questions correctly. Participants were provided with a simple calculator and pen and paper to assist during the experiment. At the end of the experiment, participants were asked to complete a short questionnaire on demographics, including age, gender, the year of university they were in, and their university major. In this questionnaire, they were also asked whether they had paid special attention during the experiment to particular features of the contracts.[13] Our participant pool was 52% female with an average age of 23.8 years (std. dev. 0.39). In total, 44.3% were studying economics, 18.2% a STEM subject, and 17.0% humanities. Participants earned an average of 25.42 euros and received their payment privately in cash at the end of the experimental session.

[13] Details in Table E4 in Appendix E.

3. RESULTS

3.1. Aggregate results

We first look at whether there are differences in aggregate contract choice between the treatments with (IC filter) and without a filter (IC). Table 2 shows the mean premium, the mean deductible, and the proportion of contracts with complementary insurance chosen by participants in the IC group, the IC filter group, and in both groups together. The lack of significant differences in the features chosen by participants in the two treatments (see Table 2) corresponds with the results reported by Samek and Sydnor (2020) and Biener and Zou (2021), who find that decision aids, such as consequence graphs, that do not reduce choice sets have no or only a very small effect on contract choices. For further analyses, we therefore pool the results from both treatments.

Table 2 Mean features of actual choices and best EV contracts

	Actual choices					**Best EV contracts**
	IC filter		IC	Overall		
Premium	83.375 (2.105)	— ns —	79.165 (1.962)	81.112 (0.625)	— *** —	45.083 (4.182)
Deductible size	10.150 (0.336)	— ns —	11.072 (0.356)	10.646 (0.248)	— ns —	10.833 (3.219)
Coverage of illness						
D (2000 talers with 1% probability of occurrence)	57.83% (0.033)	— ns —	55.27% (0.030)	56.46% (0.022)	— *** —	25.00% (0.125)
E (70 talers with 10% probability of occurrence)	50.64% (0.017)	— ns —	48.77% (0.017)	49.64% (0.012)	— *** —	16.67% (0.108)
F (40 talers with 30% probability of occurrence)	67.31% (0.014)	— ns —	63.24% (0.014)	65.12% (0.010)	— *** —	41.67% (0.142)
N	117		136	253		

Notes: For the actual choices, we calculate, for each participant, the mean value of each feature over all 12 contract decisions, and subsequently calculate the mean of this value, for each feature, across all participants. For the best expected value contract, we calculate, for each participant, the mean value of each feature over all 12 best value contracts, and subsequently calculate the mean of this value, for each feature, across all participants. The percentages shown for illnesses D, E, and F represent, in the left half of the table, the percentage of actual choices in which coverage for each illness was selected and, in the right half of the table, the percentage of choices in which coverage for each illness would be included in the best EV contracts. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns $p \geq 0.05$ (Mann-Whitney U test for between-treatment comparisons; one-sided Wilcoxon signed-rank test for comparisons between actual choices and mean values of the best EV contracts).

Because the contract features do not stand alone but are always part of a stylized contract, the average values and proportions of the contract features can only be interpreted in relation to each other. To provide context for the observed values, we compare these to the values that would result from selecting the best contract based on the EV in each decision.[14] All values are reported in the experimental currency, talers.

The mean premium of the contracts chosen in our experiment is 81.11 talers, which is nearly twice that of the best EV contracts. In contrast, the mean deductible of the contract chosen by our participants is 10.65 talers, which is not significantly different from that of the best EV contracts ($p = 0.126$). The preference for purchasing complementary insurance for illnesses D, E, and F is relatively frequent, with illness D being covered in 56.46%, illness E in 49.64%, and illness F in 65.12% of all contracts selected by participants. These percentages are all significantly higher than those we observe for the best EV contracts.

Result 1: We find no differences in the features chosen by participants between the two treatments (i.e., the one with and the other without a feature-based filter). Overall, individuals chose a significantly higher premium and significantly more complementary coverage of illnesses than would have been the case if the best EV contracts had been selected.

3.2. Heterogeneity in contract selection

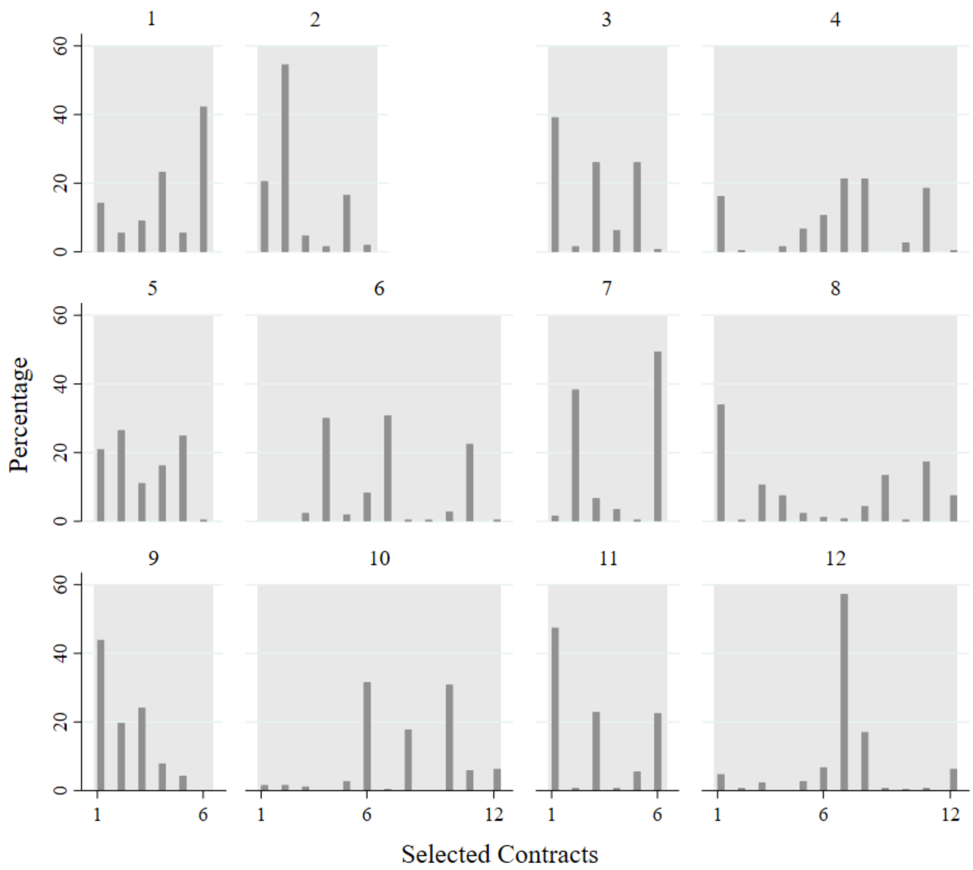
Subsequently, we look at the heterogeneity of the contract choices made by participants. As shown in Figure 2, our findings reveal that there is a significant amount of variation in these choices, with almost all available contracts selected by some individuals. Additionally, we observe that participants selected two to four contracts per choice set particularly frequently.

We employ a mixed logit regression to better understand the distribution of heterogeneity relative to each contract feature. This regression model considers all available options, including actual choices and alternatives per decision, and accounts for individual differences in preferences for contract features. The estimates presented in Table 3 provide insights into these preferences and further emphasize the heterogeneity among participants. First, the signs of the coefficients point in the expected direction: A higher premium is associated with a lower probability of the contract being selected, and the same is true if a contract includes a deductible. Contracts that cover illnesses D, E, and/or F were more likely to be selected. Second, the standard deviations are significant for the premium and all complementary insurance options. For the deductibles, only the standard deviation for the deductible of 20 talers is significant, albeit only marginally so. This indicates a particularly high

[14] Similar to Jaspersen et al. (2022), Table C1 in Appendix C provides a comparison of actual choices to a random choice. It suggests that choices rely on a planned decision process rather than on random choice because individuals' choices deviate significantly for all features from the random choices.

degree of heterogeneity across participants in terms of their preferences for coverage against illness, whereas their preferences for avoiding deductibles are less heterogeneous.

Figure 2 Selected contracts by decision rounds



Notes: In decisions 1, 2, 3, 5, 7, 9, and 11 participants can choose from among six contracts, whereas in decisions 4, 6, 8, 10, and 12, they can choose from among 12 contracts. See Table B2 in Appendix B for the corresponding contract features.

By calculating individuals' willingness to pay (WTP), we can provide more detailed information about their preferences for contract features. Our results indicate that the WTP to cover each of the three illnesses is more than three times higher than the EV. In other words, the participants were, on average, willing to insure against the illnesses at a higher cost than would have been the case for a risk-neutral, rational decision-maker. Negative values for the WTP and EV of the deductibles indicate a willingness to accept (WTA). For the lowest deductible (i.e., of 10 talers), the confidence interval of the WTA includes the corresponding EV and is, therefore, not significantly different from it, whereas the WTAs for the higher deductibles are about twice as high as the EV. Our results suggest that participants, on average, disliked high deductibles and needed to be compensated by a reduction in the premium that was greater than the EV. In the case of the deductible of 20 talers, the required compensation had to be greater, on average, than the deductible amount itself.

Table 3 Preference heterogeneity – Mixed logit regression

	Mean	SD	WTP	EV
Premium	-0.054***	0.026***		
	(0.004)	(0.003)		
Illness D (2000 talers with	3.977***	3.857***	73.37	20
1% probability of occurrence)	(0.709)	(0.572)	[44.18, 102.56]	
Illness E (70 talers with	1.617***	0.926***	29.83	7
10% probability of occurrence)	(0.134)	(0.219)	[24.33, 35.32]	
Illness F (40 talers with	2.319***	0.850***	42.78	12
30% probability of occurrence)	(0.131)	(0.204)	[36.28, 49.28]	
Deductible of 10	-0.224**	0.106	-4.14	-6.2
	(0.074)	(0.162)	[-6.71, -1.56]	
Deductible of 20	-1.302***	0.654*	-24.03	-12.4
	(0.114)	(0.261)	[-28.45, -19.61]	
Deductible of 30	-1.456***	0.391	-26.86	-14.8
	(0.114)	(0.381)	[-31.67, -22.05]	
n	25,806	25,806		
N	253	253		

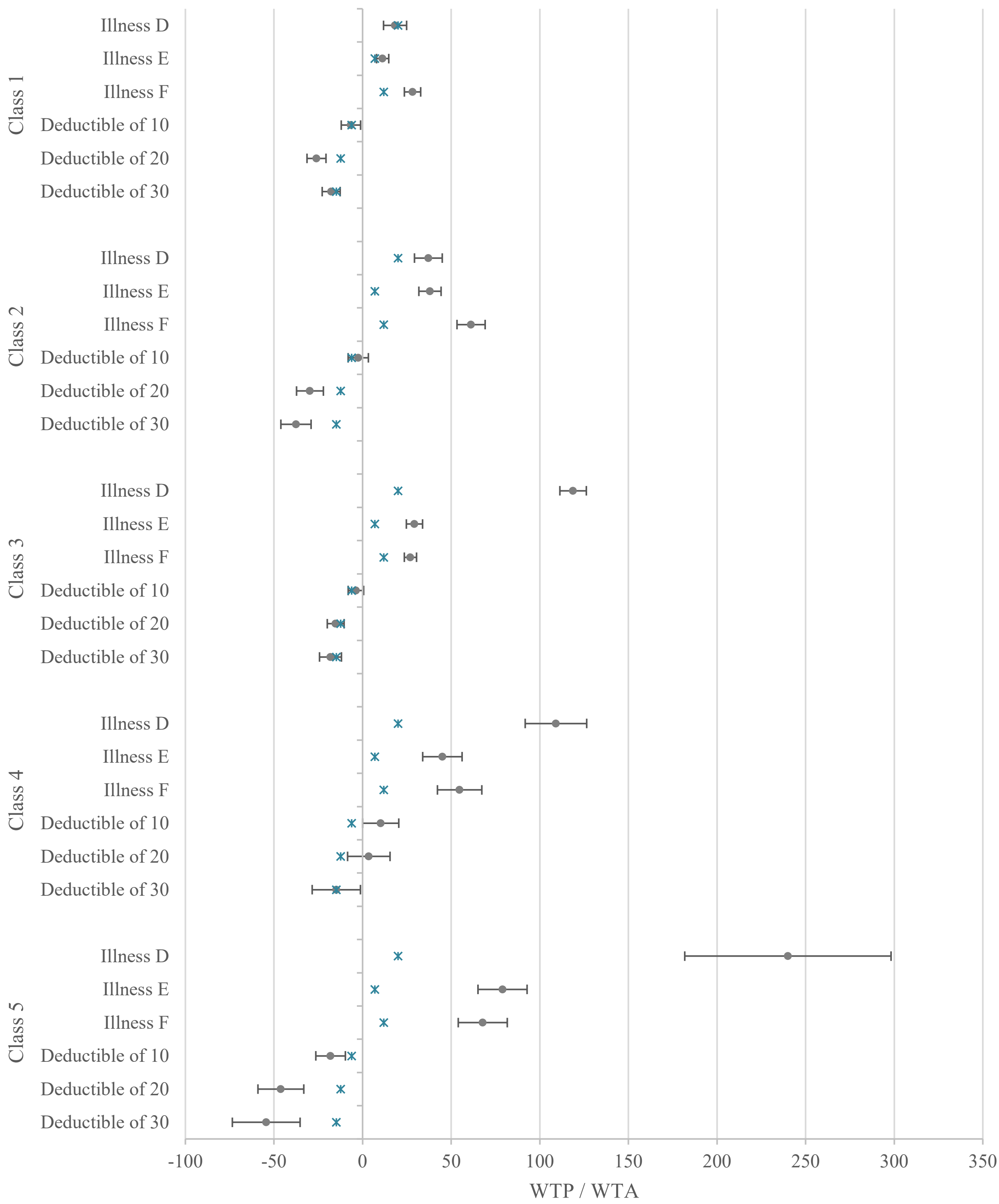
Notes: Mixed logit regression. Means, standard deviations (SD), and willingness to pay (WTP). Negative WTP values indicate a willingness to accept (WTA). EV of each contract feature are added for comparison with WTP/WTA. Standard errors clustered at the individual level are in parentheses. 95% confidence intervals of WTP/WTA values are in brackets. * p<0.05, ** p<0.01, *** p<0.001

Furthermore, we run a latent class logit model to identify classes with homogeneous preferences for contracts and their features in this heterogeneous population.[15] As with the mixed logit model, we can consider all alternatives of each choice set in addition to the chosen contract. Additionally, we can identify homogenous classes within a heterogeneous population. The treatment condition enters the model as a participant-specific independent binary variable to control for heterogeneity between the IC and IC filter. Employing the Bayesian information criterion (BIC) to select the optimal class size, which is the class size that minimizes the BIC, leads to an optimal number of nine classes.[16] This high number indicates a high degree of heterogeneity and a variety of decision patterns. However, because, with nine classes, the number of observations for class membership is small, we discuss the results for the classification of fewer classes in this analysis. In order to determine how to reduce the number of classes, we consider the elbow method (see Nylund-Gibson and Choi, 2018). Figure E1 in Appendix E visualizes statistical fits for different class sizes and reveals that the improvement in model fit plateaus with five classes. When we reduce the number of classes considered in the analyses to five, the model fit is marginally poorer than with nine (see Table E2 in Appendix E).[17] With an average probability of 0.94 (std. dev. 0.10) for the highest individual class

[15] We used the Stata routine lclogit2 to estimate the latent class model. See Yoo (2020) for a detailed model description.
[16] Fit statistics for two to nine classes can be found in Table E1 in Appendix E.
[17] Results for nine classes can be found in Table E4 and Figure E2 in Appendix E.

membership, the model with five classes still appears to distinguish very well between the several classes of preferences.

Figure 3 Willingness to pay by classes and features



Notes: Error bars represent 95% confidence intervals. Blue stars represent EV of features. Illness D has costs of 2000 talers with a 1% probability of occurrence, illness E has costs of 70 talers with a 10% probability of occurrence, and illness F has costs of 40 talers with a 30% probability of occurrence.

Figure 3 graphically illustrates the results of the latent class logit model, presenting these as the WTP estimates for a particular feature in each class.[18] The class shares range from 13.8% to 25.3%. Again, we compare the WTP estimates with each feature's EV. We sort the classes according to the summed absolute distances between the WTP estimates (dots) and the EV (blue crosses) of each feature, starting from the smallest (Class 1) to the largest (Class 5) distance. The higher the class numbering, the higher the overall WTP for coverage compared to a risk-neutral decision-maker.

As a result of this sorting, Class 1 and Class 5 show the most pronounced differences in their WTP and WTA values for the respective contract features.[19] This is mainly because of different preferences for complementary insurance. The WTP and WTA values of Class 1 members are closest to the EV. In contrast, members of Class 5 were willing to pay much more to insure against all illnesses than those in other classes. This is especially pronounced for illness D (low probability of high costs), for which the WTP was around 10 times higher than the EV. Classes 2 to 4 are located between Classes 1 and 5, with Class 2 placing a positive value on additional insurance for illness F (relatively high probability of occurrence), whereas Class 3 rather focused on insurance for illness D.

Most participants wished to avoid deductibles for the illnesses covered by basic insurance, as indicated by the WTA values. It appears that participants in Classes 2 to 4 ignored low deductibles of 10 because their WTA/WTP value is not significantly different from 0. For Class 4, this was also the case for the deductible of 20. In contrast, participants in Class 5 needed to be compensated the most for deductibles because their WTA size of deductible was significantly greater than the corresponding EV. Participants' approach to deductibles might result from calculations more complex than considerations around insuring against illnesses D, E, and F in our experiment, potentially including a tendency to avoid deductibles in general.

Result 2: We observe considerable heterogeneity in participants' choice of contracts. We identify five homogeneous classes of participants, who differ in their preferences for contract features when choosing health insurance. These classes range from (a) those who exhibit WTP and WTA that are close to the expected values to (b) those with a high willingness to pay for insurance against all illnesses.

[18] Regression results are presented in Table E3 in Appendix E. We do not find statistically significant differences between the classes regarding the experimental treatments with or without an IC filter.
[19] For nine classes, we find a similar range.

3.3. Implications for decision quality

In the following, we report the decision quality of the contract choices for our five classes based on the risk preferences of individual participants, which we deduce by fitting a value and weighting function to the data of Part 2 of the experiment by using non-linear least squares. For this analysis, we assign participants to the class to which they have the highest probability of belonging and refer to them as members of this class. To study decision quality, we first look at the risk preferences themselves. Table 4 provides an overview of the median values of the individual RDEU parameters for each class. Due to outliers, we refer here to the median rather than to the mean.[20]

For the value function, $\theta < 1$ implies risk-seeking behavior, $\theta > 1$ implies risk-averse behavior, and an overall median value for θ of 1 implies risk neutrality on average. Examining the different classes reveals that all of them have similar values for θ, indicating that there are no considerable differences in the utility functions across classes.

Table 4 Median values of individual RDEU parameters by class

Median RDEU parameter	Class 1	Class 2	Class 3	Class 4	Class 5	Overall
θ	0.955	1.032	0.983	1.000	1.131	1.000
s	0.824	0.760	0.580	0.758	0.375	0.720
r	0.693	0.896	1.441	1.016	1.530	0.985

Notes: N=253. Parameter θ belongs to the standard value function proposed by Tversky and Kahneman (1992), and parameters s and r belong to the two-parameter probability weighting function in the loss domain proposed by Prelec (1998). See Appendix D for further details.

However, we find differences in the weighting of the probabilities. All classes have median values of $s < 1$, referring to the attractiveness of gambles[21] and implying overweighting of all probabilities compared to neutral preferences ($s = 1$). Class 1 exhibits the lowest and Class 5 the highest overall overweighting. The heterogeneity of s supports the earlier picture of a considerable WTP to insure against certain additional illnesses or a WTA deductibles, especially for Classes 3 and 5. The preference of Class 5 to insure against the occurrence of illness D seems to be explained by a 10-fold increase in perceived probability of this illness (i.e., a WTP of 240 talers for illness D, which has a cost of 2000 talers and 1% probability of occurrence; see Figure 3).

For r, we observe a high degree of heterogeneity among classes in their level of discrimination between low and high probabilities. The median values of the parameter r reveal more overweighting of small than of large probabilities in Classes 1 and 2 ($r < 1$) and more

[20] Mean values of the parameters can be found in Appendix D.
[21] See Gonzalez and Wu (1999) for parameter interpretation.

overweighting of large than of small probabilities in Classes 3, 4, and 5 ($r > 1$). Because the illness probabilities in the experimental setting do not represent the full spectrum of probabilities but are entirely in the lower range, we can derive only limited information about the contract decisions from the parameter r. Additionally, prior studies show that participants either tend to underweight very low probabilities or are willing to pay much more than the expected value (McClelland et al., 1993; Jaspersen et al., 2022).

Overall, we can conclude that the differences between the classes do not seem to be due to their utility function (i.e., their risk aversion) but to their probability weighting.

The question remains as to how participants' preferences for contract features and for risk relate to decision quality. Our study follows the methodology of Kairies-Schwarz et al. (2017) in measuring the quality of individual participants' decisions by means of their RDEU. More specifically, to measure quality, we consider an individual's RDEU and rank all contracts selected in a decision round according to their RDEU value from one to six for low-complexity decisions and from one to 12 for high-complexity ones, where rank one represents the best contract for the individual in question. The best contract for an individual implies that it has the highest RDEU value for an individual given his or her RDEU parameters. Outliers in individual parameters of the value and weighting function may also influence the ranking of contracts. Thus, results regarding the ranking of contracts should be interpreted carefully. In addition to the individual ranking of contracts according to risk preferences, we report ranks based on expected costs (EV) to provide context for our findings.

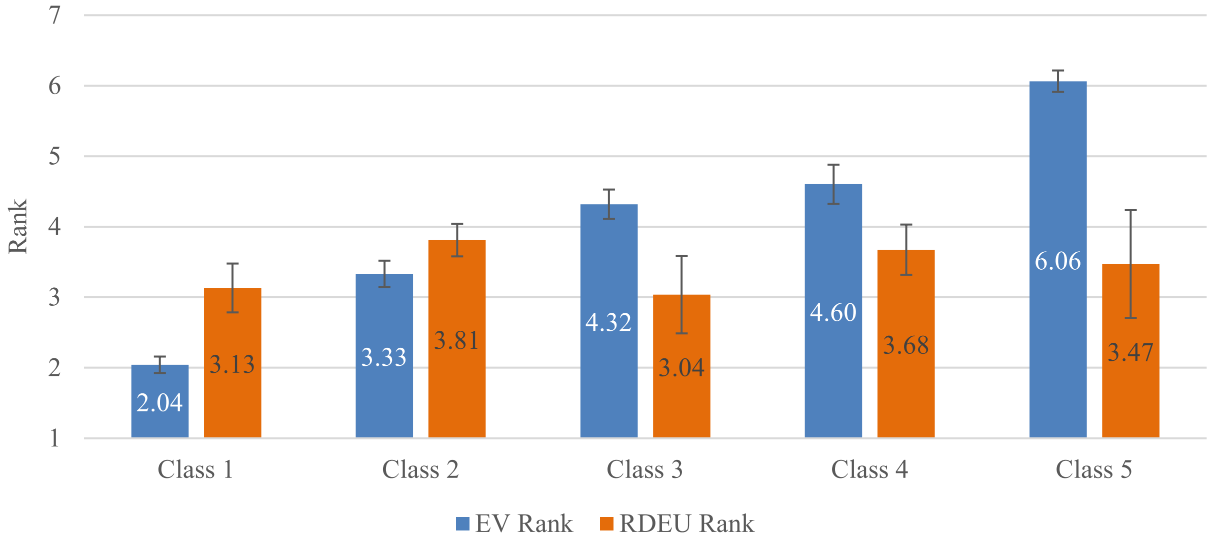
The contract with the best RDEU rank was selected in 28.66% of all decisions. The mean RDEU rank is 3.45 (std. dev. 1.52), and the average EV rank is 3.83 (std. dev. 1.49). [22] Consequently, a large number of participants appear to have chosen contracts that have a high EV. Figure 4 shows the EV and RDEU ranks by class. The RDEU ranks indicate how well the preferences of individuals in the five classes are reflected by their choice of contracts.

Not surprisingly, when we evaluate decision quality based solely on EV (blue bars), we see that Class 1 made the highest quality decisions, whereas Class 5 made the lowest. However, the picture becomes less straightforward when we consider an RDEU model of risk preferences (orange bars). The results of this model suggest that the highest quality decisions were made

[22] The RDEU rank of 3.45 means that, on average, participants chose a contract that is between the third and fourth best.

by Classes 3, 4, and 5 ($p < 0.004$, WSR test), whereas when we consider the EV, the highest quality decisions were made by Classes 1 and 2 ($p = 0.000$, WSR test).[23]

Figure 4 EV and RDEU ranks by class



Notes: The figure shows the mean of the individual average EV and RDEU ranks over all decisions by class. Rank 1 represents the best contract. The higher the rank, the further away the contract is from an individual's optimum. The worst possible average rank is reached at 8.5. Error bars represent 95% confidence intervals.

Result 3: Taking individuals' risk preferences into account by employing an RDEU model to analyze contract choices suggests that the distribution of decision quality is more homogeneous compared to assuming an EV model. Particularly, a majority of participants' decisions translates into better quality than would be suggested by the EV perspective.

3.4. Validation of preferences using data on filter use

As noted above, we find no differences in the contract features chosen by participants in the groups with or without a filter. However, data on participants' use of the filter make it possible to analyze which of the features that are selectable in the filter appear to have been most important for the participants when making their ultimate choice of contract. This can help us better understand the thought process behind contract selection and thus validate feature preferences.[24] Because each contract had a particular set of features, simply analyzing the selected contract would not provide insights into how individuals arrived at their decision.

Overall, we observe that the filter was used by 88.9% of all participants in at least one decision round. With a mean of 6.28 rounds (std. dev. 0.37) per participant, the filter was used

[23] The results remain qualitatively the same when separated by complexity, see Figure E3 in Appendix E.
[24] The advantage of the experiment is that we can exclude all other aspects, such as different health states, liquidity constraints, or expectations that may also impact choices and are not easily or perfectly observable in the field.

in about half of the 12 decision rounds. By using the filter, participants could reduce the complexity of choosing a health insurance contract out of a large choice set. Based on participants' final filter setting, we see that, in low-complexity decisions, they used the filter to reduce the number of contracts highlighted in a set within a decision round from 6 to 3.77 on average (std. dev. 1.32, median 4). For high-complexity decisions, the reduction was from 12 to 7.42 contracts (std. dev. 2.46, median 7).[25] Within any given decision round, some participants used the filter several times, i.e., they tested how their choice of features would affect which plans would be highlighted. We observe that participants selected different filter variations up to nine times, with a mean of 1.62 (std. dev. 0.04) for the decisions in which the filter was used at least once. That is, some participants did not use the filter at all, others used it once to decide on a contract, and others tried several different filter configurations before deciding on a contract.

Table 5 presents the frequency of filter use, proportions of preferred features in the filter, and proportions of these preferred features that were in the contracts ultimately chosen by members of different classes of participants. We observe that the different classes were heterogenous in their filter use: the filter was used by members of Class 1 in only a small proportion of the decisions (28.8%), which is about half of what we observe for the other classes (53.2% to 61.5%). Because members of Class 1 did not seem to place strong emphasis on contract features, participants may have chosen not to use the filter because they felt they did not need it to make their choices. Instead, they may have been guided mainly by the premium, which was not included in the filter.

The first panel of Table 5 provides insights into the composition of the contracts selected by participants. The preferences for contract features by class are in concordance with the findings from our latent class analysis: A high proportion of contracts chosen by members of Class 1 have coverage for illness F (low costs with high probability of occurrence). For Class 2, a high proportion of contracts chosen by participants include coverage both for illness F and illness E (medium costs with medium probability of occurrence). Meanwhile, the contracts chosen by members of Class 3 have the highest average deductible, and a high proportion of the contracts include coverage of illness D (high costs with low probability of occurrence). In Classes 4 and 5, a high proportion of contracts cover all illnesses. Notably, the proportion of

[25] All of the highlighted contracts correspond to the preferences selected in the filter. This suggests that the participants rarely used the filter to narrow down the selection in such a way that only one or two contracts would remain. Instead, for most decisions, there was still room to decide among a large variety of contracts. For our analysis, we defined the last selection in the filter as the relevant selection.

contracts with coverage for illness D is highest in Class 5, with this feature being included in 99.76% of participants' contract choices. The increasing proportion of coverage by class number is also reflected in a trend towards higher average premiums given that a high level of coverage is associated with a higher premium.

Table 5 Chosen and preferred features by class

	Class 1	**Class 2**	**Class 3**	**Class 4**	**Class 5**	**Overall**
I. Contracts chosen by participants						
Mean premium	52.156 (0.742)	72.745 (1.204)	95.066 (1.329)	90.345 (1.955)	115.993 (0.690)	81.112 (1.439)
Illness D covered	17.36% (0.018)	32.29% (0.020)	96.79% (0.011)	71.06% (0.023)	99.76% (0.002)	56.46% (0.022)
Illness E covered	39.03% (0.018)	64.58% (0.021)	32.48% (0.017)	51.06% (0.025)	57.38% (0.019)	49.64% (0.012)
Illness F covered	62.08% (0.022)	79.30% (0.015)	55.34% (0.012)	56.36% (0.019)	69.05% (0.013)	65.12% (0.010)
Mean deductible	8.828 (0.497)	11.125 (0.547)	13.197 (0.511)	11.303 (0.361)	8.405 (0.316)	10.646 (0.248)
n	720	768	468	660	420	3,036
N	60	64	39	55	35	253
II. Revealed preferences						
Coverage for illness D preferred	11.67% (0.054)	16.63% (0.043)	92.36% (0.029)	58.69% (0.081)	97.67% (0.018)	50.58% (0.042)
Coverage for illness E preferred	16.63% (0.073)	32.40% (0.055)	8.49% (0.049)	21.72% (0.048)	30.54% (0.085)	23.08% (0.029)
Coverage for illness F preferred	66.52% (0.099)	71.57% (0.058)	12.38% (0.048)	56.68% (0.066)	33.55% (0.090)	50.69% (0.038)
Mean preferred max deductible	21.239 (1.711)	20.189 (1.306)	26.408 (1.438)	20.938 (1.745)	25.694 (1.460)	22.527 (0.724)
n	76	246	155	134	124	735
N	15	34	21	19	15	104
Share of decisions made using the filter	0.288 (0.064)	0.586 (0.054)	0.615 (0.057)	0.532 (0.080)	0.574 (0.085)	0.524 (0.031)

Notes: The share of chosen contracts that cover illnesses D, E, or F, as well as the mean deductible of all contracts, is shown for the complete sample (n=3,036). The share of filter use where preferred coverage for illnesses D, E, or F was selected as the final filter setting, as well as the mean of the selected maximum deductible, is shown for participants who were subject to the filter treatment and also used the filter (n=735). For the mean preferred deductibles, the selected maximum deductible is taken into account; choosing nothing or "irrelevant" counts for the maximum deductible of 30 talers. Standard errors are given in parentheses.

The second panel of Table 5 provides insights into the features selected by participants who used the filter. We observe that the feature preferred most by these participants, measured in terms of the features they selected in the filter, was that which was ultimately included in the contract they chose. We also observe a prioritization of features insofar as participants focused on particular features in the filter, which then mainly drove their choice of contract. For Classes

3 and 4, it seems that insuring against illness D was the main driver of participants' contract choice, whereas for Classes 1 and 2 the main driver was insuring against illness F. It is striking that the feature preferences of the subset of participants who used the filter mirror the actual contract choices made by all members of each class. For example, even if the filter was used in only about 30% of the choices made by members of Class 1, this subset still appears representative of the average of all further choices made by participants in both the IC and IC filter treatments.

In the post-experimental questionnaire, we asked participants about the role that specific contract features played in their decisions (results are provided in Table E5 in Appendix E). For example, we asked how often a participant considered premiums and deductibles when making their decisions. Additionally, we asked how often they considered whether a contract covered the cost of 2000 talers when making their decisions. Our results reveal that Class 1 has the highest percentage of members (98.3%) who always or frequently considered the premium. In contrast, 50.0% of Class 1 members reported never having considered the coverage of the cost of 2000 talers, whereas 94.3% of Class 5 members always considered it. Notably, Class 3, which is the class that paid the least attention to deductibles, is the only one with WTP values for deductibles instead of WTA values. This suggests that participants were aware of their preferences and based their decisions on this.

Result 4: The features selected in the filter by participants who used the filter in each of the five classes are reflected in the contracts ultimately chosen by participants in each class.

4. DISCUSSION AND CONCLUSION

In this study, we investigated heterogeneity in patterns of preferences for health insurance features using health insurance choice data from a controlled laboratory experiment with a sequential design. Participants first had to decide on health insurance contracts and then go through a series of lotteries to elicit individual risk preferences. To mimic real-world insurance filters, a voluntary and feature-based filter was provided for the treatment group. The filter allowed individual participants to choose a maximum deductible and additional coverage for other illnesses, and then highlighted contracts that corresponded to these preferences while preserving the entire choice set. We elicited the risk preferences according to rank-dependent expected utility (RDEU) in the loss domain, similar to the approach taken by Wakker and Deneffe (1996).

Our study has five main findings. First, we find that there is no significant difference in aggregate contract choice between our two treatments, one with a filter and the other without. This is in concordance with the results reported by Samek and Sydnor (2020) and Biener and Zou (2021), who show that decision aids, such as consequence graphs, that do not reduce choice sets have no, or only a very small, effect on contract choices.

Second, we show that participants, on average, disliked high deductibles and only chose contracts with this feature if they were compensated by a reduction in the premium that was larger than the EV of the deductible. For example, in the case of the 20 taler deductible, the reduction in the premium had to be larger, on average, than the amount of the deductible itself. This corresponds to the findings of Abaluck and Gruber (2011, 2016), for instance, who show that individuals underweight out-of-pocket spending relative to premiums, or to the findings of Bhargava et al. (2017b) and Biener and Zou (2022), who show that individuals choose options with non-optimal deductibles.

Third, while the distribution of certain contract features among individuals is heterogeneous, our latent class model identifies five homogeneous classes that vary substantially in their willingness to pay for different features of insurance contracts. Some participants took a (financial) approach guided by expected costs, rarely using the filter and choosing contracts according to the expected value. Some were willing to pay a very high premium to ensure that as many illnesses as possible were insured. Others focused only on specific illnesses. Some wanted to avoid deductibles, while others were not concerned about these. Our participants' approach to deductibles might result from a more complex calculation than that involved in assessing the probability and costs of illnesses D, E, and F in our experiment. Indeed, they might result from a more general tendency to avoid deductibles, perhaps due to difficulties mapping the cost-sharing features of plans to their distribution of financial consequences (Samek and Sydnor, 2020). In light of evidence that decision quality is improved only by reducing the number of contracts from which participants must choose, our results suggest that a promising policy approach might be to curate choice sets according to individuals' feature preferences (see, e.g., Abaluck and Gruber, 2022).

Fourth, our findings show that, while there are no large differences in the curvature of value functions, the parameters of individual weighting functions vary substantially across classes. Some participants overestimate all probabilities, whereas others distinguish between probabilities depending on their size. These elicited RDEU parameters allow us to examine decision quality based on the preferences of individual participants. When we consider an

RDEU model of risk preferences, the difference in decision quality across classes is less pronounced than when we assume EV, indicating that heterogeneity in health insurance choices is not necessarily reflected in decision quality. Some of the classes we identified demonstrate better quality decisions when we assume an RDEU model of risk preferences, whereas others demonstrate better decision quality when we assume the EV. This suggests that the latter may not have made contract decisions based on their elicited risk preferences but rather considering other factors, such as choosing the contract with the lowest premium. This observation also corresponds to studies showing that, when faced with complex health insurance choices, consumers focus on salient contract features and make use of heuristics like choosing the health insurance contract with the lowest premium (e.g., Besedeš et al. 2012a,b and Ericson and Starc, 2012). However, even when we control for the risk preferences of individual participants according to an RDEU model, we see that they still tend to choose, on average, only the third or fourth best contract rather than their individual optimal one. From our data, it is unclear whether this is due to a discrepancy between the elicited risk preferences and actual preferences in the context of health insurance or because of other factors, such as the complexity of the decision situation itself.

Lastly, we show that the heterogeneity we identified in participants' willingness to pay for certain contract features is reflected in the observed filter usage. Participants specifically selected features in the filter for which they had a high willingness to pay. This raises the normative question of whether a high willingness to pay for a certain contract feature might not be a behavioral mistake but rather an initial preference. Moreover, this result may further support curating the choice of contracts from which individuals choose by taking their feature preferences into account.

Our study has some important limitations that must be taken into account when interpreting our findings. A general concern when interpreting results from experiments is their external validity. In our study, two aspects may be of particular concern in this regard. The first is that our participants were university students, who generally have a higher level of education than the overall population. The second aspect is that while the sets of health insurance choices used in our experimental design allow for a controlled decision scenario, our results may not be readily generalizable beyond these sets. Additionally, we base our evaluation of contracts on an exogenous measure of risk preferences. While this helps us avoid issues related to inferring risk preferences from observed insurance choices, transferring exogenously elicited risk preferences to health insurance decisions is also not without its challenges. As shown by

Jaspersen et al. (2022), insurance choices show some correlation with certain risk measures, but structural models predict insurance choices poorly. This discrepancy might be due to individuals making different decisions in different contexts. Further research is needed to fully understand the relationship between risk preferences and health insurance choices.

In conclusion, our results indicate that preferences for features of health insurance contracts are heterogeneous, and that this needs to be taken into account in policy reforms that seek to facilitate consumer choice. Approaches that apply equally to all individuals would miss this point. Rather, curating choice sets based on elicited preferences, for example, may yield a better match between what consumers want and the health insurance contracts they ultimately choose.

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Appendix A: Instructions and Comprehension Questions

A1 Instructions

Note that instructions for the first part differ for the treatment groups. The following instructions are the ones for the filter group, whereas for the IC group the "Decision support" paragraph was removed as well as the box with the insurance filter in the presented screen box.

Welcome to the experiment!

<u>Preliminary note</u>

You are participating in an investigation of decision-making behavior in the context of experimental economic research. During the experiment, you and the other participants will be asked to make decisions. In doing so, you can earn money. How much money this will be, depends on your decisions. At the end of the experiment, all your earnings will be converted into euros and paid to you in cash. In this experiment, all amounts will be in Taler, the lab currency, with the rule that 100 talers = 0.50 euros.

The experiment lasts about 135 minutes and consists of two parts. You will receive detailed instructions before each of the two parts of the experiment. Note that neither your decisions in the first part of the experiment nor your decisions in the second part of the experiment will have any influence on the other part of the experiment. Also, there are neither right nor wrong answers in either part.

Part I

Please read the following instructions carefully. If you have any questions before or during the experiment, please feel free to contact us at any time by raising your hand. We will then come to you. You will receive 2300 talers in this part.

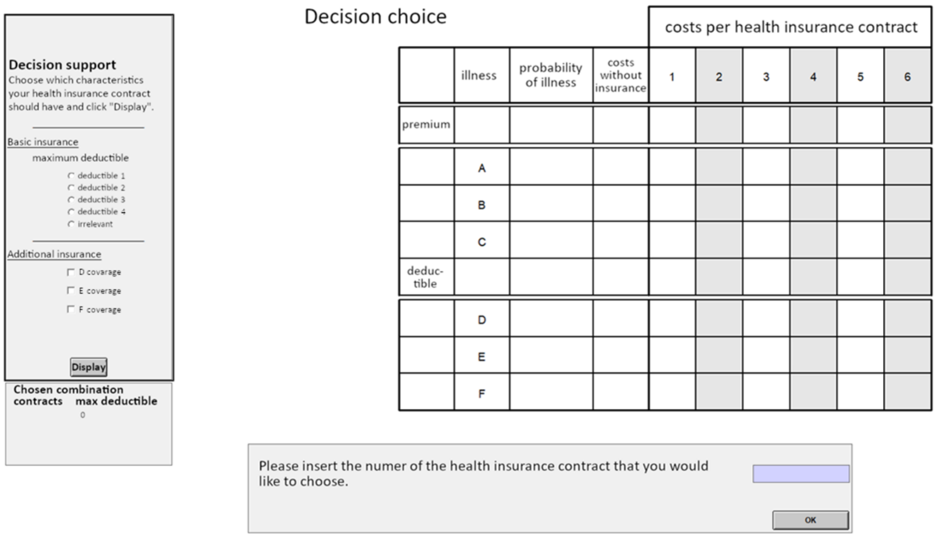
<u>Description of the decision rounds</u>

As a health insurance policyholder, you must choose one health insurance contract in each of the 12 decision rounds. Depending on the round, the number of health insurance contracts offered is either 6 or 12. For a health insurance contract, you must pay a premium that entitles you to insurance benefits in the event of illness. Furthermore, treatment costs may be incurred if you fall ill. Treatment costs are paid by you or by the health insurance company, depending on the insurance benefits of the chosen health insurance contract.

<u>Health insurance contracts</u>

Health insurance contracts may differ both in the amount of the premium and in the insurance benefits you receive from the selected contract in the event of illness. The premium corresponds to the price you have to pay for the respective health insurance contract. Each contract offers an insurance benefit to cover certain treatment costs in case of illness.

The different health insurance contracts you can choose from are shown in a table on your screen. You can read the premiums for the respective health insurance contracts in the line of the same name. On the next page, you will see an example decision screen without values.



Illnesses

There are a total of six illnesses A, B, C, D, E, and F that you can contract. Each illness occurs with a constant illness probability over all decision rounds. Whether you contract an illness in a round depends on these probabilities. You can read both on your screen in the respective columns "Illness" and "Illness probability". It is possible that you will not fall ill with any or more than one illness during a round.

At the end of the whole experiment, a decision round is determined, which is relevant for the payout. A random number generator is then used to determine for each illness in this payout-relevant decision round whether you will contract this illness. The random number generator draws a number between 1 and 100 for each of the six illnesses, with each number being equally probable. If the number drawn for an illness is less than or equal to the associated illness probability, you will contract the illness in this round. If the number drawn is greater than the probability of contracting the illness, you will not contract the illness. Whether you fall ill in the round relevant to your payout is displayed on the screen after the second part of the experiment.

Health insurance benefits in case of illness

When an illness occurs, it causes treatment costs. As shown in the example decision screen, you can see the treatment costs of the corresponding illnesses in the event of illness in the "Costs without insurance" column. By paying your premium, you acquire an entitlement to health insurance benefits in the event of illness.

Each health insurance contract consists of a basic insurance and additional insurance: illnesses A, B, and C are covered by a basic insurance in all health insurance contracts. This means that the costs of treatment in case of illness are covered by the health insurance. As additional insurance, some health insurance contracts offer coverage of the treatment costs of illnesses D, E, and F.

Some health insurance contracts also include a deductible for the total treatment costs of the illnesses from the basic insurance. A deductible means that you, as a health insurance policyholder, must pay the treatment costs for illnesses A, B, and C from the basic insurance up to the amount of the deductible in the event of illness. If the sum of treatment costs for incurred illnesses A, B, and C is greater than the deductible in your selected policy, you will pay the treatment costs only up to the amount of the deductible. If the sum of treatment costs is less than the deductible, you pay the treatment costs in full. You can read the respective deductible of a health insurance policy on your screen in the correspondent line.
The total costs to be borne by you for each decision round are the sum of the premium of the contract you have chosen, any deductible, and treatment costs for non-insured illnesses in the event of illness. They will be shown to you on the screen for the payout-relevant round after the second part of the experiment.

Decision support
To support your decision, a decision aid is displayed on the left side of the screen in each decision round. You can use the decision aid to select characteristics that your insurance contract should have. The decision aid then shows you all contracts in a decision round that have these characteristics. In this way, you can specify the maximum deductible for the treatment costs of the basic insurance that a health insurance contract should contain. For the illnesses of the supplementary insurance, you can specify in each case whether illness D, E, or F should be insured. When you have made a selection of characteristics that your contract should contain, please click on "Show". The contracts that correspond to your selection will then be highlighted in green. Under the decision support, you will see which characteristics you have previously selected. If no contract matches your previously selected characteristics, no contract will be highlighted in green, and "Sorry, no contract is available for your selection" will be displayed under the decision support. You can change your selection at any time and you can also select contracts that do not belong to your selection.

Earnings
After the entire experiment, a random number generator selects one decision round from the 12 decision rounds that is relevant for payout. For this decision round, you will have to pay the premium of your chosen policy, any deductible, and illness-related treatment costs for uninsured illnesses from your 2300 talers. Thus, all costs incurred for the health insurance contract you have chosen in this round and, if applicable, the illness(es) incurred will be added together. These total costs will be deducted from your 2300 talers. The remainder will be paid to you in cash at the end of the experiment, together with your earnings from Part II.

Comprehension questions
Before the decision rounds, we would like to ask you to answer eight comprehension questions. These comprehension questions are intended to make it easier for you to familiarize yourself with the decision situation. Please note that the comprehension questions do not serve as a recommended course of action for the experiment. The questions are only intended to sharpen your understanding of the decision situation you will encounter in the experiment. The values appearing in the comprehension questions differ from the values appearing in the experiment.

Part II

Please read the following instructions carefully. If you have any questions before or during the experiment, you can contact us at any time by raising your hand. We will then come to you. You will receive 4800 talers in this part.

Description of the decision rounds

In this part of the experiment, we ask you to participate in 70 decision rounds. In each of the 70 rounds, you will be shown two alternatives on your screen, alternative L on the left and alternative R on the right. You must choose the alternative you prefer in each case.

There are two ways in which the alternatives can be designed:

- First, both alternatives are lotteries. A lottery consists of two payouts, where on the screen, one payout is highlighted in red, and the other payout is highlighted in blue. Which of the two payouts is drawn depends on probabilities of occurrence, which are displayed to you in each case.
- Second, a lottery and a safe payout. A safe payout is a single value that occurs 100% of the time and is highlighted in gray.

The values of payouts can be zero or negative for lotteries and safe payouts. Negative values represent losses. Both payouts and entry probabilities may change from round to round.

Probabilities of occurrence of the payouts

To give you a feeling for the probabilities of occurrence, they are shown on your screen centered between alternative L and R as a circle diagram. The red area of the circle corresponds to the probability that the payoff "red" will be drawn. Correspondingly, the probability for the blue payoff can be seen by the blue area. In addition, the probabilities are indicated as a number on the lines corresponding to the payoffs. Fixed values are certain and thus occur with a probability of 100% if you choose this option.

Earnings

Following Part II, after the draw for the Part I payout, one of your chosen lotteries will be selected by a random number generator. This is relevant to your payout. If it is not a safe payout, another random number generator will determine whether the red or blue payout will occur in each case. The payouts determined in this way are deducted from your 4800 talers if they are negative. The result forms your earnings from Part II.

Your total earnings from Part I and Part II of the experiment are the sum of your earnings from both parts and will be paid to you in cash after you complete Part II.

Comprehension questions

Before the decision rounds, we would like you to answer two comprehension questions.

These comprehension questions are intended to make it easier for you to familiarize yourself with the decision situation. Please note that the comprehension questions do not serve as a recommended course of action for the experiment. The questions are only intended to sharpen your understanding of the decision situation you will encounter in the experiment. The values appearing in the comprehension questions differ from the values appearing in the experiment.

A2 Comprehension questions

Before making their decisions, the participants had to answer eight comprehension questions to familiarize themselves with the decision-making situation. The next question was asked only after the previous comprehension question had been answered correctly. In case of a wrong answer, a hint for answering the question correctly was given.

Costs	**Probability of occurrence**		**1**	**2**	**3**	**4**	**5**	**6**
		Premium	88	196	107	183	72	107
65	10%	**A**	0	0	0	0	0	0
25	60%	**B**	0	0	0	0	0	0
10	35%	**C**	0	0	0	0	0	0
		Deductible	0	35	0	45	15	15
700	5%	**D**	0	0	700	700	0	0
45	30%	**E**	45	0	45	45	0	45
30	40%	**F**	0	0	30	0	0	30

1. Which contract in the decision presented above has a deductible of 15 and also has additional coverage for illness E?

Costs	**Probability of occurrence**		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
		Premium	207	222	224	78	199	168	64	148	51	177	88	116
65	10%	**A**	0	0	0	0	0	0	0	0	0	0	0	0
25	60%	**B**	0	0	0	0	0	0	0	0	0	0	0	0
10	35%	**C**	0	0	0	0	0	0	0	0	0	0	0	0
		Deductible	35	9	35	45	15	45	45	15	35	15	25	25
700	5%	**D**	700	0	700	700	0	0	0	0	0	700	0	700
45	30%	**E**	45	45	0	0	0	45	45	45	0	45	0	45
30	40%	**F**	0	0	0	0	30	30	0	0	0	30	30	0

2. How many policies in the decision shown above include complementary insurance that provides you with coverage for illness F?

Costs	**Probability of occurrence**		**1**	**2**	**3**	**4**
		Premium	168	234	195	182
65	10%	**A**	0	0	0	0
25	60%	**B**	0	0	0	0
10	35%	**C**	0	0	0	0
		Deductible	25	0	15	0
700	5%	**D**	700	0	0	700
45	30%	**E**	0	0	0	45
30	40%	**F**	0	0	30	0

3. Assume that you have selected the health insurance contract shown above, which provides coverage for all illnesses and does not include a deductible. In addition, you acquired all illnesses A, B, C, D, E, and F. Given these assumptions, what are the costs (sum of the premium and the treatment costs) that you will have to pay yourself?

4. Suppose you have chosen health insurance contract 1 and you fall ill with all illnesses A, B, C, D, E, and F. How much are the treatment costs without the premium that you have to pay yourself?
5. Suppose you have chosen health insurance contract 3, and you fall ill solely with illness A. How much are the treatment costs without the premium that you have to pay yourself?
6. Suppose you have chosen health insurance contract 3 and you fall ill solely with illness C. How much are the treatment costs without the premium that you have to pay yourself?
7. Suppose you have chosen health insurance contract 4 and you fall ill with illnesses B and E. How much are the treatment costs without the premium that you have to pay yourself?
8. Suppose you have chosen health insurance contract 1 and you fall ill with illnesses C, D, and E. How much are the treatment costs without the premium that you have to pay yourself?

Appendix B: Design of contracts and decisions

Table B1 List of contracts

Costs in talers	Probability of occurrence		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17-32
		Premium	98	127	149	62	93	122	95	138	147	134	125	101	149	56	53	124	
60	0.05	**A**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
40	0.2	**B**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
20	0.5	**C**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
		Deductible	0	10	20	30	0	10	20	30	0	10	20	30	0	10	20	30	…
2000	0.01	**D**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
70	0.1	**E**	0	0	0	0	0	0	0	0	70	70	70	70	70	70	70	70	
40	0.3	**F**	0	0	0	0	40	40	40	40	0	0	0	0	40	40	40	40	

Costs in talers	Probability of occurrence		1-16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
		Premium		75	37	38	74	84	36	68	41	40	118	98	60	87	15	79	37
60	0.05	**A**		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
40	0.2	**B**		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0.5	**C**		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Deductible	…	0	10	20	30	0	10	20	30	0	10	20	30	0	10	20	30
2000	0.01	**D**		2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
70	0.1	**E**		0	0	0	0	0	0	0	0	70	70	70	70	70	70	70	70
40	0.3	**F**		0	0	0	0	40	40	40	40	0	0	0	0	40	40	40	40

Table B2 Features in actual choices

Decision	Contracts	1	2	3	4	5	6	7	8	9	10	11	12
1	Number	32	23	26	15	7	5						
	Premium	37	68	118	53	95	93						
	Deductible	30	20	10	20	20	0						
	D (1%)	2000	2000	2000	0	0	0						
	E (10%)	70	0	70	70	0	0						
	F (30%)	40	40	0	40	40	40						
2	Number	25	1	22	16	19	10						
	Premium	40	98	36	124	38	134						
	Deductible	0	0	10	30	20	10						
	D (1%)	2000	0	2000	0	2000	0						
	E (10%)	70	0	0	70	0	70						
	F (30%)	0	0	40	40	0	0						
3	Number	17	27	15	24	2	29						
	Premium	75	98	53	41	127	87						
	Deductible	0	0	40	40	0	0						
	D (1%)	2000	2000	0	2000	0	2000						
	E (10%)	0	70	70	0	0	70						
	F (30%)	0	0	40	40	0	40						
4	Number	17	24	32	16	22	30	11	25	31	20	10	29
	Premium	75	41	37	124	36	15	125	40	79	74	134	87
	Deductible	0	30	30	30	10	10	20	0	20	30	10	0
	D (1%)	2000	2000	2000	0	2000	2000	0	2000	2000	2000	0	2000
	E (10%)	0	0	70	70	0	70	70	70	70	0	70	70
	F (30%)	0	40	40	40	40	40	0	0	40	0	0	40
5	Number	10	20	9	11	24	13						
	Premium	134	74	147	125	41	149						
	Deductible	10	30	0	20	30	0						
	D (1%)	0	2000	0	0	2000	0						
	E (10%)	70	0	70	70	0	70						
	F (30%)	0	0	0	0	40	40						
6	Number	21	29	32	10	16	8	25	23	28	20	17	26
	Premium	84	87	37	134	124	138	40	68	60	74	75	118
	Deductible	0	0	30	10	30	30	0	20	30	30	0	10
	D (1%)	2000	2000	2000	0	0	0	2000	2000	2000	2000	2000	2000
	E (10%)	0	70	70	70	70	0	70	0	70	0	0	70
	F (30%)	40	40	40	0	40	40	0	40	0	0	0	0
7	Number	23	10	24	32	31	17						
	Premium	68	134	41	37	79	75						
	Deductible	20	10	30	30	20	0						
	D (1%)	2000	0	2000	2000	2000	2000						
	E (10%)	0	70	0	70	70	0						
	F (30%)	40	0	40	40	40	0						
8	Number	14	23	15	9	21	27	29	32	6	16	20	28
	Premium	56	68	53	147	84	98	87	37	122	124	74	60
	Deductible	10	20	20	0	0	20	0	30	10	30	30	30
	D (1%)	0	2000	0	0	2000	2000	2000	2000	0	0	2000	2000
	E (10%)	70	0	70	70	0	70	70	70	0	70	0	70
	F (30%)	40	40	40	0	40	0	40	40	40	40	0	0
9	Number	25	12	6	20	9	31						
	Premium	40	101	122	74	147	79						
	Deductible	0	30	10	30	0	20						
	D (1%)	2000	0	0	2000	0	2000						
	E (10%)	70	70	0	0	70	70						
	F (30%)	0	0	40	0	0	40						
10	Number	9	23	12	26	32	2	21	14	8	25	15	7
	Premium	147	68	101	118	37	127	84	56	138	40	53	95
	Deductible	0	20	30	20	30	10	0	10	30	0	20	20
	D (1%)	0	2000	0	2000	2000	0	2000	0	0	2000	0	0
	E (10%)	70	0	70	70	70	0	0	70	0	70	70	0
	F (30%)	0	40	0	0	40	0	40	40	40	0	40	40
11	Number	14	29	7	13	15	20						
	Premium	56	87	95	149	53	74						
	Deductible	10	0	20	0	20	30						
	D (1%)	0	2000	0	0	0	2000						
	E (10%)	70	70	0	70	70	0						
	F (30%)	40	40	40	40	40	0						
12	Number	5	20	24	16	2	15	1	25	28	6	32	17
	Premium	93	74	41	124	127	53	98	40	60	122	37	75
	Deductible	0	30	30	30	10	20	0	0	330	10	30	0
	D (1%)	0	2000	2000	0	0	0	0	2000	2000	0	2000	2000
	E (10%)	0	0	0	70	0	70	0	70	70	0	70	0
	F (30%)	40	0	40	40	0	40	0	0	0	40	40	0

Notes: In each decision, the participants see the listed characteristics of the respective six or 12 contracts on their screen and in the exact same order. The value of D, E, and F indicate the cost of illness, i.e., the cost of illness D (2000 talers with a 1% probability of occurrence), E (70 with 10%), or F (40 with 30%). On their screen, the cost of illness for A (60 with 5%), B (40 with 20%), and C (20 with 50%) is also indicated, which in all cases is 0. The contract number refers to Table B1 for a better overview; this number does not appear on the participants' screen. The order of the contracts corresponds to the displayed order.

Appendix C: Overview of contract features

Table C1 Mean features of actual choices and random choice

	Actual choices		Random choice
Premium	81.112 (0.625)	*	84.139 (2.990)
Deductible size	10.646 (0.248)	***	15.208 (0.492)
Coverage of illness			
D (2000 with 1%)	56.46% (0.022)	***	44.44% (0.045)
E (70 with 10%)	49.64% (0.012)	***	42.36% (0.025)
F (40 with 30%)	65.12% (0.010)	***	44.44% (0.048)
N	253		

Notes: For the actual choices, we take the mean over the participants' mean for the selected contracts in each of the 12 decisions. To illustrate a random choice, we assume that one of the offered 6 or 12 contracts is randomly chosen for each decision. We take the mean over the mean of the options per decision. The mean of the coverages for illnesses D, E, and F are the fractions to which these illnesses are covered. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns $p \geq 0.05$ (one-sided WSR test for comparisons between actual choices and the respective values of the random choice).

Appendix D: Elicitation process for the value function and weighting function

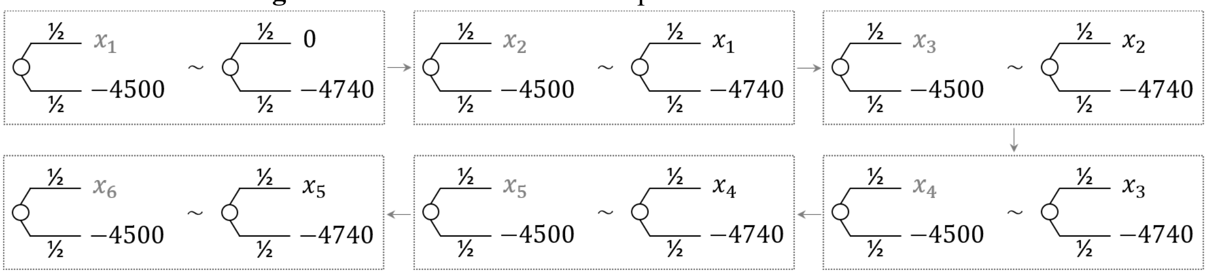
In order to elicit RDEU ranks of the contracts on an individual level, we elicit in the second part of the experiment the value function and the weighting function of every participant through the trade-off method with a bisectional method each.

Overall, 70 decisions have to be made in this part. 36 decisions (+ 2 control decisions) between two different lotteries have to be made in order to elicit six indifferences leading to six points $x_j, j \in [1,6]$ (Figure D1) that is used to calculate the individual curvature of the power utility function based on the standard value function by Tversky and Kahneman (1992) and limited to the case $x < 0$:

$$u(x_j) = -(-x_j)^{\theta_{neg}} \tag{3}$$

Since we only analyzed the preferences in the loss domain, no loss aversion parameter is needed.

Figure D1 Indifferences to elicit points for the value function



Notes: Through the tradeoff-method, the lottery outcomes $x_j, j \in [1,6]$ are elicited which leads for each to indifferences between the respective lotteries.

Each x_j was elicited via the bisectional method as exemplarily visualized in Figure D2 for x_1 with $x_0 = 0$. For each point x_j, the participants had to choose six times one out of two lotteries. In this method, each choice set is based on the decisions made before, except the very first decision.

Figure D2 Exemplary elicitation process of x_j using the bisection method

Decision choice	Prospect L	Prospect R	Prospect chosen	Inference
1	½ −239; ½ −4500	½ 0; ½ −4740	R	$(-239, ½; -4500) < (0, ½; -4740)$
2	½ −120; ½ −4500	½ 0; ½ −4740	R	$(-120, ½; -4500) < (0, ½; -4740)$
3	½ −60; ½ −4500	½ 0; ½ −4740	R	$(-60, ½; -4500) < (0, ½; -4740)$

4	$\frac{1}{2}$: -30; $\frac{1}{2}$: -4500	$\frac{1}{2}$: 0; $\frac{1}{2}$: -4740	L	$(-30, \frac{1}{2}; -4500) > (0, \frac{1}{2}; -4740)$
5	$\frac{1}{2}$: -45; $\frac{1}{2}$: -4500	$\frac{1}{2}$: 0; $\frac{1}{2}$: -4740	R	$(-45, \frac{1}{2}; -4500) < (0, \frac{1}{2}; -4740)$
6	$\frac{1}{2}$: -38; $\frac{1}{2}$: -4500	$\frac{1}{2}$: 0; $\frac{1}{2}$: -4740	L	$(-38, \frac{1}{2}; -4500) > (0, \frac{1}{2}; -4740)$
Conclusion	$x_1 = \frac{(-38) + (-45)}{2} = -42$		-	$(-42, \frac{1}{2}; -4500) \sim (0, \frac{1}{2}; -4740)$
7	$\frac{1}{2}$: -281; $\frac{1}{2}$: -4500	$\frac{1}{2}$: -42; $\frac{1}{2}$: -4740	R	$(-281, \frac{1}{2}; -4500) < (-42, \frac{1}{2}; -4740)$
8	$\frac{1}{2}$: -162; $\frac{1}{2}$: -4500	$\frac{1}{2}$: -42; $\frac{1}{2}$: -4740	R	$(-162, \frac{1}{2}; -4500) < (-42, \frac{1}{2}; -4740)$
:	:	:	:	:

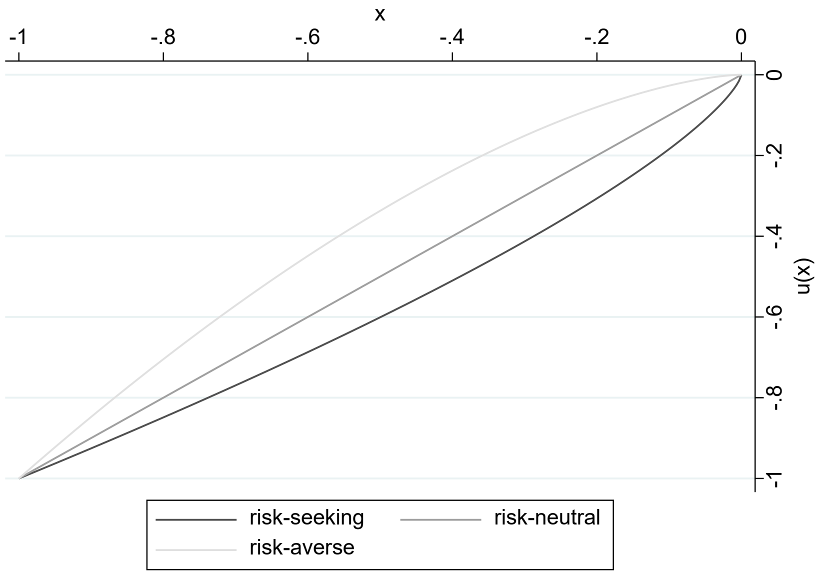
Notes: With 36 choice questions, the values of $x_j, j \in [1,6]$ are elicited, each with six decision choices. Decision choice 1 is the same for all participants. The value $x_{1,1} = -239$ is set as the starting point, this part of the left prospect changes in the following choice questions depending on previous decisions. Together with probabilities of 0.5, two of four prospect values are fixed throughout all decisions: The loss of 4500 for the left prospect and the loss of 4740 for the right prospect. Depending on the first choice (L or R) the value of $x_{1,2}$ gets determined. If L, the left prospect, is chosen, the next value doubles to $x_{1,2} = -478$. If R, the right prospect, is chosen like in this example, the next value is cut to halves of $x_{1,2} = -120$ as in this example. For the following decisions, the prospects are calculated as the mean of the boundaries building the range of possible indifferences. After six decision choices, the mean of the minimum and maximum value that could lead to the indifference is set to be x_j and this value is also the new possible outcome of the right prospect besides the loss of 4740 with the goal to elicit x_{j+1}. The second outcome for the right prospect keeps the same for six decisions choices. For the next six decision choices to elicit x_{j+1} the value of x_j will be added to the previous value.

Table D1 Utility curvature in the loss domain

		Number of Obs.	Percentage of Obs.	Median θ_{neg}	Mean θ_{neg}	Std. Dev.
θ_{neg}	Sample	253	100%	1.000	6.523	37.541
$\theta_{neg} < 1$	Risk seeking	126	49.80%	0.735	0.719	0.185
$\theta_{neg} = 1$	Risk neutral	1	0.40%	1.000	1.100	-
$\theta_{neg} > 1$	Risk averse	126	49.80%	1.569	12.372	52.654

Given the six elicited points, we estimated θ_{neg} for every participant with non-linear least squares according to (3). The value of θ_{neg} determines the curvature of the value function in the loss domain and makes it possible to categorize the participants according to their risk preferences with setting $\theta_{neg} = 1$ for risk-neutral preferences: As can be seen in Table D1, aside from one risk-neutral participant, the rest is equally divided into 50% risk-averse and 50% risk-seeking participants. Figure D3 shows the median value functions for these three types of risk preferences.

Figure D3 Curvature of the median utility functions by risk types



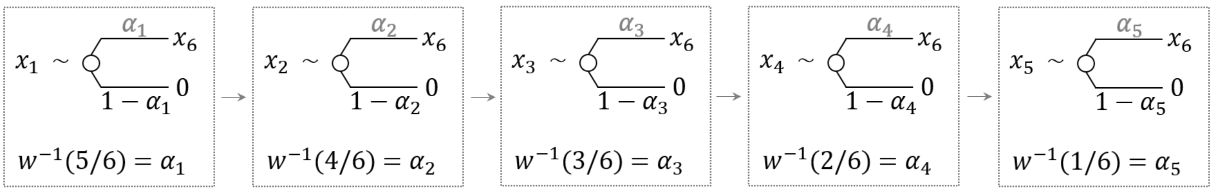
The remaining 30 decisions (+ 2 control decisions) were used to elicit the individual curvature of the weighting function. This time, each decision was between a safe option and a lottery. Five indifferences of $x_j \sim (x_6, \alpha_j; 0)$ with $x_j \in [1,5]$ are elicited (Figure D4) through six decisions each, as can be seen in Figure D5. Since the individual values of the x_j's are in the same distance of each other the elicited α_j represent the image of it, $w^{-1}((6-j)/6)$.

These values of $w^{-1}((6-j)/6)$ were used to estimate the following curvature of the two-parameter probability weighting function in the loss domain by Prelec (1998):

$$w^{-}(p) = \exp(-s(-\,ln(p))^{r}) \tag{4}$$

The estimated individual value of s and r shape the individual curvature of the weighting function. Referring to Gonzalez and Wu (1999), s can be interpreted as the attractiveness of gambling with $s < 1$ ($s > 1$) overweighting (underweighting) probabilities, comparing to an individual neutral to the attractiveness of gambles ($s = 1$). Despite this, r can be seen as the discrimination measure of probabilities, with $r < 1$ ($r > 1$) overweighting (underweighting) small probabilities.

Figure D4 Indifferences to elicit $w^{-1}(6-j/6)$ for the weighting function



Notes: Through the tradeoff-method, the probabilities $\alpha_j, j \in [1,5]$ are elicited which leads to indifferences between the safe option x_j and the lottery outcomes x_6 with a probability of α_j and 0 with a probability of $1-\alpha_j$. Probability α_j is equal to $w^{-1}((6-j/6)$ which is used to fit the weighting function.

Each α_j was elicited via the bisectional method as exemplarily visualized in Figure D5 for α_1. For each probability α_j, the participants had to choose six times between a safe option and a lottery. With this method, each choice set is based on the decisions made before. The values of $x_j \in [1,5]$ are the ones elicited before for the value function.

Figure D5 Exemplary elicitation process of $w^{-1}(6 - j/6)$ using the bisection method

Decision choice	Safe option S	Prospect P	Choice	Inference
1	-42	0.92 0 0.08 -453	P	$(-42) < (0, 0.92; -453)$
2	-42	0.42 0 0.58 -453	S	$(-42) > (0, 0.42; -452)$
3	-42	0.69 0 0.31 -453	S	$(-42) > (0, 0.69; -453)$
4	-42	0.81 0 0.19 -453	S	$(-42) > (0, 0.81; -453)$
5	-42	0.87 0 0.13 -453	S	$(-42) > (0, 0.87; -453)$
6	-42	0.90 0 0.10 -453	S	$(-42) > (0, 0.90; -453)$
Conclusion	$\alpha_1 = \dfrac{0.92 + 0.90}{2} = 0.91$		-	$(-42) \sim (0, 0.91.; -453)$
7	-114	0.76 0 0.24 -453	P	$(-114) < (0, 0.76; -453)$
8	-114	0.38 0 0.62 -453	S	$(-114) > (0, 0.38; -453)$
⋮	⋮	⋮	⋮	⋮

Notes: With 30 choice questions, the values of $\alpha_j = w^{-1}(6 - j/6), j \in [1,5]$ are elicited, each with six decision choices. Different to the elicitation of the value function, all values stay constant for one indifference elicitation, meaning six decision choices, whereas the probabilities of the lottery are changing. The safe options are equal to the first five $x_j, j \in [1,5]$ elicited before, whereas the lottery outcome consists of 0 and x_6. In this example, $x_1 = -42$, $x_2 = -114$ and $x_6 = -453$. The starting probabilities for the first decision choices of each indifference elicitation, meaning decision choices 1, 7, 13, 19, and 25, are calculated by $\alpha_{j,1} = (x_j - x_6)/(-x_6)$), $j \in [1,5]$ for the outcome of 0 and $1 - \alpha_{j,1}$ for the outcome of x_6. For the following decisions, the probabilities are calculated as the mean of the boundaries building the range of possible indifferences. After six decision choices, the mean of the minimum and maximum probability that could lead to the indifference is set to be α_j.

Given the five elicited probabilities, we estimated s and r for every participant with non-linear least squares according to (4). The value of r determines the curvature, the value of s determines the elevation of the Prelec weighting function. Table D2 and Table D3 show the distribution of the categorized types.

Table D2 Curvature (discrimination) of the Prelec weighting function (loss domain)

	Curvature of the Prelec weighting function	Number of observations	Percentage of observations	Median r_{Prelec}	Mean r_{Prelec}	Std. Dev.
r_{Prelec}	Sample	253	100.00%	0.985	1.704	2.357
$r_{Prelec} < 1$	Inverse S-shaped	131	51.78%	0.447	0.442	0.426
$r_{Prelec} = 1$	Linear	0	0.00%	-	-	-
$r_{Prelec} > 1$	S-shaped	122	48.22%	1.771	3.060	2.792

Table D3 Elevation (attractiveness) of the Prelec weighting function (loss domain)

	Elevation of the Prelec weighting function	Number of observations	Percentage of observations	Median s_{Prelec}	Mean s_{Prelec}	Std. Dev.
s_{Prelec}	Sample	253	100.00%	0.720	25.884	360.467
$s_{Prelec} < 1$	Attracted by gambles	183	72.33%	0.552	0.507	0.302
$s_{Prelec} = 1$	Neutral	0	0.00%	-	-	-
$s_{Prelec} > 1$	Averse to gambles	70	27.67%	1.665	92.227	684.380

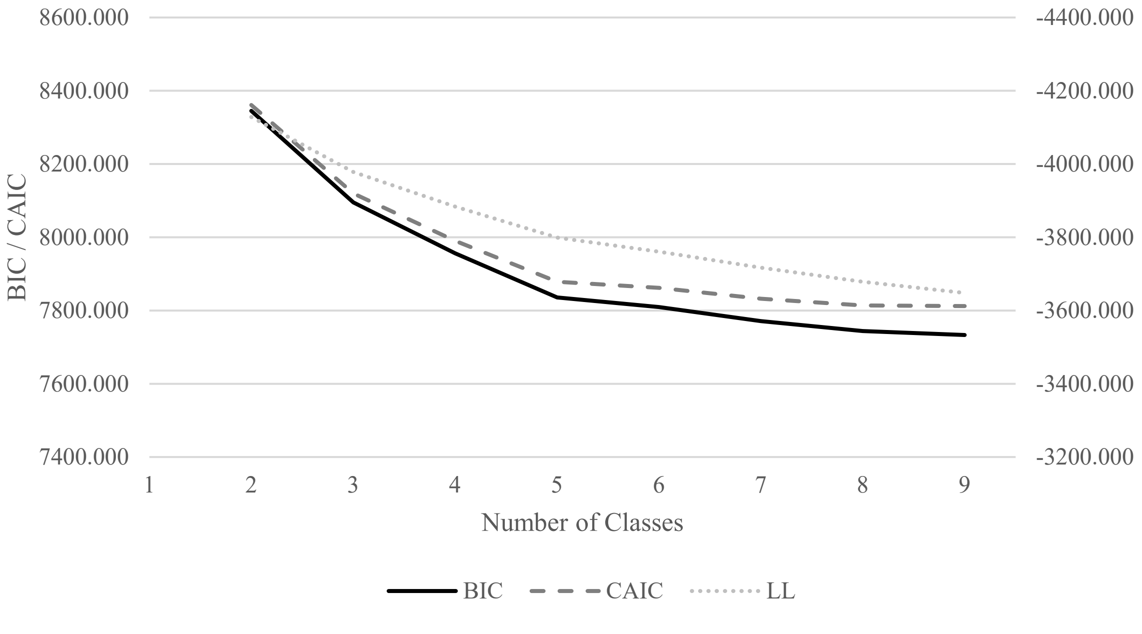
Appendix E: Results of latent class analysis

Table E1 Fit statistics by number of classes

# classes	BIC	CAIC	LL
2	8345.084	8361.084	-4128.275
3	8095.041	8120.041	-3978.353
4	7956.173	7990.173	-3884.019
5	7835.712	7878.712	-3798.888
6	7809.699	7861.699	-3760.982
7	7770.950	7831.950	-3716.707
8	7743.672	7813.672	-3678.167
9	7733.146	7812.146	-3648.004

Notes: BIC = Bayesian Information Criterion; CAIC = Consistent Akaike Information Criterion; LL = log-likelihood

Figure E1 Elbow-plot of fit indices for the latent class analyses



Notes: BIC = Bayesian Information Criterion; CAIC = Consistent Akaike Information Criterion; LL = log-likelihood

Table E2 Probability of in-sample predictions of the actual choice outcomes

# of classes	Prediction of naïve model	Unconditional probability			Conditional probability			Highest posterior probability		
		mean	min	max	mean	min	max	mean	min	max
5	0.200	0.273	0.230	0.305	0.948	0.904	0.967	0.945	0.562	1.000
9	0.111	0.253	0.161	0.313	0.931	0.872	0.996	0.924	0.405	1.000

Notes: Naïve model prediction is based on the number of alternatives (five or nine classes) per choice occasion. In comparison, we predict the unconditional probability of actual choice outcomes and the probability of actual choices conditional on being in each class. The highest posterior probability is based on the average of the individual's highest class membership probability. The allocation of individuals to the classes is based on this probability.

Table E3 Regression results of the latent class logit model with five classes

	Class 1	Class 2	Class 3	Class 4	Class 5
Preference parameter					
Premium	-0.075*** (0.005)	-0.052*** (0.004)	-0.107*** (0.014)	-0.023*** (0.002)	-0.055*** (0.011)
Illness D (costs of 2000 talers with 1% occurrence)	1.376*** (0.304)	1.932*** (0.236)	12.705*** (1.533)	2.564*** (0.197)	13.144*** (1.835)
Illness E (costs of 70 talers with 10% occurrence)	0.850*** (0.160)	1.980*** (0.153)	3.131*** (0.603)	1.058*** (0.120)	4.325*** (0.691)
Illness F (costs of 40 talers with 30% occurrence)	2.115*** (0.182)	3.187 (0.214)	2.888*** (0.409)	1.287*** (0.144)	3.714*** (0.647)
Deductible of 10 talers	-0.495 (0.215)	-0.127*** (0.150)	-0.403 (0.247)	0.240* (0.121)	-0.989** (0.327)
Deductible of 20 talers	-1.952*** (0.207)	-1.546*** (0.214)	-1.623*** (0.281)	0.083 (0.142)	-2.526*** (0.526)
Deductible of 30 talers	-1.330*** (0.157)	-1.957*** (0.239)	-1.937*** (0.366)	-0.348* (0.162)	-2.978*** (0.479)
Class membership covariates					
Treatment	-0.564 (0.461)	0.096 (0.460)	0.097 (0.504)	-0.583 (0.473)	/
Constant	1.384 (0.717)	0.430 (0.755)	-0.042 (0.824)	1.345 (0.755)	/

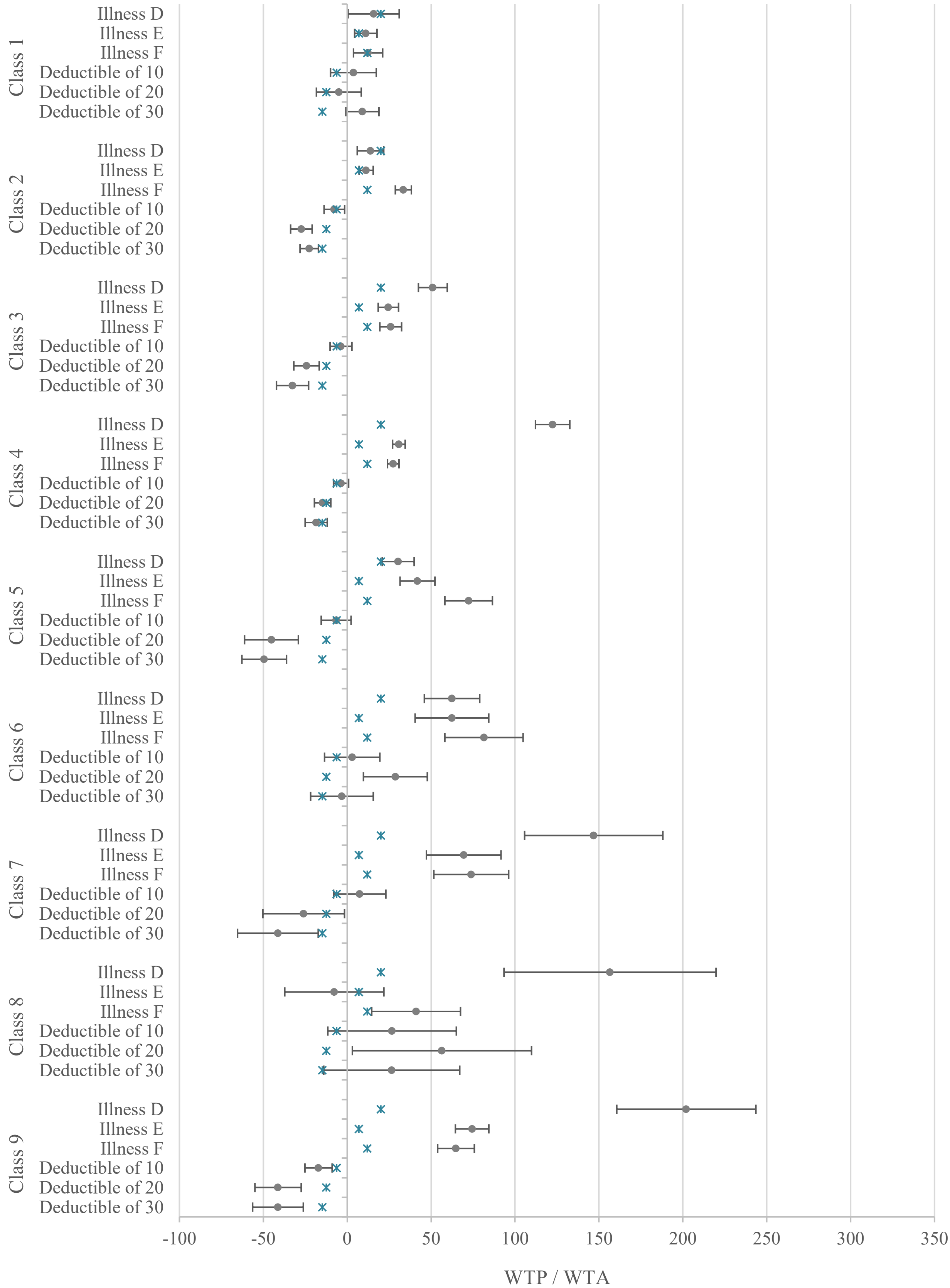
Notes: Standard errors in parentheses; Class 5 as reference class; * p<0.05, ** p<0.01, *** p<0.001.

Table E4 Regression results of the latent class logit model with nine classes

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9
Preference parameter									
Premium	-0.118*** (0.024)	-0.074*** (0.005)	-0.068*** (0.006)	-0.112*** (0.012)	-0.049*** (0.005)	-0.036*** (0.007)	-0.022*** (0.004)	-0.016*** (0.004)	-0.088*** (0.022)
Illness D (costs of 2000 talers with 1% occurrence)	1.850 (1.161)	1.019** (0.330)	3.486*** (0.356)	13.705*** (1.369)	1.476*** (0.320)	2.256*** (0.382)	3.235*** (0.312)	2.435*** (0.335)	17.872*** (3.279)
Illness E (costs of 70 talers with 10% occurrence)	1.303* (0.515)	0.830*** (0.180)	1.675*** (0.226)	3.446*** (0.508)	2.033*** (0.196)	2.253*** (0.254)	1.529*** (0.185)	-0.120 (0.219)	6.582*** (1.383)
Illness F (costs of 40 talers with 30% occurrence)	1.462* (0.706)	2.459*** (0.199)	1.770*** (0.276)	3.071*** (0.360)	3.514*** (0.308)	2.943*** (0.344)	1.628*** (0.206)	0.638** (0.240)	5.733*** (1.230)
Deductible of 10 talers	0.434 (0.819)	-0.564* (0.228)	-0.254 (0.225)	-0.412 (0.260)	-0.321 (0.211)	0.107 (0.308)	0.164 (0.176)	0.416 (0.271)	-1.513*** (0.402)
Deductible of 20 talers	-0.589 (0.811)	-2.009*** (0.224)	-1.657*** (0.251)	-1.643*** (0.290)	-2.193*** (0.306)	1.036** (0.357)	-0.571* (0.247)	0.878** (0.295)	-3.645*** (0.613)
Deductible of 30 talers	1.066 (0.679)	-1.665*** (0.172)	-2.227*** (0.306)	-2.070*** (0.383)	-2.403*** (0.254)	-0.114 (0.339)	-0.910*** (0.224)	0.413 (0.304)	-3.650*** (0.619)
Class membership covariates									
Treatment	1.193 (1.160)	1.586 (0.826)	1.239 (0.894)	2.210** (0.852)	2.176* (0.856)	1.894* (0.943)	1.738 (0.872)	/	1.988* (0.859)
Constant	-2.396 (1.537)	-0.772 (1.028)	-0.910 (1.122)	-2.076 (1.112)	-2.051 (1.120)	-2.370 (1.265)	-1.488 (1.134)	/	-1.942 (1.101)

Notes: Standard errors in parentheses; Class 9 as reference class; * p<0.05, ** p<0.01, *** p<0.001.

Figure E2 Willingness to pay by class and feature with nine classes



Notes: Error bars represent 95% confidence intervals. Blue stars represent EVs of features. Illness D has costs of 2000 talers with a 1% probability of occurrence, illness E costs of 70 talers with a 10%, probability of occurrence and illness F has costs of 40 talers with a 30% probability of occurrence.

Figure E3 EV and RDEU ranks by class and complexity

Figure E3a Low complexity

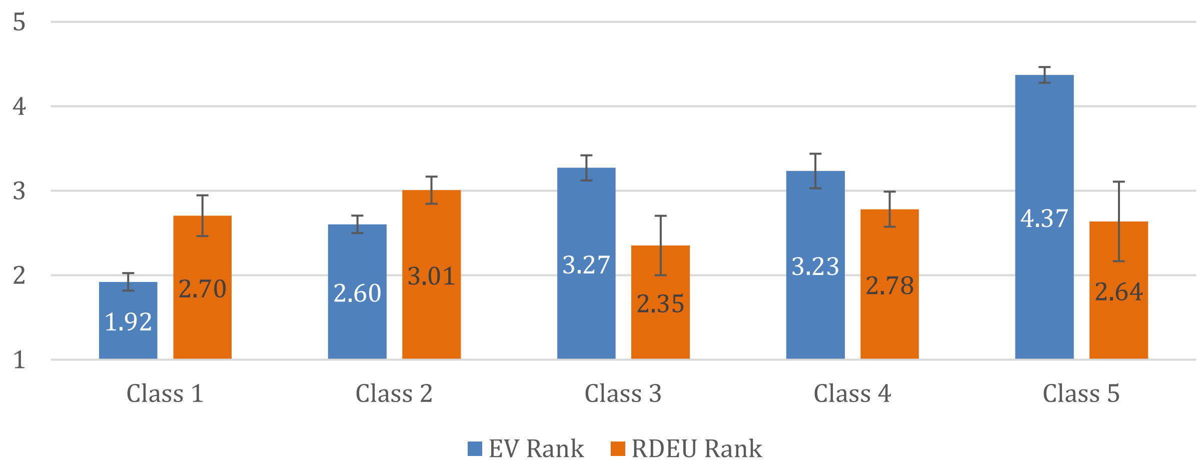
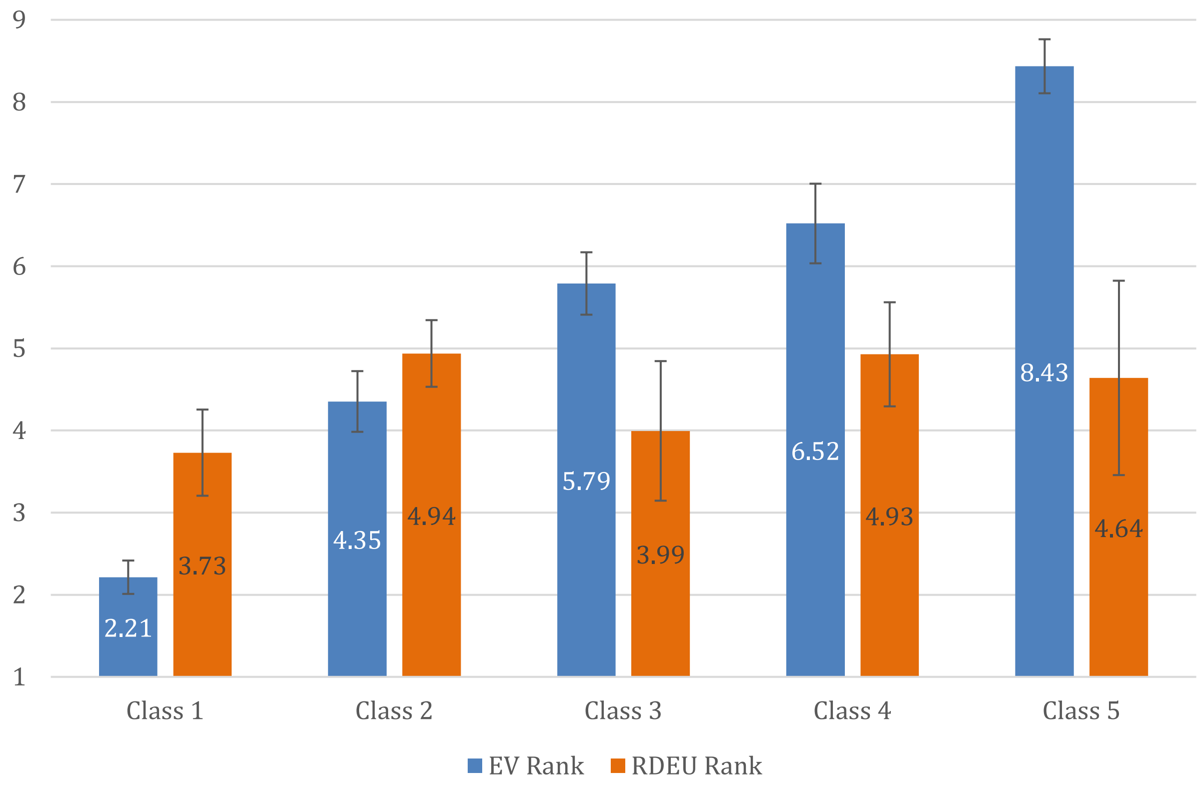


Figure E3b High complexity



Notes: The figures show the mean of the individual average EV and RDEU ranks over all decisions by classes, separately for low and high complexity. Rank 1 represents the best contract. The higher the rank, the further away the contract is from the individual optimum. For low complexity, the worst rank is 6, and for high complexity, the worst rank is 12. Error bars represent 95% confidence intervals.

Table E5 Characteristics conditional on class membership

Class	**1**	**2**	**3**	**4**	**5**	**Total**
Observations	60	64	39	55	35	253
Demographics						
Age	24.67	23.19	23.38	24.49	23.14	23.85
Female (no 0 – yes 1)	0.37	0.56	0.56	0.60	0.54	0.52
Studies (in %)						
Economics	10.28	11.07	6.72	9.49	6.72	44.27
Natural sciences	2.37	2.77	1.19	2.37	1.19	9.88
Engineering	0.79	1.58	1.98	1.98	1.98	8.30
Humanities	5.53	4.74	1.98	2.77	1.98	17.00
Educational sciences	1.19	2.37	1.19	2.37	1.19	8.30
Others	3.56	2.77	2.37	2.77	0.79	12.25
Insurance literacy						
"Have you ever taken out an insurance policy yourself?" (no 0 – yes 1)						
	0.50	0.58	0.54	0.49	0.51	0.53
"Have you ever taken out a health insurance policy yourself?" (no 0 – yes 1)						
	0.47	0.30	0.31	0.40	0.46	0.38
"How are you covered by health insurance?" (in %)						
statutory (self-payer)	45.00	31.25	15.38	38.18	34.29	33.99
statutory (family)	48.33	57.81	69.23	50.91	60.00	56.13
private	6.67	10.94	15.38	10.91	5.71	9.88
"How would you rate your willingness to take risks with regard to your health?" (risk averse 0 – risk seeking 10)						
	4.80	3.73	3.72	3.69	3.29	3.91
Experimental behavior						
"How often did you use the calculator during the experiment?" (in %)						
always	0.00	0.00	5.13	0.00	5.71	1.58
often	13.33	10.94	5.13	7.27	20.00	11.07
rarely	43.33	34.38	46.15	47.27	40.00	41.90
never	43.33	54.69	43.59	45.45	34.29	45.45
"Did you make your decisions according to the expected utility theory?" (in %)						
yes	31.17	30.08	35.90	37.69	29.39	33.32
no	23.83	13.67	17.95	16.86	4.90	15.69
don't know the EUT	45.00	56.25	46.15	45.45	65.71	50.99
"How often did you look at the premium when making your decisions?" (in %)						
always	86.67	71.88	71.79	50.91	74.29	71.15
often	11.67	25.00	17.95	41.82	8.57	22.13
rarely	1.67	3.13	10.26	5.45	11.43	5.53
never	0.00	0.00	0.00	1.82	5.71	1.19
"How often did you look at the deductible when making your decisions?" (in %)						
always	66.67	75.00	53.85	38.18	65.71	60.47
often	25.00	18.75	23.08	45.45	17.14	26.48
rarely	8.33	3.13	17.95	10.91	17.14	10.28
never	0.00	3.13	5.13	5.45	0.00	2.77
"How often did you look at whether a contract covered the cost of 2000 when making your decisions?" (in %)						
always	15.00	10.94	82.05	30.91	94.29	38.74
often	6.67	29.69	17.95	43.64	2.86	21.74
rarely	28.33	35.94	0.00	20.00	0.00	20.16
never	50.00	23.44	0.00	5.45	2.86	19.37
"How good are you at estimating probabilities?" (in %)						
very good	15.00	10.94	17.95	18.18	28.57	17.00
good	45.00	45.31	48.72	30.91	17.14	38.74
average	36.67	39.06	25.64	41.82	45.71	37.94
bad	3.33	4.69	7.69	3.64	5.71	4.74
very bad	0.00	0.00	0.00	5.45	2.86	1.58
Risk preferences						
Median RDEU parameter						
theta	0.95	0.98	1.03	1.00	1.13	1.00

s	0.82	0.76	0.58	0.76	0.37	0.72
r	0.69	0.90	1.44	1.02	1.53	0.99
Decision quality						
Mean ranks						
EV	2.04	3.33	4.32	4.60	6.06	3.83
RDEU	3.13	3.81	3.04	3.68	3.47	3.45

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