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Abstract

Do people have a preference for making choices themselves, or do they prefer to choose a preselected alternative? If consumers value choice, recommender systems which facilitate choices might trigger consumers not to choose the recommendation - even when the other alternatives are less preferred. We conduct an incentivized survey experiment with a large sample from the German population, where participants choose between three lotteries. In the main treatment, participants make a choice between a preselected lottery and a two-element choice set, from which they then make an additional choice. We find that participants' choices exhibit a bias towards the preselected alternative, and estimating a structural model reveals that the mean willingness to pay to make an additional choice is negative. Nevertheless, about 41% of the sample are estimated to have a positive value of choice. We show that measurable individual characteristics correlate with the preference for choice. Linking choices to the Big Five personality traits reveals that the preference for the preselected alternative increases in Openness. Moreover, we link participants' preferences for choice to their political attitudes, showing that right-wing participants are more likely to prefer the preselected alternative than center-left participants.

JEL Classification: N/A

Keywords: N/A

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The Value of Choice – Evidence from an Incentivized Survey Experiment[a]

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June 30, 2022

Abstract

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Keywords: Procedural Utility, Lottery Choice, Heterogeneity, Experiments, German Internet Panel.

JEL Classification: C99, D01, D81, D91

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1 Introduction

Do people enjoy making choices? Or do they prefer to have tools at hand that preselect choices for them? A vast range of technologies collects consumer data to facilitate the implementation of automated and personalized preselection mechanisms that surveil, predict, assist, or even replace human choices. Search engines, online news, entertainment media, and online marketplaces use algorithms that present items which are expected to be sparking the user's interest at the top of their search results, make recommendations based on previous preferences, and strategically place advertising catered to the user's profile. One salient example is the recommender system used by Amazon: It prominently places one specific preselected product labelled as "Amazon's choice" on the top of the search results, while still allowing customers to pick from a set of other products instead. More examples of innovative recommender systems include "quantified self" tools which can recommend e.g. personalized workout schedules and sleeping times, or smart home applications which help optimizing energy consumption. In a professional environment, firms can use algorithms which screen candidates in hiring decisions, and courts can use algorithms which predict a defendant's probability to re-offend.

All of these technologies have in common that they preselect choices for their users without restricting the overall choice set. Thus, they involve both potential advantages and disadvantages: On the one hand, they can simplify choices and thereby facilitate peoples' lives, but on the other hand, they have the potential to limit the personal freedom of choice.[1] Which of the two effects dominates is the question that we address in this paper. More specifically, we analyze whether, conditional on the outcome of a choice process being a specific alternative, individuals prefer actively choosing this alternative from a set of several alternatives over simply accepting a preselected alternative.

Our experiment is based on the following idea:[2] Consider a set of alternatives X and a partition of X, $P = (X_1, X_2)$ with $X_1 \cup X_2 = X$, $X_1 \cap X_2 = \{\}$, and $\#X_1 < \#X_2$. Thus, because choice set X_1 is smaller, choosing from X_1 is simpler than choosing from X_2. We evaluate choices in two between-subject treatments, in which we vary only the choice environments, but not the set of alternatives: In the one-stage treatment, an individual directly chooses an element in X. In the two-stage treatment, the individual first chooses a choice set X_1 or X_2, already knowing all elements of each set, and then, if necessary, an alternative in her chosen set. The two-stage treatment provides a similar choice environment as the one created by typical recommender systems. Therefore our analysis can be seen as a test of whether the large-scale employment of recommender systems by online media and marketplaces is in line with individuals' preferences.

Our experimental setup enables us to test the following hypothesis: Conditional on a specific realized outcome A, individuals do not care about whether they have actively chosen A

[1] The question of whether preselection of alternatives is socially beneficial or not arises also in the context of political reforms. In particular, agenda setting restricts the policy alternatives that are up for election. On the one hand, agenda setting can simplify choices, but on the other hand, the set of political alternatives to choose from might be limited.

[2] Testing for a preference for choice directly is difficult. If we asked "do you prefer to be given A or choosing from the set $\{A, B\}$?", we would not be able to distinguish whether a preference for choosing from the larger choice set comes from a preference for the additional items, of from a preference for choice. Similarly, letting participants chose between being given A or choosing from the set $\{B, C\}$ raises the question of how B and C compare to A. This is why we choose an indirect approach.

from a set of more than one alternative, or whether they simply accepted it when it was the preselected alternative. If this hypothesis is rejected, we can conclude that individuals either have a preference for A being the result of their own active choice, or for accepting a preselected alternative.

In our experiment, we implement the simplest setup possible with three alternatives, such that X_1 is a singleton and X_2 contains two elements. In order to make choices nontrivial, we give the alternatives two scalable dimensions: All alternatives are fair lotteries with two outcomes. This allows us to vary expected payoffs, and thus to estimate a willingness to pay for choice. We develop a structural model for the choice between the three lotteries. In both treatments, the choice of an alternative from a set depends only on the individual's risk aversion. In the two-stage treatment however, the choice between the singleton and the larger set depends also on the individual's value of choice. We assume that monetary payoffs of the alternative presented as singleton are scaled by a factor that denotes the intensity of individuals' preference for choice. Thus the value of choice is measured in percent of monetary payoffs. We use maximum likelihood methods to estimate the distribution of risk-aversion and the distribution the value of choice from this structural model.

We conduct our experiment as an incentivized online survey on the German Internet Panel (GIP). The GIP is a long-term study which, since 2012, regularly interviews around 4,000 participants. It covers a multitude of topics, including political views. We make use of these data to explore heterogeneity in the preference for choice: In particular, we correlate the participants' choices in our experiment with their political position on the left-right spectrum and with other variables that measure liberalism and individualism, as well as with their personality traits as measured by the Big Five.

Our experiment yields three main results. First, we find that, on average, participants have a preference for procedures that require them to make fewer choices: In the two-stage treatment, a significantly higher share of participants picks the preselected alternative than in the one-stage treatment. Consistent with this result, the estimation of our structural model reveals that the mean willingness to pay to make an additional choice is negative.

Second, we find substantial subject heterogeneity within our sample: According to the estimates of our structural model, around 41% of the participants have a positive value of choice. Furthermore, the estimated value of choice ranges from −11% to 8% of the monetary payoffs of the lottery presented as singleton.

Third, we show that measurable individual characteristics correlate with the preference for choice. Linking choices to the Big Five personality traits, we find that the preference for the preselected alternative in the two-stage treatment increases in Openness. We also find that there is considerable heterogeneity between two well-defined groups of society: Those participants who report to be leaning politically to the right are more likely to choose the preselected alternative in the two-stage treatment than those leaning towards the left.

2 Related Literature

Our paper is related to a recent literature that studies the role of recommender systems on digital trading platforms. This literature (see Budzinski, 2021 for a review) is mainly theoretical and focuses on the one hand on potential benefits of informed recommender systems – in particular on the reduction of transactions costs – and on the other hand on various types of agency costs. The present paper makes two empirical contributions to this literature. First, it tests the practical importance of procedural aspects and related welfare effects that may be associated with recommender systems. Second, it investigates whether prominently placed recommendations to consumers that value choice per se may trigger choices that are biased towards those products that have not been recommended - even when these products are inferior from the consumer's perspective.

On a more general level, this paper is related to the branch of social choice theory that studies preferences over choice sets. This literature emerged from Sen's seminal work on the relevance of freedom of choice for individual well-being (Sen, 2004). Sen distinguishes between two different, but interrelated aspects of freedom: On the one hand, individuals value having different options – the *opportunity aspect* of freedom. On the other hand, individuals value the process of choice itself, concerning both their own decisions as well as the rules operating in society and institutions – which is the *process aspect* of freedom.[3]

Both ideas clearly contrast with traditional rational choice theory, in which preferences over choice sets depend only on the best possible outcome each set permits. In that case, freedom of choice has only an instrumental value in the sense that a larger choice set might permit a better outcome, but no intrinsic value (Sen, 1991; Frey et al., 2004).

The idea that processes matter for choice is captured also by the concept of *procedural utility* (see Frey et al., 2004 for a review).[4] In contrast to outcome utility, procedural utility can arise from individual activities, interactions between people, and in particular from the institutions under which individuals make choices (Frey and Stutzer, 2005; Stutzer, 2020).[5]

This paper is an experimental test of one of the two main assumptions underlying this literature – that individuals care not only about outcomes but also about the choice process that led to a particular outcome.[6] Therefore, our paper relates to two further strands in this literature: the theoretical literature on measuring the degree of freedom provided by choice sets, and the

[3] The emphasis of the process aspect of freedom goes back to Mill (1859). It also lies at the heart of Hayek's theory of a liberal societal order. Hayek (2011) argues that the extent of personal liberty is not determined by the size of the set of actions that an individual can take but by the properties of a "private sphere" in which individuals can make choices without any interference of others.

[4] A psychological corroboration of procedural utility can be found in self-determination theory, which argues that the process through which outcomes are achieved is relevant to the satisfaction of the innate psychological needs of competence, relatedness and autonomy (Deci and Ryan, 2000; Ryan and Deci, 2006).

[5] Empirically, the relevance of procedural utility becomes especially evident in the context of democratic participation: Eligibility to vote increases satisfaction with the outcome of a collective decision (Frey and Stutzer, 2005), and although a single vote is unlikely to affect the outcome, voters exhibit a high willingness to pay to retain the right to vote (Güth and Weck-Hannemann, 1997). Moreover, procedural utility has been shown to play a role in the workplace: Self-employed report higher job satisfaction than employees (Benz and Frey, 2008a,b), and for employees, more involvement in pay procedures is associated with higher levels of satisfaction (Benz and Stutzer, 2002)

[6] For a thorough discussion of *why* individuals may value procedures that require them to make choices, see Duus-Otterström, 2011. Note however that distinguishing empirically between the different motivations for valuing choice is beyond the scope of this paper.

experimental literature investigating individuals' preferences for choice.

There are different attempts to formally compare choice sets according to their degree of freedom. First, under uncertain future preferences, utility maximization leads to a preference for flexibility: When an individual is uncertain about her future preferences, she will choose the set of options that contains her preferred options in terms of expected utility and offers most flexibility (Kreps, 1979; Kahn and Lehmann, 1991).[7]

Second, in absence of uncertainty about preferences, various axioms have been proposed for comparison of freedom (Sen, 1991; Bossert et al., 1994; Gravel, 1994; Puppe, 1995, 1996; Nehring and Puppe, 1996; Alcalde-Unzu et al., 2012). When preferences are known, but an individual attaches intrinsic value to freedom, the extent of freedom gained from the specification of the set needs to be weighed against the utility gained from the elements contained in the set. In particular, although a larger choice set always offers more freedom of choice, whether an individual prefers the larger set over a smaller set depends on the value of the alternatives in the set (Sen, 1991; Rosenbaum, 2000). This aspect is particularly relevant to our experiment, because we systematically test how preferences over choice sets depend on the available alternatives by permuting which alternative is excluded from the larger set.

Preferences over choice sets have been investigated in several surveys about hypothetical product choices. A series of experiments from consumer research documents for a large number of different product types that consumers are more likely to choose a brand if it is presented as part of a set rather than alone (Kahn et al., 1987; Kahn and Lehmann, 1991; Glazer et al., 1991).[8] In these studies, participants indicate their hypothetical choice among three brands of the same product type. While the control group chooses directly from the triple, the treatment group is presented with a two-stage choice, where the brands are split into a pair and a single alternative. They then first choose between the pair and the single alternative, and subsequently choose a brand if the pair was chosen. They find that being presented as the single alternative significantly decreased the share of choices for a brand compared to being presented as part of the triple. In a similar experiment, Brenner et al. (1999) find however that when asked which set they preferred, consumers preferred the set containing the single alternative. They argue that grouping increases within-group comparisons, and that when comparing alternatives within a set, the disadvantages of each alternative stand out. Therefore, the single alternative is perceived as better. Drawing on this contradicting evidence, Sood et al. (2004) demonstrate that whether the group has an advantage or a disadvantage in such treatments can crucially depend on the framing of the questions. In our experimental setup, we use an abstract and neutral framing involving lotteries instead of actual consumer products and therefore avoid such biases.

In this literature, the experiment by Bown et al. (2003) is closest to our setup, beause

[7] Arrow (2006) argues that in the context of constitutional formation, choice sets might be chosen for many individuals. Then, the choice of the choice set has to take into account many, potentially different preferences, while aiming to retain the autonomy of choice for the individuals in the future.

[8] Note that this literature is also related to the literature on choice overload, which shows that consumers are attracted to larger choice sets, but are subsequently less satisfied with their choice (Iyengar and Lepper, 2000; Chernev, 2003, 2006). Although these studies also demonstrate a trade-off between freedom of choice and outcomes, cognitive issues such as confusion play a role when consumers are faced with many options.

participants choose from a set of three hypothetical casino bets along different choice paths. The authors again compare choices from the triple to choices from a pair and a single alternative. They also establish a preference for choosing from a larger set which can be used to trick individuals into an unattractive offer that is beneficial for the designer of the path of choices.

Further aspects of preference for choice have been studied in this strand of the literature. To test whether choice has an intrinsic value independent of the available alternatives, Leotti and Delgado (2011, 2014) conduct experiments in which participants can choose between receiving an outcome immediately or after a second choice. The monetary outcome of the choice however is determined randomly, such that the expected outcome is the same in both cases. Nevertheless, participants select the path involving a second choice more often, indicating that the act of choosing itself has a value (Leotti and Delgado, 2011).[9] Moreover, reported satisfaction with a hypothetical outcome increases when it is the result of the individual's own choice rather then someone else's choice (Botti et al., 2004; DeCaro et al., 2020) – suggesting that an outcome is perceived differently depending on the process leading to the outcome.[10]

However, none of these surveys are incentivized, such that choices between choice sets do not have actual consequences for the participants. In that case, a preference for choice cannot be distinguished from choosing a larger set for the sake of entertainment only. Our incentivized experiment allows us to estimate an actual monetary value of choice.

Closest to our analysis is a recent experimental analysis of preferences over choice sets by Le Lec and Tarroux (2020). Like ours, their experiment is incentivized in the sense that subjects' choices affect real outcomes. In order to identify preferences over choice sets, they consider a two stage problem where in the first stage, participants provide a monetary willingness to pay for various choice sets of different size. Knowing that they will be randomly offered one of the choice sets at a random price, they have an incentive to report their true willingness to pay for each choice set in the first stage. Then in the second stage, participants choose an item from the set that they purchased. The authors find that on average participants value a set less than its best component, indicating that subjects have a negative value of having to choose from a set with additional alternatives.[11]

[9]The effect vanishes when the outcome involves not only gains but also losses – showing that context matters for the value of choice (Leotti and Delgado, 2014).

[10]However, again, the effect vanishes when the outcome involves losses (DeCaro et al., 2020) or hypothetically disliked alternatives (Botti et al., 2004), although in the latter case participants still prefer making their own choice.

[11]Our estimated average value of not having to make more choices is smaller in absolute value than Le Lec and Tarroux's estimate, and we find that about 41% of participants have a positive value of choice which is more than in Le Lec and Tarroux (25-30%). One potential reason why our results differ is that our experimental design excludes some potentially confounding factors that might increase the value of not having to make more choices: First, Le Lec and Tarroux suggest that individuals might fear making a bad decision in the second stage, and therefore rationally restrict their choice set in the first stage. Because we implement our experiment in an online survey, participants always have the opportunity to use the "back" button to go back to the first stage decision, which should minimize the fear of making mistakes. Second, Le Lec and Tarroux suggest that individuals might use an imperfect heuristic when valuating larger choice sets. Such a cognitive shortcut might be helpful when individual preferences are expected to change in the future, and in order to delay the cognitive costs of ranking all options in the set. This explanation however is plausible only because participants have to make a large number of decisions in Le Lec and Tarroux's experiment. In our experiment however, participants make only one decision between two choice sets, and the decision between alternatives within the set is required directly afterwards, without any delay in between. Third, the goods in the choice sets considered by Le Lec and Tarroux are access to four media websites. Participants might have a willingness to pay for expressing their views about these media

The most notable difference between our experimental approach and the one by Le Lec and Tarroux (2020) concerns the exact type of preference that both setups test for. In their setup participants are exposed to a variety of choice sets, but the choice procedure is a one-stage choice from the randomly chosen set. Participants can only influence the probability of having to choose from a certain choice set by submitting their willingness to pay. In contrast to that, we keep the choice set fixed but expose different participants to different choice environments. In particular, the choice environment is altered exogenously by the experimenters through the preselection of one alternative in the two-stage treatment. Thus the two experiments measure different types of preference for choice: Le Lec and Tarroux measure preferences for autonomously reducing or enlarging the size of a choice set. We however estimate a preference for an exogenous preselection of alternatives as compared to independently choosing between multiple alternatives without interference. Thus, our paper can be seen as a test for a preference for making self-determined choices - or in other words a taste for *freedom as independence*.[12]

3 Experimental Design

3.1 Experimental Treatments

In a between-subjects design, we employ two treatments, in which we vary the choice environment, but keep the set of alternatives to choose from constant.[13] We employ the most simple experimental design possible, using three alternatives A, B, and C. In the *one-stage treatment*, participants directly choose one alternative from the entire choice set $\{A, B, C\}$. In the *two-stage treatment*, participants first choose a choice set. In particular, they can choose between a set that is a singleton and a set that contains the remaining two alternatives. If they choose the latter, they choose an alternative from that set in the second stage.[14] In order to control for potential order effects, we randomize the order in which the alternatives appear in the choice set in both treatments, yielding six experimental groups per treatment.

This treatment design allows us to test the Null Hypothesis which states that people only care about the three alternatives at choice, not the number of steps required to choose a certain alternative. Under the Null Hypothesis, the relative frequency of choice of any alternative

that add to the measure of the value of choice. In our experiment, we use an abstract framing in which the goods are lotteries, such that no such expressive choices should play a role.

[12]In their conclusion, Le Lec and Tarroux conjecture that although "subjects are not willing to enlarge their *own* choice set, this does not necessarily mean that they are willing to let someone else [...] *interfere* with their choice opportunities" (p. 2132). Because our experiment is designed to analyze whether preselection of alternatives make a difference, our results lend themselves to this interpretation of *freedom as independence*.

[13]We pre-registered the experimental design via AsPredicted (`https://aspredicted.org/dt99n.pdf`).

[14]Note that because we implement the experiment in the German Internet Panel, there is a "back" button that allows participants in any stage of the survey to go back to any previous stage. Therefore, subjects might also choose to return to the first stage of our experiment after already having arrived at the second stage. On the one hand, changing one's mind in the second stage might be interpreted as making an additional choice, which could be relevant for the interpretation of our results. On the other hand however, going back and forth between questions does not have any consequences for the final decision, and hence for the outcome of the lottery choice. Therefore, the ability to change one's mind should not affect the value of choice. Although in theory the "back" button might make a difference, an analysis of the timestamps indicating when and for how long a participant visited each question page in the online survey reveals that the "back" button was used by at most one participant at the second stage.

presented as singleton in the two-stage treatment is equal to the relative frequency of choice of the respective alternative in the one-stage treatment.[15] If however the Null Hypothesis is rejected, and participants attach a positive value to making a second choice (alternative Hypothesis H1a), the relative frequency of choice of the singleton in the two-stage treatment should be lower than the relative frequency of choice of the same alternative in the one-stage treatment. If participants attach a negative value to making a second choice (alternative Hypothesis H1b), the relative frequency of choice of the singleton in the two-stage treatment should be higher than the relative frequency of choice of the respective alternative in the one-stage treatment.

In order to make choices between the alternatives non-trivial, we give the alternatives two scalable dimensions. Participants choose between three lotteries with different expected returns and different variances. We use a choice task similar to the Eckel and Grossman (2002) task in which each lottery has two possible outcomes that occur with equal probability. This lottery choice task has been shown to be easily understandable for participants (Dave et al., 2010). Moreover, the use of lotteries allows us to identify a willingness to pay for the choice amongst more than one alternative.

Table 1 shows the three increasingly risky lotteries in the baseline choice set. A risk-neutral participant prefers lottery C, as it yields the highest expected payoff. A risk-seeking participant will prefer lottery C as well, as it is the most risky alternative. A risk averse participant however will be willing to sacrifice expected payoff in order to reduce risk. Therefore, individuals with an intermediate level of risk-aversion will prefer lottery B, while individuals with a high level of risk-aversion will prefer lottery A.

Table 1: Baseline choice set

Lottery	L	H	Expected payoff	Standard deviation
A	9	11	10	1
B	7	14	10.5	3.5
C	5	17	11	6

Because we expected participants to be more likely to select the alternative presented as a singleton in the two-stage treatment than in the one-stage treatment, we included an additional treatment to exclude an alternative explanation: the *group attractiveness effect*. This effect has so far only been studied in Psychology, in particular concerning the physical attractiveness or likability of groups of people. It says that when asked to judge the attractiveness of a group of people, participants "find the group more attractive than the average of its members" (van Osch et al., 2015). In our experimental setup, presenting two items as a group might cause a similar effect: During the first choice in the two-stage treatment, i.e. the choice between the two sets $\{A\}$ or $\{B, C\}$, the presentation of $\{B, C\}$ as a group might prevent participants from

[15] Note that this hypothesis can be tested either by pooling data with different sequences of the alternatives not listed first or by comparing data from the one-and the two stage treatment with the same sequence of all alternatives.

carefully considering the two individual alternatives the set contains. They might see only the most positive attributes of the two alternatives and match them to form a new, more attractive lottery in their minds. Specifically, they might only consider the highest available low outcome L and the highest available high outcome H. Then, the new, imaginary lottery becomes more attractive then those in the group. If this imagined lottery is preferred over A, it might cause them to choose the set $\{B, C\}$ – although the imagined lottery is not actually available. To test for such a group attractiveness effect, we construct another choice set by adding exactly this more attractive lottery to the baseline choice set.

Because the additional treatment reduces the number of participants available for each treatment, we only test the group attractiveness effect for the case where C is presented as a singleton and $\{A, B\}$ as a group in the two-stage treatment. Specifically, we construct the additional lottery D from the highest available payoff of event L and the highest available payoff of event H of the lotteries A and B. Table 2 shows the additional choice set. Note that in this choice set, alternative D dominates alternatives A and B. Therefore, participants should choose only between C and D.

Table 2: Additional choice set to test for group attractiveness effects

lottery	L	H	Expected payoff	Standard deviation
A	9	11	10	1
B	7	14	10.5	3.5
C	5	17	11	6
D	9	14	11.5	2.5

If in the baseline choice set $\{A, B, C\}$, the difference in choices between the one-stage treatment and the two-stage treatment is *only* driven by the group attractiveness effect, we should observe no such difference anymore with the additional choice set $\{A, B, C, D\}$, because the more attractive alternative D is available in both treatments. If however the share of choices of C is still lower in the two-stage treatment than in the one-stage treatment, the result cannot be attributed to the group attractiveness effect.

To test for potential order effects in the larger choice set in the two-stage treatment, we use three permutations of the alternatives A, B and D, resulting in 3 additional experimental groups.

3.2 Implementation of the Experiment in the German Internet Panel

The German Internet Panel (GIP) is a long-term online panel collecting survey data on political attitudes and preferences, individual behavior, as well as socio-demographic variables. As the central infrastructure project of the Collaborative Research Center (SFB) 884 "Political Economy of Reforms" at the University of Mannheim, the GIP was established in 2012, and has since then been fielded on a bimonthly basis. The GIP relies on a random probability sample of the general population of Germany aged 16 to 75.[16] With additional participants having been recruited in 2014 and 2018, it now offers a pool of over 6,000 panelists, and around 4,000 take part in each wave. All panelists are invited to the survey on the first day of every other month, and have the entire month to complete it. The questionnaire takes around 20 to 25 minutes and completing it is rewarded with a conditional incentive of 4 euros. Participation is further incentivized with a yearly bonus payment of 10 euros if all surveys in that year were completed, or of 5 euros if all but one were completed. The GIP data are publicly available in the GIP data archive at the GESIS-Leibniz Institute for the Social Sciences.

We implemented our experiment as part of the questionnaire of GIP wave 57, which was fielded in January 2022. To simplify the setup for the participants, we framed the lotteries as the toss of a fair coin. We showed them a picture of three coins depicting the respective outcome for heads and tails.[17] To incentivize participants, we randomly drew 750 participants to whom we paid the randomly determined outcome of their selected lottery. This fact and our expected number of participants (around 4,000) were communicated in the instructions (see Appendix B). On average, the participants selected for payment received 10.49 euros.[18]

4 Results

In total, 4,079 participants took part in GIP wave 57. Some of them did not complete the survey or skipped our experiment, resulting in an effective sample size of 3,984 participants (population: average age 53 years, 48% female, 35% have an academic education). We now present the insights from our experiment in terms of descriptive statistics, and then the results from a regression analysis in which we investigate potential heterogeneity in the treatment effect concerning the participants' individual characteristics and their political attitudes.

4.1 Descriptive Results

Overall, 24% of the participants choose the alternative presented first in the one-stage treatment, while 38% choose the alternative presented as singleton in the two-stage treatment.[19] The difference is statistically significant ($p < 0.0001$, two-proportions z-test)[20], such that our Null Hypothesis is rejected in favor of alternative Hypothesis H1b, revealing that on average participants attach a negative value to making a second choice.

Table 3 shows the relative frequencies of choices in the baseline choice set $\{A, B, C\}$, depending on which alternative was presented first.[21] In the one-stage treatment, independent of

[16] For details on the GIP methodology, see Blom et al. (2015, 2016, 2017); Herzing and Blom (2019) and Cornesse et al. (2020).

[17] See appendix B for screen shots of the original instructions as well as English translations.

[18] As a comparison, the German hourly minimum wage was 9.82 euros at the time when the experiment was fielded.

[19] The relative frequencies of first alternative choices are significantly different from 1/3 in the one-stage treatment ($p < 0.0001$, binomial test), and from 1/2 in the two-stage treatment ($p < 0.0001$, binomial test), which would correspond to random choice between the presented options.

[20] All reported statistical tests are two-sided tests.

[21] The relative frequencies of choices for all permutations of the three alternatives can be found in appendix table A.1. We only distinguish between which alternative was presented first here because the relative frequencies of first alternative choices differ only slightly when comparing the permutations of the remaining two elements in

the order of alternatives, a relative majority of participants chooses alternative A, i.e. the least risky lottery, indicating that the participants are relatively risk-averse. Therefore, the shares of first alternative choices differ depending on which alternative was presented first: In particular, in both treatments, when the least risky alternative A is presented first, the relative frequency of first alternative choices is significantly higher than when any of the other alternatives is presented first (figure 1).

Table 3: Relative frequencies of choices in the baseline choice set

Treatment	Alternative presented first	Choice of A	Choice of B	Choice of C
One-stage	A	0.42	0.30	0.27
	B	0.50	0.20	0.30
	C	0.49	0.27	0.25
Two-stage	A	0.50	0.24	0.26
	B	0.35	0.40	0.24
	C	0.43	0.20	0.37

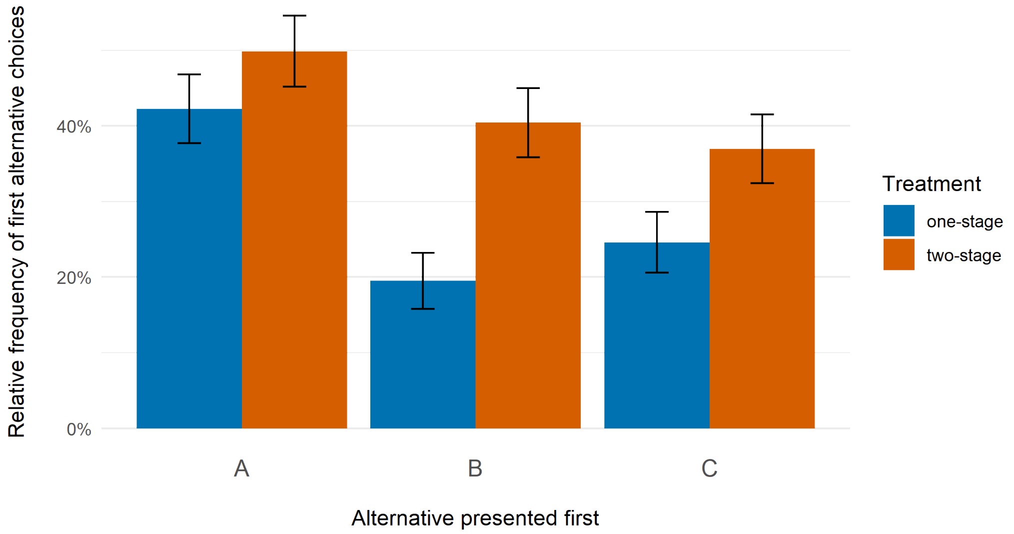

Figure 1: Share of choices of the alternative which was presented first in the one-stage treatment, and as singleton in the two-stage treatment. Error bars represent 95% confidence intervals.

Moreover, independent of the order of alternatives, the share of first alternative choices increases significantly in the two-stage treatment, compared to the one-stage treatment. The size of the treatment effect however differs slightly depending on which alternative was presented first: In particular, the treatment effect when B is presented first is significantly higher than the treatment effect when A is presented first (figure 2).

the choice sets: The difference is only significantly different from zero between the two permutations $\{B, A, C\}$ and $\{B, C, A\}$ in the one-stage treatment ($p = 0.083$ two-proportions z-test). When A or C are presented first, the difference between the two permutations of the respective choice sets is not significantly different from zero.

Because the treatment effect on first alternative choices is positive, we can conclude that there are some participants who choose the alternative presented as singleton in the two-stage treatment, but who would have chosen a different alternative in the one-stage treatment. Which type of participant's choices are affected by the treatment depends on which alternative was presented as the first. Figure 2 shows that when A or C are presented first, the share of B-choices decreases significantly in the two-stage treatment, while the other choices do not change significantly. When B is presented first, only the share of A-choices decreases significantly. Thus, only those participants who would have chosen the less risky alternatives A or B in the one-stage treatment are willing to trade-off expected utility from their lottery choice against their utility from making a more simple choice in the two-stage treatment. Those participants who would have chosen the most risky alternative C in the one-stage treatment however are less willing to change their choice in the two-stage treatment.

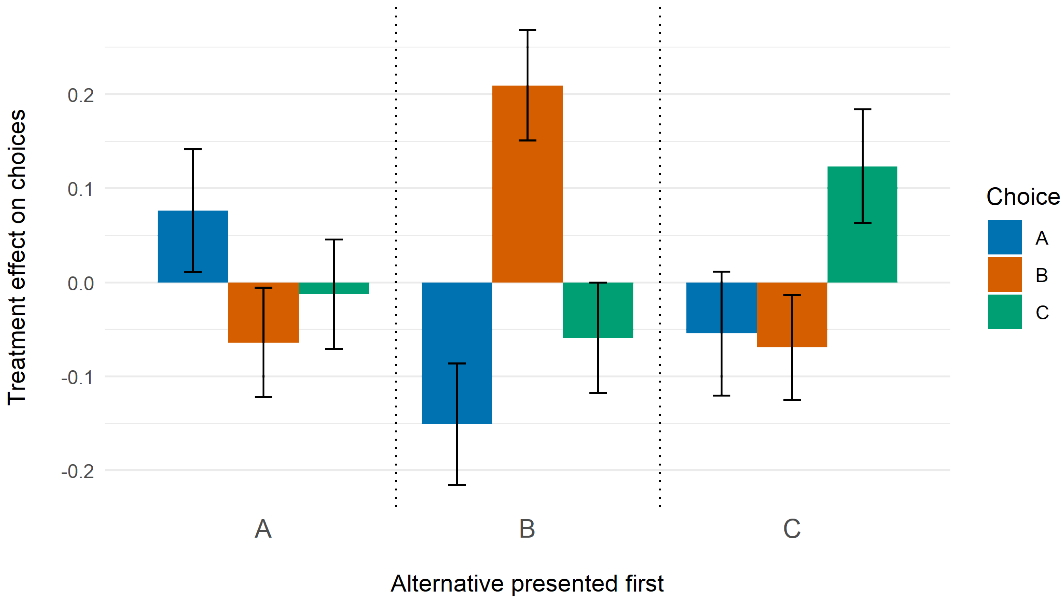

Figure 2: Effect of the two-stage treatment on the relative frequency of choices of each alternative, compared to the one-stage treatment. The sample contains only the experimental groups with the baseline choice set $\{A, B, C\}$. Error bars represent 95% confidence intervals.

Table 4 shows the relative frequencies of choices for each alternative in the additional choice set $\{A, B, C, D\}$, where C was always presented first.[22] In the one-stage treatment, a relative majority of participants chooses alternative D, which is less risky and has a higher expected payoff than alternative C. Although in this choice set, alternative A and B are dominated by alternative D, some participants still choose these alternatives. In particular, a significant share

[22] The relative frequencies of choices for all permutations of the four alternatives can be found in appendix table A.2. Again, the relative frequencies of C-choices differ slightly when comparing the permutations of the remaining three elements in the choice sets: The difference is significantly different from zero when comparing the permutation $\{C, A, B, D\}$ to the permutation $\{C, A, D, B\}$ ($p = 0.005$, two-proportions z-test) and to $\{C, D, A, B\}$ ($p = 0.017$, two-proportions z-test) in the two-stage treatment. When comparing $\{C, A, D, B\}$ to $\{C, D, A, B\}$ the difference in the share of C-choices between the permutations is not significantly different from zero.

chooses A, which cannot be explained by rational choice theory.

Recall that we included this additional choice set to test for a potential group attractiveness effect, which would have been an alternative explanation for a negative treatment effect on first alternative choices. However, the treatment effect on first alternative choices is clearly positive in both the baseline choice set as well as in the additional choice set.

Table 4: Relative frequencies of choices in the additional choice set with four alternatives

Treatment	Alternative presented first	Choice of A	Choice of B	Choice of C	Choice of D
One-stage	C	0.30	0.09	0.15	0.47
Two-stage	C	0.16	0.08	0.29	0.46

To ensure that the observed treatment effect indeed captures a preference for choice, and not a preference for completing the questionnaire quickly by avoiding the second stage of the two-stage treatment, we analyze the response times contained in the GIP paradata.[23] If participants in the two-stage treatment chose the preselected alternative only to reduce time spent on the questionnaire, the observed treatment effects on first alternative choices should become smaller once we remove participants who exhibit a preference for quickly completing the experiment from the sample. Therefore, we repeat our analysis on the subsample of those participants with response times equal to or above the 25th percentile of the one-stage treatment or the first stage of the two-stage treatment.[24] The treatment effect in this subsample is similar to the effect observed in the overall sample: 23% of the participants choose the alternative presented first in the one-stage treatment, and 36% choose the alternative presented as singleton in the two-stage treatment, where the difference is statistically significant ($p < 0.0001$, two-proportions z-test). The treatment effects on the relative frequencies of choices for each alternative are of similar magnitude in this subsample compared to the overall sample as well (appendix tables A.3 and A.4).

4.2 Regression Analysis

To investigate whether participants who differ in terms of individual attitudes also differ in terms of their preference for choice, we exploit several questions from previous GIP waves.[25] First, we are interested in whether political preferences are correlated with preferences for choice. To do so, we use participants' self-reported placement on the left-right spectrum. This analysis is motivated by the observation that parties on the political right emphasize personal and in particular entrepreneurial freedom and self-responsibility more than those on the left, leading to

[23] The median response time required to complete our experiment is 1 minute and 3 seconds for the participants in the one-stage treatment, and 1 minute and 14 seconds for the participants in the two-stage treatment, where a median time of 12 seconds is required for the second stage.

[24] The 25th percentile response time is 38 seconds in the one-stage treatment, and 40 seconds in the first stage of the two-stage treatment. Note that dropping all participants who answer our questions relatively quickly, we remove those who generally do not make an effort in the lottery choice task. The set of those participants who want to reduce their time spent on the questionnaire by avoiding the second stage in the two-stage treatment are a subset of those generally not making an effort.

[25] Appendix table A.5 gives an overview of how we construct our variable from the GIP questions.

the conjecture that those on the right might be less inclined to personally accept a preselected alternative. However, on the other hand, one may conjecture that those on the right believe more in formal authority (see e.g. Altemeyer, 1988 on the concept of right-wing authoritarianism) and thus might be more willing to also personally accept a preselected alternative.

Second, we use those variables from the GIP that most closely capture any underlying preferences for making autonomous decisions in life. The GIP contains a range of questions asking participants about their motivation in their job, including whether it is important to them to (i) realize their own ideas, and (ii) to work independently. Additionally, we use a question that asks about support for the statement "the most important political decisions should be made by the people, not politicians".

Third, we explore heterogeneity in terms of personality traits. In particular, the GIP contains the 10-item Big Five Inventory (BFI-10), which is well-established as a reliable and valid assessment of the five core personality traits Extraversion, Neuroticism, Openness, Conscientiousness, and Agreeableness (Rammstedt, 2007; Rammstedt and John, 2007).

As dependent variable in all regressions we use an indicator variable capturing whether the participant chose the lottery presented first (in the one-stage treatment) or as singleton (in the two-stage treatment). We estimate several specifications: The baseline specification includes only an indicator variable for the treatment and the variable for the individual attitude as well as their interaction, which is the effect of interest. We then add the order of lotteries capturing which alternative was presented first, and, in a third specification, we control for the usual sociodemographic variables, i.e. gender, age, income, and education.

Preferences for Choice and Political Preferences

To analyze political preferences, we classify participants on the left-right spectrum into those positioned strictly to the right of the median participant's position, and those positioned to the left of or on the median. Table 5 presents the regression results. The effect of interest is captured by the coefficient on the interaction between *two-stage treatment* and *right-wing*, and it is positive and significant.[26] We can conclude that in the two-stage treatment, those who are leaning towards the right are more likely to choose the alternative presented singleton than those who are leaning towards the left. This conclusion continues to hold when including the order effect induced by presenting different alternatives first as well as the usual set of controls.[27]

As a robustness check to ensure that the observed effects are not driven by a preference for completing the questionnaire quickly, we repeat the regression analysis on the subsample of those participants with response times above the 25th percentile of response times in the one-stage treatment or the first stage of the two-stage treatment respectively (appendix tables A.9 and A.10). In all specifications the coefficients on the interactions between *two-stage treatment* and *right-wing* remain positive and significant, and they are larger in magnitude than in the regressions for the overall sample.

[26]We also estimate a Probit model, which can be found in appendix table A.8. The sign and significance of the coefficients of interest remain unchanged.

[27]The full table including the coefficients for the effects of different first alternatives and all controls can be found in appendix table A.6. The OLS regression results for all permutations of the alternatives within the choice set can be found in appendix table A.7.

Table 5: Lottery choice and political orientation

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.116***	0.046	0.062
	(0.018)	(0.038)	(0.040)
Right-wing	−0.025	−0.033	−0.027
	(0.025)	(0.024)	(0.026)
Two-stage treatment * right-wing	0.072*	0.076**	0.069*
	(0.039)	(0.038)	(0.040)
Constant	0.252***	0.442***	0.391***
	(0.012)	(0.026)	(0.045)
First alternative	No	Yes	Yes
Controls	No	No	Yes
Observations	3,266	3,266	2,897
R^2	0.021	0.064	0.069
Adjusted R^2	0.020	0.061	0.065

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *Right-wing* is a binary indicator variable for the participant's political position on the left-right spectrum. *First alternative* captures which alternative was presented first and its interaction with the treatment variable, with the omitted reference category being "A presented first". The additional control variables include gender, age, income, and education.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

The results are clearly at odds with our (first) conjecture that those leaning to the right tend to emphasize self-determination in their own lives. Instead, they are consistent with the view that those leaning to the right are more willing to accept authority – in this case the authority of the designers of the experiment.

Preferences for Choice and Decision Making in Life

To investigate individual preferences decision making in life, we separately look at the questions about autonomous decision-making in the job, and about the wish for direct political participation.

First, concerning the work life, we create two variables which capture whether the participant finds it very important to (i) realize own ideas and (ii) work independently, or not. Table 6 presents the regression results.[28] The effects of interest are captured by the coefficient on the interactions between *two-stage treatment* and the individual characteristics. However, these coefficients are small and not statistically significant at any conventional level, suggesting that the treatment effect is not different between those who have a preference for autonomous decision-making in the job and those who do not.

[28]The full table including the coefficients on all controls can be found in appendix table A.11 .

Second, concerning political decision-making, we again classify participants into those who want the most important political decisions to be made by the people instead of politicians, and those who do not. Table 7 presents the regression results.[29] The effect of interest is again captured by the coefficient on the interaction term, but it is small and not statistically significant at any conventional level, suggesting that the treatment effect is not different between those who have a preference for direct political decision-making and those who do not.

Table 6: Lottery choice and job motivation

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.121***	0.037	0.060
	(0.031)	(0.044)	(0.049)
Independence	−0.036	−0.041*	−0.030
	(0.022)	(0.022)	(0.024)
Own ideas	0.029	0.024	0.023
	(0.023)	(0.022)	(0.024)
Two-stage treatment * independence	0.041	0.043	0.038
	(0.033)	(0.032)	(0.036)
Two-stage treatment * own ideas	−0.023	−0.022	−0.029
	(0.034)	(0.033)	(0.037)
Constant	0.250***	0.455***	0.408***
	(0.021)	(0.031)	(0.048)
First alternative	No	Yes	Yes
Controls	No	No	Yes
Observations	3,638	3,638	2,920
R^2	0.021	0.063	0.069
Adjusted R^2	0.019	0.060	0.064

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *Independence* is a binary indicator variable for the importance of working independently. *Own ideas* is a binary indicator variable for the importance of realizing own ideas. *First alternative* captures which alternative was presented first and its interaction with the treatment variable, with the omitted reference category being "A presented first". The additional control variables include gender, age, income, and education.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Preferences for Choice and Big-Five Personality Traits

Beyond our pre-registered analysis of the correlation of preferences for choice with political preferences and personal attitudes towards decision-making, the GIP data allow us to explore heterogeneity in terms of the Big Five personality traits: Extraversion, Neuroticism, Openness, Conscientiousness, and Agreeableness. Table 8 presents the regression results.[30] We find that, in the one-stage treatment, higher levels of Openness are associated with a slightly lower probability of choosing the first lottery. In the two-stage treatment however, higher levels of Openness are

[29] The full table including the coefficients on all controls can be found in appendix table A.12.

[30] The full table including the coefficients on all controls can be found in appendix table A.13. We also estimate a Probit regression (appendix table A.14). The sign and significance of the coefficients of interest remain unchanged.

Table 7: Lottery choice and political decision making

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.123***	0.046	0.050
	(0.019)	(0.037)	(0.041)
People's decisions	−0.022	−0.023	−0.031
	(0.020)	(0.020)	(0.022)
Two-stage treatment * people's decisions	0.040	0.041	0.053
	(0.031)	(0.030)	(0.034)
Constant	0.252***	0.445***	0.412***
	(0.013)	(0.026)	(0.045)
First alternative	No	Yes	Yes
Controls	No	No	Yes
Observations	3,721	3,721	2,990
R^2	0.023	0.063	0.070
Adjusted R^2	0.022	0.061	0.065

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *People's decisions* is a binary indicator variable for whether the participant wants important decisions to be made by the people instead of politicians. *First alternative* captures which alternative was presented first and its interaction with the treatment variable, with the omitted reference category being "A presented first". The additional control variables include gender, age, income, and education.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

associated with a higher probability of choosing the first lottery. This conclusion continues to hold when including the order effect induced by presenting different alternatives first and the usual set of controls. The other personality traits do not display any significant effects on first alternative choices. High levels of openness are generally related to creativity, curiosity, and a desire for breaking up routines (John et al., 2008). Thus, a potential interpretation of the regression results is that, more open-minded participants might be more likely to choose the preselected alternative because it is a welcome change compared to having to make their own decisions.

As a robustness check, we again repeat the regression analysis on the subsample of those participants with response times above the 25th percentile of response times in the one-stage treatment or the first stage of the two-stage treatment respectively (appendix tables A.15 and A.16). In all specifications sign and significance of the coefficients of interest remain unchanged. The effect of Openness in the two-stage treatment is even larger in magnitude than in the regressions for the overall sample.

Because high Openness has been shown to increase the probability of voting left-wing (see Gerber et al., 2011 for a review of the relationship between the Big Five personality traits and political attitudes), we also estimate a specification which includes both the classification into left- and right-wing and the Big Five as explanatory variables (appendix table A.17). We find that both those leaning towards the right and those more open-minded are more likely to choose the first lottery.

Table 8: Lottery choice and Big Five personality traits

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	−0.009	−0.087	0.002
	(0.121)	(0.122)	(0.139)
Extraversion	−0.004	−0.003	0.003
	(0.011)	(0.011)	(0.012)
Agreeableness	−0.002	−0.005	−0.006
	(0.013)	(0.013)	(0.014)
Conscientiousness	−0.002	−0.003	0.011
	(0.014)	(0.013)	(0.016)
Neuroticism	−0.005	−0.004	−0.019
	(0.012)	(0.011)	(0.013)
Openness	-0.022^{*}	-0.020^{*}	−0.016
	(0.011)	(0.011)	(0.012)
Two-stage treatment * Extraversion	−0.001	−0.0004	−0.007
	(0.017)	(0.017)	(0.019)
Two-stage treatment * Agreeableness	−0.010	−0.002	−0.005
	(0.020)	(0.020)	(0.022)
Two-stage treatment * Conscientiousness	0.023	0.023	0.002
	(0.020)	(0.020)	(0.023)
Two-stage treatment * Neuroticism	−0.025	−0.027	−0.010
	(0.018)	(0.017)	(0.019)
Two-stage treatment * Openness	0.049^{***}	0.046^{***}	0.040^{**}
	(0.016)	(0.016)	(0.018)
Constant	0.357^{***}	0.545^{***}	0.478^{***}
	(0.081)	(0.082)	(0.096)
First alternative	No	Yes	Yes
Controls	No	No	Yes
Observations	3,888	3,888	3,065
R^2	0.027	0.065	0.070
Adjusted R^2	0.024	0.061	0.064

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. All personality traits range from 1 to 5, where higher values mean that the participant exhibits a higher level of this personality trait. *First alternative* captures which alternative was presented first and its interaction with the treatment variable, with the omitted reference category being "A presented first". The additional control variables include gender, age, income, and education.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

5 A Structural Model

Consider a structural choice model with individual risk aversion and an individual willingness to pay for choice, both parameterized. Assume that individuals care about monetary payoffs x and choice sets S.

When choosing an alternative from a choice set with $\#S \geq 2$, the individual cares only about the monetary payoff x of the alternatives. The utility from the outcome x is given by a constant relative risk aversion (CRRA) utility function

$$u(x) = \begin{cases} \frac{x^{1-r}}{1-r} \text{ if } r \neq 1 \\ \ln(x) \text{ if } r = 1 \end{cases} \tag{1}$$

with r being the coefficient of relative risk aversion. If $r = 0$ the individual is risk-neutral, if $r > 0$ the individual is risk-averse, and if $r < 0$ the individual is risk-seeking. We assume that r is distributed normally with mean μ_r and variance σ_r^2.

However, when choosing between two choice sets, the relative size of the choice sets plays a role. More specifically, assume that the utility of an outcome x of a lottery that is presented as the singleton is

$$U(x, v) = u((1-v)x) \tag{2}$$

where $v < 1$ expresses the extent to which an individual is willing to pay for choosing from the larger set with $\#S = 2$. It can be interpreted as the percentage change in valuation of all outcomes of a lottery when it is the singleton compared to when it is part of a larger choice set. Thus $1-v > 0$ becomes a scaling factor of the payoff x of an alternative in the smaller choice set. When $1-v < 1$, the payoffs from a lottery are valuated lower when it is the singleton compared to when it is part of a larger choice set, while when $1-v > 1$, they are valuated higher.

Because $v \in (-\infty, 1)$ we assume that $1-v$ follows a log-normal distribution with parameters μ_v and σ_v.[31] The mean and variance of $1-v$ are given by

$$\mathbb{E}[1-v] = \exp\left(\mu_v + \frac{1}{2}\sigma_v^2\right)$$

and

$$\text{Var}[1-v] = \exp\left(2\mu_v + \sigma_v^2\right)\left(\exp(\sigma_v^2) - 1\right)$$

and hence the standard deviation of $1-v$ is

$$\text{sd}[1-v] = \exp\left(\mu_v + \frac{1}{2}\sigma_v^2\right)\sqrt{\exp(\sigma_v^2) - 1}.$$

[31] We pre-registered a model with a normally distributed value of choice. Note that because $1-v$ is log-normally distributed, $\log(1-v)$ is normally distributed. It is possible to alternatively model the value of choice by an additive parameter d in the utility function, such that $U(x,d) = u(x) + d$ and $d \sim N(\mu_d, \sigma_d)$. Then however the value of choice is measured in utility units, not in monetary units, which makes the interpretation of the value of choice more difficult. The main result, i.e. that the mean value of choice μ_d is negative, however remains the same in this model specification.

We assume that r and v are stochastically independent.

In the following analysis, we will focus on the baseline choice set containing the three increasingly risky lotteries $\{A, B, C\}$, with a sample size of $n = 2,661$.[32]

5.1 Estimating Risk Aversion

First consider the one-stage treatment, where participants do not choose between choice sets, but only between alternatives in the entire set. In that case, risk aversion alone matters for the decision between the three lotteries A, B and C.

Consider the constant relative risk aversion utility function $u(x)$ as defined in 1. Then, participants derive expected utility

$$EU(L, H) = \frac{1}{2}(u(L) + u(H)) \tag{3}$$

from a fair lottery $X = (L, H)$.

For each binary choice between two lotteries, we calculate the value of r for which the lotteries yield the same expected utility. Let $\tilde{r}_{AB}$ denote the threshold risk aversion coefficient at which an individual is exactly indifferent between lotteries A and B, and let $\tilde{r}_{BC}$ denote the threshold risk aversion coefficient at which an individual is exactly indifferent between lotteries B and C. For the baseline choice set, the thresholds are given by $\tilde{r}_{AB} = 0.91$ and $\tilde{r}_{BC} = 0.43$. Thus, in the one-stage treatment, an individual i with $r_i > \tilde{r}_{AB}$ chooses A, an individual with $\tilde{r}_{BC} < r_i < \tilde{r}_{AB}$ chooses B, and an individual with $r_i < \tilde{r}_{BC}$ chooses C. Let $y_i \in \{A, B, C\}$ denote the lottery choice of individual i. Then, the probabilities of choosing each alternative in the one-stage treatment are given by

$$P(y_i = A) = P(r_i > \tilde{r}_{AB}) = \Phi\left(\frac{\mu_r - \tilde{r}_{AB}}{\sigma_r}\right)$$

$$P(y_i = B) = P(\tilde{r}_{BC} < r_i < \tilde{r}_{AB}) = \Phi\left(\frac{\tilde{r}_{AB} - \mu_r}{\sigma_r}\right) - \Phi\left(\frac{\tilde{r}_{BC} - \mu_r}{\sigma_r}\right)$$

$$P(y_i = C) = P(r_i < \tilde{r}_{BC}) = \Phi\left(\frac{\tilde{r}_{BC} - \mu_r}{\sigma_r}\right)$$

where Φ denotes the cumulative distribution function (CDF) of the standard normal distribution.

The likelihood of an individual observation y_i given the parameters μ_r and σ_r is, in the one-stage treatment

$$\ell_{1i}(\mu_r, \sigma_r) = P(y_i = A)^{\mathbb{1}\{yi=A\}} P(y_i = B)^{\mathbb{1}\{yi=B\}} P(y_i = C)^{\mathbb{1}\{yi=C\}}$$

where $\mathbb{1}\{\cdot\}$ denotes an indicator function for the choice of individual i.

[32] Recall that in the additional choice set containing four alternatives $\{A, B, C, D\}$, a considerable share of participants chose alternative A or B, although these are strictly dominated by alternative D. These choices cannot be explained by expected utility theory, such that we exclude this choice set from the further analysis.

Hence, the sample log-likelihood function for the one-stage treatment is

$$L_1(\mu_r, \sigma_r) = \sum_{i=1}^{n_1} \log\left(\ell_{i1}(\mu_r, \sigma_r)\right)$$

where n_1 denotes the sample size in the one-stage treatment. Maximizing $L_1(\mu_r, \sigma_r)$ with respect to μ_r and σ_r allows us to estimate the distribution of risk aversion in the one-stage treatment.

5.2 Estimating the Value of Choice

In the two-stage treatment, an individual's lottery choice is affected by both her risk aversion and her value of choice. Therefore, the choice probabilities differ depending on which alternative is presented as the singleton. Consider first the case where A is presented as the singleton and $\{B, C\}$ is the choice set to choose from in the second step. The optimal choice can be derived using a backward induction logic. In the second step, only risk aversion matters for the choice between B and C, i.e. an individual i with a risk aversion coefficient r_i chooses B over C if $r_i > \tilde{r}_{BC}$ and C otherwise. Then in the first step, when the individual chooses between the singleton and the set with $\#S = 2$, her expected utility from the singleton is affected by her value of choice v_i. Hence if $r_i > \tilde{r}_{BC}$, the individual chooses A if $EU(A, v_i, r_i) > EU(B, r_i)$ and B otherwise. Similarly, $r_i < \tilde{r}_{BC}$, the individual chooses A if $EU(A, v_i, r_i) > EU(C, r_i)$ and C otherwise.

To derive the thresholds of the scaling factor $1-v$ for which individual i chooses the singleton A, consider first the case where $r_i > \tilde{r}_{BC}$ and assume $r_i \neq 1$. Then the individual chooses A if and only if

$$\begin{aligned}
\frac{1}{2}\left[\frac{((1-v_i)L_A)^{1-r_i}}{1-r_i} + \frac{((1-v_i)H_A)^{1-r_i}}{1-r_i}\right] &> \frac{1}{2}\left[\frac{L_B^{1-r_i}}{1-r_i} + \frac{H_B^{1-r_i}}{1-r_i}\right] \\
\Leftrightarrow 1 - v_i &> \left(\frac{L_B^{1-r_i} + H_B^{1-r_i}}{L_A^{1-r_i} + H_A^{1-r_i}}\right)^{\frac{1}{1-r_i}}
\end{aligned}$$

Note that if $r_i = 1$, the individual chooses A if and only if

$$\begin{aligned}
\frac{1}{2}\left[\ln((1-v_i)L_A) + \ln((1-v_i)H_A)\right] &> \frac{1}{2}\left[\ln(L_B) + \ln(H_B)\right] \\
\Leftrightarrow 1 - v_i &> \sqrt{\frac{L_B H_B}{L_A H_A}}
\end{aligned}$$

Hence an individual with $r_i > \tilde{r}_{BC}$ chooses alternative A if and only if $1 - v_i > \nabla_{AB}(r_i)$ where

$$\nabla_{AB}(r_i) = \begin{cases} \left(\frac{L_B^{1-r_i}+H_B^{1-r_i}}{L_A^{1-r_i}+H_A^{1-r_i}}\right)^{\frac{1}{1-r_i}} & \text{if } r_i \neq 1 \\ \sqrt{\frac{L_B H_B}{L_A H_A}} & \text{if } r_i = 1 \end{cases}$$

Analogously, an individual with $r_i < \tilde{r}_{BC} < 1$ chooses alternative A if and only if $1 - v_i >$

$\nabla_{AC}(r_i)$ where

$$\nabla_{AC}(r_i) = \left(\frac{L_C^{1-r_i} + H_C^{1-r_i}}{L_A^{1-r_i} + H_A^{1-r_i}} \right)^{\frac{1}{1-r_i}}.$$

Then, the probability of choosing A in the two-stage treatment when A is presented as the singleton is

$$\begin{aligned}
P_A(y_i = A) &= P(r_i > \tilde{r}_{BC} \cap 1 - v_i > \nabla_{AB}(r)) + P(r_i < \tilde{r}_{BC} \cap 1 - v_i > \nabla_{AC}(r)) \\
&= \int_{\tilde{r}_{BC}}^{\infty} \int_{\nabla_{AB}(r)}^{\infty} f_{V,R}(v, r)\mathrm{d}v\mathrm{d}r + \int_{-\infty}^{\tilde{r}_{BC}} \int_{\nabla_{AC}(r)}^{\infty} f_{V,R}(v, r)\mathrm{d}v\mathrm{d}r \\
&= \int_{\tilde{r}_{BC}}^{\infty} \int_{\nabla_{AB}(r)}^{\infty} f_V(v)\mathrm{d}v f_R(r)\mathrm{d}r + \int_{-\infty}^{\tilde{r}_{BC}} \int_{\nabla_{AC}(r)}^{\infty} f_V(v)\mathrm{d}v f_R(r)\mathrm{d}r \\
&= \int_{\tilde{r}_{BC}}^{\infty} \left[1 - F_V(\nabla_{AB}(r))\right] f_R(r)\mathrm{d}r + \int_{-\infty}^{\tilde{r}_{BC}} \left[1 - F_V(\nabla_{AC}(r))\right] f_R(r)\mathrm{d}r
\end{aligned}$$

where $F_V(\cdot)$ denotes the CDF of $1-v$, $f_V(\cdot)$ denotes the corresponding density function of $1-v$, $f_R(\cdot)$ denotes the density function of r, and $f_{V,R}$ denotes the joint density function of v and r. Note that the third line follows from the assumption that v and r are independent.

Similarly, the probability of choosing B in the two-stage treatment when A is presented as the singleton is

$$\begin{aligned}
P_A(y_i = B) &= P(r_i > \tilde{r}_{BC} \cap 1 - v_i < \nabla_{AB}(r_i)) \\
&= \int_{\tilde{r}_{BC}}^{\infty} \int_{0}^{\nabla_{AB}(r)} f_{V,R}(v, r)\mathrm{d}v\mathrm{d}r \\
&= \int_{\tilde{r}_{BC}}^{\infty} F_V\left(\nabla_{AB}(r)\right) f_R(r)\mathrm{d}r
\end{aligned}$$

and the probability of choosing C in the two-stage treatment when A is presented as the singleton

$$\begin{aligned}
P_A(y_i = C) &= P(r_i < \tilde{r}_{BC} \cap 1 - v_i < \nabla_{AC}(r)) \\
&= \int_{-\infty}^{\tilde{r}_{BC}} \int_{0}^{\nabla_{AC}(r)} f_{V,R}(v, r)\mathrm{d}v\mathrm{d}r \\
&= \int_{-\infty}^{\tilde{r}_{BC}} F_V\left(\nabla_{AC}(r)\right) f_R(r)\mathrm{d}r.
\end{aligned}$$

Then, the likelihood of an individual observation y_i in the two-stage treatment with A as singleton is given by

$$\ell_{2Ai}(\mu_r, \sigma_r, \mu_v, \sigma_v) = P_A(y_i = A)^{\mathbb{1}\{yi=A\}} P_A(y_i = B)^{\mathbb{1}\{yi=B\}} P_A(y_i = C)^{\mathbb{1}\{yi=C\}}$$

where again $\mathbb{1}\{\cdot\}$ denotes an indicator function for the choice of individual i.

For the other two treatments, where B and C are presented as the singleton, the choice probabilities are calculated in an analogous manner, yielding the likelihood functions $\ell_{2Bi}(\mu_r, \sigma_r, \mu_v, \sigma_v)$ and $\ell_{2Ci}(\mu_r, \sigma_r, \mu_v, \sigma_v)$.

Let $t_i \in \{A, B, C\}$ denote the experimental group allocation of individual i in terms of which alternative is presented to i as singleton. Then, the sample log-likelihood function for the two-stage treatment is

$$\begin{aligned} L_2(\mu_r, \sigma_r, \mu_v, \sigma_v) = \sum_{i=1}^{n_2} & [1\{t_i = A\} \log(\ell_{2Ai}(\mu_r, \sigma_r, \mu_v, \sigma_v)) \\ & + 1\{t_i = B\} \log(\ell_{2Bi}(\mu_r, \sigma_r, \mu_v, \sigma_v)) \\ & + 1\{t_i = C\} \log(\ell_{2Ci}(\mu_r, \sigma_r, \mu_v, \sigma_v))] . \end{aligned}$$

where n_2 denotes the sample size in the two-stage treatment, and where for each i, the log-likelihood function differs according to which treatment i received.

To estimate all parameters of interest, μ_r, σ_r, μ_v and σ_v, we follow a two-step procedure. First, on the subsample with the one-stage treatment, we estimate the parameters of the distribution of risk aversion, $\hat{\mu}_r$ and $\hat{\sigma}_r$, that maximize the sample log-Likelihood $L_1(\mu_r, \sigma_r)$. Under the assumption that the distribution of risk aversion remains the same between the two treatments, we can then use these estimates to estimate the distribution of the value of choice on the subsample of the two-stage treatment. More specifically, we keep $\hat{\mu}_r$ and $\hat{\sigma}_r$ fixed and then maximize the sample log-likelihood function $L_2(\hat{\mu}_r, \hat{\sigma}_r, \mu_v, \sigma_v)$ with respect to μ_v and σ_v. Another possibility is to estimate all four parameters jointly by maximizing the overall log-likelihood function of the entire sample. This procedure is computationally more demanding, and the estimated parameters of the distribution of the value of choice are more volatile with respect to the initial guess. Nevertheless, the estimation yields similar results (appendix tables A.19 and A.22).

All algorithms suited to maximize our log-likelihood function require an initial guess, which, if multiple local maxima exist, can strongly affect which maximum the algorithm converges to. To reduce the dependence on the initial guess, we proceed as follows: We repeat the estimation for 100 randomly drawn initial guesses, and then select the estimation results which yield the highest value of the log-likelihood function. Moreover, we validate the estimates by ensuring that different maximization algorithms obtain the same results.

Another approach that does not rely on the assumption that the distribution of risk aversion remains the same between the two treatments is to estimate the parameters μ_r, σ_r, μ_v and σ_v jointly for the subsample of the two-stage treatment only. The estimates for μ_r and σ_r from the one-stage treatment are used only as initial guesses for the estimation on the two-stage sample. The success of this estimation procedure depends even more on the initial guess, but after reducing this dependence by again repeating the estimation for 100 randomly drawn initial guesses, it nevertheless yields similar estimates (appendix tables A.20 and A.22).

Note that we have to impose non-negativity constraints on σ_r and σ_v for the maximum likelihood estimation. Therefore, these constrained parameters do not necessarily satisfy asymptotic normality, such that inference based on the asymptotic standard errors obtained from the constrained maximization can be incorrect (Barnett and Seck, 2008). A potential solution is to estimate standard errors by bootstrap instead. However, the bootstrap requires to repeat the maximum likelihood estimation for $1,200$ bootstrap replications. As the maximum likelihood estimation critically depends on the choice of the initial value, several randomly chosen initial guesses are required to make sure that the algorithm converges to the global maximum. Therefore, the bootstrap procedure becomes computationally extremely demanding. We use the bootstrap only as a robustness check for the main results, and otherwise report the asymptotic standard errors obtained from the constrained maximization. We find that the estimated bootstrap standard errors are similar in magnitude. Details on the bootstrap procedure and the estimated bootstrap statistics are explained in appendix section A.3.1.

5.3 Results

Table 9 presents the maximum likelihood estimation results.[33] The estimated mean $\hat{\mu}_r$ of the distribution of the risk aversion coefficient r implies that the average participant has an intermediate level of risk-aversion. Because $\tilde{r}_{BC} < \hat{\mu}_r < \tilde{r}_{AB}$, the average participant favors alternative B. From the estimated standard deviation we can derive the 95% confidence interval of r, which is $CI_r^{0.95} = [-0.540, 2.252]$. Hence our sample contains participants who are strongly risk-averse but also risk-seeking participants.

Table 9: Results of the structural model estimation for $r \sim \mathcal{N}(\mu_r, \sigma_r)$ and $(1 - v) \sim \text{Lognormal}(\mu_v, \sigma_v)$.

Parameter	Estimate	Standard error	p-value
μ_r	0.856	0.024	< 0.001
σ_r	0.712	0.034	< 0.001
μ_v	0.010	0.002	< 0.001
σ_v	0.048	0.010	< 0.001

From the estimated parameters $\hat{\mu}_v$ and $\hat{\sigma}_v$ of the distribution of the scaling factor $1 - v$, we can derive further properties of the distribution of $1 - v$. The estimated mean $\mathbb{E}[1 - v] = 1.012$ indicates that the estimated value of choice v is negative, as expected from the positive treatment effect on first alternative choices. The average individual valuates the outcomes of a lottery 1.2% higher when this lottery is the singleton compared to when it is part of a larger choice set.[34] The estimated standard deviation is $sd[1 - v] = 0.049$ and the estimated 95% confidence interval of $1 - v$ is $CI_{1-v}^{0.95} = [0.920, 1.111]$. This indicates that participants with a positive value of choice valuate the outcomes of a lottery up to 8% lower when this lottery is the singleton compared to when it is part of a larger choice set, while participants with a negative value of choice valuate them up to 11% higher. Moreover, we estimate $P(1 - v < 1) = 0.411$, indicating that around 41% of the participants have a positive value of choice.

As a robustness check, we repeat the estimation on the subsample of participants with response times equal to or above the 25th percentile. The estimated mean of the scaling factor

[33]The bootstrap simulation results can be found in appendix table A.18.

[34]Given that the outcomes of the lotteries in our experiment are in the ballpark of 10 euros, the average willingness to pay for not having to choose is around 10 cents. As the median response time for the second stage in the two-stage treatment is 12 seconds, interpreting this value as a measure of opportunity costs would correspond to an hourly net wage of 30 euros, which is not unusual but nevertheless quite high. We thus conclude that, on average, participants must perceive their choice as costly for additional and different reasons.

$1-v$ is slightly lower in this subsample, and the variance is slightly higher (appendix tables A.21 and A.22). In this subsample, around 43% are estimated to have a positive value of choice.[35] Thus, all in all, our results indicate that – hidden behind the average treatment effect – there is considerable heterogeneity in terms of the value of choice within our sample.

6 Conclusion

In this paper, we investigate whether people enjoy making choices. On the one hand, recommendations might benefit consumers who do not care about making choices themselves. On the other hand, if consumers value choice per se, then even well founded recommendations that are supposedly in the consumer's best interest may trigger opposition, and lead to inferior choices and thus to welfare losses.

The evidence from our experiment yields three main insights. First, a larger share of participants picks the first alternative in the two-stage treatment than in the one-stage treatment, indicating that the majority of participants has a preference for not making active choices: They are more likely to choose a particular course of action if that choice requires less steps in their decision making process. Consistent with that, the estimation of our structural model yields a negative mean value of choice. This result indicates that algorithms based on paternalistic or assisted choices can make many individuals better off. It can also explain the widespread use of such technologies in practice.

Second, we find that hidden behind the average treatment effect, there is substantial subject heterogeneity. According to the estimates of our structural model, around 41% of the participants have a positive value of choice, and the value of choice ranges from -11% to 8% of the monetary payoffs of the lottery presented as singleton. This heterogeneity indicates that there is not one choice structure that fits all preferences. On the one hand, consumers with a positive value of choice are better off when they are presented a full range of alternatives and hence suffer substantial welfare losses from a binding preselection of alternatives. On the other hand, those with a negative value of choice benefit from the preselection. Thus, even conditional on the individually preferred alternative being the recommended one, the impact of the choice structure on consumers' decicisons critically depends on their preferences for choice. This result stresses the importance of consumer heterogeneity for those who design recommender systems, and raises the question of whether one can tailor the choice structure to choice preferences.

Our third finding is that measurable individual characteristics correlate with the preference

[35] Overall, our results indicate that the estimation is robust to restricting the sample to other subsets, as long as the size of the subsamples is sufficiently large. To investigate whether the distribution of the value of choice differs between right-wing and center-left participants, we also ran two estimations on these two subsamples. Restricting the sample to those who are strictly to the right of the median participant's position ($n_{\text{right}} = 500$) however yields unreliable estimation results. In particular, while the estimated mean of $1-v$ is the same in the right-wing subsample as in the overall sample, the estimated variance of $1-v$ is very close to zero. The distribution of the left-wing subsample however is very similar to the distribution on the overall sample. Therefore, the combination of the estimated distributions of the two subsamples is hardly compatible with the estimated distribution of the overall sample. We further studied the effect of sample size by randomly creating a subsample of size 500 and repeating the estimation on this subsample as well as on the remaining sample. In this case again the estimated mean remains the same in both samples, but the estimated variance of $1-v$ is again smaller in the small sample than in the large sample. This exercise indicates that sample size matters for the reliability our estimates.

for choice. Such variables are often available to firms or institutions and might be used to adapt the choice structure in order to cater to individuals' preferences – thus opening a path to increase the efficiency of recommender systems beyond the current level.

Moreover, the availability of consumer data allows firms to personalize the recommended alternative in order to match the individual's preferences. Future research might investigate how personalizing the preselected alternative impacts the treatment effect. In our experiment, we randomize which alternative is presented as the singleton. Because participants already exhibit a negative value of choice when the preselected alternative is randomized, the natural conjecture is that the preference for not choosing will increase when the preselected alternative is personalized.

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A Additional Results

A.1 Descriptive Results

Table A.1: Relative frequencies of choices in the baseline choice set, for all permutations of the three alternatives

Treatment	Permutation	Choice of A	Choice of B	Choice of C
One-stage	$\{A, B, C\}$	0.41	0.35	0.23
	$\{A, C, B\}$	0.43	0.25	0.32
	$\{B, A, C\}$	0.48	0.23	0.29
	$\{B, C, A\}$	0.52	0.16	0.32
	$\{C, A, B\}$	0.55	0.21	0.24
	$\{C, B, A\}$	0.42	0.32	0.26
Two-stage	$\{A\}$ vs $\{B, C\}$	0.50	0.24	0.26
	$\{A\}$ vs $\{C, B\}$	0.50	0.24	0.26
	$\{B\}$ vs $\{A, C\}$	0.37	0.41	0.22
	$\{B\}$ vs $\{C, A\}$	0.33	0.40	0.27
	$\{C\}$ vs $\{A, B\}$	0.46	0.20	0.33
	$\{C\}$ vs $\{B, A\}$	0.40	0.19	0.40

Table A.2: Relative frequencies of choices in the additional choice set, for all permutations of the four alternatives

Treatment	Permutation	Choice of A	Choice of B	Choice of C	Choice of D
One-stage	$\{C, A, B, D\}$	0.25	0.13	0.13	0.49
	$\{C, A, D, B\}$	0.32	0.05	0.15	0.48
	$\{C, D, A, B\}$	0.31	0.08	0.16	0.45
Two-stage	$\{C\}$ vs $\{A, B, D\}$	0.18	0.11	0.21	0.49
	$\{C\}$ vs $\{A, D, B\}$	0.14	0.08	0.34	0.45
	$\{C\}$ vs $\{D, A, B\}$	0.18	0.06	0.32	0.44

Table A.3: Robustness check: Relative frequencies of choices in the baseline choice set, for the subsample with response times equal to or above the 25th percentile

Treatment	Alternative presented first	Choice of A	Choice of B	Choice of C
One-stage	A	0.39	0.32	0.29
	B	0.50	0.19	0.31
	C	0.48	0.25	0.26
Two-stage	A	0.50	0.26	0.24
	B	0.36	0.39	0.25
	C	0.44	0.20	0.36

Table A.4: Robustness check: Relative frequencies of choices in the additional choice set with four alternatives, for the subsample with response times equal to or above the 25th percentile

Treatment	Alternative presented first	Choice of A	Choice of B	Choice of C	Choice of D
One-stage	C	0.26	0.08	0.13	0.52
Two-stage	C	0.16	0.08	0.26	0.50

A.2 Regression Analysis

Table A.5: Overview of the variables used in the regression analysis and how they are constructed from the GIP questions

Variable	GIP wave	Description
Age	57	denotes the mid point (in years) of the 14 age categories
Agreeableness	13, 37	average score of the two items on agreeableness from the BFI-10 (where the negatively coded item is re-coded before averaging), ranges from 1 to 5, where higher values mean higher levels of agreeableness
Choosing the first alternative	57	binary indicator variable which takes the value 1 if participant chose the alternative presented first
Conscientiousness	13, 37	average score of the two items on conscientiousness from the BFI-10 (where the negatively coded item is re-coded before averaging), ranges from 1 to 5, where higher values mean higher levels of conscientiousness
Extraversion	13, 37	average score of the two items on extraversion from the BFI-10 (where the negatively coded item is re-coded before averaging), ranges from 1 to 5, where higher values mean higher levels of extraversion
Female	57	binary indicator variable which takes the value 1 if the participant reported to be female
First alternative	57	categorical variable, indicates which alternative was presented first (one-stage treatment) or as singleton (two-stage treatment), with "A first" as the omitted reference category
Group	57	categorical variable for the assignment to the permutation of the three alternatives, with "ABC" as the omitted reference category
High income	55	binary indicator variable which takes the value 1 if the participant's household income is above the median (i.e. above 3500 Euro)
High-school education	57	binary indicator variable which takes the value 1 if the participant completed the high-school diploma (Abitur)
Neuroticism	13, 37	average score of the two items on neuroticism from the BFI-10 (where the negatively coded item is re-coded before averaging), ranges from 1 to 5, where higher values mean higher levels of neuroticism
Ideas	42	binary indicator variable which takes the value 1 if the participant's level of agreement with the statement "it is important to me to realize my own ideas" is equal to or above the median participant's level
Independence	42	binary indicator variable which takes the value 1 if the participant's level of agreement with the statement "it is important to me to work independently" is equal to or above the median participant's level
Openness	13, 37	average score of the two items on openness from the BFI-10 (where the negatively coded item is re-coded before averaging), ranges from 1 to 5, where higher values mean higher levels of openness
People's decisions	46	binary indicator variable which takes the value 1 if the participant's level of agreement with the statement "the most important political decisions should be made by the people, not by politicians" is above the median participant's level
Right-wing	55	binary indicator variable which takes the value 1 if, on a scale from 1 (left) to 11 (right), the participant reported to be strictly further on the right than the median participant's position (which is 6)
Two-stage treatment	57	binary indicator variable which takes the value 1 if the participant was assigned to the two-stage treatment

Table A.6: Full Table: OLS regression for lottery choice and political orientation

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.116^{***}	0.046	0.062
	(0.018)	(0.038)	(0.040)
Right-wing	−0.025	−0.033	−0.027
	(0.025)	(0.024)	(0.026)
B first		-0.241^{***}	-0.254^{***}
		(0.033)	(0.034)
C first		-0.178^{***}	-0.176^{***}
		(0.035)	(0.037)
C first (additional)		-0.286^{***}	-0.283^{***}
		(0.030)	(0.031)
Female			−0.022
			(0.017)
Age			0.001^{*}
			(0.001)
High-school education			0.014
			(0.018)
High income			−0.006
			(0.017)
Two-stage treatment * right-wing	0.072^{*}	0.076^{**}	0.069^{*}
	(0.039)	(0.038)	(0.040)
Two-stage treatment * B first		0.147^{***}	0.132^{**}
		(0.049)	(0.052)
Two-stage treatment * C first		0.057	0.040
		(0.050)	(0.053)
Two-stage treatment * C first (additional)		0.071	0.047
		(0.044)	(0.047)
Constant	0.252^{***}	0.442^{***}	0.391^{***}
	(0.012)	(0.026)	(0.045)
Observations	3,266	3,266	2,897
R^2	0.021	0.064	0.069
Adjusted R^2	0.020	0.061	0.065

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *Right-wing* is a binary indicator variable for the participant's political position on the left-right spectrum. *First alternative* captures which alternative was presented first, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which *C* was always presented first.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table A.7: Robustness check: OLS regression for lottery choice and political orientation

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.116***	0.068	0.098*
	(0.018)	(0.053)	(0.055)
Right-wing	−0.025	−0.033	−0.025
	(0.025)	(0.024)	(0.026)
Group ACB		0.010	0.042
		(0.052)	(0.054)
Group BAC		−0.183***	−0.181***
		(0.049)	(0.051)
Group BCA		−0.286***	−0.280***
		(0.044)	(0.046)
Group CAB		−0.179***	−0.155***
		(0.049)	(0.052)
Group CBA		−0.166***	−0.153***
		(0.050)	(0.052)
Group CABD		−0.292***	−0.265***
		(0.045)	(0.047)
Group CADB		−0.278***	−0.244***
		(0.046)	(0.049)
Group CDAB		−0.272***	−0.274***
		(0.045)	(0.046)
Female			−0.022
			(0.017)
Age			0.001
			(0.001)
High-school education			0.014
			(0.018)
High income			−0.007
			(0.017)
Two-stage treatment * right-wing	0.072*	0.078**	0.069*
	(0.039)	(0.038)	(0.040)
Two-stage treatment * group ACB		−0.045	−0.071
		(0.074)	(0.077)
Two-stage treatment * group BAC		0.046	0.021
		(0.071)	(0.075)
Two-stage treatment * group BCA		0.201***	0.168**
		(0.069)	(0.072)
Two-stage treatment * group CAB		−0.0003	−0.039
		(0.071)	(0.075)
Two-stage treatment * group CBA		0.067	0.046
		(0.072)	(0.076)
Two-stage treatment * group CABD		−0.005	−0.047
		(0.066)	(0.069)
Two-stage treatment * group CADB		0.086	0.015
		(0.068)	(0.072)
Two-stage treatment * group CDAB		0.066	0.065
		(0.067)	(0.070)
Constant	0.252***	0.437***	0.370***
	(0.012)	(0.037)	(0.052)

Observations	3,266	3,266	2,897
R^2	0.021	0.068	0.074
Adjusted R^2	0.020	0.063	0.067

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *Right-wing* is a binary indicator variable for the participant's political position on the left-right spectrum. *Group* is a categorical variable for the permutation of the alternatives in the choice set. The omitted reference category is "group ABC". Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table A.8: Robustness check: Probit regression for lottery choice and political orientation

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.331***	0.106	0.150
	(0.052)	(0.097)	(0.103)
Right-wing	−0.079	−0.113	−0.090
	(0.082)	(0.084)	(0.091)
B first		−0.702***	−0.758***
		(0.100)	(0.108)
C first		−0.491***	−0.487***
		(0.098)	(0.104)
C first (additional)		−0.878***	−0.882***
		(0.093)	(0.099)
Female			−0.071
			(0.051)
Age			0.003*
			(0.002)
High-school education			0.045
			(0.054)
High income			−0.017
			(0.052)
Two-stage treatment * right-wing	0.201*	0.227**	0.205*
	(0.112)	(0.114)	(0.122)
Two-stage treatment * B first		0.463***	0.447***
		(0.137)	(0.148)
Two-stage treatment * C first		0.182	0.140
		(0.136)	(0.144)
Two-stage treatment * C first (additional)		0.310**	0.252*
		(0.127)	(0.136)
Constant	−0.668***	−0.139**	−0.300**
	(0.038)	(0.069)	(0.129)
Observations	3,266	3,266	2,897
Log Likelihood	−1,993.034	−1,920.856	−1,679.567
AIC	3,994.068	3,861.713	3,387.134

Note: Probit regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *Right-wing* is a binary indicator variable for the participant's political position on the left-right spectrum. *First alternative* captures which alternative was presented first, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which C was always presented first. AIC is the Akaike information criterion.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table A.9: Robustness check: OLS regression for lottery choice and political orientation on the subsample with response times equal to or above the 25th percentile

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.112^{***}	0.086^{**}	0.115^{**}
	(0.020)	(0.043)	(0.046)
Right-wing	−0.017	−0.017	−0.021
	(0.028)	(0.028)	(0.030)
B first		-0.200^{***}	-0.203^{***}
		(0.038)	(0.039)
C first		-0.108^{***}	-0.103^{**}
		(0.041)	(0.043)
C first (additional)		-0.253^{***}	-0.242^{***}
		(0.033)	(0.035)
Female			−0.018
			(0.019)
Age			0.001
			(0.001)
High-school education			−0.007
			(0.020)
High income			0.013
			(0.019)
Two-stage treatment * right-wing	0.087^{**}	0.082^{*}	0.091^{**}
	(0.044)	(0.043)	(0.046)
Two-stage treatment * B first		0.114^{**}	0.080
		(0.057)	(0.060)
Two-stage treatment * C first		−0.024	−0.058
		(0.059)	(0.062)
Two-stage treatment * C first (additional)		0.021	−0.020
		(0.050)	(0.052)
Constant	0.237^{***}	0.392^{***}	0.344^{***}
	(0.014)	(0.030)	(0.050)
Observations	2,498	2,498	2,231
R^2	0.023	0.064	0.070
Adjusted R^2	0.021	0.061	0.064

Note: OLS regression, robust standard errors in parentheses. The regression is estimated on the subsample of participants with response times equal to or above the 25th percentile of the one-stage treatment or the first stage of the two-stage treatment. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *Right-wing* is a binary indicator variable for the participant's political position on the left-right spectrum. *First alternative* captures which alternative was presented first, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which C was always presented first.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table A.10: Robustness check: Probit regression for lottery choice and political orientation on the subsample with response times equal to or above the 25th percentile

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.328***	0.212*	0.288**
	(0.060)	(0.112)	(0.119)
Right-wing	−0.057	−0.059	−0.071
	(0.095)	(0.098)	(0.106)
B first		−0.600***	−0.624***
		(0.117)	(0.126)
C first		−0.298***	−0.287**
		(0.114)	(0.121)
C first (additional)		−0.816***	−0.798***
		(0.106)	(0.112)
Female			−0.060
			(0.059)
Age			0.003
			(0.002)
High-school education			−0.024
			(0.062)
High income			0.044
			(0.060)
Two-stage treatment * right-wing	0.240*	0.233*	0.258*
	(0.129)	(0.131)	(0.141)
Two-stage treatment * B first		0.383**	0.310*
		(0.159)	(0.171)
Two-stage treatment * C first		−0.040	−0.130
		(0.158)	(0.168)
Two-stage treatment * C first (additional)		0.192	0.086
		(0.147)	(0.156)
Constant	−0.715***	−0.271***	−0.430***
	(0.044)	(0.079)	(0.150)
Observations	2,498	2,498	2,231
Log Likelihood	−1,495.805	−1,441.530	−1,268.998
AIC	2,999.609	2,903.061	2,565.996

Note: Probit regression, robust standard errors in parentheses. The regression is estimated on the subsample of participants with response times equal to or above the 25th percentile of the one-stage treatment or the first stage of the two-stage treatment. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *Right-wing* is a binary indicator variable for the participant's political position on the left-right spectrum. *First alternative* captures which alternative was presented first, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which C was always presented first. AIC is the Akaike information criterion.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table A.11: Full table: OLS regression for lottery choice and job motivation

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.121***	0.037	0.060
	(0.031)	(0.044)	(0.049)
Independence	−0.036	−0.041*	−0.030
	(0.022)	(0.022)	(0.024)
Own ideas	0.029	0.024	0.023
	(0.023)	(0.022)	(0.024)
B first		−0.256***	−0.261***
		(0.032)	(0.035)
C first		−0.199***	−0.191***
		(0.033)	(0.037)
C first (additional)		−0.293***	−0.299***
		(0.029)	(0.032)
Female			−0.011
			(0.017)
Age			0.001
			(0.001)
High-school education			0.011
			(0.018)
High income			−0.010
			(0.017)
Two-stage treatment * independence	0.041	0.043	0.038
	(0.033)	(0.032)	(0.036)
Two-stage treatment * own ideas	−0.023	−0.022	−0.029
	(0.034)	(0.033)	(0.037)
Two-stage treatment * B first		0.161***	0.140***
		(0.047)	(0.053)
Two-stage treatment * C first		0.069	0.040
		(0.048)	(0.054)
Two-stage treatment * C first (additional)		0.090**	0.061
		(0.042)	(0.047)
Constant	0.250***	0.455***	0.408***
	(0.021)	(0.031)	(0.048)
Observations	3,638	3,638	2,920
R^2	0.021	0.063	0.069
Adjusted R^2	0.019	0.060	0.064

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *Independence* is a binary indicator variable for the importance of working independently. *Own ideas* is a binary indicator variable for the importance of realizing own ideas. *First alternative* captures which alternative was presented first, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which *C* was always presented first.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table A.12: Full table: OLS regression for lottery choice and political decision making

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.123***	0.046	0.050
	(0.019)	(0.037)	(0.041)
People's decisions	−0.022	−0.023	−0.031
	(0.020)	(0.020)	(0.022)
B first		−0.248***	−0.256***
		(0.031)	(0.034)
C first		−0.191***	−0.189***
		(0.032)	(0.036)
C first (additional)		−0.287***	−0.291***
		(0.028)	(0.031)
Female			−0.016
			(0.017)
Age			0.001
			(0.001)
High-school education			0.016
			(0.018)
High income			−0.010
			(0.017)
Two-stage treatment * people's decisions	0.040	0.041	0.053
	(0.031)	(0.030)	(0.034)
Two-stage treatment * B first		0.154***	0.149***
		(0.046)	(0.052)
Two-stage treatment * C first		0.060	0.046
		(0.047)	(0.053)
Two-stage treatment * C first (additional)		0.086**	0.066
		(0.042)	(0.046)
Constant	0.252***	0.445***	0.412***
	(0.013)	(0.026)	(0.045)
Observations	3,721	3,721	2,990
R^2	0.023	0.063	0.070
Adjusted R^2	0.022	0.061	0.065

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *People's decisions* is a binary indicator variable for whether the participant wants important decisions to be made by the people instead of politicians. *First alternative* captures which alternative was presented first, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which C was always presented first.

Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table A.13: Full table: OLS regression for lottery choice and Big Five Personality Traits

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	−0.009	−0.087	0.002
	(0.121)	(0.122)	(0.139)
Extraversion	−0.004	−0.003	0.003
	(0.011)	(0.011)	(0.012)
Agreeableness	−0.002	−0.005	−0.006
	(0.013)	(0.013)	(0.014)
Conscientiousness	−0.002	−0.003	0.011
	(0.014)	(0.013)	(0.016)
Neuroticism	−0.005	−0.004	−0.019
	(0.012)	(0.011)	(0.013)
Openness	-0.022^{*}	-0.020^{*}	−0.016
	(0.011)	(0.011)	(0.012)
B first		-0.232^{***}	-0.247^{***}
		(0.030)	(0.034)
C first		-0.177^{***}	-0.171^{***}
		(0.032)	(0.036)
C first (additional)		-0.275^{***}	-0.282^{***}
		(0.028)	(0.030)
Female			−0.028
			(0.017)
Age			0.001
			(0.001)
High-school education			0.015
			(0.018)
High income			−0.006
			(0.017)
Two-stage treatment * Extraversion	−0.001	−0.0004	−0.007
	(0.017)	(0.017)	(0.019)
Two-stage treatment * Agreeableness	−0.010	−0.002	−0.005
	(0.020)	(0.020)	(0.022)
Two-stage treatment * Conscientiousness	0.023	0.023	0.002
	(0.020)	(0.020)	(0.023)
Two-stage treatment * Neuroticism	−0.025	−0.027	−0.010
	(0.018)	(0.017)	(0.019)
Two-stage treatment * Openness	0.049^{***}	0.046^{***}	0.040^{**}
	(0.016)	(0.016)	(0.018)
Two-stage treatment * B first		0.142^{***}	0.140^{***}
		(0.046)	(0.051)
Two-stage treatment * C first		0.052	0.025
		(0.046)	(0.052)
Two-stage treatment * C first (additional)		0.076^{*}	0.057
		(0.041)	(0.045)
Constant	0.357^{***}	0.545^{***}	0.478^{***}
	(0.081)	(0.082)	(0.096)
Observations	3,888	3,888	3,065
R^2	0.027	0.065	0.070

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. All personality traits range from 1 to 5, where higher values mean that the participant exhibits a higher level of this personality trait. *First alternative* captures which alternative was presented first and its interaction with the treatment variable, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which C was always presented first.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table A.14: Probit regression for lottery choice and Big Five personality traits

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	−0.065	−0.335	−0.058
	(0.352)	(0.367)	(0.421)
Extraversion	−0.013	−0.011	0.010
	(0.036)	(0.037)	(0.042)
Agreeableness	−0.004	−0.016	−0.020
	(0.042)	(0.043)	(0.049)
Conscientiousness	−0.008	−0.009	0.040
	(0.044)	(0.045)	(0.053)
Neuroticism	−0.015	−0.014	−0.062
	(0.037)	(0.039)	(0.044)
Openness	-0.069^{**}	-0.069^{*}	−0.057
	(0.035)	(0.035)	(0.041)
B first		-0.681^{***}	-0.733^{***}
		(0.093)	(0.105)
C first		-0.494^{***}	-0.472^{***}
		(0.090)	(0.102)
C first (additional)		-0.850^{***}	-0.878^{***}
		(0.086)	(0.096)
Female			−0.087
			(0.053)
Age			0.003
			(0.002)
High-school education			0.048
			(0.054)
High income			−0.017
			(0.051)
Two-stage treatment * Extraversion	0.0001	0.003	−0.020
	(0.049)	(0.050)	(0.057)
Two-stage treatment * Agreeableness	−0.025	−0.004	−0.011
	(0.058)	(0.059)	(0.068)
Two-stage treatment * Conscientiousness	0.064	0.064	−0.002
	(0.060)	(0.061)	(0.070)
Two-stage treatment * Neuroticism	−0.064	−0.069	−0.019
	(0.051)	(0.052)	(0.059)
Two-stage treatment * Openness	0.142^{***}	0.140^{***}	0.122^{**}
	(0.048)	(0.048)	(0.055)
Two-stage treatment * B first		0.451^{***}	0.459^{***}
		(0.127)	(0.144)
Two-stage treatment * C first		0.173	0.097
		(0.125)	(0.141)
Two-stage treatment * C first (additional)		0.325^{***}	0.281^{**}
		(0.117)	(0.132)
Constant	−0.331	0.212	−0.025
	(0.259)	(0.273)	(0.324)
Observations	3,888	3,888	3,065
Log Likelihood	−2,358.123	−2,280.746	−1,782.807
AIC	4,740.245	4,597.493	3,609.613

Note: Probit regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. All personality traits range from 1 to 5, where higher values mean that the participant exhibits a higher level of this personality trait. *First alternative* captures which alternative was presented first and its interaction with the treatment variable, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which C was always presented first. AIC is the Akaike information criterion.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table A.15: Robustness check: OLS regression for lottery choice and Big Five personality traits on the subsample with response times equal to or above the 25th percentile

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	−0.229	−0.248*	−0.163
	(0.140)	(0.141)	(0.159)
Extraversion	−0.023*	−0.019	−0.012
	(0.013)	(0.013)	(0.014)
Agreeableness	−0.015	−0.017	−0.021
	(0.015)	(0.015)	(0.017)
Conscientiousness	0.006	0.002	0.007
	(0.016)	(0.016)	(0.018)
Neuroticism	−0.002	−0.001	−0.020
	(0.013)	(0.013)	(0.015)
Openness	−0.035***	−0.032**	−0.023
	(0.013)	(0.012)	(0.014)
B first		−0.197***	−0.205***
		(0.035)	(0.039)
C first		−0.123***	−0.109***
		(0.037)	(0.042)
C first (additional)		−0.252***	−0.251***
		(0.031)	(0.034)
Female			−0.024
			(0.020)
Age			0.001
			(0.001)
High-school education			−0.007
			(0.020)
High income			0.011
			(0.019)
Two-stage treatment * Extraversion	0.020	0.020	0.007
	(0.020)	(0.019)	(0.021)
Two-stage treatment * Agreeableness	0.001	0.008	0.017
	(0.023)	(0.023)	(0.026)
Two-stage treatment * Conscientiousness	0.024	0.025	0.008
	(0.024)	(0.023)	(0.026)
Two-stage treatment * Neuroticism	−0.013	−0.016	0.001
	(0.020)	(0.020)	(0.022)
Two-stage treatment * Openness	0.069***	0.063***	0.052**
	(0.019)	(0.018)	(0.021)
Two-stage treatment * B first		0.092*	0.084
		(0.053)	(0.059)
Two-stage treatment * C first		−0.011	−0.065
		(0.054)	(0.060)
Two-stage treatment * C first (additional)		0.024	−0.011
		(0.046)	(0.051)
Constant	0.454***	0.608***	0.577***
	(0.096)	(0.097)	(0.115)
First alternative	No	Yes	Yes
Controls	No	No	Yes
Observations	2,937	2,937	2,350

R^2	0.029	0.068	0.073
Adjusted R^2	0.025	0.062	0.065

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. The regression is estimated on the subsample of participants with response times equal to or above the 25th percentile of the one-stage treatment or the first stage of the two-stage treatment. All personality traits range from 1 to 5, where higher values mean that the participant exhibits a higher level of this personality trait. *First alternative* captures which alternative was presented first and its interaction with the treatment variable, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which C was always presented first. Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table A.16: Robustness check: Probit regression for lottery choice and Big Five personality traits on the subsample with response times equal to or above the 25th percentile

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	-0.726^{*}	-0.866^{**}	-0.633
	(0.418)	(0.436)	(0.498)
Extraversion	-0.076^{*}	-0.068	-0.040
	(0.042)	(0.044)	(0.050)
Agreeableness	-0.048	-0.056	-0.073
	(0.051)	(0.052)	(0.060)
Conscientiousness	0.020	0.008	0.028
	(0.052)	(0.055)	(0.062)
Neuroticism	-0.008	-0.004	-0.070
	(0.044)	(0.046)	(0.053)
Openness	-0.114^{***}	-0.109^{***}	-0.080
	(0.042)	(0.042)	(0.049)
B first		-0.594^{***}	-0.627^{***}
		(0.109)	(0.123)
C first		-0.344^{***}	-0.303^{**}
		(0.105)	(0.119)
C first (additional)		-0.817^{***}	-0.824^{***}
		(0.099)	(0.110)
Female			-0.076
			(0.061)
Age			0.003
			(0.002)
High-school education			-0.021
			(0.062)
High income			0.038
			(0.059)
Two-stage treatment * Extraversion	0.070	0.070	0.029
	(0.058)	(0.059)	(0.067)
Two-stage treatment * Agreeableness	0.011	0.033	0.065
	(0.069)	(0.071)	(0.081)
Two-stage treatment * Conscientiousness	0.061	0.067	0.013
	(0.071)	(0.073)	(0.082)
Two-stage treatment * Neuroticism	-0.032	-0.042	0.016
	(0.060)	(0.061)	(0.068)
Two-stage treatment * Openness	0.205^{***}	0.197^{***}	0.163^{**}
	(0.056)	(0.057)	(0.065)
Two-stage treatment * B first		0.326^{**}	0.318^{*}
		(0.149)	(0.168)
Two-stage treatment * C first		-0.002	-0.148
		(0.146)	(0.165)
Two-stage treatment * C first (additional)		0.204	0.114
		(0.136)	(0.152)
Constant	-0.005	0.465	0.349
	(0.315)	(0.331)	(0.397)
First alternative	No	Yes	Yes
Controls	No	No	Yes
Observations	2,937	2,937	2,350

Log Likelihood	−1,744.528	−1,684.156	−1,338.890
AIC	3,513.056	3,404.312	2,721.781

Note: Probit regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. The regression is estimated on the subsample of participants with response times equal to or above the 25th percentile of the one-stage treatment or the first stage of the two-stage treatment. All personality traits range from 1 to 5, where higher values mean that the participant exhibits a higher level of this personality trait. *First alternative* captures which alternative was presented first and its interaction with the treatment variable, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which C was always presented first. AIC is the Akaike information criterion.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table A.17: OLS regression for lottery choice, political attitude, and Big Five personality traits

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.027	-0.077	-0.071
	(0.136)	(0.138)	(0.145)
Right-wing	-0.032	-0.041^{*}	-0.039
	(0.026)	(0.025)	(0.027)
Extraversion	0.001	0.004	0.006
	(0.013)	(0.012)	(0.013)
Agreeableness	-0.008	-0.011	-0.017
	(0.015)	(0.014)	(0.015)
Conscientiousness	0.004	0.003	0.009
	(0.015)	(0.015)	(0.016)
Neuroticism	-0.012	-0.013	-0.027^{**}
	(0.013)	(0.013)	(0.014)
Openness	-0.017	-0.019	-0.014
	(0.013)	(0.012)	(0.013)
B first		-0.248^{***}	-0.260^{***}
		(0.033)	(0.035)
C first		-0.179^{***}	-0.175^{***}
		(0.036)	(0.037)
C first (additional)		-0.287^{***}	-0.281^{***}
		(0.030)	(0.032)
Female			-0.039^{**}
			(0.018)
Age			0.001
			(0.001)
High-school education			0.015
			(0.018)
High income			-0.005
			(0.017)
Two-stage treatment *Right-wing	0.081^{**}	0.087^{**}	0.082^{**}
	(0.040)	(0.039)	(0.041)
Two-stage treatment * Extraversion	-0.007	-0.010	-0.007
	(0.019)	(0.018)	(0.019)
Two-stage treatment * Agreeableness	-0.012	-0.005	0.005
	(0.022)	(0.022)	(0.023)
Two-stage treatment * Conscientiousness	0.023	0.022	0.010
	(0.023)	(0.023)	(0.024)
Two-stage treatment * Neuroticism	-0.023	-0.021	-0.010
	(0.020)	(0.019)	(0.020)
Two-stage treatment * Openness	0.037^{**}	0.039^{**}	0.036^{*}
	(0.019)	(0.018)	(0.019)
Two-stage treatment * B first		0.158^{***}	0.144^{***}
		(0.050)	(0.053)
Two-stage treatment * C first		0.064	0.045
		(0.051)	(0.054)
Two-stage treatment * C first (additional)		0.082^{*}	0.057
		(0.045)	(0.047)
Constant	0.355^{***}	0.561^{***}	0.540^{***}
	(0.092)	(0.092)	(0.101)

First alternative	No	Yes	Yes
Controls	No	No	Yes
Observations	3,197	3,197	2,832
R^2	0.025	0.067	0.073
Adjusted R^2	0.021	0.061	0.065

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *Right-wing* is a binary indicator variable for the participant's political position on the left-right spectrum. All personality traits range from 1 to 5, where higher values mean that the participant exhibits a higher level of this personality trait. *First alternative* captures which alternative was presented first and its interaction with the treatment variable, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which C was always presented first. Significance levels: *p<0.1; **p<0.05; ***p<0.01

A.3 Estimation of the Structural Model

A.3.1 Bootstrap

For the maximum likelihood estimation, we have to impose two inequality constraints on the parameters σ_r and σ_v, which naturally cannot be negative. In that case, although the point estimates of the parameters can be estimated correctly, inference based on the asymptotic standard errors obtained from the constrained maximization can be incorrect (Barnett and Seck, 2008). Therefore, we estimate standard errors by bootstrap. The bootstrap method allows for consistent estimation of the standard errors when asymptotic inference is unreliable, by approximating the distribution of the parameters of interest through Monte Carlo simulation. In particular, we randomly draw with replacement from our sample to create $B = 1,200$ bootstrap samples of the same size n as the original sample. Then we obtain the maximum likelihood estimates of the four parameters for each of the B bootstrap samples. To make sure that the maximum likelihood estimates are reliable, we use 10 randomly drawn initial guesses within each bootstrap replication.[36] We use the estimated bootstrap parameters to construct a bias-corrected estimator, the bootstrap standard errors, and confidence intervals. In particular, let θ denote any parameter of interest, and θ^* its maximum likelihood estimate obtained for the original sample. Let $\{\hat{\theta}_1, ..., \hat{\theta}_B\}$ denote the estimates from the B bootstrap replications. Moreover, let $\overline{\theta}$ denote the arithmetic mean of the B bootstrap estimates. Then, the estimated bootstrap bias-corrected estimator is

$$\tilde{\theta} = 2\theta^* - \overline{\theta}.$$

The bootstrap standard error of the maximum likelihood estimate θ^* is

$$\hat{s}(\theta^*) = \sqrt{\frac{1}{B}\sum_{b=1}^{B}\left(\hat{\theta}_b - \overline{\theta}\right)^2}.$$

Let $\hat{q}(\alpha)$ denote the α-th sample quantile of the statistics $\hat{\theta} - \theta^*$. Then a bootstrap $(1-\alpha)\%$ confidence interval is

$$\hat{C} = \left[\theta^* + \hat{q}\left(\frac{\alpha}{2}\right), \theta^* + \hat{q}\left(1 - \frac{\alpha}{2}\right)\right].$$

Note however that $\hat{C}$ might work poorly when the bootstrap estimates $\hat{\theta}$ are not symmetrically distributed around θ^*, i.e. when the sampling distribution is biased. For further details on the bootstrap procedure and the simulation estimates, see Hansen (2002).

Table A.18 presents the bootstrap simulation results. We conduct Kolmogorov-Smirnov tests for normality of the bootstrap distribution of each parameter. Although limiting normality is impossible for the constrained σ_r and σ_v parameters, where the non-negativity constraints

[36] Note that especially the estimation of μ_v and σ_v critically depends on the initial guess. Because conducting 12,000 maximum likelihood estimations is computationally already very demanding, we cannot increase the number of initial guesses further. The bootstrap distributions of μ_v and σ_v both exhibit some outliers, indicating that in some cases, the algorithm does not converge to the global maximum. Therefore, the results below should be taken with caution.

truncate the limiting distribution, the validity of using asymptotic standard errors might be strengthened if the Kolmogorov-Smirnov tests fail to reject normality (Barnett and Seck, 2008). We find that normality of μ_r, σ_r, and μ_v cannot be rejected ($p = 0.719$, $p = 0.508$, and $p = 0.310$ respectively). For σ_v however normality is rejected ($p = 0.001$). Moreover, the bootstrap results are in line with the previous results based on aymptotic theory: The bootstrap standard errors are similar in magnitude to the asymptotic standard errors, and the bootstrap 95% confidence intervals indicate that μ_v or σ_v are significantly different from zero.

Table A.18: Estimation results and bootstrap statistics for $r \sim \mathcal{N}(\mu_r, \sigma_r)$ and $(1 - v) \sim \text{Lognormal}(\mu_v, \sigma_v)$

Parameter	Maximum likelihood estimate	Bootstrap bias-corrected estimate	Bootstrap standard error	Bootstrap 95% confidence interval
μ_r	0.856	0.892	0.015	[0.793, 0.851]
σ_r	0.712	0.741	0.023	[0.641, 0.729]
μ_v	0.011	0.011	0.002	[0.006, 0.015]
σ_v	0.048	0.053	0.010	[0.026, 0.066]

A.3.2 Robustness Checks

Table A.19: Joint estimation of all four parameters of $r \sim \mathcal{N}(\mu_r, \sigma_r)$ and $(1 - v) \sim \text{Lognormal}(\mu_v, \sigma_v)$

Parameter	Estimate	Standard error	p-value
μ_r	0.863	0.0163	< 0.001
σ_r	0.690	0.024	< 0.001
μ_v	0.011	0.002	< 0.001
σ_v	0.048	0.010	< 0.001

Table A.20: Separate estimation of $r \sim \mathcal{N}(\mu_r, \sigma_r)$ and $(1 - v) \sim \text{Lognormal}(\mu_v, \sigma_v)$ for the one-stage treatment ($n_1 = 1,336$) and the two-stage treatment ($n_2 = 1,325$)

Subsample	Parameter	Estimate	Standard error	p-value
One-stage	μ_r	0.856	0.024	< 0.001
	σ_r	0.712	0.034	< 0.001
Two-stage	μ_r	0.844	0.059	< 0.001
	σ_r	0.878	0.217	< 0.001
	μ_v	0.012	0.004	< 0.001
	σ_v	0.080	0.049	0.094

Table A.21: Maximum likelihood estimates of $r \sim \mathcal{N}(\mu_r, \sigma_r)$ and $(1 - v) \sim \text{Lognormal}(\mu_v, \sigma_v)$ on the subsample of participants with response times equal to or above the 25th percentile ($n_{25} = 2,015$)

Parameter	Estimate	Standard error	p-value
μ_r	0.830	0.026	< 0.001
σ_r	0.694	0.0377	< 0.001
μ_v	0.009	0.003	< 0.001
σ_v	0.051	0.012	< 0.001

Table A.22: Properties of the estimated distribution of $1 - v$ for the robustness checks I (joint estimation of all four parameters), II (separate estimation for the one-stage and the two-stage treatment), and III (estimation on the subsample of participants with response times equal to or above the 25th percentile)

Estimation	Mean $\mathbb{E}[1 - v]$	Standard deviation sd$[1 - v]$	95% Confidence interval	$P(1 - v < 1)$
I	1.012	0.051	[0.915 , 1.117]	0.414
II	1.015	0.082	[0.865, 1.184]	0.441
III	1.010	0.051	[0.913, 1.114]	0.430

B Experimental Instructions

B.1 English Translation of the Instructions and Questions

Instructions

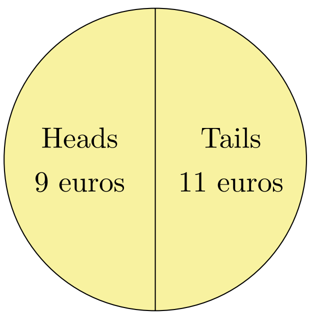
In the following we want to give you the opportunity to win money in a lottery. You will be offered different lotteries to choose from. All you have to do is to choose a lottery. Your potential payoff depends on your own decisions and on chance.

The amounts of money at stake are real. Among those who participate in this study, we will randomly draw 750 people and pay the respective outcomes of the lotteries to the drawn people. All other people will not receive money. Nobody can be drawn more than once. We estimate that approximately 4,000 people will participate in this study. We will notify those who were drawn by April 2022 and transfer the amount to their study account.

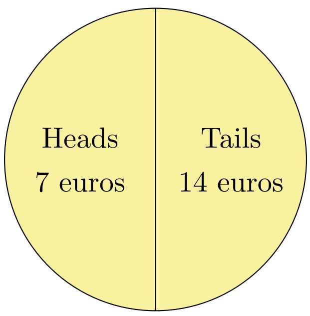
One-stage treatment

Below you see the three lotteries to choose from. You can choose exactly one of the three lotteries.

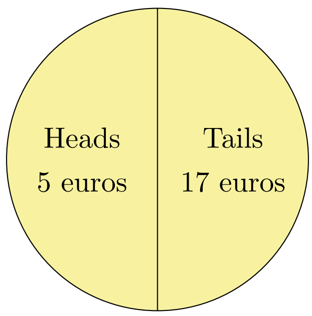
Each lottery is composed of the toss of a fair coin. Therefore each lottery has two possible outcomes – heads or tails. The probability to get heads or tails is equally high for each coin. When the coin shows tails, you will always receive a higher payoff than when the coin shows heads. The lotteries are only different in how high the payoff is for heads or tails respectively.



Lottery A



Lottery B



Lottery C

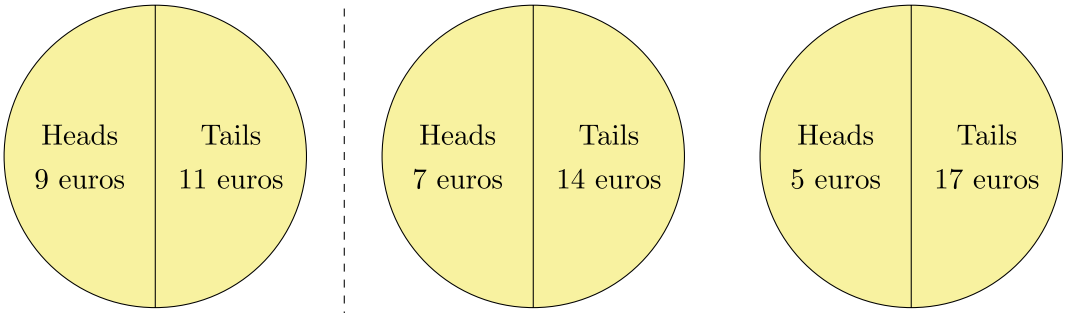
Please choose a lottery now.

- ◯ Lottery A
- ◯ Lottery B
- ◯ Lottery C

Two-stage treatment: Stage 1

Below you see the three lotteries to choose from. You can choose exactly one of the three lotteries. You can choose now whether you immediately take lottery A, or whether you want to make the choice between lottery B and lottery C in the next step.

Each lottery is composed of the toss of a fair coin. Therefore each lottery has two possible outcomes – heads or tails. The probability to get heads or tails is equally high for each coin. When the coin shows tails, you will always receive a higher payoff than when the coin shows heads. The lotteries are only different in how high the payoff is for heads or tails respectively.



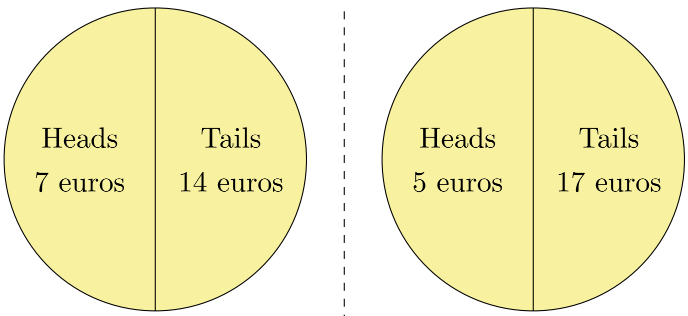
Lottery A **Lottery B** **Lottery C**

Please choose now whether you immediately take lottery A, or whether you want to make the choice between lottery B and lottery C in the next step.

◯ I want lottery A immediately.

◯ I want to make the choice between lottery B and lottery C in the next step.

Two-stage treatment: Stage 2



Lottery B **Lottery C**

Please choose a lottery now.

◯ Lottery B

◯ Lottery C

B.2 Screenshots of the Original Instructions and Questions

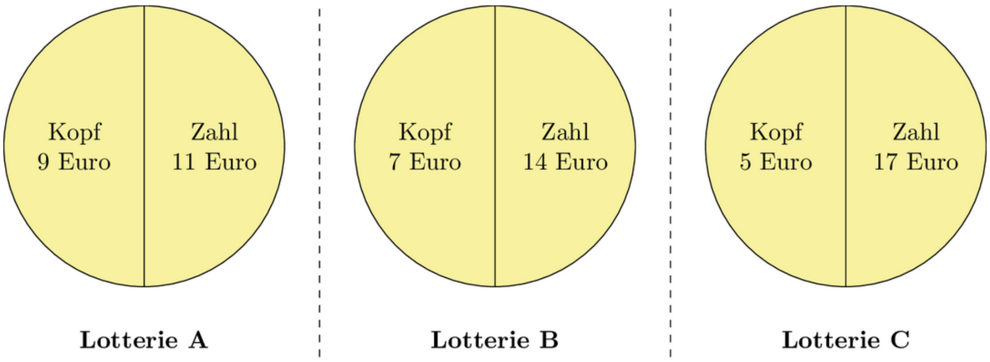
Figure B.1: Instructions

Gesellschaft im Wandel

Hilfe

Unten sehen Sie die drei möglichen Lotterien, die Ihnen zur Auswahl stehen. Sie können genau eine der drei Lotterien auswählen.

Jede Lotterie besteht aus dem Wurf einer fairen Münze. Somit hat jede Lotterie zwei mögliche Ergebnisse - Kopf oder Zahl. Die Wahrscheinlichkeit, Kopf oder Zahl zu werfen, ist bei jeder Münze gleich groß. Wenn die Münze Zahl zeigt, bekommen Sie immer eine höhere Auszahlung, als wenn die Münze Kopf zeigt. Die Lotterien unterscheiden sich nur darin, wie hoch Ihre Auszahlung bei Kopf oder bei Zahl jeweils ist.



Bitte wählen Sie nun eine Lotterie aus.

- ◯ Lotterie A
- ◯ Lotterie B
- ◯ Lotterie C

‹ Zurück | Weiter ›

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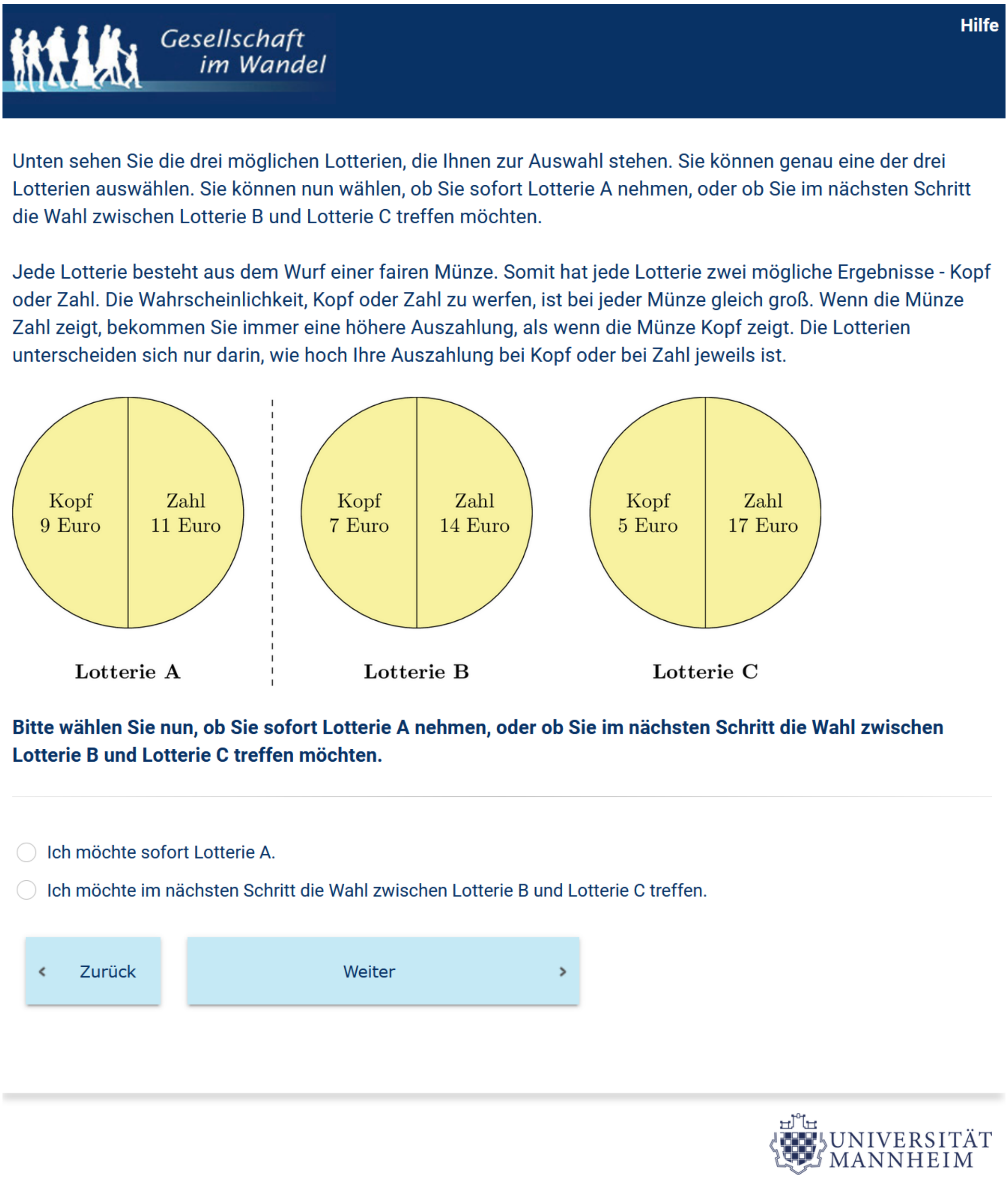
Figure B.2: One-stage treatment



Gesellschaft im Wandel

Hilfe

Unten sehen Sie die drei möglichen Lotterien, die Ihnen zur Auswahl stehen. Sie können genau eine der drei Lotterien auswählen. Sie können nun wählen, ob Sie sofort Lotterie A nehmen, oder ob Sie im nächsten Schritt die Wahl zwischen Lotterie B und Lotterie C treffen möchten.

Jede Lotterie besteht aus dem Wurf einer fairen Münze. Somit hat jede Lotterie zwei mögliche Ergebnisse - Kopf oder Zahl. Die Wahrscheinlichkeit, Kopf oder Zahl zu werfen, ist bei jeder Münze gleich groß. Wenn die Münze Zahl zeigt, bekommen Sie immer eine höhere Auszahlung, als wenn die Münze Kopf zeigt. Die Lotterien unterscheiden sich nur darin, wie hoch Ihre Auszahlung bei Kopf oder bei Zahl jeweils ist.

Kopf 9 Euro | Zahl 11 Euro

Lotterie A

Kopf 7 Euro | Zahl 14 Euro

Lotterie B

Kopf 5 Euro | Zahl 17 Euro

Lotterie C

Bitte wählen Sie nun, ob Sie sofort Lotterie A nehmen, oder ob Sie im nächsten Schritt die Wahl zwischen Lotterie B und Lotterie C treffen möchten.

- Ich möchte sofort Lotterie A.
- Ich möchte im nächsten Schritt die Wahl zwischen Lotterie B und Lotterie C treffen.

‹ Zurück | Weiter ›

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Figure B.3: Two-stage treatment: Stage 1

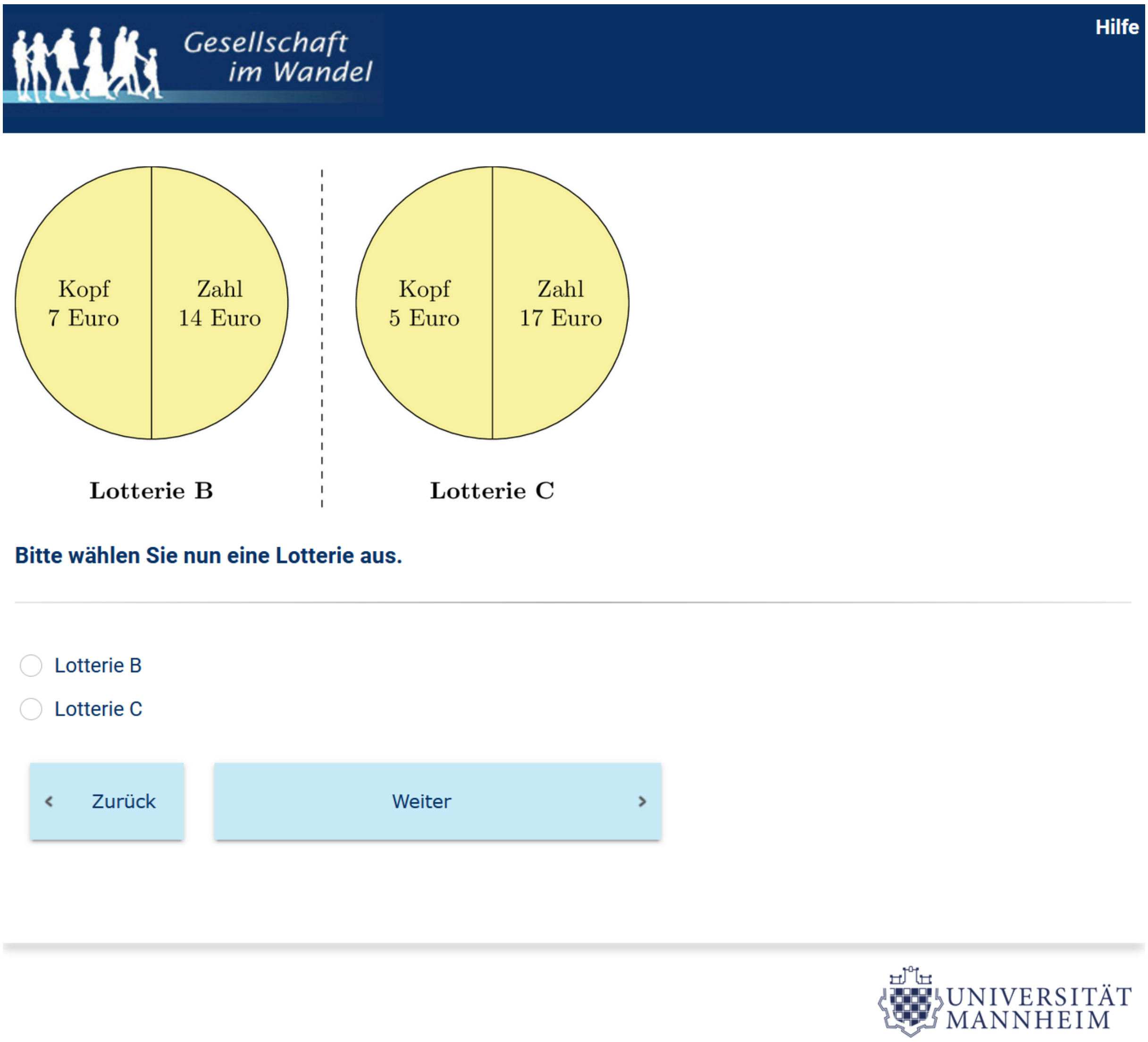

Figure B.4: Two-stage treatment: Stage 2