CESifo WORKING PAPERS

10342
2023

Original Version: March 2023
This Version: November 2023

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
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CESifo *Working Paper No. 10342*

Intrinsic Preferences for Choice Autonomy

Abstract

Personal autonomy has been argued to be fundamental to well-being and is often discussed as an important driver of economic and political behavior. However, preferences for autonomy remain poorly understood. The major factor contributing to this limitation is the necessity to separate instrumental and intrinsic value components of autonomous choice. We propose a novel elicitation method that solves this identication challenge. We establish the existence of intrinsic preferences for choice autonomy and show substantial heterogeneity in a large online sample. We further study their antecedents by relating them to existing personality scales, socioeconomic characteristics and other attitudes.

JEL-Codes: D010, D900, C910.

Keywords: autonomy, preference measurement, experiment.

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November 29, 2023
We thank the audiences at the 2022 World Economic Science Association Conference, the 2022 North American Summer Meeting of the Econometric Society, the Behavioral Measurement Conference 2022 (in particular our discussant Michael Kosfeld), the Annual Congress of the Swiss Society of Economics and Statistics 2022, the ECONtribute Workshop on Autonomy and Paternalism 2022, the 12th International Conference of the French Association of Experimental Economics, the Foundations of Utility and Risk Conference 2022, the European ESA Meeting 2022, the Workshop on Paternalism at the Max Planck Institute for Tax Law and Public Finance 2022, the iSee workshop at NYU Abi Dhabi 2023, the behavioural and experimental economics seminar at the University of Zurich, the microeconomics seminar in Konstanz, the IIPF Annual Conference 2023 (in particular our discussant Matthias Rodemeier), the CESifo Behavioral Economics Conference 2023 as well as Arno Apffelstaedt, Berno Buechel, Alexis Ghersengorin, Yoram Halevy, Menusch Khadjavi, Florian Schneider, Christian Thöni, Stephanie Wang, Leeat Yariv and Christian Zihlmann for helpful comments. We thank Kay Waeer for excellent research assistance. We gratefully acknowledge financial support from ERC Starting Grant 2018-803332 CONTROL.

1 Introduction

Understanding individual preferences is fundamental to properly model and predict economic behavior. As a consequence, a vast economic literature has empirically studied and substantially advanced our understanding of individual preferences, in particular in the domains of risk, time, and social behavior.

In this paper, we study the empirical foundations of intrinsic preferences for choice autonomy. Arguments for the importance of personal autonomy can be found, for example, in Deci and Ryan's self-determination theory (Deci and Ryan, 1985), who hypothesize that autonomy is "essential for ongoing psychological growth, integrity and well-being" (Deci and Ryan, 2000, p.229). The capabilities approach by Sen and Nussbaum (Sen, 1985; Nussbaum, 2000) emphasizes that freedom of choice, and not only outcomes, is important for a person's quality of life, Frey, Benz and Stutzer (2004) argue that independence and autonomy at the workplace are sources of procedural utility that raise happiness, and according to John Stuart Mill, liberty is "one of the elements of wellbeing" (1859, Chapter III). Building on this philosophical approach, we study how individuals value having personal autonomy.

The dominant view in economics has been that choice autonomy is instrumentally valued, since it allows individuals to maximize their utility through own choices. Potential intrinsic value components of autonomy have been largely ignored, despite them probably being a crucial determinant of economically relevant behavior and welfare. Studies that discuss their potential relevance usually treat them as a residual theory, for example to explain otherwise unexplained wage differentials in self-employment, entrepreneurship and science (Hamilton, 2000; Stern, 2004; Hurst and Pugsley, 2011; Astebro et al., 2014) or as an explanation for the underdelegation of decision rights in organizations (Fehr, Herz and Wilkening, 2013; Fehrler and Janas, 2021). While intrinsic preferences for autonomy may thus plausibly be a crucial determinant of economically important decisions and outcomes, ascribing observed residuals to a preference poses an identification challenge because the residuals could be the result of potential measurement error in relevant control variables (Gillen, Snowberg and Yariv, 2019) or due to omitted variables bias. The underlying preference ultimately remains unidentified.

Furthermore, individual heterogeneity in intrinsic preferences for autonomy remains largely unexplored. Although the above examples universally suggest that autonomy is positively valued by individuals, individual differences might be substantial. In particular, some people may also exhibit an aversion to making own choices. Agranov and Ortoleva (2017), Dwenger, Kübler and Weizsäcker (2018), and Cettolin and Riedl (2019) show that some individuals display a preference to delegate choices between risky and/or ambiguous lotteries to a randomization device, which means that they willingly, and sometimes at a cost, forego the possibility to directly choose one of the available alternatives.[1]

Separating instrumental and intrinsic value components of choice autonomy using observational data or survey measures is, in most circumstances, impossible. Whenever an individual faces a choice or is asked about the importance of having choice autonomy, as is done in commonly used surveys that aim to measure perceptions and attitudes towards autonomy, there is likely instrumental value associated with the choice or question. Importantly, due to heterogeneity in preferences over outcomes or differences in beliefs, there can be large individual heterogeneity in the (subjectively perceived) instrumental value component of autonomy. Consequently, controlling for the instrumental utility component at the individual level is essential in order to identify *intrinsic* preferences for autonomy.

We propose a simple and easily applicable preference elicitation tool that allows such separation.[2] We define intrinsic preferences for choice autonomy as a desire to make decisions oneself rather than having someone else decide over own consequences on one's behalf — independent of the instrumental

[1] Agranov and Ortoleva (2017) argue that such behavior is an expression of preferences for randomization. We will discuss the connection between our conceptualization of intrinsic preferences for autonomy and randomization preferences below.

[2] Our approach is inspired by Bartling, Fehr and Herz (2014), who have developed an experimental measurement of the intrinsic value of decision rights. However, their experiment did not isolate preferences for autonomy and relied on a lengthy laboratory experiment unsuitable for wide-scale application.

utility associated with the decision. The preference elicitation tool relies on a simple two-step procedure: First, a choice set is identified that contains only alternatives between which an individual is revealed indifferent. Second, an individual's willingness to pay to make a choice from the choice set herself, rather than having someone else choose on her behalf, is elicited. Identification of intrinsic preferences for autonomy follows from the revealed indifference between the choice alternatives elicited in step 1, which implies that there is no instrumental value attached to choosing oneself. Therefore, only if an individual has an intrinsic preference for (or aversion to) choice autonomy should she display a positive (or negative) willingness to pay. Step 2 thus elicits the intrinsic preference for choice autonomy, without the need to control for *any* other preferences or beliefs.[3]

The principle underlying our elicitation tool can be used for any type of alternatives over which individuals have well-defined preferences; it can thus be applied across a large variety of contexts. In this application, we use lotteries as alternatives.[4] In step 1, to identify a subject's point of indifference, subjects make 10 binary decisions between lotteries, where one lottery remains fixed throughout while the high payoff of the other lottery is adjusted from decision to decision. For step 2, a choice set is constructed that contains two lotteries such that the individual is expected to be revealed indifferent between them, based on the information gained in step 1. We then elicit the willingness to pay to make a choice from this choice set herself, rather than having someone else make this choice on the subject's behalf.

Given that identification critically relies on indifference between alternatives in step 2, it is important to obtain information on how well the point of indifference is identified. A caveat of many methods used to elicit indifference (Becker, DeGroot and Marschak, 1964; Holt and Laury, 2002) is that they only deliver reliable estimates if individuals are *consistent in their choices*. Instead

[3]Note that, because the individual is indifferent between the alternatives in the choice set, models of ambiguity aversion cannot offer an explanation for a desire to keep choice autonomy in our setting either.

[4]Lotteries are particularly suitable because they allow for incremental adjustment of value, which is essential to closely approximate an individual's point of indifference.

of assuming consistency, we control for potential bias by jointly maximizing the information gain about an individuals' point of indifference and her choice consistency. To this end, we designed both step 1 and step 2 as a 'Dynamically Optimized Sequential Experiment' (DOSE, Wang, Filiba and Camerer (2010); Chapman et al. (2022)), which delivers an estimate of an individual's indifference point and her willingness to pay, respectively, together with a structural estimate of a consistency parameter.

Based on data from two large-scale online experiments on Prolific.co with a total of 1422 individuals from around the globe, we find that, on average, individual willingness to pay for choice autonomy is significantly larger than zero. On average, the intrinsic value component accounts for 5.2% of the overall expected utility generated by the decision. We also find substantial heterogeneity in preferences for choice autonomy. While 53.8% of our subjects have a strictly positive willingness to pay, 19.1% have a willingness to pay of zero, and the willingness to pay is strictly negative for 27.1% of subjects.

To assess the robustness of our findings, we use information on choice consistency at the individual level. First, 49% of our sample showed highly consistent choice patterns and thus have precisely identified indifference points. When conditioning on this subset, the average willingness to pay for choice autonomy remains similar at 5.3% of the expected utility generated by the decision. Second, utilizing structural assumptions on utility functions, we can calculate the expected residual instrumental utility of choice autonomy. For highly consistent subjects, this residual is very small, accounting for less than 1% of the overall utility generated by the lotteries. However, the residual instrumental value also remains small for those individuals that displayed choice inconsistencies in step 1. Thus, an imprecise measurement of the indifference set cannot explain the existence of a willingness to pay for choice autonomy in our setting. Furthermore, to assess robustness, we replicate our experiment in the laboratory with university students. The data confirm the original results; both the average willingness to pay for choice autonomy and its distribution are quite similar to the online setting.

It is interesting to note that the 27.1% of subjects with a negative willingness represent a frequency similar to the 29% of subjects who are willing to pay to delegate the choice between two lotteries to an objective coin flip in Agranov and Ortoleva (2017). The models of Machina (1985) and Cerreia-Vioglio et al. (2019) explain such behavior by means of deliberately stochastic preferences, that is, preferences that are quasiconcave in probabilities. However, Machina already noted the possibility that individuals could also be averse to such stochasticity, which would imply that an "individual is (weakly or strictly) averse to randomization over indifferent alternatives" (Machina, 1985, p.590). Such behavior would then correspond to quasiconvex preferences in probabilities. The 53.8% of subjects with a positive willingness to pay provide empirical evidence for precisely such behavior: They prefer to keep choice autonomy when faced with choice sets containing indifferent alternatives in the context of delegation to another person.

To shed further light on underlying microfoundations of intrinsic preferences for choice autonomy, we conducted a "COIN" treatment, in which delegation to a human decision maker is replaced by delegation to an objective coin toss. In this treatment, the average willingness to pay remains significantly positive but drops by half. 46.7% of participants still exhibit a positive willingness to pay. These data deliver two essential insights: First, the fact that the willingness to pay is significantly higher when delegating to a human decision maker suggests that intrinsic preferences for choice autonomy are affected by the identity of the delegate. One may even argue that delegation to a coin toss no longer constitutes a loss of choice autonomy, as it can be viewed as a deliberate choice to randomize between the two alternatives (Machina, 1985; Cerreia-Vioglio et al., 2019). If this presumption were true, the willingness to pay to choose oneself in the COIN treatment would reflect only instrumental utility resulting from such deliberately stochastic preferences. However, our postulated view is that preferences for choice autonomy provide a reasonable microfoundation for preferences that are represented as being concave over lotteries. Second, since almost half of the subjects still display a preference for choosing oneself, the data show that representations of preferences that are concave over lotteries are in fact more prevalent than convex preferences, but so far only the latter have received attention in the literature.

Having established the existence of intrinsic preferences for autonomy, we assess their relation to well-established related constructs in psychology that measure different aspects of people's perceptions of their internal control and freedom of choice (The Index of Autonomy (Deci and Ryan, 2006), Locus of Control (Rotter, 1966), the world value survey question on perceived freedom and control (Inglehart, 2014)). We find that our preference measure is unrelated to these constructs, which points to a fundamental conceptual difference between measures of *perceptions of autonomy* and our measure of intrinsic preference. With respect to socio-demographic and personal characteristics, we find limited evidence for strong socio-economic antecedents of preferences for choice autonomy. Instead, such preferences appear to be similarly distributed across socio-demographic groups such as age and income.

This paper enhances our understanding of preferences for autonomy in multiple ways. Previous work has demonstrated the general existence of an intrinsic value of decision rights in an organizational setting, more specifically the right to implement effort in a project selection task that had consequences for multiple parties (Bartling, Fehr and Herz, 2014). Subsequent papers have further assessed the utility consequences from (i) controlling own payoffs and non-interference (Owens, Grossman and Fackler, 2014; Neri and Rommeswinkel, 2016; Ferreira, Hanaki and Tarroux, 2020; Boissonnet and Ghersengorin, 2022; Meemann, 2023), (ii) the size of choice sets (Sethi-Iyengar et al., 2004; Iyengar and Kamenica, 2010; Scheibehenne, Greifeneder and Todd, 2010; Le Lec and Tarroux, 2020), and (iii) the desirability of the consequences of choice (Botti, Orfali and Iyengar, 2009; Bobadilla-Suarez, Sunstein and Sharot, 2017; Bartling and Fischbacher, 2012). Our novel elicitation tool isolates intrinsic preferences for choice autonomy and provides essential methodological innovations that (i) make it easy to administer and (ii) provide control for measurement error. Both innovations will allow researchers to study the antecedents and consequences of preferences for choice autonomy in a variety of contexts.

Our methodology may also be valuable for the recent literature on paternalism and decision making for others. Ambuehl, Bernheim and Ockenfels

(2021) suggest that people may project their own preferences on others when being able to influence their choice sets. Such preferences for making choices for others are conceptually distinct, but may be correlated with a preference for own choice autonomy. In addition, Ackfeld and Ockenfels (2021) suggest that people tend to take the other person's autonomy into account when taking paternalistic actions. It is thus of fundamental interest to the literature on paternalism to understand if and when people exhibit an intrinsic preference for making own choices.

2 The Preference Elicitation Tool

Our preference elicitation tool consists of two steps: First, participants are repeatedly confronted with a choice between two alternatives in order to identify two alternatives, A and B, between which an individual is revealed indifferent ($A \sim B$). The first step serves the purpose to eliminate any instrumental value considerations in the second step. Second, a choice set containing alternatives A and B is constructed, and the individual's willingness to pay for making a choice from this set oneself, rather than having another person choose on her behalf, is elicited. If instrumental value were the sole determinant of the value of choice autonomy in our setting, the decision maker should be indifferent between choosing herself and having someone else choose for her, and thus the willingness to pay should be zero. Alternatively, if choice autonomy is intrinsically valuable, individuals should display a positive willingness to pay. Vice versa, individuals who are averse to choosing themselves are expected to show a negative willingness to pay.

2.1 Step 1: Eliciting an indifference set

To create a choice set that only contains alternatives between which the decision maker is indifferent, we made the following design choices: (i) we use choice alternatives whose value can be easily and incrementally adjusted, (ii) we create a simple and easy to understand choice environment to minimize confusion, and (iii) we structurally model and measure the degree of choice consistency of participants, providing us with important information about the accuracy with which we have identified the indifference point.

The nature of the alternatives is, in principle, irrelevant. However, because it is important that alternatives can be incrementally adjusted to best approximate an indifference point, we decided to use lotteries over monetary payments as alternatives. Each participant goes through an individual sequence of 10 choice situations in each of which she faces the simple choice between two lotteries A and B. Lottery A is fixed and always provides a payoff of 600 points with 25% probability and a payoff of 1600 points with 75% probability. Lottery B provides a payoff of 600 points with 50% probability and a payoff of X selected from $\mathcal{X} \in \{1890, ..., 2840\}$ points with 50% probability. The value X is adjusted from choice to choice. Probabilities and payments are represented both in numerical and graphical terms.[5]

We adjust X from choice to choice using DOSE—Dynamically Optimized Sequential Experimentation (Wang, Filiba and Camerer, 2010; Chapman et al., 2022), meaning that X is always selected in such a way that it maximizes the information gain regarding an individual's risk preference and choice consistency.[6] To apply DOSE, we need to impose some structural assumptions. We assume that individuals exhibit CRRA utility given by

$$u_i(w) = \frac{w^{1-r_i}}{1-r_i} \tag{1}$$

where w is the payoff in points and r_i is the individual's risk aversion parameter. Further, we assume that individual choice behavior is governed by the following probabilistic function

$$Pr_i(A) = \frac{1}{1 + e^{-\mu_i(U_i(A)-U_i(B))}}, \tag{2}$$

[5]A screenshot of the decision screen that participants faced is displayed in Figure A.15.

[6]An exception are choice situations 5 and 10, in which X was chosen via a random procedure that ensured substantial difference of the displayed X value from the values previously seen. We implemented this procedure to break the monotonicity of the choice sequence that would otherwise result for highly consistent subjects.

where $Pr_i(A)$ is the probability of choosing lottery A, μ_i specifies individual i's degree of stochastic response in choice, and U_i denotes individual i's expected utility from a lottery given u_i.

The key individual parameter estimates that we want to obtain are $\hat{r}_i$ and $\hat{\mu}_i$. To this end, we define a discrete parameter space for r and μ. The parameter space for r is determined by the set of payoffs $\mathcal{X}$ of lottery B and contains 96 values given by $\mathcal{R} \in \{-1.2, ..., 1.2\}$.[7] μ can take on the 13 different values given in $\mathcal{M} \in \{1, 10, ..., 120\}$, ranging from almost exclusive stochasticity in choice to very high consistency in choice.[8] Finally, the function $f(r, \mu) : \mathcal{R} \times \mathcal{M} \rightarrow [0, 1]$ assigns a probability to each parameter combination (r, μ), and we assume as a prior that the probability distribution over (r, μ) is uniform. After each choice situation t, the joint distribution $f(r, \mu)$ is then updated based on individual i's choice using Bayes Rule, and based on the posterior distribution, DOSE selects the value X for the next choice situation such that the information gain is maximized.

At the end of step 1, the estimates $\hat{r}_i$ and $\hat{\mu}_i$ are determined based on the posterior joint distribution over r and μ. Based on $\hat{r}_i$, we can then construct the *indifference lottery* $\hat{B}_i$ that pays a high payoff $\hat{X}_i$ (rounded to the nearest multiple of 10, which was the smallest point unit used in our experiment), such that individual i is expected to be just indifferent between lotteries A and $\hat{B}_i$. Further details about the exact procedures, parameterization, and estimation of $\hat{r}$ and $\hat{\mu}$ are given in Appendix A.1.

One might wonder if the structural assumptions on individuals' utility and choice functions exhibit a strong influence on the identified point of indifference. While this section may generate such an impression, we can show that this is not the case, at least as long as choice patterns are reasonably consistent.

[7] The 96 values contained in the vector $\mathcal{R}$ are determined based on the identifiable parameters of r given the set of lotteries B defined by X above.

[8] Note that μ is simply a scaling parameter for differences in expected utility (see equation 2). Thus, the values of μ have to be interpreted in connection with the values of the utility function defined in eq. 1, and cannot be interpreted in isolation. The value of 0, which implies completely random choice, has been excluded as otherwise DOSE would excessively try to learn whether or not the participants' choices are fully random, which hinders learning about the risk parameter given the limited amount of choices that we can elicit.

First, we provide an assessment of the precision with which the indifference set is identified that does not rely on the structural assumptions made here in section 3.1. Second, in Appendix A.1.3, we re-run our estimation of the implied indifference point based on each participant's actual choice data using alternative structural assumptions, and show that differences are minimal. For subjects with moderately consistent choice patterns, which constitute 78% of our overall sample, the identified indifference set is identical for at least 66% of subjects and $\hat{B}$ only varies by the smallest possible unit of 10 points for at least 97% when assuming CARA or prospect theory.

2.2 Step 2: Eliciting the Willingness to Pay For Choice

In step 2, participants are then presented with a choice between lottery A and the indifference lottery $\hat{B}_i$. Participants are told that either A or $\hat{B}$ will determine their payoff, but that the choice between them is either made by the participant herself, or by another participant.[9]

The key purpose of step 2 is to obtain an estimate of the willingness to pay to choose oneself in this setting. To this end, participants are again faced with a sequence of 10 choice situations, in each of which they must choose between choosing themselves (phrased "I choose") and paying a price p, or delegating the choice to an anonymous study participant (phrased "I delegate").[10] The price p can take on values defined in $\mathcal{P} \in \{-600, -590, ..., -10, 10, 20, ..., 600\}$, it varies from situation to situation, and it can either be positive or negative.[11] We assume that a participant's utility function can be characterized as follows:

[9]Participants were told that another study participant would choose a lottery on their behalf and receive a fixed base payment. They are informed that the fixed payment is independent of whether the participant delegates and independent of the lottery choices the other participant makes. The other participant made lottery choices for all possible choice situations that may occur in step 2. The data are collected prior to the main experiment in order to guarantee a smooth experience without delay due to matching.

[10]The experimental interface that participants faced in step 2 is shown in Figure A.25.

[11]Negative prices were framed as "bonuses" that the participant receives if s/he chooses him/herself. $p = 0$ was excluded because we expected a significant fraction of participants to have a true willingness to pay of 0, and forcing a choice at 0 (which would reflect a forced tie breaker) would bias our estimate in the positive or negative domain.

$$v_i(d_i, p, c) = \begin{cases} U_i(A) + d_i - p, & \text{if participant chooses herself } (c = 1) \\ U_i(A), & \text{if participant delegates choice } (c = 0) \end{cases} \tag{3}$$

where $U_i(A)$ is the expected utility derived from lottery A (note that $U_i(A) = U_i(\hat{B}_i)$ when $A \sim \hat{B}_i$), d_i captures the difference in intrinsic utility of the participant between deciding herself and having the lottery chosen by the other participant, p is the (positive or negative) price she has to pay, and c is a dummy that indicates choosing oneself ($c = 1$) or delegating ($c = 0$).[12] Given this utility specification, the price p at which an individual is just indifferent between choosing oneself and delegating is exactly equal to d_i.

The goal is thus to estimate $\hat{d}_i$, and we again apply a DOSE procedure, assuming a probabilistic choice function with consistency parameter γ to maximize the information gain about d and γ from choice situation to choice situation. Estimates of $\hat{d}_i$ and $\hat{\gamma}_i$ are then again obtained from the individual posterior distribution over d and γ. Further details about the exact procedures, parameterization, and estimation are given in Appendix A.1.

2.3 Implementation and Procedures

We conducted two surveys on the platform Prolific Academic (www.prolific.co) in June 2021 and in January 2022. Each survey consists of three parts, the two behavioral tasks described in section 2 and a subsequent questionnaire. Subjects complete part 1 and part 2 as described above. The lotteries are explained in detail before the beginning of part 1 and subjects can spin wheels of fortune that selects the lottery outcome in order to better understand the functioning of the lotteries, see screenshots in Figures A.9 and A.11. For each of part 1 and 2, one of the 10 choice situations is randomly selected to determine an individual's payment. Feedback on lottery outcomes and payoffs is only given at the very end of the study. The instructions of the behavioral task, including

[12] Note that this utility representation is chosen for modeling purposes only, a discussion of possible micro-foundations of a preference for choice autonomy is provided in Section 4.

the consent form, can be found in Appendix A.3, the questionnaire is displayed in Appendix A.4. The questionnaire of the June wave consists of ten question blocks that were presented to participants in random order. We include several scales measuring preferences for and perceptions of autonomy that have been widely used in psychology (locus of control (Rotter, 1966), autonomous functioning (Deci and Ryan, 1985), generalized self-efficacy (Schwarzer, Jerusalem et al., 1995) and desirability of control (Burger and Cooper, 1979)) together with several questions capturing personal characteristics, related preferences and socio-demographic information.

Implementation of June 2021 wave. The data for the June 2021 wave were collected between June 15$^{\text{th}}$ and June 21$^{\text{st}}$ 2021 in batches of 200 participants starting at different times of the day. Participants completed the behavioral experiment and could then enter the questionnaire within 24 hours (retention rate of 89.9%). The study was open to anyone,[13] but participants were predominantly Europeans.[14] On average, participants earned £7.09 (consisting of a base payment of £2, an average variable bonus of £2.09, and a payment of £3 for completing the questionnaire) and spent 15.55 minutes on the behavioral experiment and 28.92 minutes on the questionnaire.

Implementation of January 2022 wave. The implementation and procedures of the survey in January 2022 were similar to the June 2021 wave. The replication study was run between January 6 and 12, 2022 on Prolific Academic.[15] We excluded subjects who participated in the previous study and, in addition, we took advantage of the option to restric participation to

[13]Data was collected during the UEFA EURO 2020. Because of the emotions triggered by this event, we excluded nationalities whose team had a game on the same day.

[14]Nationalities: Greece (5.4%), Italy (6.2%), Mexico (5.7%), Poland (11.2%), Portugal (14.0%), South Africa (9.8%), United Kingdom (13.4%), the remaining nationalities were represented with less than 5% of the sample.

[15]The behavioral task and the (shorter) questionnaire were now run as one study. In addition, the study was run together with another parallel one that addresses different research questions. For this study, we balanced the nationalities that we recruited in the following way: 30-40% Continental Europe, 25% US, 25%, 5-10% South Africa, and 5-10% Mexico. Given these restrictions, we recruited participants with the following nationalities (plus several others with less than 5% of participants in our sample): Italy (7.2%), Mexico (6.4%), Poland (9.9%), Portugal (10.1%), South Africa (6.6%), United Kingdom (23.9%), United States (23.8%).

subjects with a Prolific Score of at least 99/100. This means they behaved in a reliable way in previous studies on Prolific. The complete study took on average 20.66 minutes and the base payment for participation was £3.5 plus an average variable payment of £2.12.

Sample composition. We recruited 998 participants in June 2021 and 794 participants in January 2022. Control questions make sure that participants understand the instructions in the behavioral task and in addition there are several clearly marked attention checks throughout the questionnaire. A participant is excluded from the survey if they fail a set of control questions or the attention checks a third time. The final dataset thus consists of participants who successfully completed the whole study and passed the control questions and attention checks within the allowed number of trials. From this dataset, we exclude participants who chose lottery A in the choice situation with the highest value of X in their individual sequence, or lottery B in the choice situation with the lowest value of X in their individual sequence. These are individuals that either never switch between lotteries in part 1, and thus are categorized as extremely risk averse/risk loving—and as highly consistent—in our data, or individuals who switch at least once but are inconsistent and display extreme risk aversion / risk lovingness at the boundary of the parameter space. There are different explanations for such choices: subjects might not pay attention and just click the same button, they might have extreme risk preferences, or they might use a simple heuristic for making the choices between lotteries. While we cannot distinguish these possibilities, the key reason for excluding them is that we cannot identify an indifference set for these participants, and therefore the elicitation of the willingness to pay in part 2 does not work accurately (370 observations). This leaves us with a dataset with 1422 observations.

3 Results

3.1 Elicitation of Indifference in Step 1

We begin our analysis by examining the precision with which we identified indifference in step 1 of our elicitation procedure. Figure 1 shows exemplary choice patterns of three subjects, based on the presented value X of the B-lottery as well as the associated choice, and gives an intuition for the indifference lotteries selected by the algorithm presented in section 2 as well as for occurring inconsistencies. The left panel shows a perfectly consistent participant for whom our algorithm assigns an $\hat{X}$ of 2190. This subject has chosen lottery B whenever confronted with a high value larger or equal to 2200, and lottery A when confronted with a high value smaller or equal to 2180. The participant in the middle panel shows a slightly inconsistent choice pattern, with a preference reversal between rounds 6 and 8. The participant in the right panel shows an inconsistent choice pattern with multiple inconsistencies.

To quantify the extent of imprecision in the estimated $\hat{X}$ given individual choice patterns without strong parametric assumptions, we can determine a range $\rho = [\underline{X}, \overline{X}]$, where $\underline{X}$ is the lowest value of X such that an individual consistently chose lottery A whenever $X \leq \underline{X}$, and equivalently, $\overline{X}$ is the highest value of X such that an individual consistently chose lottery B whenever $X \geq \overline{X}$. Thus, ρ identifies the range of potential values X outside of which an individual behaved perfectly consistent. ρ can thus be seen as a range of potential true points of indifference, expressed in terms of the high value of the B lottery. The shaded areas in Figure 1 display ρ for each of the three choice patterns. It can be seen that ρ is very small when an individual behaves consistently, but increases when choice inconsistencies occurred.

We can then calculate the average distance between the determined indifference value $\hat{X}$ and the potential values $X \in \rho$ that could also reflect the true

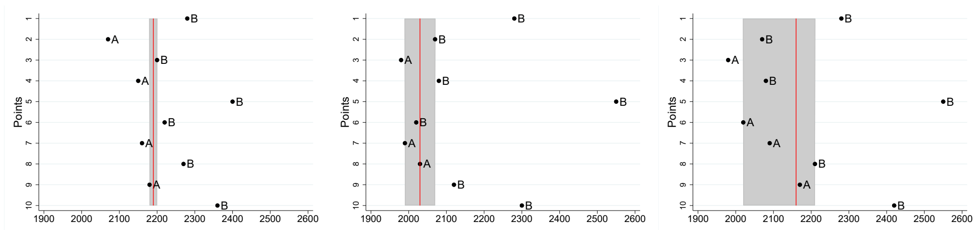

Figure 1: Choice Patterns of three selected participants. On the y-axis of each panel, choice situations, or rounds, 1 to 10 are displayed. The x-axis indicates the value X of lottery B that was presented in the respective round of step 1. Each subject's choice of lotteries A vs. B is shown for each round. Vertical red lines represent the identified indifference lottery, based on the estimated risk parameter $\hat{r}$.

indifference point.[16] This average distance is then given by

$$\delta = \int_{\underline{X}}^{\overline{X}} \frac{|X - \hat{X}|}{\overline{X} - \underline{X}} dX \tag{4}$$

Note that the smallest value of δ in our setting for a perfectly consistent participant is 5, as the smallest unit of variation in X was 10 points.[17] For the participant in the left panel of Figure 1, δ is 5 points, 20 points for the participant in the middle, and 58 points for the participant on the right.

The left panel of Figure 2 shows the cumulative distribution of δ in our data. The average distance is equal to it's smallest possible value for 22 percent, and is below or equal to 10 for 36 percent of the sample. The median average distance is equal to 25 points, and 75 percent of the sample have an average distance below or equal to 50 points. Thus, we are able to identify relatively tight ranges of potential indifference points for a large majority of our subjects. In addition, our method allows us to observe the degree of precision at the

[16]Under the assumption that any point on ρ is equally likely to be the true indifference point, δ would be the expected deviation between $\hat{B}$ and the true point of indifference. Note that this is a conservative assumption that likely overestimates the expected deviation, as the selected $\hat{X}$ is based on $\hat{r}$, which is calculated using the posterior probability distribution over r conditional on the actual choice pattern, which is often much less dispersed than a uniform distribution over ρ.

[17]To give some context, a variation of 5 points in the high value of the A lottery is equivalent to a 0.28% variation in the expected value of the lottery.

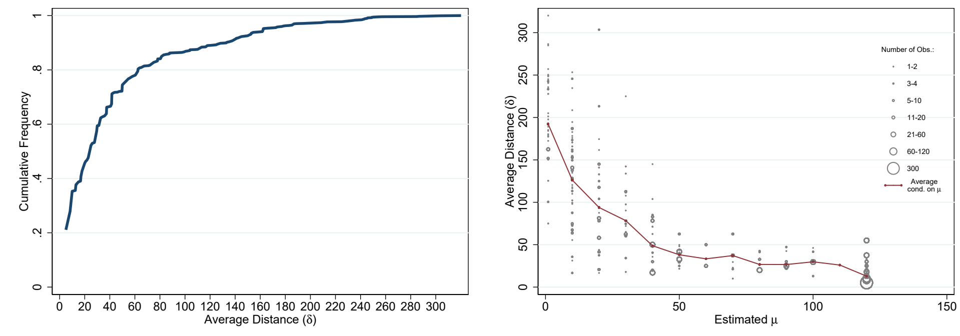

Figure 2: Left panel: Cumulative distribution of δ. Right Panel: Scatterplot of δ conditional on the estimated consistency parameter $\hat{\mu}$.

individual level, and thus allows us to account for it in our analysis.

Our elicitation method based on DOSE also directly provides us with a structurally estimated choice consistency parameter at the individual level, $\hat{\mu}$. The right panel in Figure 2 shows how $\hat{\mu}$ relates to δ. It can be seen that for subjects with relatively high degrees of consistency, δ is small. For subjects with the highest consistency score of $\hat{\mu} = 120$, who constitute 49 percent of our sample, the average δ is equal to 13.[18] But even if $\hat{\mu} < 120$, expected deviations remain relatively small as long as subjects do not become too inconsistent. The 28 percent of participants with $\hat{\mu}$ between 40 and 110 on average have a δ of 36. It is only when $\hat{\mu}$ becomes very small that the precision of the identified point of indifference substantially decreases. In particular, those with $\hat{\mu}$ equal to 1 display substantial distance, implying that the indifference point is very imprecisely estimated.[19] Again, to give an intuition of these values, the participant with the choice pattern in the left panel of Figure 1 had a $\hat{\mu} = 120$, the participant in the middle had $\hat{\mu} = 80$, and the one on the right had $\hat{\mu} = 10$. Overall, the data reveals that our procedure in step 1

[18] The distribution of the estimated consistency parameters in the June and January samples for both tasks is displayed in Figure A.1. In the elicitation of the willingness to pay in part 2, 61% of subjects were assigned the highest possible estimated consistency parameter given our parameterization, $\hat{\gamma} = 15$. 8.4% of subjects are assigned the lowest possible value, $\hat{\gamma} = 1$.

[19] The heterogeneity in choice consistency partly reflects differences in socio-economic backgrounds. Male participants and participants with a higher education level exhibit somewhat higher consistency scores, especially in part 1 (see Table A.2 in Appendix A.2).

succeeded in identifying points of indifference with substantial precision, and it also succeeded in identifying those participants for whom we cannot ensure that an indifference set was identified with sufficient confidence.

To facilitate this discussion in the reminder of the paper, we will use the structural estimate $\hat{\mu}$ as the individual indicator of choice consistency and define the following subgroups based on the insights we gained in this subsection:

Definition 1 *A subject is described as highly inconsistent if* $\hat{\mu} = 1$*, as inconsistent if* $1 < \hat{\mu} < 40$*, as moderately consistent if* $40 \leq \hat{\mu} < 120$*, and as highly consistent if* $\hat{\mu} = 120$*.*

4.3% of subjects are thus classified as highly inconsistent, 18.5% as inconsistent, 28.27% are moderately consistent and 49% of subjects are highly consistent.

3.2 Willingness to Pay for Choice Autonomy

The data from our preference elicitation task reveal that individuals on average have a positive willingness to pay for choice autonomy.

Result 1

a) The average and median willingness to pay for autonomous choices in our decision task is significantly positive. We thus infer that, on average, individuals have intrinsic preferences for choice autonomy.

b) The average intrinsic utility component of choice autonomy amounts to 5.2% of the total expected utility from the choice individuals faced.

c) There is substantial heterogeneity in the willingness to pay for autonomous choices: While the majority of subjects (53.8%) displays a positive willingness to pay, it is negative for more than one fourth of subjects (27.1%), and equal to zero for 19.1%.

Support for Result 4a) is provided in Figure 3, which shows the distribution of the willingness to pay for all individuals on the left panel, and for the 49%

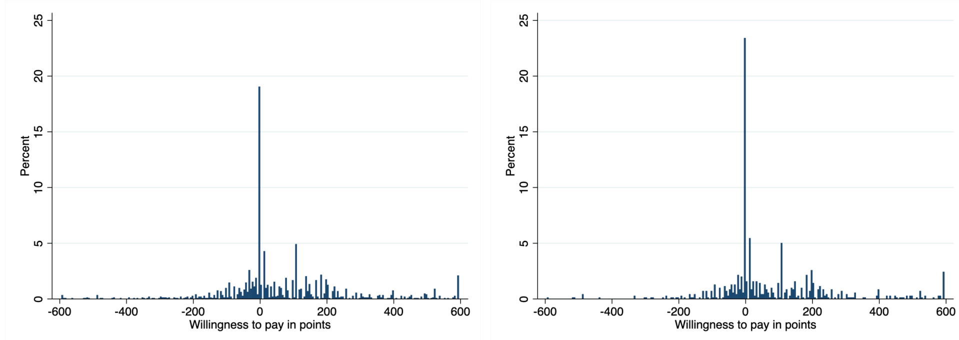

Figure 3: Distribution of the willingness to pay in points (June 2021 and January 2022. LHS: all subjects, $N = 1422$, RHS only highly consistent subjects, $N = 696$).

of highly consistent subjects on the right panel. Taking the whole sample, the average willingness to pay amounts to 67 points, which is significantly different from 0 (t-test, Wilcoxon sign-rank test (in the following WSR): $p < 0.001$, N= 1422). The median willingness to pay is 12 points. When conditioning on being highly consistent in part 1, the average willingness to pay amounts to 76 points (t-test, WSR: $p < 0.001$, N= 696), and the median remains 12 points. Similarly, the average willingness to pay of the 36% who exhibit a very small average distance of $\delta \leq 10$ is 66 points (t-test, WSR: $p < 0.001$, N= 502).

To support Result 4b), we calculate how much individuals are willing to give up for choice autonomy in terms of the value of the underlying decision at hand. We can assess this relative value by calculating the utility from monetary outcomes that an individual is willing to forgo by keeping the choice. In our task, an individual receives the following expected utility when delegating the decision to another individual:[20]

$$v_i(c = 0) = 0.75\frac{1600^{(1-\hat{r}_i)}}{1 - \hat{r}_i} + 0.25\frac{600^{(1-\hat{r}_i)}}{1 - \hat{r}_i}, \tag{5}$$

based on the individually estimated risk parameter $\hat{r}_i$. When the individual keeps the choice, she has to pay a price p to do so. When $p = WTP$, the

[20]Remember that given the nature of our task, the utility is the same for lottery A and lottery B. We thus use lottery A for every individual to calculate the individual utility.

individual is just indifferent between deciding herself and delegating. Thus, the utility from the resulting monetary payments when keeping the decision right at a price of WTP can be written as

$$v_i(c=1) = 0.75\frac{(1600 - WTP)^{(1-\hat{r}_i)}}{1-\hat{r}_i} + 0.25\frac{(600 - WTP)^{(1-\hat{r}_i)}}{1-\hat{r}_i}. \tag{6}$$

Using these terms, $\frac{v_i(c=0)-v_i(c=1)}{|v_i(c=1)|}$ gives us the percentage difference in utility from monetary payoffs between delegating the choice and choosing oneself. Because at $p = WTP$ the individual is revealed indifferent between delegating and choosing herself, it must be that this difference in utility from monetary payoffs is just compensated by intrinsic utility from choice autonomy.

We find that the intrinsic value of choice autonomy in our sample on average amounts to 5.2% of the utility received from monetary payoffs. Conditioning on the subset of highly consistent participants, the value is 5.3%, for those with a very small $\delta \leq 10$, the value is 6.6%. Quite similarly, expressed in expected value, we find that the willingness to pay for choice autonomy on average amounts to 5% of the expected value of lottery A (5.6% for the highly consistent, 4.9% for those with a very small $\delta \leq 10$).

Result 4c) states that there is substantial heterogeneity in the measured preference. 53.8% of individuals have a strictly positive willingness to pay, 19.1% have a willingness to pay of zero, and for 27.1%, the willingness to pay is strictly negative. This implies that preferences over autonomous choices can take a positive or a negative value, the latter expressing an aversion to choosing oneself. The distribution again looks fairly similar when conditioning on the subsample of highly consistent participants (54.74%, 23.4%, and 21.8%).

Finally, it is noteworthy that some individuals indicate either a very high or very low willingness to pay for autonomy (see Figure 3), and one might be worried that these values do not reflect the true preference. Our results are robust to excluding participants who indicate an extremely high or extremely low willingness to pay (i.e. those who always accepted or always rejected an offer in part 2 and thus exhibit a WTP at one of the corners of the range that we can estimate). The average WTP remains positive without these observations and it amounts to 57.9 points, which is still significantly different from 0 (t-test: $p < 0.001$, WSR: $p < 0.001$, N=1387).[21]

To assess whether our results are influenced by the online environment in which the study was conducted, we replicated the main results in May 2022 in a lab experiment at the University of Fribourg, Switzerland. We recruited 152 participants for a total of 13 sessions. In each session, one subject participant was randomly selected to be the person to whom all other participants can choose to delegate their choice.[22] Another potentially important difference to the online setting were significantly higher stakes in the in-person lab setting, although the framing of the experiment in terms of points remained the same.[23] After applying the exclusion restrictions outlined in section 2.3, we obtained data from 139 decision makers in part 2 of the experiment.

In the lab sample, the average willingness to pay to choose oneself was 43.3 points (the median willingness to pay is zero), which is again significantly different from 0 (t-test, WSR: $p < 0.001$, N=123). Overall, 31.7% of the students display a willingness to pay of zero, 22.8% have a negative willingness to pay and 45.5% a positive willingness to pay. Both the average and the median are thus somewhat lower compared to the online sample and we observe fewer participants with a positive and more participants with zero willingness to pay for autonomy. Overall, the results from the in-person lab experiment confirm the results obtained from the Prolific sample (the differences in mean and median willingness to pay are not significant, t-test/MWU with p>0.1).

[21] 30 subjects were willing to pay every price offered to them. 5 subjects were willing to delegate for every bonus offered to them.

[22] Subjects were university students. The person to whom decisions were delegated participated normally in step 1, and received a fix payment of CHF 10 for part 2. The experimental design and presentation was otherwise identical to the studies on Prolific, the payoffs were adapted to commonly paid salaries for student jobs in Fribourg (CHF 24.25 on average, including a CHF 10 show-up fee).

[23] Higher stakes were achieved through a higher exchange rate in the laboratory, where 1000 points were worth CHF 5.

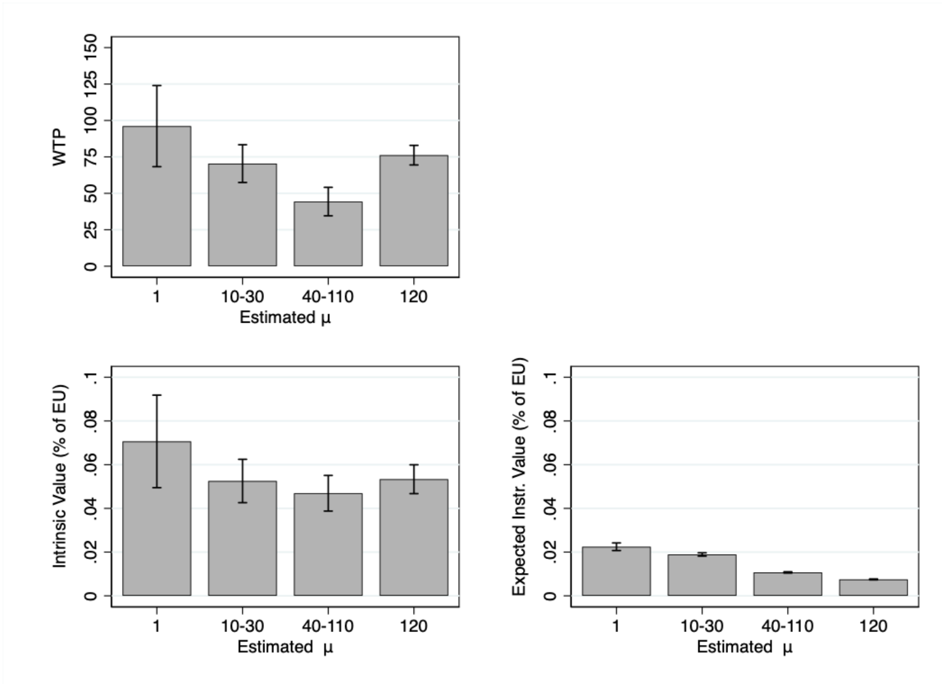

Figure 4: Panel 1: relationship between the estimated mean willingness to pay and the estimated consistency parameter $\hat{\mu}$. Panel 2: relationship between the expected average intrinsic value of autonomy and $\hat{\mu}$. Panel 3: relationship between the estimated instrumental utility derived from choice autonomy in percent of EU and the estimated consistency parameter $\hat{\mu}$.

3.3 Choice inconsistency and instrumental value

Our analysis in Section 3.2 showed that participants on average had a positive willingness to pay to retain choice autonomy, and revealed that this result holds for subjects with precisely identified indifference sets. In this subsection, we further explore the relationship between our preference measure and the precision with which the indifference set was identified.

The top left panel of figure 4 displays the average willingness to pay to retain choice autonomy for the four consistency classes defined in subsection 3.1. It can be seen that the average willingness to pay is significantly positive for all four categories. Consistent with the notion that the choice in step 2 contains more expected instrumental value the less precisely the indifference set was estimated, we do observe a decrease in the willingness to pay when moving from inconsistent to consistent participants, although the overall trend is not very strong and not statistically significant. However, perhaps surprisingly, the average willingness to pay is lowest for the subgroup with $40 \leq \hat{\mu} \leq 120$. Indeed, the willingness to pay of this subgroup is (weakly) significantly smaller than the willingness to pay of the highly inconsistent subgroup (t-test: $p = 0.059$) and significantly smaller than the willingness to pay of the highly consistent subgroup (t-test: $p = 0.006$). The difference to the inconsistent subgroup is not statistically significant.

Furthermore, the distribution of the willingness to pay between the consistent and highly consistent subgroups differs significantly. Among the highly consistent subjects, 22% display a negative willingness to pay, 23% a willingness to pay of zero, and 55% a positive willingness to pay. In contrast, the willingness to pay is negative for 34% of the moderately consistent subjects, zero for 15%, and positive for 51%. These distributional differences are statistically significant ($p < 0.001$, Kolmogorov Smirnoff test, N=402+696).

One potential rationalization of this observation could be that a subset of our subjects display preferences for randomization, as suggested by Agranov and Ortoleva (2017). Agranov and Ortoleva (2023) show that preferences for randomization manifest themselves around a potential indifference point, and do not imply randomness over the whole interval. In our setting, such preferences would thus most likely be classified as being "moderately consistent", but not highly consistent or inconsistent. At the same time, preferences for randomization would predict that subjects display a *negative* willingness to pay when prompted with a choice from a set that contains alternatives between which the participant is (near) indifferent. In contrast, highly consistent subjects do not display preferences for randomization, and are thus also less likely to display a negative willingness to pay for choice autonomy in step 2 of our elicitation task. Preferences for randomization are thus one potential microfoundation of preferences for choice autonomy, in this case a microfoundation that *reduces* the individual desire to be autonomous in choice in our decision task. The fact that those subjects who display minor inconsistencies in their choice patterns in step 1 are the most likely to display a negative willingness to pay for choice autonomy is consistent with such an interpretation.

Result 2 *Moderately consistent subjects display the lowest average willingness to pay for choice autonomy, and contain the highest fraction of subjects with a negative willingness to pay for choice autonomy. This observation is consistent with a subset of our participants displaying preferences for randomization.*

To further deepen our understanding of the potential relevance of inconsistent choice on the measured willingness to pay, we next consider whether residual instrumental value might explain the observed willingness to pay for choice autonomy in step 2 of our elicitation process. To this end, we utilize the structural model underlying our DOSE procedure. In particular, we use the posterior probability distribution $f(r|\hat{\mu})$ on which $\hat{r}$ was estimated (see Section 2.1 and Appendix A.1 for details) to estimate the expected remaining *instrumental* value of choice autonomy. If a participant is presented with an indifference lottery $\hat{B}$ based on $\hat{r}$, but the true risk preference parameter is $\tilde{r}$, the choice in part 2 contains instrumental value. More precisely, the instrumental value, expressed in expected utility terms, is given by:

$$U_{instr} = |U(A|\tilde{r}) - U(\hat{B}(\hat{r})|\tilde{r})|,$$

where $U(A|\tilde{r})$ is the expected utility of the fixed lottery A, and $U(\hat{B}(\hat{r})|\tilde{r})$ is the expected utility of the lottery $\hat{B}$ that was chosen based on the estimated risk preference parameter $\hat{r}$, given the true risk preference parameter $\tilde{r}$. Thus, for each participant, we can calculate the expected instrumental value of choice given $\hat{B}(\hat{r})$ and given $f(r|\hat{\mu})$:

$$U_{instr} = \int_{\mathcal{R}} f(r|\hat{\mu})|U(A|r) - U(\hat{B}(\hat{r})|r)|dr$$

The bottom left panel of Figure 4 displays the relationship between U_{instr} and the estimated consistency parameter $\hat{\mu}$, expressed as a percentage of the utility obtained from lottery A (assuming that $\hat{r} = \tilde{r}$). We see that the expected instrumental value of choice is substantial when subjects are highly inconsistent, but decreases as consistency increases. The mean expected instrumental value drops to 1 percent of the estimated expected utility of lottery A once subjects are at least moderately consistent ($\hat{\mu} \geq 40$), see bottom right panel of Figure 4. The bottom left panel of Figure 4, in contrast, shows the average estimated intrinsic value of choice autonomy for all levels of $\hat{\mu}$, expressed as a percentage of utility received from the choice.[24] The difference between the measured intrinsic value of choice autonomy (in percent of overall utility) and the calculated expected instrumental value of choice autonomy (in percent of overall utility) is significantly different from zero using a t-test, both overall ($p < 0.01$) and for each of the $\hat{\mu}$ categories shown in Figure 4 ($p = 0.026$ for $\hat{\mu} = 1$, $p < 0.001$ for $\hat{\mu} > 1$). Thus, residual instrumental value, due to imprecise measurement of the point of indifference in step 1, cannot explain the measured willingness to pay for choice autonomy in our experiment.

Combining the insights from all panels of Figure 4 as well our analyses in Subsection 3.1 suggests that it is only for highly inconsistent subjects that we find a possibly substantially inflated willingness to pay because of a substantial instrumental value component. However, for subjects with moderate to high levels of consistency ($\hat{\mu} > 30$) inconsistencies are fairly small and remaining instrumental value does not seem to play a major role in determining the individual willingness to pay.

Result 3 *The expected instrumental utility component is negligible except for highly inconsistent subjects. For all subjects, we observe that the instrumental utility due to imprecise measurement of the indifference set cannot explain the measured willingness to pay for choice autonomy.*

3.4 Delegating to a Coin Toss

In order to better understand the microfoundations of the observed behavioral preference for choice autonomy in our decision task, we conducted a control experiment in which in step 2 participants had the possibility to delegate the choice between the two lotteries to a coin toss that chooses either option with

[24]See section 3.2 for details.

50% probability (treatment COIN). All other procedures and design features remained identical to the previously described experiment in which delegation took place to another human decision maker (treatment HUMAN).

While delegation to another human decision maker unambiguously constitutes a loss of choice autonomy, it remains elusive whether this is also the case when delegating to a coin. For example, it could be argued that the decision maker fully retains choice autonomy even in case of delegation because delegation then simply constitutes the choice of an objective compound lottery over the two individual lotteries, which may simply express the deliberate preference over lotteries of the decision maker. This is precisely the argument underlying models of deliberate stochasticity (Cerreia-Vioglio et al., 2019; Machina, 1985), whose primary application so far has been to explain expressed preferences for randomization (Agranov and Ortoleva, 2017, 2023) via quasiconcave preferences over probability mixtures, which would predict a *positive willingness to pay to delegate* the choice to the objective coin in our setting. However, Machina (1985) already noted the possibility that individuals could also be averse to stochasticity in this framework, which would imply *quasiconvex* preferences in probabilities, and that an "individual is (weakly or strictly) averse to randomization over indifferent alternatives" (Machina, 1985, p.590). Given the construction of the choice set in our experiment, the coin toss treatment provides us precisely with the ability to observe the extent to which individual behavior is consistent with a quasiconcave or quasiconvex representation of preferences in probability mixtures.

However, also in the COIN treatment it remains conceivable that delegation still constitutes a loss of choice autonomy, as the decision maker forgoes the possibility to choose a specific alternative and thus looses agency in determining her outcomes.[25] More generally, it seems plausible that there is individual heterogeneity in how individuals perceive delegation in the COIN treatment in this respect. Behavior that can be represented by concave prefer-

[25]In principle, there is no a priori reason to believe that individuals couldn't even be *more* averse when delegating to an automated draw (which they may perceive as a "machine") than when delegating to a human decision maker.

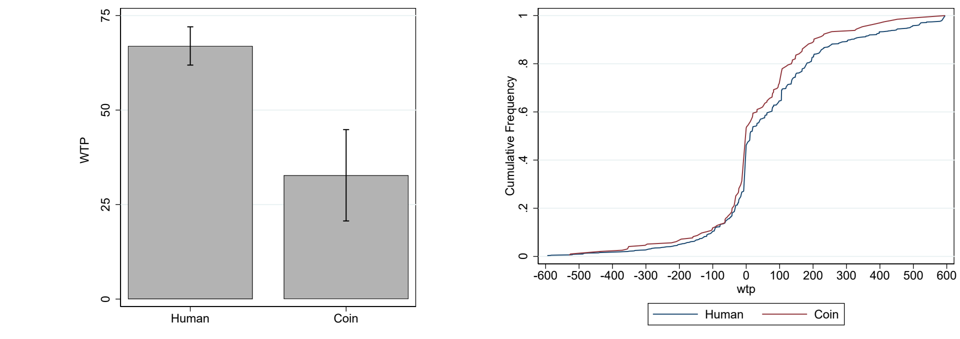

Figure 5: Left Panel: Average willingness to pay in points by treatment, N=1422 (human) and N=195 (coin). Right Panel: Cumulative distribution of the willingness to pay by treatment.

ences over lotteries could then in fact be microfounded in intrinsic preferences for choice autonomy.

We collected data from 246 subjects on August 22, 2023 on the platform Prolific.co.[26] Applying the same exclusion restrictions as before, we are left with 195 observations. We find that the willingness to pay in COIN is positive but lower: The median decreases to 0 and the mean value is 32.75 (std.dev.=168.66), which is still significantly larger than zero (t-test, WSR: $p < 0.01$, N= 195), but half the magnitude compared to the case of delegation to another person. This difference is statistically significant (two-sample ttest p=0.018, MWU: p=0.032). The individual heterogeneity shows a similar pattern: The willingness to pay is positive for 46.67% , zero for 22.05%, and negative for 31.28%. Among the 97 highly consistent subjects, the mean willingness to pay is 14.82 points, which is no longer significantly larger than zero. The median value is zero.

Figure 5 contrasts the findings from the COIN treatment with our previous results when the choice was delegated to a human decision maker. The left panel shows that the average willingness to pay in COIN is indeed significantly

[26]US Americans were not allowed to enter the study because we collected data with only US American subjects for another (large) experiment at the same time. Except for this restriction, there were no pre-screening criteria for participation in the study in addition to, again, an approval rate of at least 99/100 on Prolific. The average payoff was £4.15, including a £2 base payment, the median duration was 18 minutes.

smaller (t-test: $p = 0.02$; MWU: $p = 0.03$). When restricting the sample to those that are at least moderately consistent or highly consistent, these results are confirmed and remain significant. The right hand panel shows the distribution of the willingness to pay to retain choice autonomy across the two experiments. It appears that there is a shift in the willingness to pay towards smaller values in particular in the positive domain, although distributional differences are only marginally significant (Kolmogorov-Smirnov Test: $p = 0.09$). Again, restricting the sample to those participants that are moderately or highly consistent confirms these results ($p = 0.08$ and $p = 0.07$, respectively).

Result 4 *When subjects can delegate to an objective random draw, the willingness to pay to choose oneself is significantly positive, but significantly smaller compared to the situation in which subjects can delegate to another human decision maker (33 compared to 67 points).*

The results of the COIN treatment reveal that the displayed preference to retain choice autonomy becomes significantly weaker when choice is delegated to an objective coin toss rather than a human decision maker. It thus appears that the existence of a human decision maker, or more generally the identity of the delegate, is a fundamental determinant of the value of choice autonomy. While it is not obvious whether (all) individuals perceive delegation to an objective coin toss as a loss of choice autonomy, the fact that we still observe a significantly positive willingness to pay suggests either that there is substantial heterogeneity in this perception, or, if one were willing to assume that there is indeed no loss of choice autonomy, that there is a significant fraction of individuals that display concave preferences over lotteries for other (unexplained) reasons. In the latter case, the difference in the willingness to pay between the COIN treatment and the HUMAN treatment would then represent the true intrinsic value of choice autonomy, above and beyond any instrumental value from deliberate (non-)stochasticity. However, as argued above, we postulate that preferences that can be expressed as concave over lotteries in our setting are plausibly microfounded in intrinsic preferences for choice autonomy.

A second important element of delegating to a human rather than to an objective randomization device is that in the first case the probabilities with which each of the two alternatives is chosen is ambiguous, whereas the probabilities are objective in the latter, which may be a contributing factor towards an aversion to delegate. For example, Jabarian and Lazarus (2022) argue that individuals may be averse to ambiguity *per se*. Note, however, that such aversion does not follow from standard models of ambiguity aversion (for example, all models that satisfy the Anscombe-Aumann monotoniciy axiom (Anscombe and Aumann, 1963), as there is only ambiguity in the probabilities with which lotteries A and B get chosen, but lotteries A and B remain objective lotteries with identical expected utility.[27] Such models can therefore not explain behavior in our setting. More generally, it should also be noted that uncertainty in choice probabilities is an inherent feature of a loss of choice autonomy.

3.5 What Predicts Preferences for Choice Autonomy?

Having established the existence of and heterogeneity in intrinsic preferences for choice autonomy, we now provide a first assessment of potential antecedents, and explore to what extent such preferences are associated with socio– demographics and other selected personal characteristics and attitudes.

Table 1 displays the results of linear regressions on willingness to pay that include the following socio-demographic variables: gender, age, income, education, marital status, number of kids as well as whether a person is an English native speaker. In columns (4-8), we additionally include the Big 5 personality traits (Gosling, Rentfrow and Swann Jr, 2003), which were only collected in the June 2021 sample. Columns (3, 4) and (7, 8) repeat the same estimations using median regressions, to account for the fact that the mean and median of the dependent variable WTP differ quite substantially due to the presence of outlier values with a very high willingness to pay.

Columns (1-4) of Table 1 show the results for the entire sample. It can be

[27] Relatedly, Heydari and Chabris (2019) provide empirical evidence that individuals' preference for an ambiguous rather than a risky choice between two objective lotteries increases when the lotteries become harder to compare, which they arguably are in our setting. It is thus not obvious whether uncertainty in choice probabilities is necessarily a negative influence relative to an objective draw in our setting.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	June+Jan (OLS)		**June+Jan (Median R.)**		**June (OLS)**		**June (Median R.)**	
Male	33.563	33.114	23.133	18.618	32.596	38.499	28.492	28.153
	(10.243)	(10.491)	(9.224)	(7.405)	(14.609)	(15.277)	(10.589)	(11.926)
Age	0.270	0.875	0.166	0.534	0.145	0.148	–0.146	0.789
	(0.717)	(0.759)	(0.511)	(0.497)	(1.401)	(1.449)	(1.209)	(1.137)
Income	–1.833	–1.082	–0.663	–0.202	–3.852	–3.988	–2.578	–2.458
	(1.738)	(1.815)	(0.638)	(0.682)	(2.413)	(2.655)	(1.266)	(1.535)
Education	1.334	1.110	–4.141	–1.333	–1.601	–1.000	–5.801	–1.957
	(5.171)	(5.417)	(2.545)	(2.892)	(7.364)	(7.760)	(6.138)	(5.497)
Married	–15.259	–16.930	–15.309	–15.099	–21.248	–24.763	–5.559	–4.616
	(16.543)	(16.603)	(11.101)	(8.571)	(23.464)	(23.656)	(19.563)	(19.310)
Number_kids	–3.701	–7.356	–4.693	–6.050	–7.985	–7.555	10.132	7.680
	(6.751)	(6.751)	(4.541)	(4.412)	(11.553)	(11.612)	(11.149)	(11.798)
English_Speaker	–12.626	10.727	–0.994	6.911	–1.685	9.481	9.799	–8.863
	(12.658)	(24.249)	(5.284)	(11.915)	(17.649)	(33.927)	(13.608)	(24.688)
Big5_extraverted					–2.365	–2.715	–3.369	–5.580
					(4.028)	(4.230)	(3.403)	(3.143)
Big5_agreeable					–4.486	–3.620	–0.091	–0.578
					(5.289)	(5.438)	(4.541)	(4.451)
Big5_conscientious					3.535	5.065	–0.058	1.403
					(4.851)	(5.057)	(4.129)	(3.617)
Big5_calm					5.527	4.180	–0.547	–0.350
					(4.202)	(4.442)	(3.586)	(3.480)
Big5_open					8.668	5.115	4.798	–0.170
					(5.832)	(6.934)	(4.562)	(4.692)
Constant	62.510	586.896	33.696	1325.980	39.786	542.484	40.658	1015.164
	(31.563)	(510.835)	(20.295)	(497.150)	(64.105)	(539.502)	(48.141)	(653.547)
R^2 / Pseudo R^2	0.012	0.041	0.006	0.026	0.022	0.066	0.012	0.038
Controls	no	yes	no	yes	no	yes	no	yes
Observations	1406	1406	1406	1406	782	782	782	782

Table 1: Correlation between willingness to pay and personal characteristics. Dependent variable: WTP. Columns (1,2) and (5,6): OLS estimates with robust standard errors. Columns (3,4) and (7,8): Median regressions with robust standard errors in parentheses. January and June waves in columns (1-4), June 2021 wave in columns (5-8). Controls in columns (2, 4, 6, 8) include risk_taking, nationality, highly_inconsistent_part1, highly_inconsistent_part2, prolific_score and not_failed.[a]

[a]Not_failed is a dummy variable that is equal to one if the person has not failed any attention check (93.5%). The Prolific Score tells us to what extend participants behaved in a reliable way in previous studies. Remember that subjects with a Prolific Score <99 were excluded in the January wave. 100 is the perfect score which is reached by 79.9% in the June sample. Based on Definition 1, highly_inconsistent_part1=1 if $\hat{\mu} = 1$ and highly_inconsistent_part2=1 if $\gamma = 1$ control for subjects making highly inconsistent choices in either of the two parts of the experiment.

seen that the coefficient of Male remains significant at the 1% or 5% level in each specification. It loses statistical significance in the smaller subsample of June only, although the magnitudes of the coefficients remain similar in size. The coefficients of the dummy variable for being married and for the number of kids are rather large and negative, but insignificant across the estimations in Table 1. Interestingly, all other socio-economic characteristics are of limited explanatory power. Similarly, as can be seen in columns (5-8), the BIG 5 remain insignificant predictors of intrinsic preferences for choice autonomy.

Are preferences for choice autonomy associated with other fundamental attitudes such as risk preferences or trust? Since our measure is designed to eliminate any instrumental value considerations, we expect trust in others to be unrelated to the willingness to pay. Trust in others should only matter for the willingness to delegate a choice *if* the outcome of that choice matters to the decision-maker, and thus beliefs about the actions of the other party matter. Table A.4 in the Appendix shows that correlations of the willingness to pay with four different survey questions capturing facets of trust in other people (see Section A.4) are negative, small, and not statistically significant. Overall, these observations support our previous conclusion that we successfully excluded instrumental value aspects of choice.

In contrast, we find a significant correlation for a person's self-reported willingness to take risks, see Table A.5 in the Appendix. The more willing to take risks, the higher the willingness to pay.[28] While one might worry that this correlation contains some experimental confound since we elicit the individual's willingness to pay via choices between lotteries, note that columns (3-6) show that the correlation is equally strong between our measure of risk taking and independent survey measures of a preference for or perception of free choice. In particular, we observe a significant positive correlation with the world value survey question on freedom and control (Inglehart, 2014) and with the desirability of control index (Burger and Cooper, 1979). The correlation

[28]Note that, if anything, delegation increases outcome risk. Thus, this observation is inconsistent with an interpretation related to instrumental value—if instrumental value would drive this correlation, a person should be less willing to delegate if she is risk averse.

is mostly—but not perfectly—robust to the inclusion of control variables and to the estimation method, see Table A.5. This suggests that an intrinsic preference for autonomy and a willingness to take more risk may be related characteristics (see also Dean and Ortoleva (2019) for a discussion of related behavioral characteristics).

To ensure the robustness of our results and show that they are not driven by inconsistent subjects, we replicate all results excluding subjects with $\hat{\mu} < 40$ in Appendix A.2.2. Table A.11 shows that the coefficients on Male are similar across most specifications (except for insignificant results in columns (4) and (8) with median regressions with control variables). We will continue to provide results for the subsample of moderately and highly consistent subjects for all analyses, but only refer to them in case there are noteworthy deviations.

Overall, socio-demographics do not seem to be strong predictors of intrinsic preferences for choice autonomy. With the exception of gender, intrinsic preferences for choice autonomy seem to be fairly equally distributed in the population regarding socio-economic characteristics. Concerning other personal characteristics and attitudes, risk taking appears to be a highly correlated characteristic that may be interesting to explore further in future research.

3.6 Related Psychological Constructs

How does our measured preference relate to established concepts in psychology? Our questionnaire includes measurements of locus of control (LOC, Rotter (1966)), autonomous functioning (IA, Deci and Ryan (1985)), generalized self-efficacy (GSE, Schwarzer, Jerusalem et al. (1995)) and desirability of control (DC, Burger and Cooper (1979)), as well as the world value survey question measuring a person's perceived freedom and control (Inglehart, 2014).

Table 2 displays coefficients of OLS regressions of the psychological constructs on WTP, in column (1) without and in column (2) with controls. In columns (3) and (4), the same estimations are repeated using median regressions. The correlations with locus of control, the index of autonomy, generalized self-efficacy and the world value survey question on freedom and control are generally insignificant. Only the positive correlations with the desirability of control index show a weak and unstable significance that vanishes when including socio-demographic controls. In contrast, the correlations between the psychological constructs themselves are large and significant (see Table A.6 in Appendix A.2), confirming previous literature (Aldama et al., 2021).

	WTP (OLS)		**WTP (Median R.)**	
LOC	9.23	1.71	7.311	6.173
	(11.994)	(12.589)	(12.550)	(9.596)
IA	1.778	2.442	-12.825	-10.165
	(7.686)	(8.167)	(8.420)	(6.621)
GSE	10.518	5.293	10.165	4.698
	(7.660)	(8.743)	(8.174)	(6.158)
DC	15.94	8.527	23.284	10.748
	(9.245)	(10.309)	(10.218)	(9.113)
WVS	7.328	5.463	4.611	-.640
	(4.486)	(4.738)	(4.037)	(3.842)
Controls	no	yes	no	yes
Observations	791	782	791	782

Table 2: Each cell shows the coefficient of one regression with willingness to pay as the dependent variable. Columns (1, 2): OLS regressions with robust standard errors in parentheses. Columns (3, 4): Median regressions with robust standard errors. Constants are omitted. Respective independent variables in the 20 regressions are: LOC: index of internal control (Rotter, 1966), IA: index of autonomy (Deci and Ryan, 2006), GSE: self-efficacy index (Schwarzer, Jerusalem et al., 1995), DC: index of desirability of control (Burger and Cooper, 1979), WVS: world value survey question on freedom and control (Inglehart, 2014). Columns (1, 3) without controls, columns (2, 4) include controls for age, gender, income, education, risk_taking, nationality, highly_inconsistent_part1, highly_inconsistent_part2, prolific_score and not_failed. June 2021 wave.

Considering the nature of the different concepts may help understanding these results. The main distinction between LOC, IAF, GSE, the WVS question and our measure is that we elicit a *preference*, whereas the other four measures express a *perception*, in other words, a person's belief about the degree of autonomy (freedom/control/self-efficacy) that she has. It is not ex ante clear how these two should relate. Verme (2009) argues that for a person to value freedom of choice she has to believe to have an internal locus of control—because the latter allows her to take advantage of free choices. On the other hand, experiencing poverty and restricted freedom of choice that may be associated with a low locus of control can possibly induce a strong desire for autonomy in the individual. One can thus construct arguments for a positive as well as for a negative relationship. The fact that the constructs are overall rather independent of each other in our data thus either means that the relationship between the constructs is complex and we are missing important control variables when assessing the correlations, or that we indeed measure a conceptually distinct psychological construct.

Result 5 *The willingness to pay for choice autonomy in our task is not related to well-established survey-based measures used in the psychology literature. This indicates that we measure a psychological construct that is different from perceptions of own autonomy, locus of control and self-efficacy.*

4 Discussion

Our preference elicitation method revealed that individuals have intrinsic preferences for choice autonomy. More specifically, it documents the difference in utility that individuals receive when taking a decision from a choice set containing indifferent options themselves vs. having someone else take that decision for them. This difference can have multiple microfoundations, and we would like to discuss several candidates (that are not mutually exclusive).

Autonomy is a direct source of utility. One perspective is that autonomy directly functions as a consumption good. This view is consistent with the idea that autonomy is a human need (Deci and Ryan, 1985) and can generate procedural utility (Frey, Benz and Stutzer, 2004). Such a need could either constitute positive consumption value from exercising autonomy, or it could stem from an aversion to being other-determined. The fact that subjects facing the possibility to delegate to a random draw display a smaller average value for choice autonomy suggests that an aversion to having choices over own payoff consequences made by *another person* can party explain the observed value for autonomous choice. If one adopts the view of choice autonomy as a consumption value, it becomes pertinent to explore the structure of the respective utility function and its manifestations. For instance, if autonomy resembles a consumption good, one may expect that it displays decreasing marginal utility. For our elicitation tool, it would imply that it measures the marginal utility received from an additional choice, which may depend on the degree of choice autonomy that a decision-maker experiences in everyday life.

The process of choice changes the utility of outcomes. Another possibility is that agency in choice changes the utility that the decision maker receives from specific outcomes. Indeed, a few studies in social psychology suggest that the value of choice autonomy might be determined by the utility derived from the outcome of a choice. For example, the (non)-involvement in the choice process may affect the feelings and emotions that are experienced when specific outcomes are obtained, and thus the process of choice may affect the utility associated with the lotteries contained in the choice set in our experiment. Under this view, the utility function would need to be defined over the metachoice (Bernheim and Taubinsky, 2018). Step 1 of our elicitation task only reveals indifference between lotteries A and B in the decision frame in which the lotteries are evaluated without the option to delegate. A positive willingness to pay in step 2 then reveals that the decision maker has a preference for choice autonomy in the frame in which she faces the possibility to delegate that choice to another individual (for example, due to feelings and emotions associated with the two procedures of choice) .[29]

Preferences over probabilities. Finally, as discussed previously, given that we elicit preferences for autonomy in the context of lottery choices, a preference for choice autonomy in our setup could also be represented by an extension of the utility framework to the probability space, and thus reflect a preference for or against randomization in the spirit of Machina (1985) or

[29]Note that, if one adapts the notion of metapreferences, as Bernheim and Taubinsky (2018) point out, one faces the so-called comparability problem. Our decision experiment only reveals the preference for choice autonomy, given that the decision maker actually has the possibility to delegate. In principle, it is possible that the decision maker would be even better off in a situation in which she never faced the choice whether or not to delegate, and another party simply chose lottery A or B for her. However, the utility associated with such a decision frame remains unobserved in our experiment.

Cerreia-Vioglio et al. (2019). If one adopts this perspective, intrinsic preferences for choice autonomy can be seen as a microfoundation of preferences that can be represented as concave preferences over lotteries.

5 Conclusion

In this paper, we develop a novel incentivized behavioral measurement tool for intrinsic preferences for choice autonomy that is suitable for wide-scale applications in the laboratory as well as in online and lab-in-the-field experiments. Our innovative elicitation method identifies the intrinsic utility component of choice autonomy while excluding any instrumental benefit that is attached to choice and controlling for measurement error. We provide evidence for the existence of such preferences in a large online sample and conclude that the value of choice autonomy cannot be reduced to its purely instrumental benefits. We also find substantial heterogeneity in preferences, with about half of the subjects exhibiting a positive value, but a sizeable minority of more than a fourth of participants showing an aversion to making autonomous choices.

We find that the average willingness to pay is reduced to about half the size in another experiment in which participants faced the choice to delegate to a random draw instead to another person, suggesting that it matters to whom one can delegate. Future research is needed to better understand how the identity of the delegate shapes preferences for choice autonomy.

We believe that our behavioral measure will enable a stream of future research that analyzes the role of preferences for choice autonomy in economic and political behavior. For example, Sugden (2008) or Arad and Rubinstein (2018) suggest that a preference for freedom of choice might play a role in how some people react to libertarian paternalist policies, including commonly employed nudges such as defaults. Similarly, one cause of the British vote to leave the EU appears to have been a desire to "take back control" (May, 2017).

Intrinsic preferences for autonomy may also have an important impact on optimal organizational design. Dessein and Holden (2022) show theoretically how private benefits stemming directly from decision making, such as intrinsic preferences for autonomy, can shape organizational design. Bloom, Sadun and Van Reenen (2012) show a cross-country correlation between the degree of decentralization of organizations and the power distance index (Hofstede, 2001), which "measures the perceptions of and preferences for hierarchical relationships" (Bloom, Sadun and Van Reenen (2012), p.1687). Differences in decentralization can be caused by differences in intrinsic preferences for autonomy, but are likely also caused by differences in the instrumental value of different organizational forms across countries. Our tool can help in investigating the factors underlying such relationships.

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Appendix

A.1 DOSE Method

A.1.1 DOSE Method for Step 1 of the elicitation procedure

DOSE adjusts the value of X from choice situation to choice situation in such a way that given an individual's decision pattern in choice situations 1 to t, the choice between alternatives A and B in choice situation $t+1$ maximizes the information regarding the individual's degree of risk aversion as well as his/her choice consistency. In particular, we assume that the participant's risk preferences and choice behavior can be characterized by the following two equations:

$$u_i(w) = \frac{w^{1-r_i}}{1-r_i} \tag{7}$$

where w is the payoff in points and r_i is the individual's risk aversion parameter.

$$Pr(A) = \frac{1}{1+e^{-\mu_i(U_i(A)-U_i(B))}} \tag{8}$$

where $Pr(A)$ is the probability of choosing lottery A over B, μ_i specifies the individual's degree of stochastic response in choice, and U_i denotes the expected utility of a lottery given u_i.

For estimating $\hat{r}_i$ and $\hat{\mu}_i$, DOSE uses sequential Bayesian updating and combines it with information entropy to increase speed of inference. To initialize DOSE, we first decided on the appropriate discrete parameter space for r given by $\mathcal{R} \in (r_1, r_2, ..., r_n)$ and μ, given by $\mathcal{M} \in (\mu_1, \mu_2, ..., \mu_m)$ whereby we define $\mathcal{R} \times \mathcal{M} = \mathcal{K}$ models k, one for each possible combination of r and μ. We then assign to each model k a prior probability $p_k = Pr(r_k, \mu_k) = Pr(r_k)Pr(\mu_k)$.

Like Wang, Filiba and Camerer (2010), we use a similar range for the risk parameter as Holt and Laury (2002), namely from -1.2 to 1.2. The range for μ is sensitive to the chosen payoff values for A and B. Based on precision in estimating parameters of simulated subjects, we found that $\mathcal{M} \in \{1, 10, 20, ..., 120\}$ provides a sensible parameter space for our setup. Finally, regarding the assumed prior distribution over models, we choose a uniform prior, i.e. $\forall j, i : p_j = p_i$, given that estimates that are made using different priors only slightly differ (Wang, Filiba and Camerer, 2010; Chapman et al., 2022) and given that data on the distribution of the choice consistency parameter in our setting is non-existent.

Second, we define a reference lottery A that pays a high payoff of 1600 points with 75% probability and a low payoff of 600 points with 25% probability, and a set of lotteries $\mathcal{B} = \{B_1, B_2, ..., B_n\}$ with B_j paying a high payoff of X_j points with 50% probability and a low payoff of 600 points with 50% probability. We then define the set of all binary combinations of lottery A and some lottery B as $\mathcal{Q} \in \{(A, B_1), (A, B_2), ..., (A, B_n)\}$.

This setup allows updating prior probabilities for every model k with Bayes' rule when asking a participant to make a choice for a choice situation $Q_i \in \mathcal{Q}$ as follows:

$$p(k|a) = p(r_k, \mu_k|a) = \frac{p(a|r_k, \mu_k)p(r_k, \mu_k)}{\sum_j^k p(a|r_j, \mu_j)p(r_j, \mu_j)} \tag{9}$$

where $a \in \{\text{choosing A, choosing B}\}$ denotes the individual's choice.

Iterating this procedure of asking a question and updating beliefs leads to a lower variance in the posterior probability distribution over models, i.e. a more precise estimation of an individual's true parameters. To optimize the sequence of questions with respect to the speed of inference, an information criterion is used: Following Wang, Filiba and Camerer (2010) and Chapman et al. (2022), we define a Kullback-Leibler information number for each model k for question $Q_i \in \mathcal{Q}$:

$$I(k; Q_i) = \sum_a log(\frac{l_k(a; Q_i)}{\sum_{j=1}^k p_j l_j(a; Q_i)}) p_k l_k(a; Q_i) \tag{10}$$

where $a \in \{\text{choosing A, choosing B}\}$ denotes the binary choice between choosing lottery A or B and l_k is the associated likelihood of choosing a in Q_i under model k. $I(k; Q_i)$ measures how informative question Q_i is if k is the correct model. By summing up $I(k; Q_i)$ for every model and weighing according to the model's probability p_k, we get the Kullback-Leibler information number for a given question $Q_i \in Q$:

$$KL(Q_i) = \sum_k^n p_k I(a; Q_i) \tag{11}$$

Asking a participant the question $Q^* = \max_Q KL(Q)$ maximizes information gained from the observed choice. In other words, Q^* is the question that in expectation updates the prior the strongest. Iterating the process of (i) choosing Q^* given the current probability distribution and (ii) updating beliefs delivers the most informative sequence of questions at the participant level.

It is important to note that, after every iteration, the current Q^* is excluded from Q for the next round.

Each participant makes a total of 10 choices, where one choice is chosen at random for payment at the end of the experiment. In each round, questions were selected according to the DOSE procedure explained above, except for rounds 5 and 10. For participants that are very consistent in their choice patterns, the DOSE algorithm quickly converges to a narrow range of lotteries B_j, in order to fine-tune the risk aversion parameter at incremental levels. Thus, to break the monotonicity of the choice situation sequence, in round 5 a lottery B_j was chosen for which the expected value of the corresponding lottery B is significantly different[30] to the prior choice situations. In round 10, we have an additional reason for selecting a different choice situation. In step 2 of our elicitation procedure, we will use the lottery B_j^* that makes the individual indifferent to lottery A. DOSE would likely choose a lottery in round 10 that is very close to B_j^*, which we wanted to avoid, and rather create more variety in the lotteries the individual faced in the final choice of part 1.[31]

Because every participant starts with the same prior distribution over models k, the most informative choice situation in the first round is always the same for each participant. Because each choice situation has 2 options (choosing lottery A or lottery B), there are a total of $2^{10} = 1024$ possible decision paths in our elicitation procedure. We pre-specified and stored the optimal sequence of choice situations for each decision path in our experimental implementation, which made intensive computations during the experiment unnecessary.[32]

To obtain the estimates for $\hat{r}$ and $\hat{\mu}$, we proceed as follows: After each choice, the distribution $f(r, \mu)$ is updated leading to a posterior distribution $f(r, \mu | C_1(t))$, where $C_1(t)$ denotes the sequence of choices in the first t choice situations of step 1 of the elicitation process. To identify an individual i's indifference lottery, we consider the posterior probability distribution after the ninth choice, denoted by $f(r, \mu | C_{1i}(9))$. The tenth choice was not included in the calculation of the indifference lottery because it only served the purpose of breaking the monotonicity of the lottery choice sequence and not of obtaining

[30]Based on simulations, we decided to randomly select a lottery B in choice situation 5 whose value X differed between 50 and 150 points from the B_j in the previous choice situation.

[31]While we lose some information relative to the application of DOSE in 10 rounds, simulations have shown that the 8 rounds in which DOSE is applied deliver sufficient information on the parameters r and μ to obtain precise parameter estimates at the individual level, at least for high levels of consistency.

[32]The fact that using an information criterion like Kullback-Leibler needs a lot of computing power to calculate the optimal question for a given round makes the calculation of optimal decision paths in real time a major implementation challenge for experiments.

further information about the risk preference. We then first determine the maximum a posteriori probability (MAP) estimate for μ, denoted μ_{MAP} given the posterior distribution $f(r, \mu|C_{1i}(9))$, which is equal to the modal value of μ in $f(r, \mu|C_{1i}(9))$. Then, we calculate $\hat{r}$ as the mean value of r conditional on μ_{MAP}, that is

$$\hat{r}_i = \sum_{r \in \mathcal{R}} r f(r|C_{1i}(9), \mu_{i,MAP}).$$

Based on $\hat{r}_i$, we then construct an *indifference lottery* $\hat{B}_i$ that pays a high payoff $\hat{X}_i$ such that individual i is expected to be just indifferent between lotteries A and $\hat{B}_i$ (rounded to the nearest multiple of 10, which was the smallest point unit used in our experiment).[33] In addition, for each individual, we obtain an estimate for $\hat{\mu}$ based on the MAP estimate for μ given $f(r, \mu|C_1(10))$.[34]

A.1.2 DOSE Method for Step 2 of the elicitation procedure

In step 2, we want to estimate d_i and γ_i. We assume that an individual's choice behavior is determined by the following choice function:

$$Pr_i(c = 1) = \frac{1}{1 + e^{-\gamma_i(v_i(d_i,p,c=1) - v_i(d_i,p,c=0))}} = \frac{1}{1 + e^{-\gamma_i(d_i - p)}} \tag{12}$$

[33]We condition on the MAP of μ instead of the mean because convergence to the true μ parameter is relatively slow. Given that we initially assume a uniform distribution over models, the posterior probability distribution over models when using the unconditional expectation still puts considerable probability mass on low levels of μ even if choice patterns are perfectly consistent. But since convergence on the true r parameter is slower conditional on low levels of μ (because there is a larger probability that any choice is the consequence of an error rather than an expression of the true preference), taking the conditional expectation improves the precision of the chosen indifference lottery for participants whose true consistency is high (but may worsen it for participants with inconsistent choice patterns). However, we can show in Figure A.2 in Appendix A.2 that the choice between the unconditional expectation of r and the expectation of r conditional on the modal value of μ to determine the indifference lottery is not particularly consequential for the large majority of our participants (except for highly inconsistent ones). The differences in the estimation of $\hat{r}$ are small, unless subjects are highly inconsistent. In turn, differences in the identified indifference lottery do not differ much depending on the method. For participants with at least moderate degrees of choice consistency, $\hat{B}$ only varies by approx. 0.2% across the two methods. We still re-run all our main analyses using an alternative estimator of the willingness to pay based on the unconditional mean in Appendix A.2.1. As results are highly similar, we do not discuss them in the text.

[34]Here, we include the tenth choice because it contains substantial information about an individual's choice consistency.

where $Pr(c = 1)$ is the probability of choosing to pay p for choosing oneself, and γ_i specifies participant i's degree of stochastic response in choice.

We initialize DOSE by defining the parameter space for d, given by $\mathcal{D} \in (d_1, d_2, ..., d_n)$ and the parameter space for γ, given by $\Gamma \in (\gamma_1, \gamma_2, ..., \gamma_m)$ and assign prior probabilities to all $n \times m = k$ models. Second, we define the parameter space for prices p given by $\mathcal{P} \in (p_1, p_2, ..., p_n)$. The set of choice situations is defined by all combinations of a price p as $Q = \{([p_1, \text{"I choose"}], [0, \text{"I delegate"}]), ..., ([p_n, \text{"I choose"}], [0, \text{"I delegate"}])\}$. We again chose a uniform prior distribution over all models. Based on pilot data and simulations, we chose a discrete parameter space of $\mathcal{P} \in \{-600, -590, ..., -10, 10, 20, ..., 600\}$ and $\gamma \in \{1, 2, ..., 15\}$.[35] As in step 1, we pre-specified and stored the optimal sequence of choice situations in our experimental implementation, creating 1024 predetermined decision paths.

After individual i has completed her sequence of ten choices in step 2 (denoted $C_2(10)$), we consider the posterior probability distribution $f(d, \gamma | C_{2i}(10))$ to estimate the individual willingness to pay for choice autonomy.[36] To this end, we determine the MAP estimate of γ conditional on $C_{2i}(10)$, denoted γ_{MAP}, and then calculate the expected value for d conditional on γ_{MAP}:[37]

$$\hat{d}_i = \sum_{d_i \in \mathcal{D}} d f_i(d | \gamma_{i,MAP}, C_{2i}(10)). \tag{13}$$

Finally, we make one adjustment to the estimated willingness to pay $\hat{d}$. For subjects who delegate the decision whenever there is a price, and keep the decision whenever there is a bonus, which is consistent with having no intrinsic preference for choice autonomy, equation 13 delivers an estimate of -1.48. We round these values to $\hat{d} = 0$, which we believe better reflects the true preference.

[35] The values of γ have to be interpreted in connection with $v_i(d_i, p)$, as it simply scales up differences in expected utility, and values cannot be interpreted in isolation. We again chose the range of γ such that highly inconsistent and highly consistent choice behaviors are covered.

[36] Note that we use the information from all 10 decisions to estimate $\hat{d}$. Contrary to step 1, there was no reason to choose the tenth round at random, since it is the last decision of the experiment.

[37] We condition on the MAP of γ for the same reasons as before. Again, Figure A.3 in Appendix A.2 shows that the choice between the unconditional expectation of d and the expectation of d conditional on the modal value of γ to determine the willingness to pay for autonomy is not particularly consequential for the large majority of our participants (except for highly inconsistent ones), and differences in the estimation of $\hat{d}$ are small. However, we replicate all analyses in this paper using the alternative construction of $\hat{d}$ based on the unconditional mean in Appendix A.2.1.

A.1.3 Estimated Indifference Lotteries using different underlying utility functions

In order to apply the DOSE method, we had to impose a structural model of utility and assumed that participants' utility function has constant relative risk aversion (CRRA). In principle, one could worry that this choice introduces bias or arbitrariness into our estimation procedure. In this appendix, we show that the choice of CRRA utility had very little impact on the estimated indifference lotteries, at least as long as participants were reasonably consistent. Only when choice patterns of participants were wildly inconsistent, the structural assumptions on the utility function matter more for the best estimate of the indifference lottery, which by the nature of inconsistency is less precisely estimated in any case.

To show this, we assume that the "true" utility function of participants is either constant absolute risk aversion (CARA) or that participants have reference dependent preferences and are loss averse. More precisely, we assume the following two additional potential utility functions:

$$u_i^{CARA}(w) = \frac{1 - e^{-aw}}{a}, \tag{14}$$

where a is the coefficient of absolute risk aversion, and $u_i^{CARA}(w) = w$ when $a = 0$.

$$u_i^{PT}(w) = \begin{cases} w + (w - R) & \text{if } w \geq R \\ w - \lambda(R - w) & \text{if } w < R, \end{cases} \tag{15}$$

where λ is the degree of loss aversion and R is the assumed reference point against which gains and losses are judged. We chose to keep the utility function simple and assume that the reference point is given by the expected value of the A lottery, which is 1350.

Similar to our procedure with CRRA, the parameter space for a and λ is chosen based on the implied parameters from the set of lotteries B (defined by the set of high payoffs X). For a, it contains 96 values and is given by $\mathcal{A} \in \{-0.89, ..., 0.825\}$. For λ, it contains 96 values and is given by $\Lambda \in \{-0.12, ..., 5\}$. The value range of potential consistency parameters μ is identical to the CRRA case. We again assume that the prior joint distributions $f(a, \mu)$ and $f(\lambda, \mu)$ over these parameters is uniform.

Identical to our procedure with CRRA, we then consider the posterior probability distributions conditional on the actual choice sequence $C_1(9)$ to determine the expected value of a resp. λ, conditional on the MAP of μ.

$\hat{\mu}$	$\lvert B^H_{CRRA} - B^H_{CARA}\rvert$	$\lvert B^H_{CRRA} - B^H_{PT}\rvert$
1	31.63934	44.91803
10	37.81513	44.28571
20	33.75	32.15909
30	19.28571	24.46429
40	12.29167	12.70833
50	9.158879	9.065421
60	3.333333	0
70	5.185185	7.407407
80	0	0
90	9.230769	.9615385
100	.862069	0
110	10	0
120	2.571839	2.025862

Table A.1: Absolute difference between the estimated $\hat{B}$ with different underlying utility functions. $\hat{B}_{CRRA}$ is the calculated high value for the B lottery under CRRA, $\hat{B}_{CARA}$ under CARA, and $\hat{B}_{PT}$ under Prospect Theory.

These expected values are then in turn used to determine the best estimate of the indifference lottery for each individual, where $\hat{B}$ is rounded to the nearest multiple of 10, as this was the lowest unit displayed in the experiment.

Table A.1 displays the absolute difference in the estimated $\hat{X}$ when using CARA or prospect theory rather than CRRA as the underlying utility function, conditional on the estimated consistency parameter (when using the CRRA specification).

It can be seen that differences are substantial only when participants are (highly) inconsistent, but become marginal once consistency improves. Once $\hat{\mu} \geq 40$, the average absolute difference between the CRRA and CARA estimates is 4.3 points, and between the CRRA and the Prospect Theory estimates 3.5 points. Moreover, the identified indifference lottery is then identical for 73.4% of the subjects when assuming prospect theory, and varied by at most 10 points (the smallest possible unit) for 95.6% of participants. Under CARA; the identified indifference lottery is identical for 60.1% of the subjects with $\hat{\mu} \geq 40$, and varies by at most 10 points (the smallest possible unit) for 97.9% of the subject. Thus, the structural assumptions on the utility function had only a very minor impact on the identified indifference point for consistent subjects.

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A.2 Additional analyses

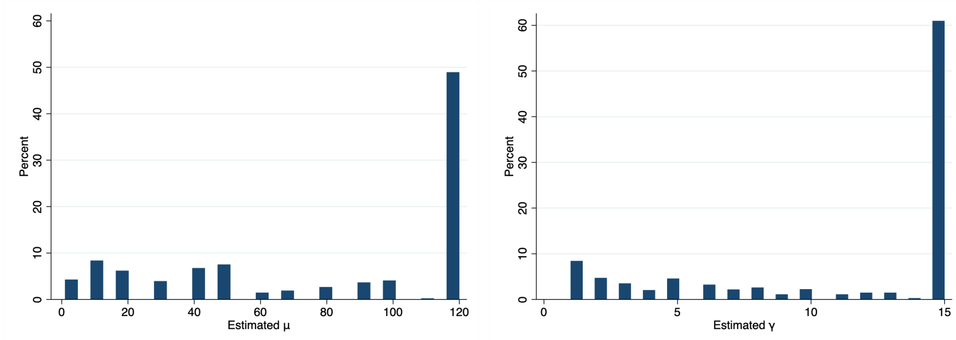


Figure A.1: Distribution of individual modal choice consistency parameters in part 1 ($\hat{\mu}$) and part 2 ($\hat{\gamma}$), $N = 1422$.

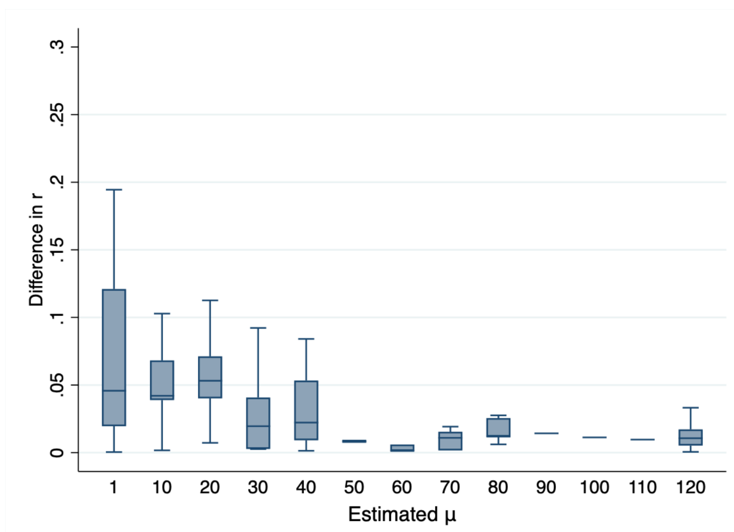


Figure A.2: Absolute Difference in $\hat{r}$ (the individually estimated risk preference parameter) depending on whether it is determined using the unconditional expectation of r or conditional on the MAP of μ.

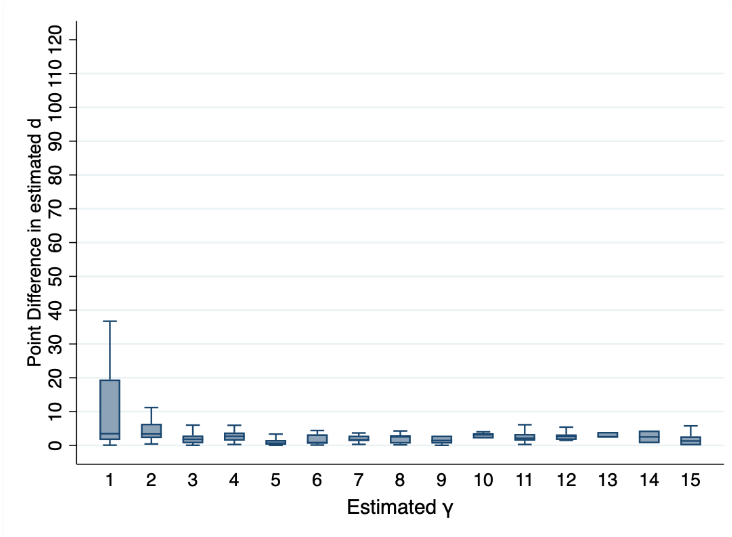


Figure A.3: Absolute Difference in $\hat{d}$ (the individually estimated willingness to pay) depending on whether it is determined using the unconditional expectation of d or conditional on the MAP of γ.

	(1)	(2)
	$\hat{\mu}$	$\hat{\gamma}$
Male	7.678	0.036
	(2.401)	(0.292)
Age	0.115	–0.020
	(0.135)	(0.015)
Income	–0.382	0.048
	(0.451)	(0.051)
Education	3.378	0.166
	(1.153)	(0.140)
Wave	0.023	0.001
	(0.024)	(0.003)
Constant	70.072	5.198
	(99.720)	(9.710)
R^2	0.052	0.04
Controls	yes	yes
Observations	1406	1406

Table A.2: Consistency in part 1 and part 2($\hat{\mu}$ and $\hat{\gamma}$), as estimated by DOSE. OLS regressions with robust standard errors in parentheses, including controls risk_taking, nationality, prolific_score and not_failed. June 2021 and January 2022 waves.

	Mean	**Std.dev.**	**Median**	**% of EU**
Highly inconsistent (4.29%)	96.10	217.33	23.03	7.06
Inconsistent (18.5%)	70.4	209.96	24.42	5.25
Moderately consistent (28.27%)	44.33	195.65	4.68	4.69
Highly consistent (48.95%)	76.19	176.89	11.98	5.34
Minor average error (35.3%)	65.77	172.72	2.56	6.57
All (1422 obs.)	66.97	190.93	11.98	5.22

Table A.3: Willingness to pay for different subgroups of participants. A subject is described as highly inconsistent if $\hat{\mu} = 1$, as inconsistent if $1 < \hat{\mu} < 40$, as moderately consistent if $30 < \hat{\mu} < 120$, and as highly consistent if $\hat{\mu} = 120$. Minor average error=1 if average error$\leq$10.

	Trust (General)	**Trust in Intentions**	**Trust in Expertise**	**Trust in Decisions**
WTP/100	–0.022	–0.020	–0.017	–0.009
	(0.026)	(0.024)	(0.024)	(0.024)
Constant	4.245	4.609	4.901	4.423
	(0.052)	(0.049)	(0.044)	(0.046)
R^2	–0.001	–0.001	–0.001	–0.000
Controls	no	no	no	no
Observations	791	791	791	791
WTP/100	–0.010	–0.021	–0.015	–0.013
	(0.026)	(0.024)	(0.024)	(0.023)
Constant	6.007	5.767	6.753	10.362
	(2.508)	(2.287)	(2.058)	(2.136)
R^2	0.07	0.051	0.07	0.080
Controls	yes	yes	yes	yes
Observations	782	782	782	782

Table A.4: Willingness to pay divided by 100 on different measures of trust: general trust towards other people, trust in others' good intentions, expertise and quality of decision-making. OLS regressions with robust standard errors in parentheses. First panel without controls, second panel including controls for age, gender, income, education, risk_taking, nationality, highly_inconsistent_part1, highly_inconsistent_part2, prolific_score and not_failed. June 2021 wave.

	WTP		WVS		DC	
OLS Reg						
Risk_Taking	7.313	5.811	0.159	0.158	0.114	0.113
	(2.346)	(2.466)	(0.030)	(0.032)	(0.012)	(0.013)
Constant	22.687	561.119	6.358	8.288	7.240	8.355
	(14.493)	(507.986)	(0.196)	(3.413)	(0.078)	(1.042)
R^2	0.006	0.017	0.042	0.049	0.123	0.126
Median Reg						
Risk_Taking	3.366	1.961	0.167	0.157	0.111	0.127
	(1.341)	(1.472)	(0.040)	(0.027)	(0.014)	(0.012)
Constant	–6.731	1312.883	6.667	7.185	7.278	6.634
	(4.394)	(570.582)	(0.263)	(6.358)	(0.085)	(1.288)
Pseudo R^2	0.002	0.024	0.024	0.048	0.068	0.100
Controls	no	yes	no	yes	no	yes
Observations	1422	1406	791	782	791	782

Table A.5: Risk taking on willingness to pay, DC: index of desirability of control (Burger and Cooper, 1979), WVS: world value survey question on freedom and control (Inglehart, 2014). First panel: OLS regressions with robust standard errors in parentheses. Second panel: Median regressions with robust standard errors. Columns (1, 3, 5) without controls, columns (2, 4, 6) including controls for age, gender, income, education, risk_taking, nationality, highly_inconsistent_part1, highly_inconsistent_part2, prolific_score and not_failed. June 2021 and January 2022 waves.

	WTP	LOC	IA	GSE	DC	WVS
WTP	1.000					
LOC	.03	1.000				
IA	.008	.306	1.000			
GSE	.05	.241	.374	1.000		
DC	.057	.15	.241	.546	1.000	
WVS	.062	.294	.487	.383	.231	1.000

Table A.6: Correlation coefficients of the willingness to pay and autonomy indices: LOC: locus of control (Rotter, 1966), IA: index of autonomy (Deci and Ryan, 1985), GSE: generalized self-efficacy (Schwarzer, Jerusalem et al., 1995), DC: desirability of control (Burger and Cooper, 1979), WVS: question on perceived freedom and control from wave 6 of the world value survey (Inglehart, 2014). June 2021 wave.

A.2.1 Additional analyses: Replication using an estimate of the willingness to pay based on the unconditional mean

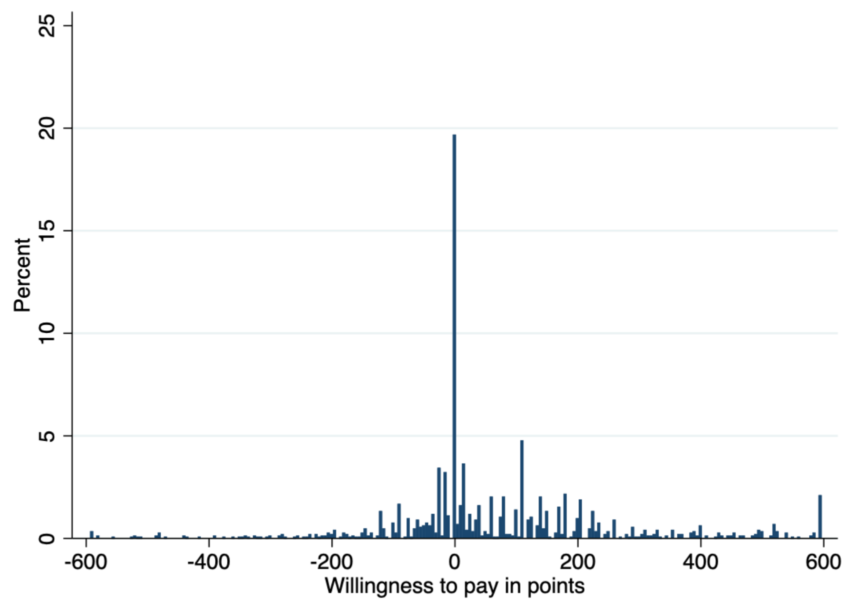


Figure A.4: Distribution of the willingness to pay, calculated using the unconditional expectation, June 2021 and January 2022, $N = 1422$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	June+Jan (OLS)		**June+Jan (Median R.)**		**June (OLS)**		**June (Median R.)**	
Male	34.644	34.176	24.596	17.498	33.138	38.935	29.585	25.586
	(10.176)	(10.424)	(9.432)	(7.148)	(14.545)	(15.210)	(11.082)	(11.810)
Age	0.338	0.933	0.182	0.658	0.237	0.259	−0.144	1.291
	(0.712)	(0.755)	(0.533)	(0.523)	(1.395)	(1.445)	(1.185)	(1.110)
Income	−1.941	−1.225	−0.554	−0.474	−3.891	−4.020	−2.819	−2.256
	(1.720)	(1.795)	(0.410)	(0.722)	(2.412)	(2.652)	(1.207)	(1.704)
Education	1.430	1.243	−3.632	−1.334	−1.710	−1.075	−6.034	−3.032
	(5.146)	(5.387)	(2.751)	(2.768)	(7.335)	(7.722)	(6.195)	(5.438)
Married	−14.643	−16.195	−18.535	−13.501	−20.780	−24.128	0.399	2.226
	(16.465)	(16.531)	(9.584)	(8.689)	(23.397)	(23.620)	(19.023)	(19.748)
Number_Kids	−3.491	−7.071	−5.312	−6.761	−7.963	−7.652	8.632	3.493
	(6.727)	(6.728)	(4.483)	(3.793)	(11.519)	(11.578)	(10.312)	(11.385)
English_Speaker	−12.282	9.748	−1.960	5.575	−1.862	7.139	0.758	−3.944
	(12.550)	(24.192)	(4.886)	(9.073)	(17.527)	(34.028)	(13.555)	(24.305)
Big5_extraverted					−2.379	−2.729	−1.853	−5.660
					(4.018)	(4.216)	(3.429)	(3.344)
Big5_agreeable					−4.293	−3.436	−0.645	−2.056
					(5.273)	(5.432)	(4.553)	(4.883)
Big5_conscientious					3.281	4.771	0.778	1.932
					(4.842)	(5.046)	(4.221)	(3.950)
Big5_calm					5.778	4.461	1.250	0.339
					(4.199)	(4.441)	(3.472)	(3.531)
Big5_open					8.290	4.666	3.350	−0.780
					(5.780)	(6.830)	(4.477)	(4.788)
Constant	60.082	564.588	33.799	1305.420	39.022	527.378	35.398	1008.160
	(31.392)	(512.180)	(19.904)	(599.285)	(63.861)	(539.494)	(48.100)	(626.566)
R^2 / Pseudo R^2	0.013	0.041	0.007	0.026	0.023	0.066	0.011	0.036
Controls	no	yes	no	yes	no	yes	no	yes
Observations	1406	1406	1406	1406	782	782	782	782

Table A.7: Willingness to pay calculated using the unconditional expectation on socio-demographics and Big5: gender, age, income education, family status ($Married \in [0,1]$), number of kids, English native speaker. Columns (1, 2, 5, 6): OLS regression with robust standard errors in parentheses. Columns (3, 4, 7, 8): Median regression with robust standard errors. Additional controls in columns (2, 4, 6, 8): risk_taking, nationality, highly_inconsistent_part1, highly_inconsistent_part2, prolific_score, not_failed. June 2021 and January 2022 waves in columns (1-4), June 2021 wave in columns (5-8).

	(1)	(2)	(3)	(4)
	WTP_uncond.(OLS)		**WTP_uncond.(Median R.)**	
LOC	10.003	2.551	2.859	7.993
	(11.971)	(12.566)	(12.509)	(9.424)
IA	1.614	2.269	–12.132	–9.942
	(7.602)	(8.054)	(8.254)	(6.658)
GSE	11.019	5.913	8.607	1.123
	(7.623)	(8.714)	(8.382)	(6.668)
DC	16.271	8.879	22.968	10.467
	(9.240)	(10.31)	(9.82)	(7.845)
WVS	7.032	5.227	4.148	–.423
	(4.492)	(4.734)	(4.027)	(3.546)
Controls	no	yes	no	yes
Observations	791	782	791	782

Table A.8: Each cell shows the coefficient of one OLS regression with robust standard errors (in parentheses) with willingness to pay (WTP calculated using the unconditional expectation) as the dependent variable. Constants are omitted. Respective independent variables in the five regressions are: LOC: index of locus of control (Rotter, 1966), IA: index of autonomy (Deci and Ryan, 2006), GSE: generalized self-efficacy index (Schwarzer, Jerusalem et al., 1995), DC: index of desirability of control (Burger and Cooper, 1979), WVS: world value survey question on freedom and control (Inglehart, 2014). Columns (1-2): OLS regressions with robust standard errors. Columns (3-4): Median regressions with robust standard errors. Columns (2) and (4) include controls age, gender, income, education, risk_taking, nationality, highly_inconsistent_part1, highly_inconsistent_part2, prolific_score, not_failed. June 2021 wave.

	(1) **Trust (General)**	(2) **Trust in Intentions**	(3) **Trust in Expertise**	(4) **Trust in Decisions**
WTP_uncond./100	–0.022	–0.020	–0.016	–0.009
	(0.025)	(0.024)	(0.024)	(0.024)
Constant	4.245	4.609	4.900	4.423
	(0.052)	(0.049)	(0.045)	(0.046)
R^2	0.001	0.001	0.001	0.000
Controls	no	no	no	no
Observations	791	791	791	791
WTP_uncond./100	–0.010	–0.021	–0.013	–0.012
	(0.026)	(0.024)	(0.024)	(0.023)
Constant	6.007	5.762	6.744	10.359
	(2.509)	(2.287)	(2.056)	(2.137)
R^2	0.07	0.051	0.07	0.081
Controls	yes	yes	yes	yes
Observations	782	782	782	782

Table A.9: Willingness to pay (WTP calculated using the unconditional expectation) divided by 100 and trust: general trust towards other people, trust in others' good intentions, expertise and quality of decision-making. Controls in the second panel: gender, age, income, education, risk_taking, nationality, highly_inconsistent_part1, highly_inconsistent_part2, prolific_score, not_failed. OLS regressions with robust standard errors in parentheses. June 2021 wave.

	(1)	(2)	(3)	(4)
	WTP_uncond.(OLS)		**WTP_uncond.(Median R.)**	
Risk_Taking	7.239	5.795	3.615	2.102
	(2.330)	(2.448)	(1.182)	(1.657)
Constant	23.705	540.110	–7.231**	1283.152
	(14.420)	(509.423)	(2.885)	(437.117)
R^2 / Pseudo R^2	0.007	0.04	0.003	0.024
Controls	no	yes	no	yes
Observations	1422	1406	1422	1406

Table A.10: Risk attitudes on willingness to pay (WTP calculated using the unconditional expectation). Columns (1-2): OLS regressions with robust standard errors in parentheses. Columns (3-4): Median regressions with robust standard errors. Controls in columns (2, 4): gender, age, income, education, risk_taking, nationality, highly_inconsistent_part1, highly_inconsistent_part2, prolific_score, not_failed. OLS regressions with robust standard errors. June 2021 and January 2022 waves.

A.2.2 Additional analyses: Replications with consistent and highly consistent subjects

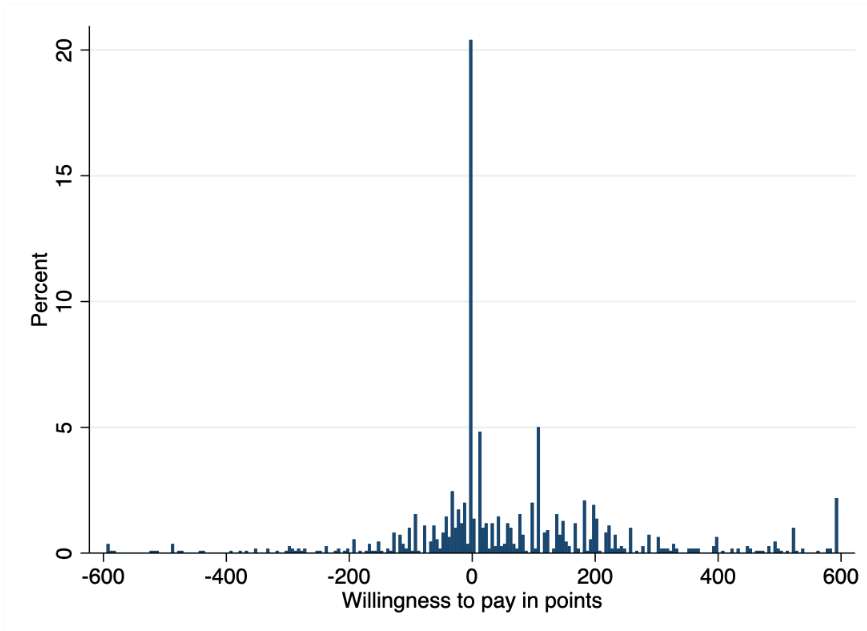


Figure A.5: Distribution of the willingness to pay among subjects with $\hat{\mu} > 30$, June 2021 and January 2022, $N = 1098$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	June+Jan (OLS)		**June+Jan (Median R.)**		**June (OLS)**		**June (Median R.)**	
Male	34.102	28.107	13.344	9.884	41.890	40.928	24.228	19.850
	(11.615)	(11.925)	(5.409)	(7.714)	(16.909)	(17.253)	(11.294)	(11.935)
Age	–0.041	0.704	0.102	0.524	–1.037	–1.216	–0.682	–0.625
	(0.806)	(0.861)	(0.687)	(0.590)	(1.656)	(1.695)	(1.270)	(1.346)
Income	–2.767	–2.314	–0.425	–0.508	–7.434	–8.900	–3.930	–6.113
	(1.942)	(2.048)	(0.972)	(0.841)	(2.689)	(2.898)	(1.837)	(2.050)
Education	–1.475	–1.688	–2.472	–0.940	–2.968	–3.010	–8.016	–0.475
	(5.796)	(6.050)	(3.790)	(3.623)	(8.436)	(8.798)	(7.001)	(6.632)
Married	–11.863	–14.292	–13.688	–12.107	–16.363	–22.019	5.972	–6.949
	(17.902)	(17.953)	(10.859)	(9.415)	(27.022)	(26.846)	(18.595)	(17.585)
Number_kids	–2.950	–6.697	–4.420	–7.468	–2.775	0.416	19.121	8.542
	(8.017)	(8.100)	(4.992)	(4.827)	(13.795)	(14.197)	(11.075)	(10.857)
English_speaker	–12.649	28.713	–0.754	9.619	8.554	60.888	11.217	30.607
	(14.078)	(26.407)	(6.825)	(9.106)	(19.180)	(37.817)	(14.682)	(27.998)
Big5_extraverted					–2.539	–4.349	–0.368	–1.816
					(4.456)	(4.680)	(3.992)	(3.513)
Big5_agreeable					–0.124	2.468	–0.175	–1.063
					(6.001)	(6.093)	(5.589)	(5.180)
Big5_conscientious					4.976	8.267	2.417	1.680
					(5.382)	(5.791)	(4.851)	(4.179)
Big5_calm					4.196	0.411	–1.913	–4.819
					(4.719)	(4.976)	(4.244)	(4.068)
Big5_open					6.767	1.362	1.912	–1.753
					(6.782)	(7.635)	(5.829)	(6.284)
Constant	77.918	931.550	25.354	1859.940	62.748	912.929	55.481	1440.293
	(33.142)	(421.534)	(22.578)	(747.669)	(71.172)	(470.444)	(55.733)	(665.817)
R^2 / Pseudo R^2	0.015	0.056	0.004	0.025	0.033	0.101	0.014	0.047
Controls	no	yes	no	yes	no	yes	no	yes
Observations	1085	1085	1085	1085	596	596	596	596

Table A.11: Correlation between willingness to pay and personal characteristics with subjects with $\hat{\mu} > 30$ only. Dependent variable: WTP. Columns (1,2) and (5,6): OLS estimates with robust standard errors in parentheses. Columns (3,4) and (7,8): Median regressions with robust standard errors. January and June waves in columns (1-4), June 2021 wave in columns (5-8). Controls in columns (2, 4, 6, 8) include risk_taking, nationality, highly_inconsistent_part2, prolific_score, not_failed.

	(1)	(2)	(3)	(4)
	WTP (OLS)		**WTP (Median R.)**	
LOC	–1.233	–8.394	0.000	3.755
	(13.872)	(15.124)	(13.325)	(10.575)
IA	–10.151	–10.3	–18.069	–16.655
	(8.581)	(8.883)	(8.614)	(7.301)
GSE	11.625	7.981	8.151	6.106
	(8.426)	(9.091)	(9.145)	(6.186)
DC	15.985	10.621	23.466	9.62
	(10.752)	(11.499)	(11.634)	(7.877)
WVS	6.335	5.511	5.59	2.476
	(5.068)	(5.154)	(4.308)	(3.887)
Controls	no	yes	no	yes
Observations	604	596	604	596

Table A.12: Each cell shows the coefficient of one regression with willingness to pay as the dependent variable. Subjects with $\hat{\mu} > 30$ only. Columns (1, 2): OLS regressions with robust standard errors in parentheses. Columns (3, 4): Median regressions with robust standard errors. Constants are omitted. Respective independent variables in the 20 regressions are: LOC: index of internal control (Rotter, 1966), IA: index of autonomy (Deci and Ryan, 2006), GSE: self-efficacy index (Schwarzer, Jerusalem et al., 1995), DC: index of desirability of control (Burger and Cooper, 1979), WVS: world value survey question on freedom and control (Inglehart, 2014). Columns (1, 3) without controls, columns (2, 4) include controls for age, gender, income, education, risk_taking, nationality, highly_inconsistent_part2, prolific_score, not_failed. June 2021 wave.

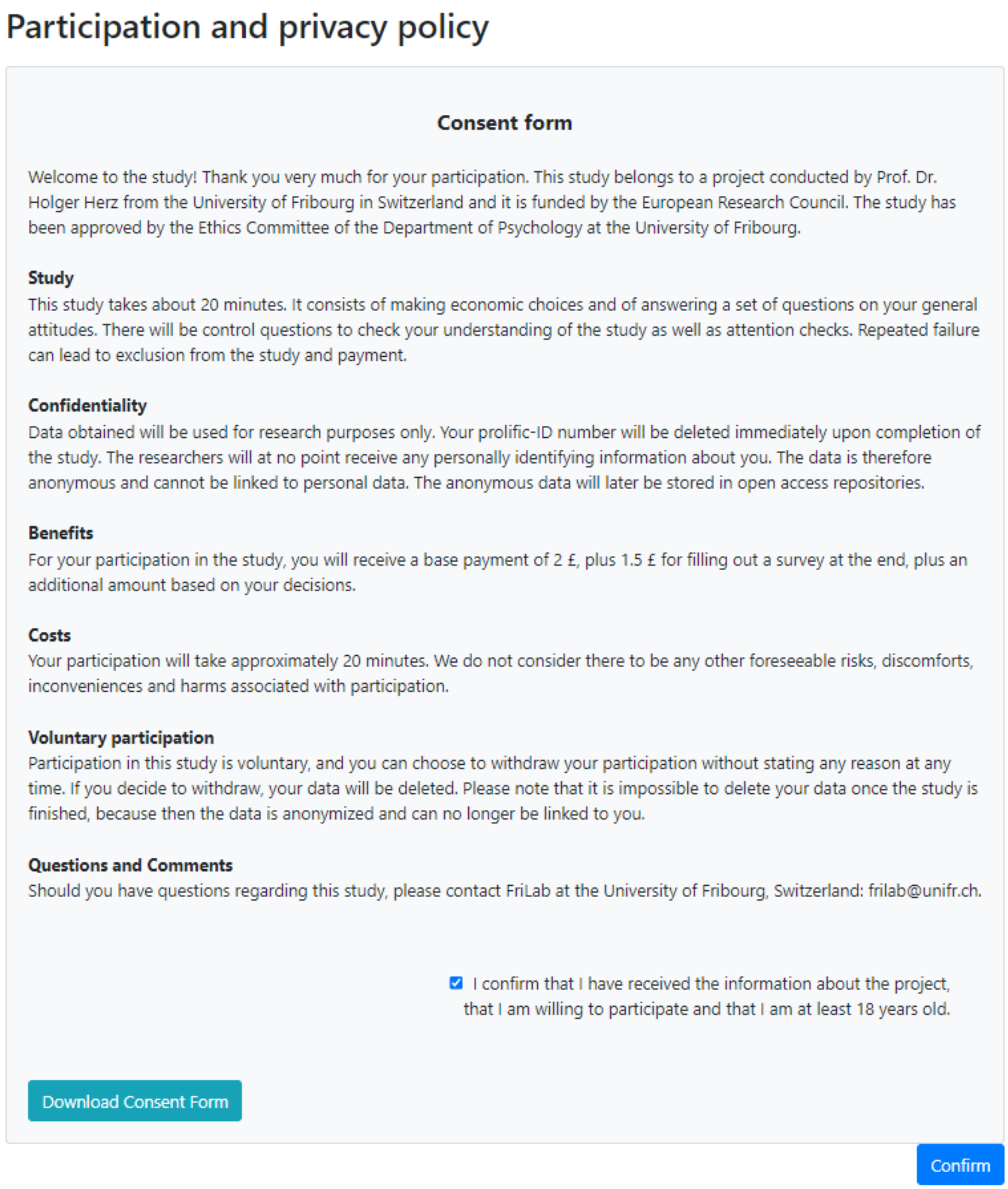
	(1) **Trust (General)**	(2) **Trust in Intentions**	(3) **Trust in Expertise**	(4) **Trust in Decisions**
WTP/100	–0.040	–0.043	–0.037	–0.050*
	(0.031)	(0.027)	(0.027)	(0.026)
Constant	4.303	4.643	4.931	4.417
	(0.059)	(0.055)	(0.050)	(0.051)
R^2	0.003	0.004	0.004	0.006
Controls	no	no	no	no
Observations	604	604	604	604
WTP/100	–0.024	–0.043	–0.031	–0.057**
	(0.032)	(0.030)	(0.027)	(0.027)
Constant	7.907	7.840	8.610	11.988
	(2.583)	(2.327)	(2.006)	(2.408)
R^2	0.059	0.053	0.082	0.093
Controls	yes	yes	yes	yes
Observations	596	596	596	596

Table A.13: Willingness to pay divided by 100 on different measures of trust: general trust towards other people, trust in others' good intentions, expertise and quality of decision-making. Subjects with $\hat{\mu} > 30$ only. OLS regressions with robust standard errors in parentheses. First panel without controls, second panel including controls for age, gender, income, education, risk_taking, nationality, highly_inconsistent_part2, prolific_score, not_failed. June 2021 wave.

	(1)	(2)	(3)	(4)	(5)	(6)
	WTP		**WVS**		**DC**	
OLS Reg						
Risk_Taking	8.329	7.959	0.116	0.109	0.117	0.121
	(2.516)	(2.670)	(0.032)	(0.035)	(0.014)	(0.015)
Constant	14.823	896.223	6.615	9.226	7.224	8.215
	(15.440)	(418.612)	(0.203)	(3.585)	(0.091)	(1.171)
R^2	0.01	0.054	0.023	0.072	0.127	0.168
Median Reg						
Risk_Taking	2.995	2.193	0.167	0.126	0.130	0.126
	(1.098)	(1.854)	(0.043)	(0.029)	(0.017)	(0.015)
Constant	–5.990	2076.677	6.667	9.159	7.148	6.482
	(1.312)	(760.929)	(0.278)	(6.792)	(0.111)	(1.578)
Pseudo R^2	0.003	0.024	0.023	0.055	0.071	0.105
Controls	no	yes	no	yes	no	yes
Observations	1098	1085	604	596	604	596

Table A.14: Risk taking on willingness to pay, DC: index of desirability of control (Burger and Cooper, 1979), WVS: world value survey question on freedom and control (Inglehart, 2014). Subjects with $\hat{\mu} > 30$ only. First panel: OLS regressions with robust standard errors in parentheses. Second panel: Median regressions with robust standard errors. Columns (1, 3, 5) without controls, columns (2, 4, 6) including controls for age, gender, income, education, nationality, highly_inconsistent_part2, prolific_score, not_failed. June 2021 and January 2022 waves.

A.3 Experimental Instructions (Preference Elicitation Tool)



Participation and privacy policy

Consent form

Welcome to the study! Thank you very much for your participation. This study belongs to a project conducted by Prof. Dr. Holger Herz from the University of Fribourg in Switzerland and it is funded by the European Research Council. The study has been approved by the Ethics Committee of the Department of Psychology at the University of Fribourg.

Study
This study takes about 20 minutes. It consists of making economic choices and of answering a set of questions on your general attitudes. There will be control questions to check your understanding of the study as well as attention checks. Repeated failure can lead to exclusion from the study and payment.

Confidentiality
Data obtained will be used for research purposes only. Your prolific-ID number will be deleted immediately upon completion of the study. The researchers will at no point receive any personally identifying information about you. The data is therefore anonymous and cannot be linked to personal data. The anonymous data will later be stored in open access repositories.

Benefits
For your participation in the study, you will receive a base payment of 2 £, plus 1.5 £ for filling out a survey at the end, plus an additional amount based on your decisions.

Costs
Your participation will take approximately 20 minutes. We do not consider there to be any other foreseeable risks, discomforts, inconveniences and harms associated with participation.

Voluntary participation
Participation in this study is voluntary, and you can choose to withdraw your participation without stating any reason at any time. If you decide to withdraw, your data will be deleted. Please note that it is impossible to delete your data once the study is finished, because then the data is anonymized and can no longer be linked to you.

Questions and Comments
Should you have questions regarding this study, please contact FriLab at the University of Fribourg, Switzerland: frilab@unifr.ch.

☑ I confirm that I have received the information about the project, that I am willing to participate and that I am at least 18 years old.

Download Consent Form

Confirm

Figure A.6: Screenshot: Consent form

Thank you for your participation!

The study consists of **3 parts**. The instructions for each part will be shown on your screen. During part 1 and 2 of the study you have the possibility to earn additional money. The additional payoffs will be calculated in points. They will be converted into £ at the end of the study. The exchange rate is:

1000 points = 0.75 £

Therefore, your total earnings from the study consist of your payoff from part 1 plus your payoff from part 2 plus 1.5£ for a short survey (part 3) plus your base payment of 2 £ for your participation.

Total earnings = payoff part 1 + payoff part 2 + 2 £ + 1.5 £

Continue

Figure A.7: Screenshot: Payoffs and exchange rate

Part 1

Continue

Figure A.8: Screenshot: Begin of part 1

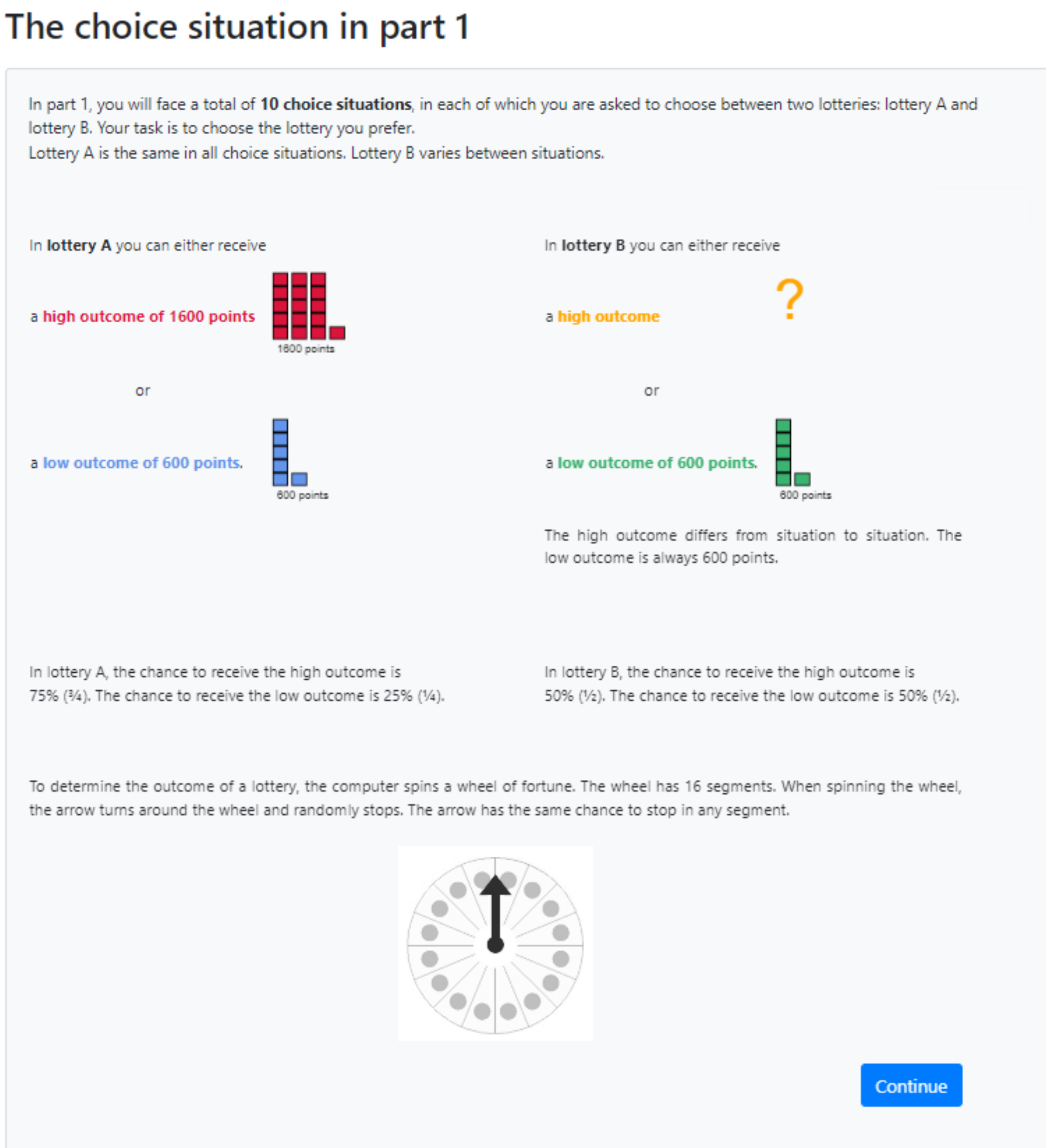


Figure A.9: Screenshot: Description of the lotteries (Elements of the screen appear sequentially. When the participant clicks "continue", the next picture and description appears.)

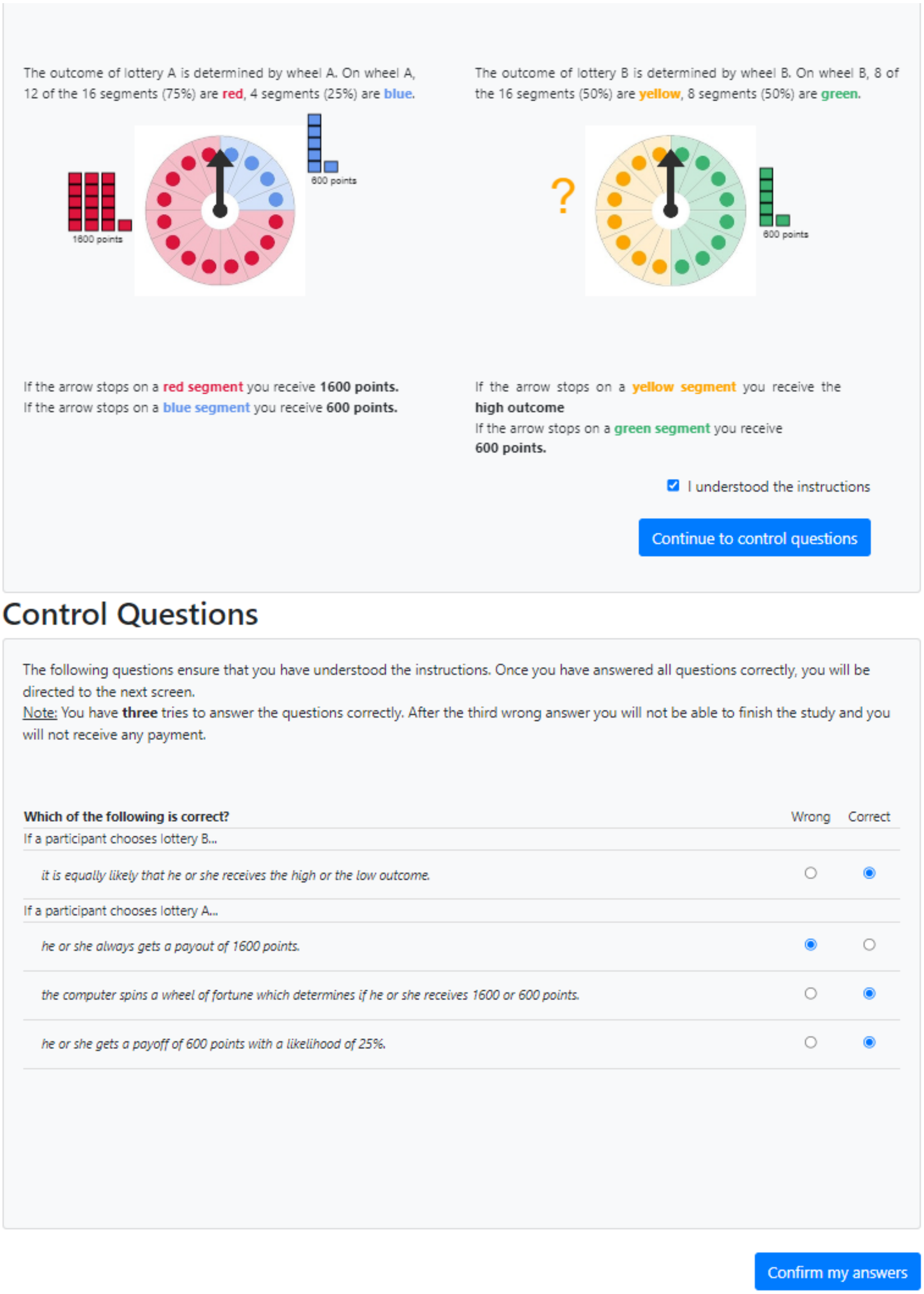


Figure A.10: Screenshot: Description of the lotteries continued and control questions part 1

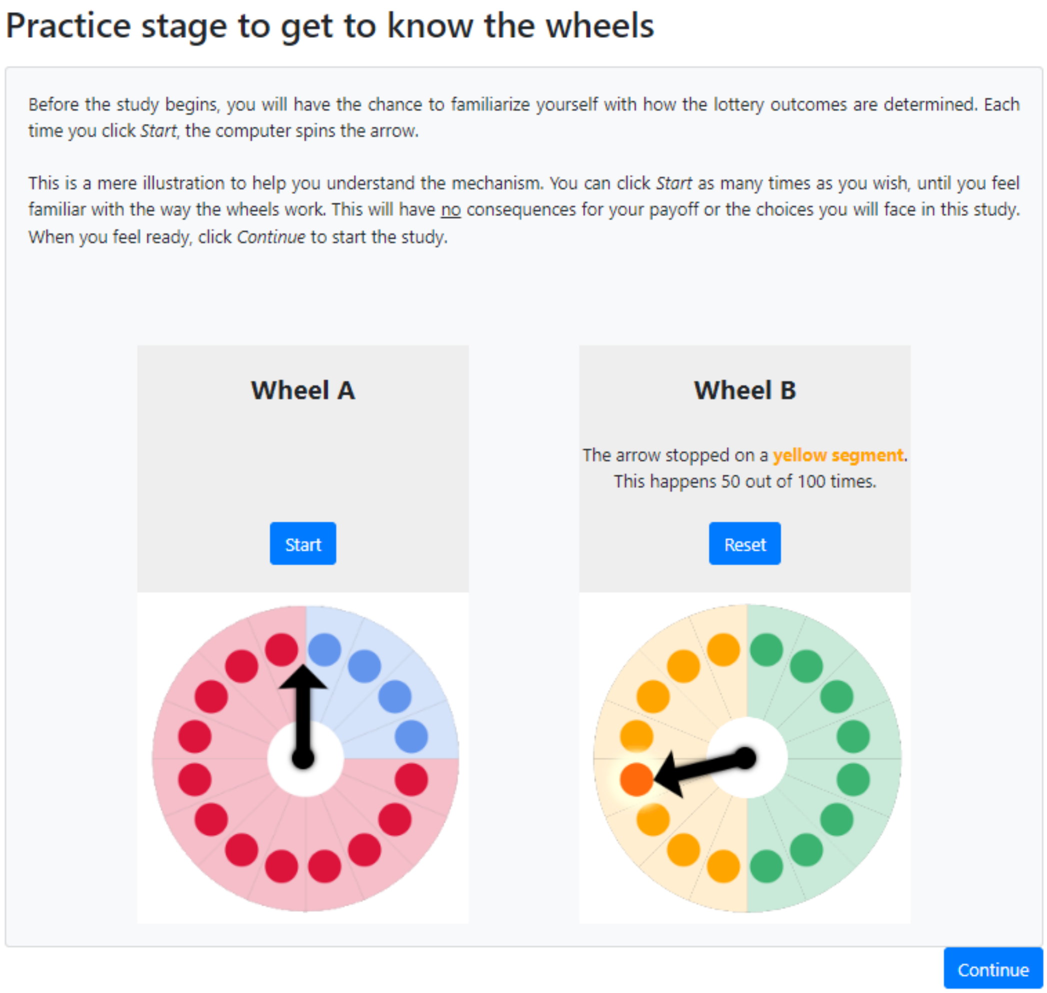


Figure A.11: Screenshot: Practice wheels (The participant can spin each wheel as often as she wishes. After each spin, the outcome is displayed together with an explanation how often this happens to prevent biases.)

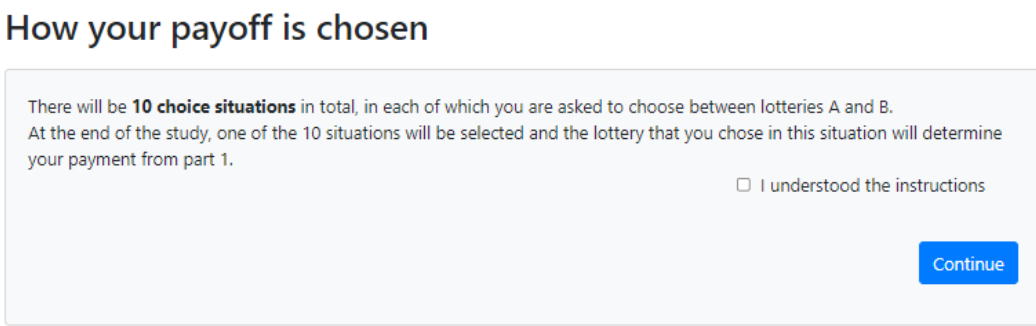


Figure A.12: Screenshot: Procedure part 1

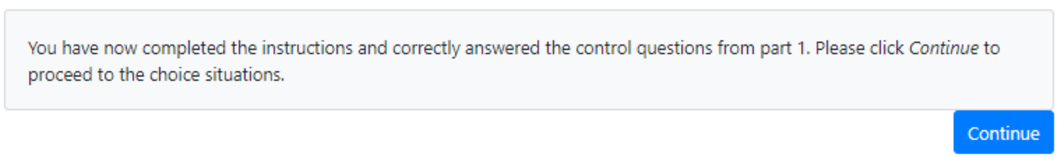


Figure A.13: Screenshot: Transition to choice situations part 1

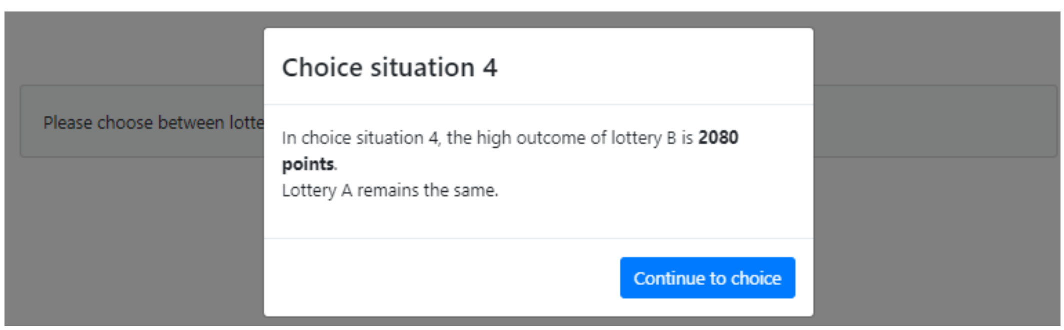


Figure A.14: Screenshot: Announcement of the next choice situation in part 1 (same for choice situations 1 to 10)

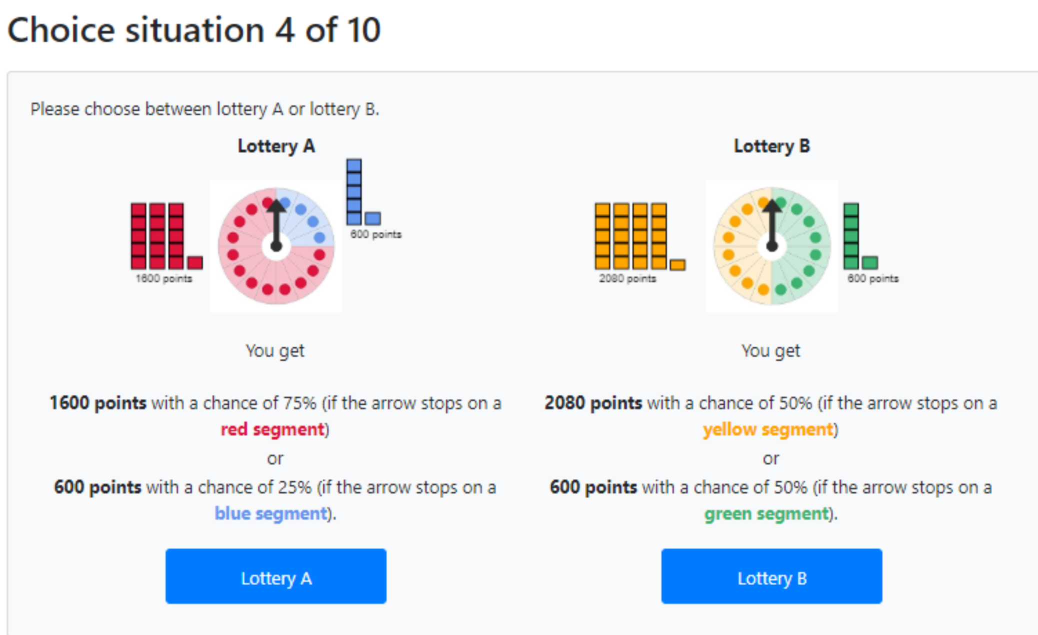


Figure A.15: Screenshot: Choice situation 4 in part 1 (same for choice situations 1 to 10)

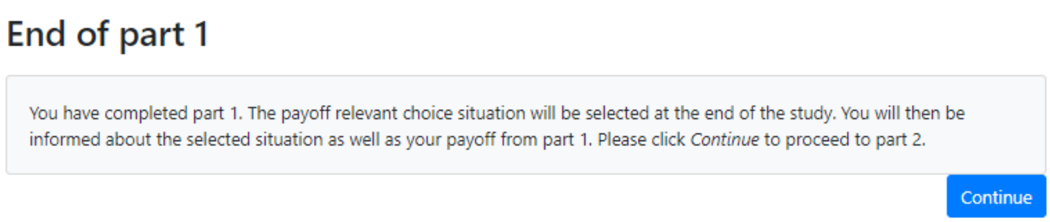


Figure A.16: Screenshot: End of part 1

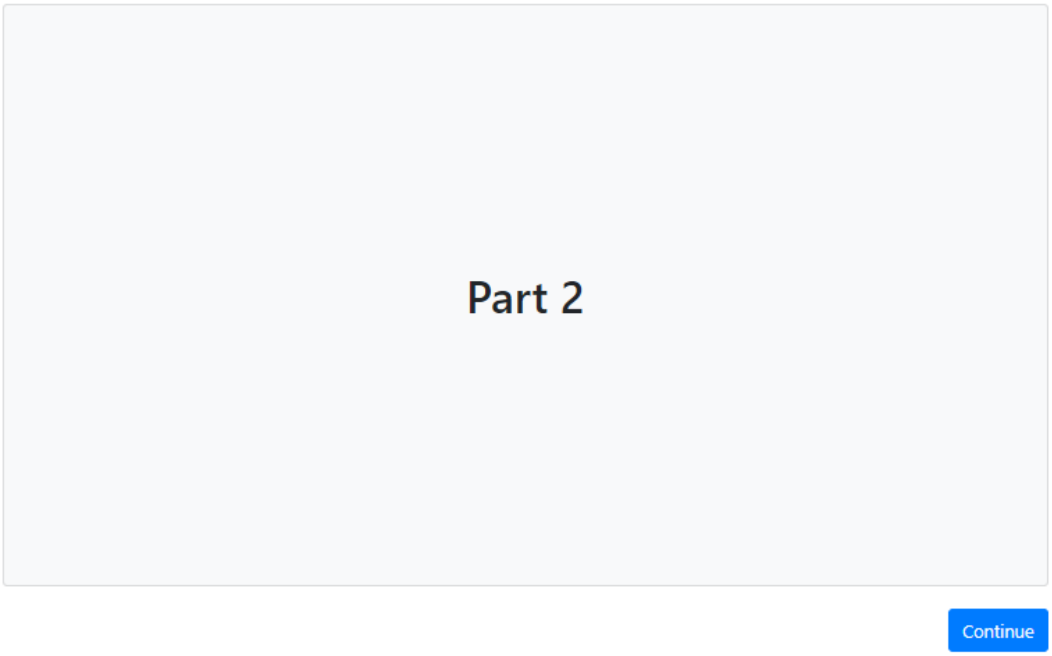


Figure A.17: Screenshot: Begin of part 2

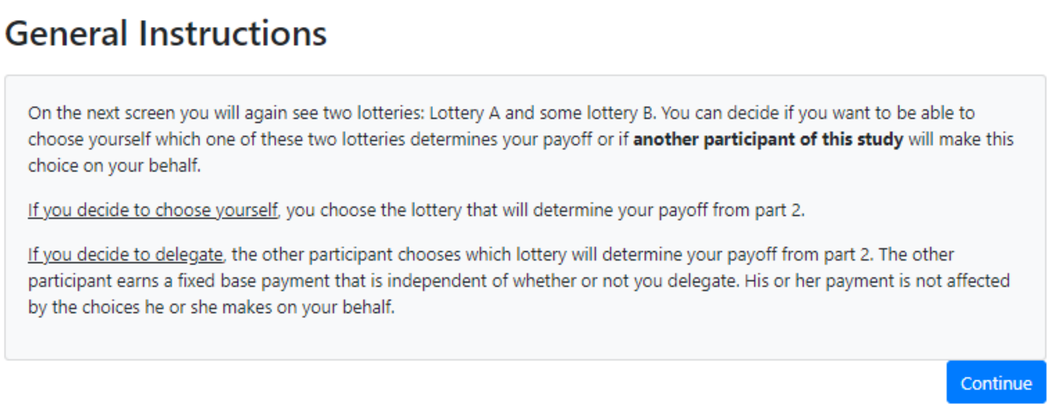


Figure A.18: Screenshot: General instructions for part 2

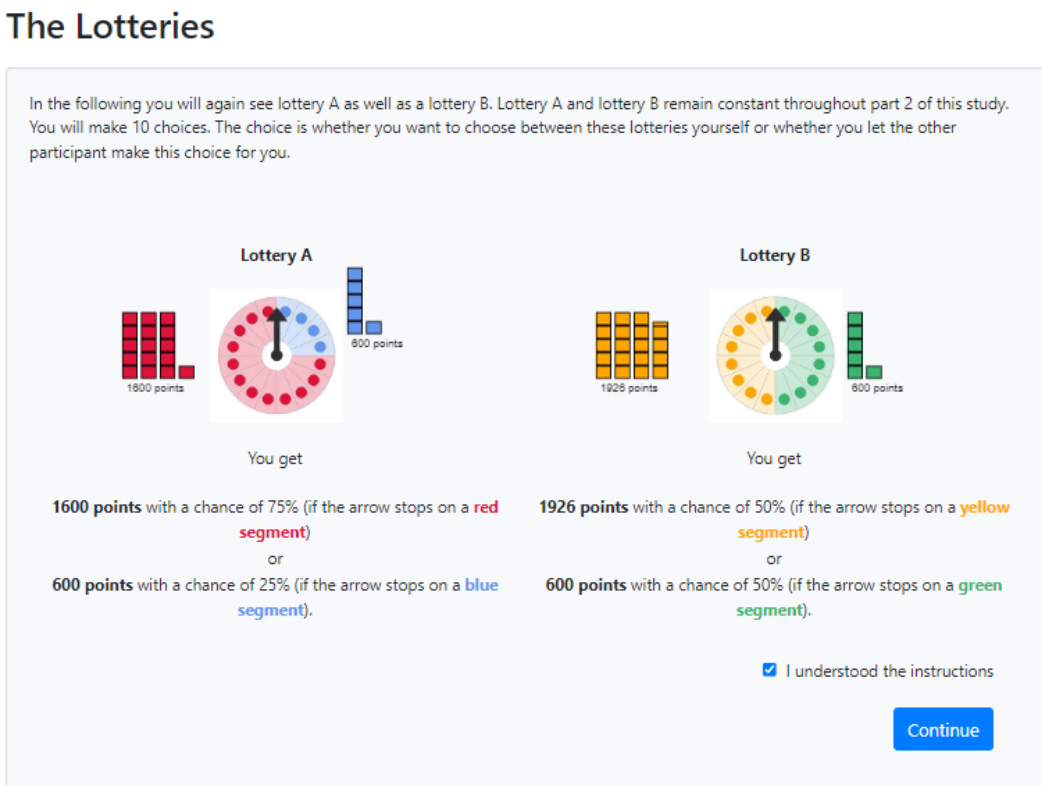


Figure A.19: Screenshot: Choice set for part 2

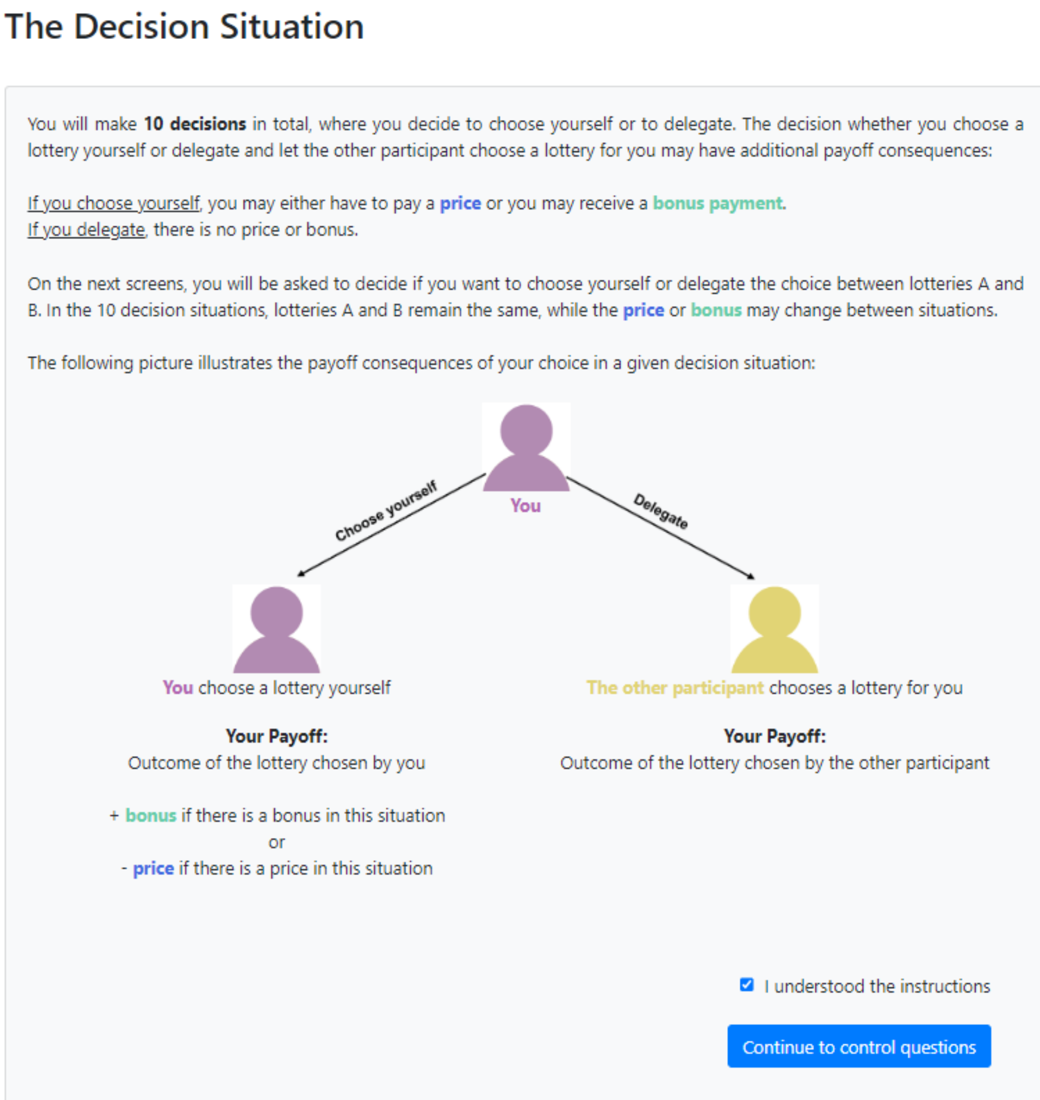
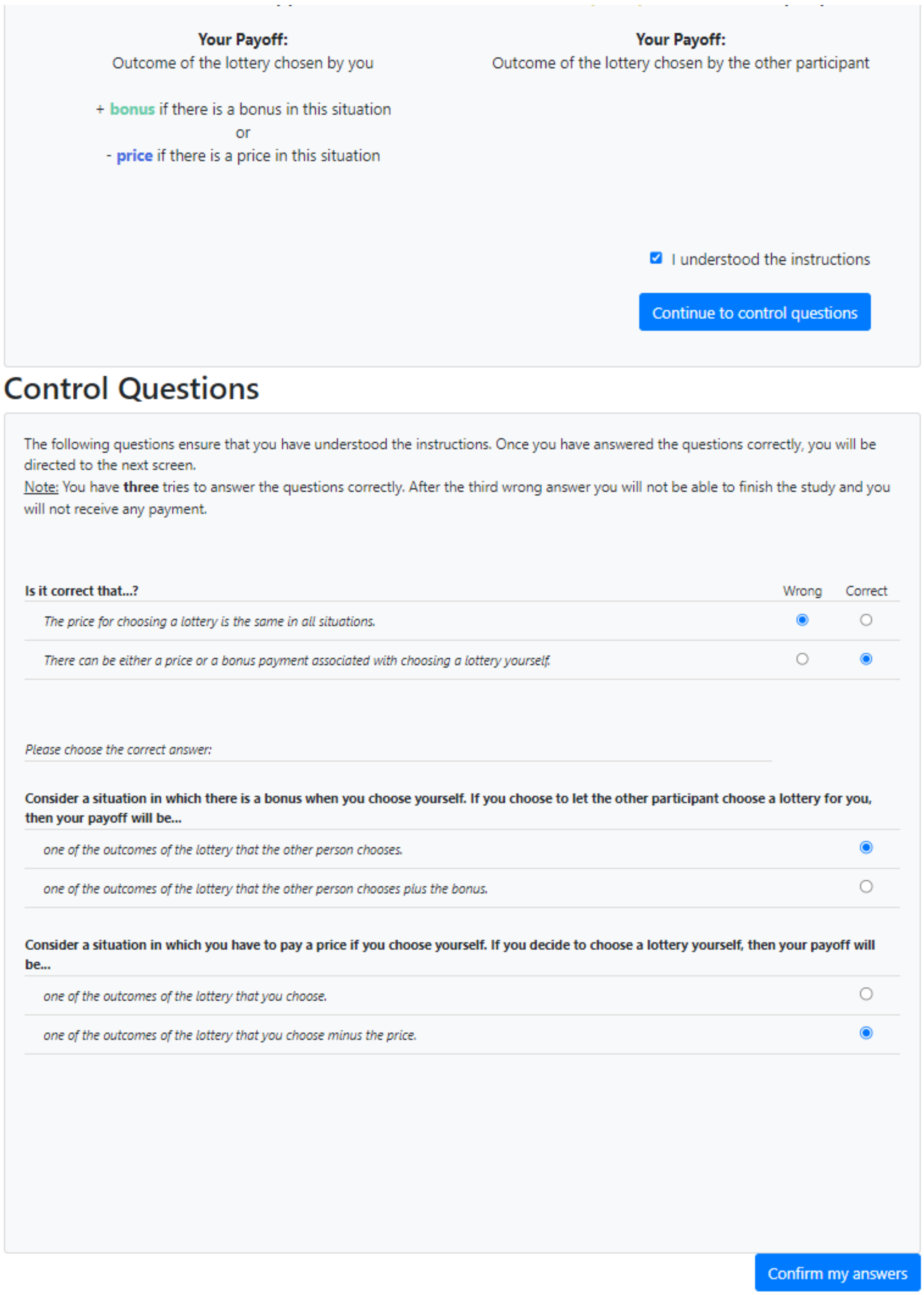


Figure A.20: Screenshot: Description of the delegation decision



Your Payoff:
Outcome of the lottery chosen by you

+ **bonus** if there is a bonus in this situation
or
- **price** if there is a price in this situation

Your Payoff:
Outcome of the lottery chosen by the other participant

☑ I understood the instructions

Continue to control questions

Control Questions

The following questions ensure that you have understood the instructions. Once you have answered the questions correctly, you will be directed to the next screen.
Note: You have **three** tries to answer the questions correctly. After the third wrong answer you will not be able to finish the study and you will not receive any payment.

Is it correct that...?	Wrong	Correct
The price for choosing a lottery is the same in all situations.	◉	○
There can be either a price or a bonus payment associated with choosing a lottery yourself.	○	◉

Please choose the correct answer:

Consider a situation in which there is a bonus when you choose yourself. If you choose to let the other participant choose a lottery for you, then your payoff will be...

- *one of the outcomes of the lottery that the other person chooses.* ◉
- *one of the outcomes of the lottery that the other person chooses plus the bonus.* ○

Consider a situation in which you have to pay a price if you choose yourself. If you decide to choose a lottery yourself, then your payoff will be...

- *one of the outcomes of the lottery that you choose.* ○
- *one of the outcomes of the lottery that you choose minus the price.* ◉

Confirm my answers

Figure A.21: Screenshot: Control questions part 2

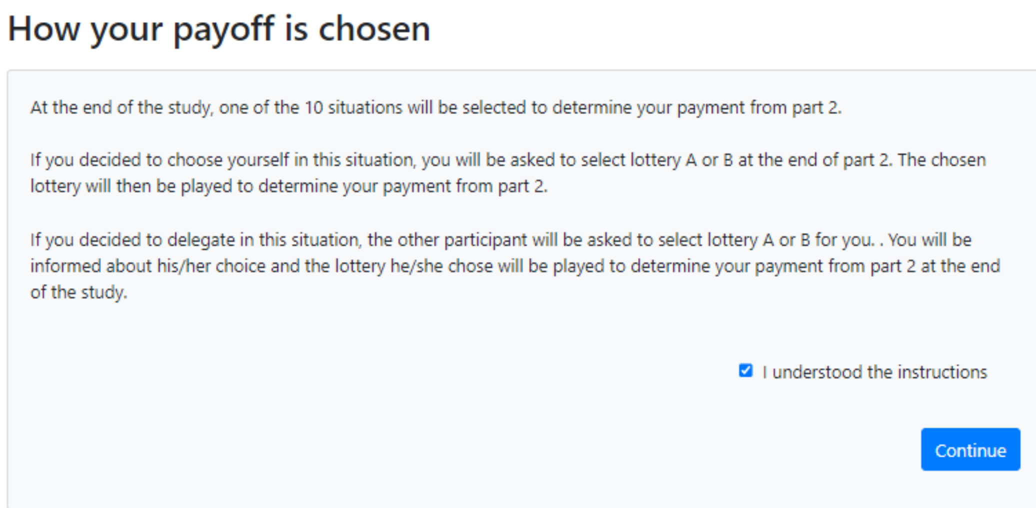


Figure A.22: Screenshot: Payoffs in part 2

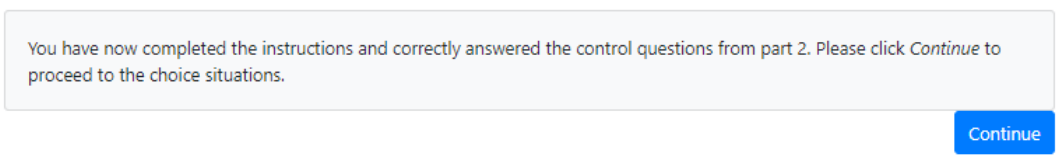


Figure A.23: Screenshot: Transition to choice situations part 1

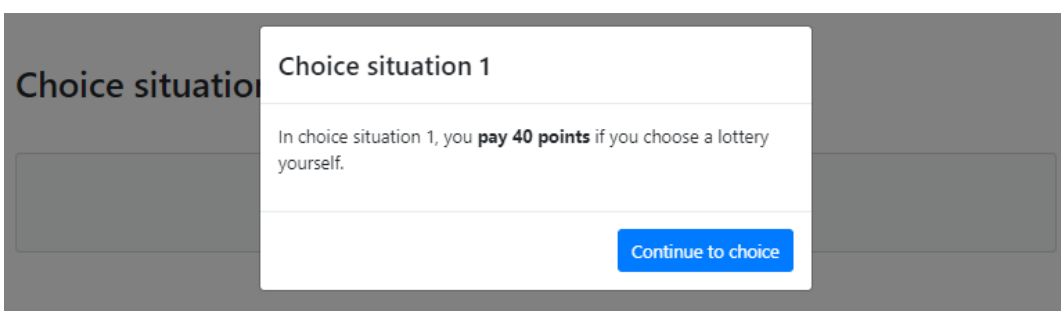


Figure A.24: Screenshot: Announcement of the next choice situation in part 2 (same for choice situations 1 to 10)

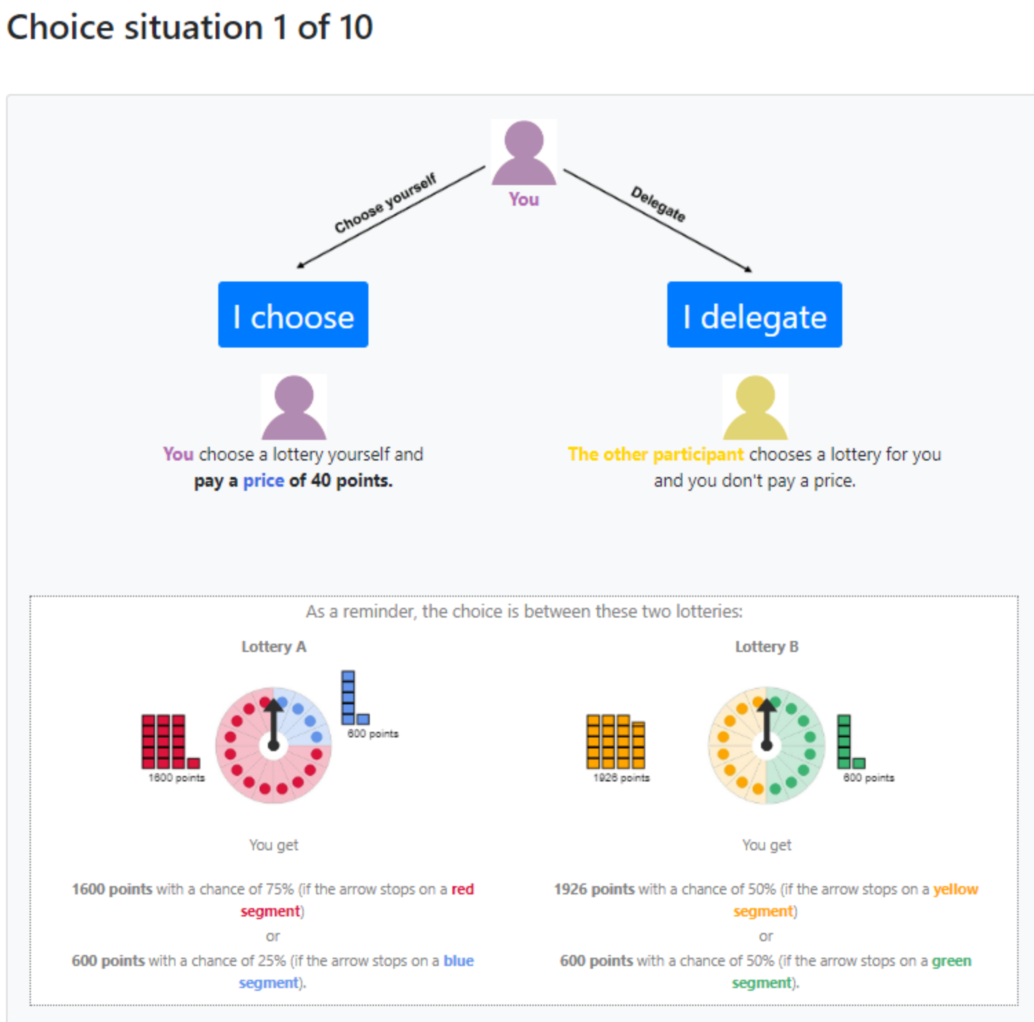


Figure A.25: Screenshot: Choice situation 1 in part 2 (same for choice situations 1 to 10)

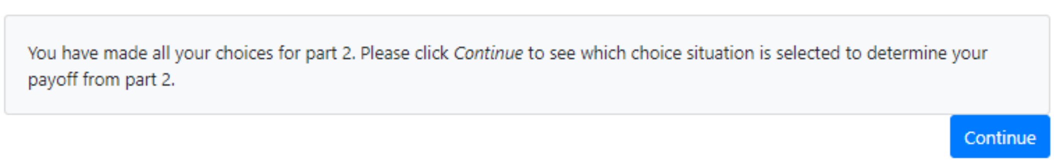


Figure A.26: Screenshot: Transition part 2

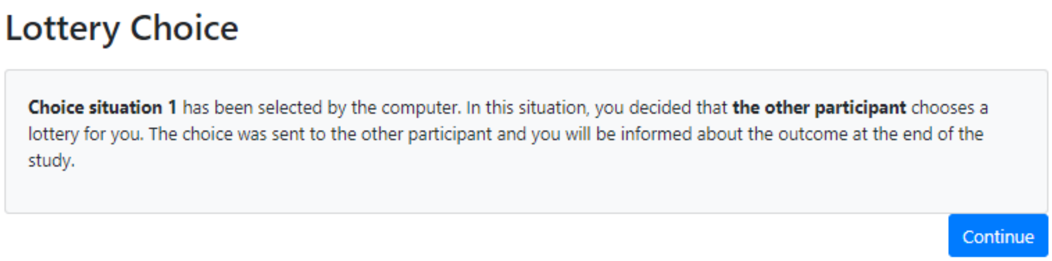


Figure A.27: Screenshot: Information about delegation of the lottery choice in case of delegation

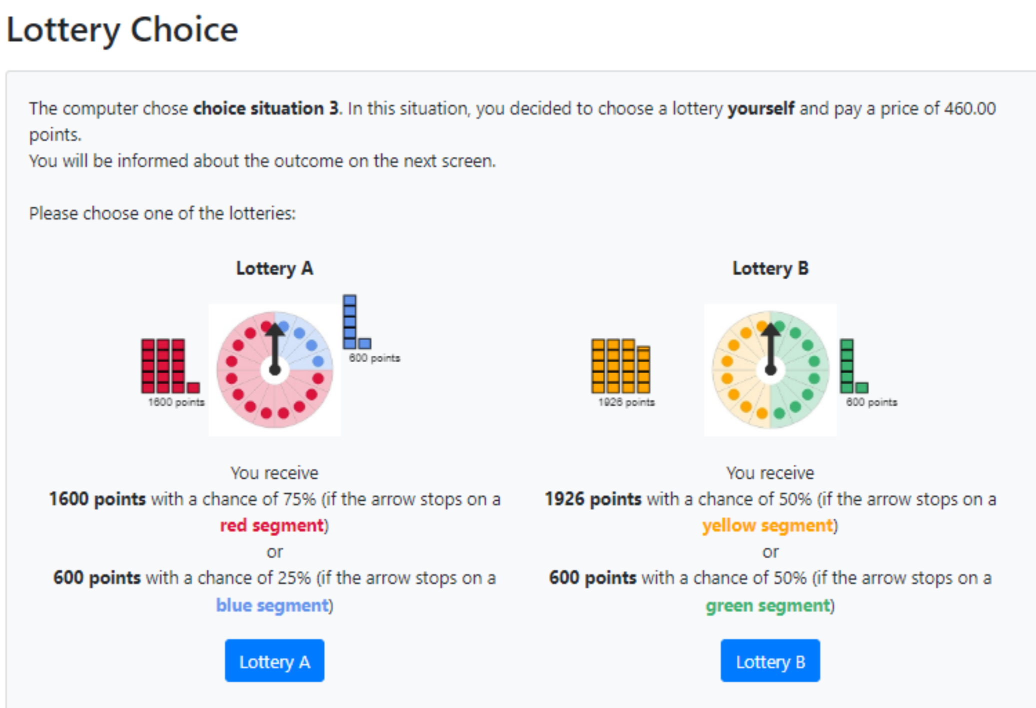


Figure A.28: Screenshot: Information and own lottery choice in case of choosing oneself

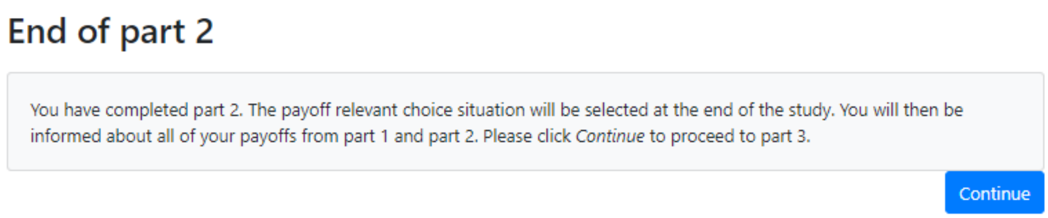


Figure A.29: Screenshot: End of part 2

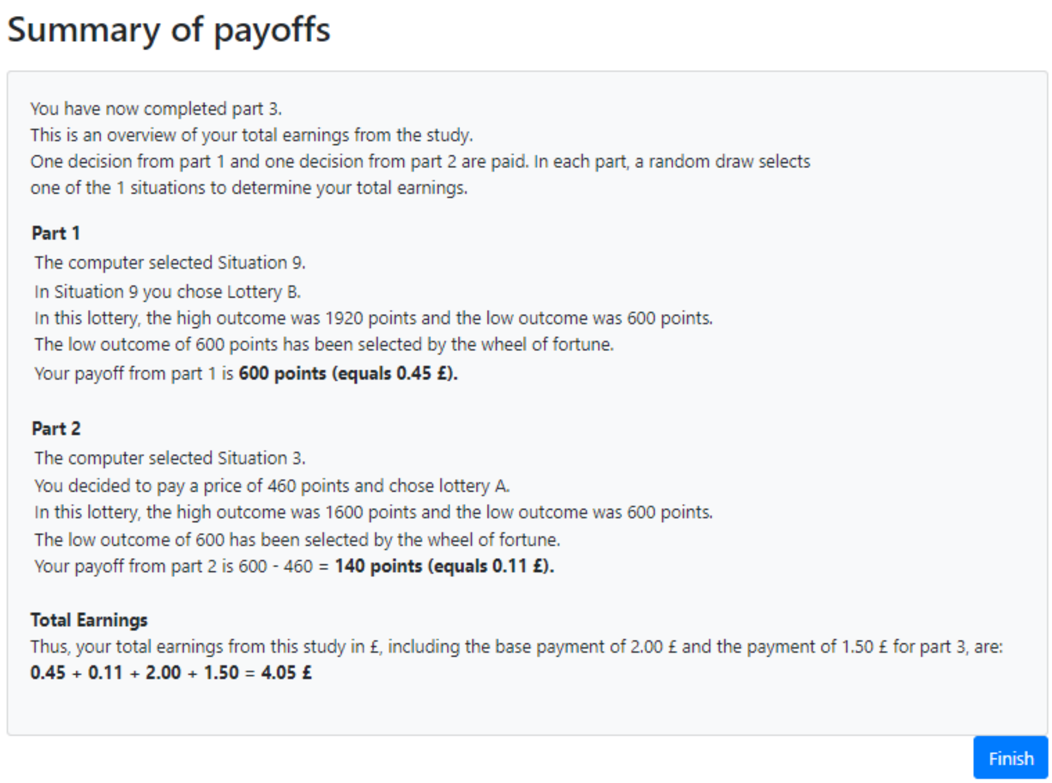


Figure A.30: Screenshot: Summary of payoffs

A.4 Questionnaires

We show the questionnaire of the June 2020 data collection here. Questions in the January 2021 wave were similar, however, several items were not asked anymore and the questionnaire was significantly shortened. In particular, the three Additional Trust Measures, the Big 5 (Gosling, Rentfrow and Swann Jr, 2003) and all perceived autonomy scales (Rotter, 1966; Deci and Ryan, 1985; Schwarzer, Jerusalem et al., 1995; Burger and Cooper, 1979) were not included anymore.
We only list the questionnaire items that were used in the analysis for this paper here. Additional questionnaire items are available from the authors upon request. The order of the question blocks had been randomized at the individual level and the titles shown in this appendix were replaced by, e.g., "Part 1". Explanations are added in italic.

Perceived Autonomy

Locus of Control (Rotter, 1966) For each question select the statement that you agree with the most. *(Six additional buffer items for distraction in the original scale are omitted here. Reversed items: 2, 3, 4, 8, 9, 10, 11, 12, 18, 21, 22.)*

1.	a.Many of the unhappy things in people's lives are partly due to bad luck.	b.People's misfortunes result from the mistakes they make.
2.	a.One of the major reasons why we have wars is because people don't take enough interest in politics.	b.There will always be wars, no matter how hard people try to prevent them.
3.	a.In the long run people get the respect they deserve in this world.	b.Unfortunately, an individual's worth often passes unrecognized no matter how hard he tries.
4.	a.The idea that teachers are unfair to students is nonsense.	b.Most students don't realize the extent to which their grades are influenced by accidental happenings.
5.	a.Without the right breaks (opportunities, good fortune) one cannot be an effective leader.	b.Capable people who fail to become leaders have not taken advantage of their opportunities.
6.	a.No matter how hard you try some people just don't like you.	b.People who can't get others to like them don't understand how to get along with others.
7.	a.I have often found that what is going to happen will happen.	b.Trusting to fate has never turned out as well for me as making a decision to take a definite course of action.
8.	a.In the case of the well prepared student there is rarely if ever such a thing as an unfair test.	b.Many times exam questions tend to be so unrelated to course work that studying is really useless.
9.	a.Becoming a success is a matter of hard work, luck has little or nothing to do with it.	b.Getting a good job depends mainly on being in the right place at the right time.
10.	a.The average citizen can have an influence in government decisions	b.This world is run by the few people in power, and there is not much the little guy can do about it.

11.	a.When I make plans, I am almost certain that I can make them work.	b.It is not always wise to plan too far ahead because many things turn out to be a matter of good or bad fortune anyhow.
12.	a.In my case getting what I want has little or nothing to do with luck.	b.Many times we might just as well decide what to do by flipping a coin.
13.	a.Who gets to be the boss often depends on who was lucky enough to be in the right place first.	b.Getting people to do the right thing depends upon ability. Luck has little or nothing to do with it.
14.	a.As far as world affairs are concerned, most of us are the victims of forces we can neither understand, nor control.	b.By taking an active part in political and social affairs the people can control world events.
15.	a.Most people don't realize the extent to which their lives are controlled by accidental happenings.	b.There really is no such thing as "luck".
16.	a.It is hard to know whether or not a person really likes you.	b.How many friends you have depends upon how nice a person you are.
17.	a.In the long run the bad things that happen to us are balanced by the good ones.	b.Most misfortunes are the result of lack of ability, ignorance, laziness, or all three.
18.	a.With enough effort we can wipe out political corruption.	b.It is difficult for people to have much control over the things politicians do in office.
19.	a.Sometimes I can't understand how teachers arrive at the grades they give.	b.There is a direct connection between how hard I study and the grades I get.
20.	a.Many times I feel that I have little influence over the things that happen to me.	b.It is impossible for me to believe that chance or luck plays an important role in my life.
21.	a.People are lonely because they don't try to be friendly.	b.There's not much use in trying too hard to please people, if they like you, they like you.
22.	a.What happens to me is my own doing.	b.Sometimes I feel that I don't have enough control over the direction my life is taking.
23.	a.Most of the time I can't understand why politicians behave the way they do.	b.In the long run the people are responsible for bad government on a national as well as on a local level.

General Index of Autonomy (Basic Personality Needs Scale, Deci and Ryan (1985)) Please read each of the following items carefully, thinking about how it relates to your life, and then indicate how true it is for you on a scale from 'Not at all true' to 'Very true'.

1. I feel like I am free to decide for myself how to live my life. (Scale from 1=Not at all True to 7=Very True)
2. I feel pressured in my life.
3. I generally feel free to express my ideas and opinions.
4. In my daily life, I frequently have to do what I am told.
5. People I interact with on a daily basis tend to take my feelings into consideration.
6. I feel like I can pretty much be myself in my daily situations.
7. There is not much opportunity for me to decide for myself how to do things in my daily life.

Generalized Self-Efficacy Scale (Schwarzer, Jerusalem et al., 1995)
Please read each of the following items carefully, thinking about how it relates to your life, and then indicate how true it is for you.

1. I can always manage to solve difficult problems if I try hard enough. (Scale from 1=Not at all True to 7=Very True)
2. If someone opposes me, I can find the ways and means to get what I want.
3. I am certain that I can accomplish my goals.
4. I am confident that I could deal efficiently with unexpected events.
5. Thanks to my resourcefulness, I can handle unforeseen situations.
6. I can solve most problems if I invest the necessary effort.
7. I can remain calm when facing difficulties because I can rely on my coping abilities.
8. When I am confronted with a problem, I can find several solutions.
9. If I am in trouble, I can think of a good solution.
10. I can handle whatever comes my way.

Desirability of Control (Burger and Cooper, 1979) Please read each of the following items carefully, thinking about how it relates to your life, and then indicate how true it is for you from on a scale from 'Not at all true' to 'Very true'. *(Please note that we deleted items 7 and 16 from the original 20-item scale since they specifically refer to driving a car and they have an ambiguous interpretation in addition to their lack of generality.)*

1. I prefer a job where I have a lot of control over what I do and when I do it. (7-Point Scale from 'Not at all true' to 'Very true')
2. I enjoy political participation because I want to have as much of a say in running government as possible.
3. I try to avoid situations where someone else tells me what to do.
4. I would prefer to be a leader rather than a follower.
5. I enjoy being able to influence the actions of others.
6. Others usually know what is best for me.
7. I enjoy making my own decisions.
8. I enjoy having control over my own destiny.
9. I would rather someone else took over the leadership role when I'm involved in a group project.
10. I consider myself to be generally more capable of handling situations than others are.
11. I'd rather run my own business and make my own mistakes than listen to someone else's orders.
12. I like to get a good idea of what a job is all about before I begin.
13. When I see a problem I prefer to do something about it rather than sit by and let it continue.
14. When it comes to orders, I would rather give them than receive them.
15. I wish I could push many of life's daily decisions off on someone else.
16. I prefer to avoid situations where someone else has to tell me what it is I should be doing.

17. There are many situations in which I would prefer only one choice rather than having to make a decision.

18. I like to wait and see if someone else is going to solve a problem so that I don't have to be bothered by it.

Freedom and Control: Some people feel they have completely free choice and control their lives while other people feel that what they do has no real effect on what happens to them. Please use this scale where 1 means "no choice at all" and 10 means "a great deal of choice" to indicate how much freedom of choice and control you feel you have over the way your life turns out. (Scale: 1 (No choice at all) to 10 (A great deal of choice)), *original question of the world value survey wave 6, Inglehart (2014)*

General Questions

Risk: On a scale from 0 to 10, where 0 means you are "completely unwilling to take risks" and a 10 means you are "very willing to take risks", how willing are you to take risks in general?

Trust Others: Generally speaking, how much do you trust other people? (Scale: Completely Distrust to Completely Trust)

Additional Trust Measures:

1. In general, I have trust in other people's good intentions. (Scale: Completely Distrust to Completely Trust)

2. In general, I have trust in other people's expertise.

3. In general, I have trust in other people ability to make decisions of high quality.

Very short Big 5: *(Gosling, Rentfrow and Swann Jr, 2003)* Here are a number of personality traits that may or may not apply to you. Please indicate to what extent you agree or disagree that these personality traits apply to you. Note: You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other. I see myself as... (Scale: 1=Disagree strongly, 2=Disagree moderately, 3=Disagree a little, 4=Neither agree nor Disagree, 5=Agree a little, 6=Agree moderately, 7=Agree strongly)

- Extraverted, enthusiastic (NOT reserved or shy)
- Agreeable, kind (NOT quarrelsome or critical)
- Dependable, self-disciplined (NOT careless or disorganized)
- Emotionally stable, calm (NOT anxious or easily upset/stressed)
- Open to new experiences, creative (NOT conventional)

Socio-demographics *(This block always came second-last.)*

Income: The next question is about the total income of you and your family members living in your household in 2020. This figure should include income from all sources including salaries, wages, pensions, social security, dividends, interest and any other income. Please select the category that represents your household income. (Less than GBP 10,000 / steps of 10 000 GPB / More than GBP 150,000)

Marital Status: Please indicate your marital status:

- Divorced
- Married
- Single
- Widowed

Children: How many children do you have? (field to enter number)

Employment Status: Are you...

- Employed?
- Retired?
- Self-employed?
- A stay-at-home mother/father?
- A student?
- Unemployed?

Education: What is the highest level of education that you have achieved?

- Less than High School
- High School diploma
- Some college or associate degree
- 4-year college degree
- More than 4-year college degree

Information on age, gender, and nationality has been extracted from prolific, where subjects are asked to provide this information.