Online Appendix: Choosing (not) to Choose: Uncovering Intrinsic Preferences for Choice Autonomy

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Online Appendix

A.1 DOSE Method

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

Step 1 is conducted under a fixed decision mode $c = 1$ with price $p = 0$, so that utility reduces to the purely consequentialist component $\tilde{V}(x, 0)$.

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. For the sole purpose of implementing DOSE in Step 1, we model choice behavior using Expected Utility with CRRA preferences and stochastic choice. In line with the theoretical framework, this amounts to setting the intrinsic value of choice autonomy to zero in Step 1, such that observed choices reflect instrumental utility only. In particular, we assume that the participant's risk preferences and choice behavior can be characterized by the following two equations. Consistent with the theoretical framework, in Step 1 we set $p = 0$ and abstract from decision-mode effects, so that $\tilde{V}(x, 0)$ is instantiated as expected utility $U_i(x)$:

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

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

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

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:

$$p(k|a) = p(r_k, \mu_k|a) = \frac{p(a|r_k, \mu_k)p(r_k, \mu_k)}{\sum_j^k p(a|r_j, \mu_j)p(r_j, \mu_j)} \tag{A.3}$$

where $a \in \{$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 $Q_i \in \mathcal{Q}$:

$$I(k; Q_i) = \sum_a log(\frac{l_k(a; Q_i)}{\sum_{j=1}^k p_j l_j(a; Q_i)}) p_k l_k(a; Q_i) \tag{A.4}$$

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 $Q_i \in Q$:

$$KL(Q_i) = \sum_k^n p_k I(a; Q_i) \tag{A.5}$$

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[1] to the prior choice situations. In round 10, we have an additional reason for selecting a different choice situation. In

[1]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.

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.[2]

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.[3]

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 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).[4] In addition, for each individual, we obtain

[2]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.

[3]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.

[4]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

an estimate for $\hat{\mu}$ based on the MAP estimate for μ given $f(r, \mu|C_1(10))$.[5]

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 using the utility formulation for $V(x, p, c)$ presented in equation 4 in the main paper:

$$Pr_i(c = 1) = \frac{1}{1 + e^{-\gamma_i(V_i(A,p,1) - V_i(A,p,0))}} = \frac{1}{1 + e^{-\gamma_i(d_i - p)}} \tag{A.6}$$

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 $\gamma \in \{1, 2, ..., 15\}$.[6] As in step 1, we pre-specified and stored the optimal se-

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.3 in Online 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 Online Appendix A.2.1. As results are highly similar, we do not discuss them in the text.

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

[6] The values of γ have to be interpreted in connection with $V_i(x, p, c)$, as it simply scales up differences in 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.

quence 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.[7] 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}:[8]

$$\hat{d}_i = \sum_{d_i \in \mathcal{D}} d f_i(d | \gamma_{i,MAP}, C_{2i}(10)). \tag{A.7}$$

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 A.7 delivers an estimate of -1.48. We round these values to $\hat{d} = 0$, which we believe better reflects the true preference.

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' Bernoulli utility function over monetary outcomes has constant relative risk aversion (CRRA). In principle, one could worry that this choice introduces bias or arbitrariness into our estimation procedure. In this Online 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.

[7] 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.

[8] We condition on the MAP of γ for the same reasons as before. Again, Figure A.4 in Online 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 Online Appendix A.2.1.

To show this, we assume that the "true" utility function u_i of participants over monetary outcomes 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:

$$u_i^{CARA}(w) = \frac{1 - e^{-aw}}{a}, \tag{A.8}$$

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

$$u_i^{PT}(w) = \begin{cases} w + (w - R) & \text{if } w \geq R \\ w - \lambda(R - w) & \text{if } w < R, \end{cases} \tag{A.9}$$

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. 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

$\hat{\mu}$	$\lvert B^H_{CRRA} - B^H_{CARA}\rvert$	$\lvert B^H_{CRRA} - B^H_{PT}\rvert$
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 reference dependence with loss aversion.

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.

A.1.4 Estimated Intrinsic Value of Autonomy using different underlying utility functions

In order to apply the DOSE method for part 2 of our elicitation procedure, we again had to impose a structural model of utility. Here, we assumed a utility function in which the utility from the lottery was additively separable from the intrinsic value of autonomy and the utility loss from the price paid (equation (3) on p. 12):

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

Obviously, this is just an assumption and other utility specifications could have been used. In particular, additive separability of the price is a strong assumption, and the paid price could also have been integrated with the payoffs of the lottery.

A primary reason for using the additively separable structure for our main analysis and the determination of the choice sequence via DOSE is that it significantly simplified the computational complexity and comparability of the program. Equation A.6 makes clear that the probability whether a subject delegates or not depends on the difference between utilities of delegation versus not delegation. With the additively separable specification, the utility of the lottery drops out, and this boils down to the difference between the price and the individual intrinsic value of autonomy. Without additive separability of the price, the softmax function remains dependent on $U_i(A)$, and thus also on the individually estimated utility parameters from step 1. In turn, the optimal sequence of decisions would not be independent of step 1, causing path dependency and additional complexity. To avoid this, we opted for the additively separable specification in our implementation.

However, to assess whether our results are sensitive to this assumption, we can provide robustness checks for our estimation of the willingness to pay for autonomy. While the sequence of choices is optimized based on the assumed utility function presented in equation 4 in the main paper, we can again use the actual choice sequence and estimate utility parameters for other types of utility functions in which the price is integrated with the lottery payoffs, and then compare the results to the original estimate. We do so for the three types of alternative utility functions used in the paper as well as in Online Appendix A.1.3. The general structure of utility is:

$$V_i(x,p,c) = \begin{cases} U_i^j(A - p) + d_i, & \text{if participant chooses herself } (c=1) \\ U_i(A), & \text{if participant delegates choice } (c=0) \end{cases} \tag{A.10}$$

with $j = \{CRRA, CARA, PT\}$, as defined in equations 2 in the main paper, A.8 and A.9. Moreover, the individually estimated risk preference parameter from step 1 (r, a, λ) is used to evaluate the utility of the resulting prospects.

In a first step,for each participant and each utility function, we initiated the set of identifiable preference parameters d given the set of possible prices p, which depends on the individually estimated preference parameter for the respective utility function given th choice sequence in step 1. The resulting range of identifiable utility parameters d was used to initialize the distribution of potential utility parameters for this subject and utility function. For the choice consistency parameter ρ, we multiplied each value by 10 relative to the original specification with additively separable utility. The reason for this adjustment is due to the fact that ρ simply scales differences in utilities, and therefore the absolute value of these utilities matters for the predicted choice probabilities. Given that the numerical magnitude of these utilities is significantly smaller when integrating the price and evaluating the prospects using CRRA, CARA or Prospect Theory, the original range of values of ρ only covered values of ρ that all implied high degrees of choice inconsistency. The adjusted range of parameter values was therefore $\rho \in \{10, 20, \cdots, 150\}$, comparable to the range of μ used in step 1.

Given these individually constructed parameters, we again assumed a uniform joint distribution and applied Bayesian Updating using the actually realized choice sequence to recover estimates for the individual intrinsic value of choice autonomy $\hat{d}$ as well as an estimated individual choice consistency parameter $\hat{\rho}$. In order to compare the estimated values $\hat{d}$ across the different utility specifications, we then calculated the willingness to pay implied by $\hat{d}$. For each individual, we thus estimated three additional estimates for the willingness to pay, WTP^{CRRA}, WTP^{CARA} and WTP^{PT}, one for each alternative utility specification.

Again, we can show that the choice of the additively separable utility function had very little impact on the estimated willingness to pay, at least as long as participants were reasonably consistent. Figure A.1 displays a histogram of the individual level differences in the estimated willingness to pay for choice autonomy using additively separable utility versus using CRRA, CARA or prospect theory instead. It can be seen that differences are mainly clustered around zero. The average difference is -0.07 for CRRA with a standard deviation of 10.8, 0.57 for CARA with a standard deviation of 10.0 and -0.42 for prospect theory with a standard deviation of 16.6. The lower panel shows these distributions conditional on having the highest consistency score of $\rho = 15$ (using the linearly additive utility specification). It can be seen that differences in the estimated WTP now are always in the single digits, and again on average very close to zero (average differences are -0.08 (1.92), 0.07 (1.80) and -0.15 (2.49), respectively (standard deviations in brackets)).

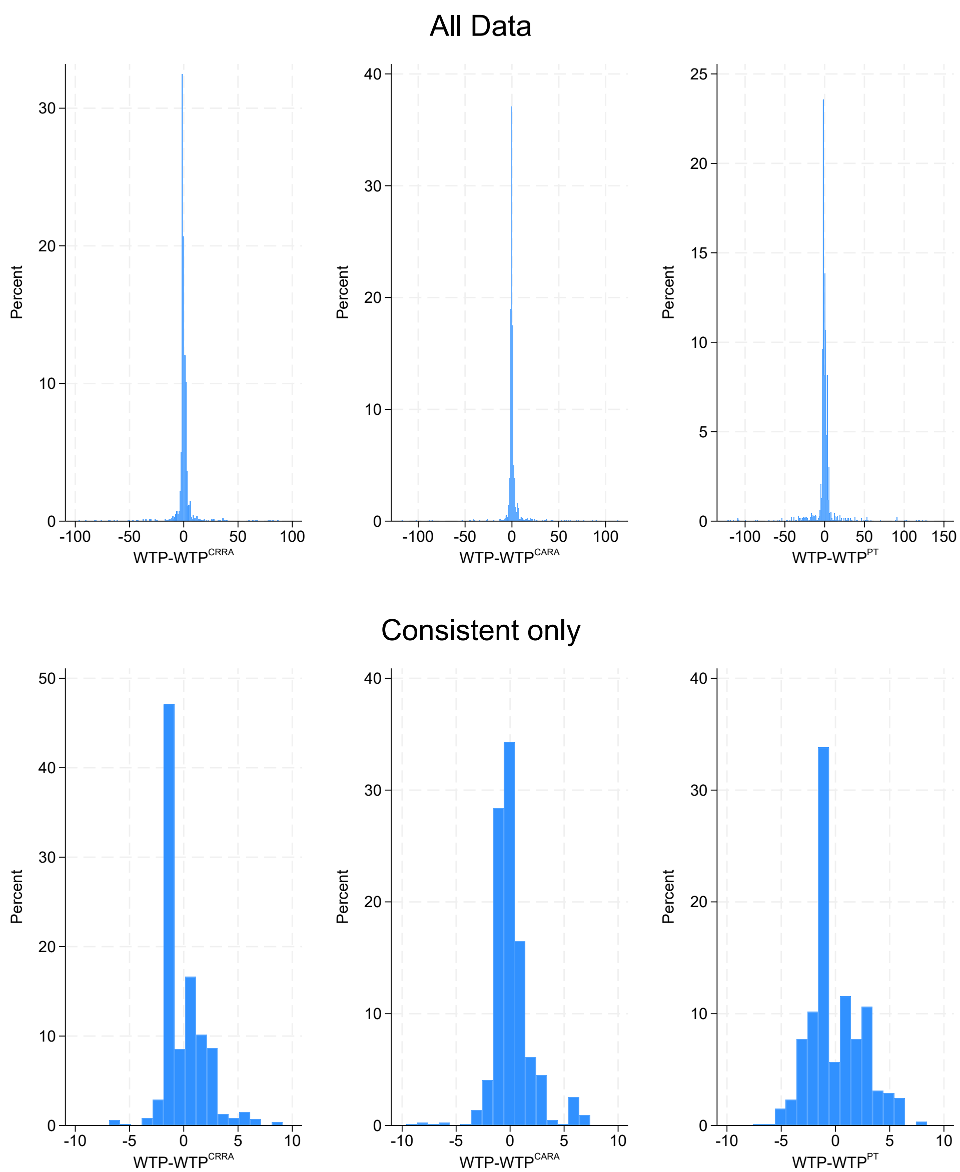

Figure A.1: Histogram of individual differences between the estimated WTP using additively separable utility versus alternative specifications (CRRA, CARA and Prospect Theory)

WTP estimates are thus very similar across estimations, and standard deviations are relatively small. Consequently, estimated WTP's are also very highly correlated across the different specifications. Table A.2 displays pairwise correlation coefficients for the four different WTP estimates:

Table A.2: Correlation between different estimates of WTP at the individual level

	Willingness to pay using different utility functions			
	WTP	WTP^{CRRA}	WTP^{CARA}	WTP^{PT}
WTP	1.0000			
WTP^{CRRA}	0.9984	1.0000		
WTP^{CARA}	0.9986	0.9988	1.0000	
WTP^{PT}	0.9963	0.9992	0.9969	1.0000

Taken together, the estimation of the willingness to pay is very robust to alternative specifications of utility, and thus does not seem to be strongly dependent on the assumption of additively separable utility in step 2 of the elicitation mechanism.

A.1.5 Calculating the intrinsic value of choice autonomy as a percentage of instrumental utility

Calculating the intrinsic value of choice autonomy as a percentage of the instrumental utility of lottery A requires structural assumptions on $V(x, p, c)$. TO do this, we maintain the assumption used in the implementation of DOSE in step 2 that the intrinsic value of choice autonomy is additively separable from the instrumental utility, but, diverging from the previous structural implementation, now assume that p is integrated with the lottery outcomes and evaluated using CRRA utility, just as we did in the exercise in section A.1.4. If p remained additively separable, $U(A)$ would drop out of the utility comparison between $c = 1$ and $c = 0$, implying that any percentage measure relating the intrinsic value of choice autonomy to $U(A)$ would be ill-defined. $V(x, p, c)$ is then given by:

$$V_i(x, p, c) = \begin{cases} U_i(x - p) + d_i, & \text{if the participant retains the decision right } (c = 1), \\ U_i(x), & \text{if the participant delegates } (c = 0). \end{cases}$$

where $U_i(\cdot)$ denotes expected utility over monetary outcomes, derived from a CRRA Bernoulli utility function with parameter $\hat{r}_i$ estimated in Step 1. Since Step 1 constructs an indifference lottery $\hat{B}_i$ such that $A \sim \hat{B}_i$, we evaluate instrumental utility using lottery A only, and set $p = wtp_i$.

At the elicited willingness to pay, the individual is revealed indifferent between delegating and retaining the decision right, i.e.,

$$U_i(A - wtp_i) + d_i = U_i(A).$$

Thus, the intrinsic utility from choice autonomy exactly compensates for the loss in instrumental utility due to paying wtp_i. We therefore recover the intrinsic component as

$$d_i = U_i(A) - U_i(A - wtp_i),$$

and express it as a percentage of instrumental utility under self-choice:

$$\frac{d_i}{|U_i(A - wtp_i)|}.$$

This normalization yields a unit-free measure of the intrinsic value of choice autonomy that is comparable across individuals with different risk preferences.

While we report all numbers based on assuming CRRA utility, the exercise can also be conducted assuming CARA or Prospect Theory, as in section A.1.4. While results assuming CARA are very comparable to CRRA, the intrinsic value of choice autonomy as a percentage of instrumental utility of lottery A is substantially larger when assuming Prospect Theory (when assuming a constant reference point), as paying a price increases experienced losses, resulting in larger differences in experienced utility from the lottery (which in turn must be compensated by larger intrinsic value of choice autonomy). We do not report details on these additional analyses here. They are available upon request from the authors.

A.2 Additional analyses

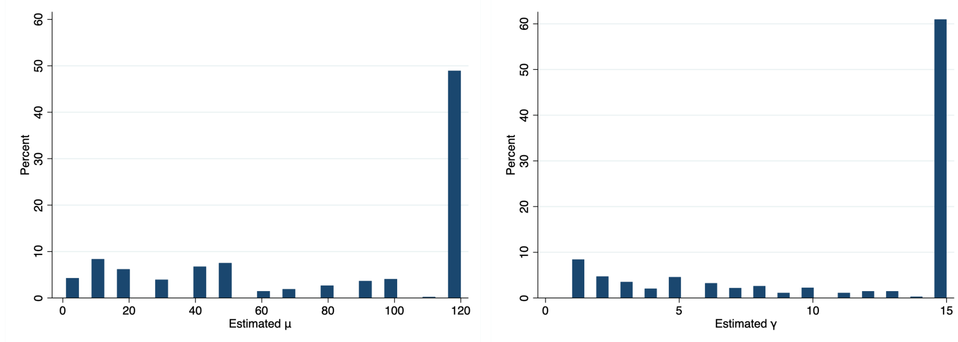

Figure A.2: Distribution of individual modal choice consistency parameters in part 1 ($\hat{\mu}$) and part 2 ($\hat{\gamma}$), $N = 1422$.

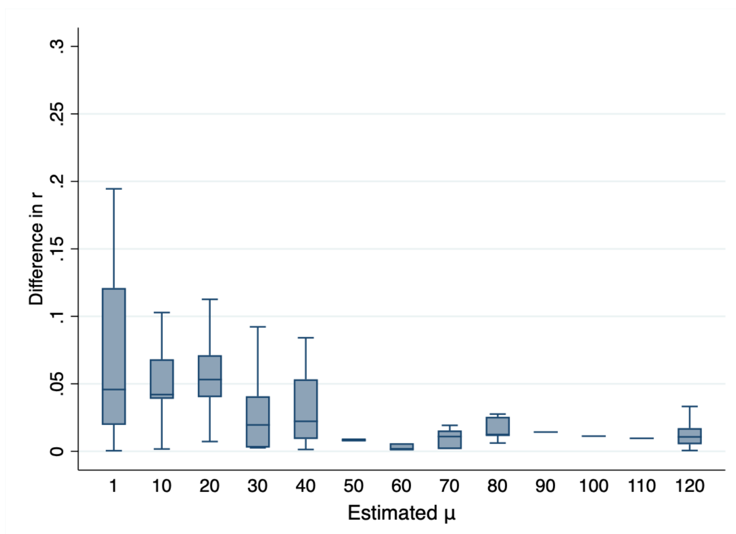

Figure A.3: Absolute Difference in $\hat{r}$ (the individually estimated risk preference parameter) depending on whether it is determined using the unconditional expectation of r or conditional on the MAP of μ.

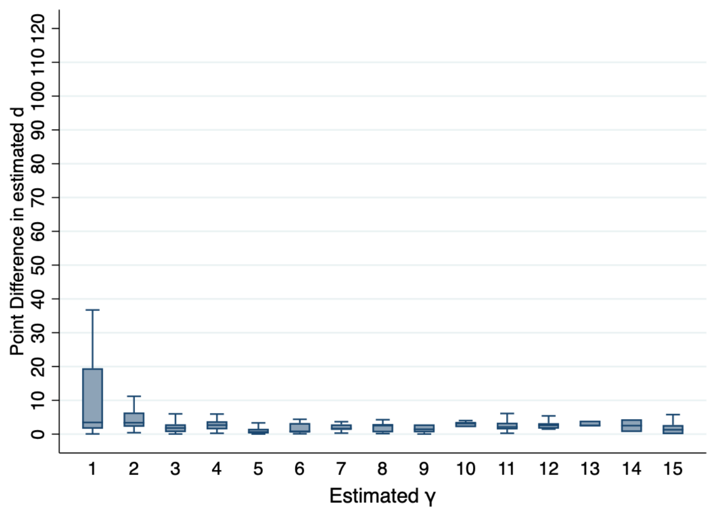

Figure A.4: Absolute Difference in $\hat{d}$ (the individually estimated willingness to pay) depending on whether it is determined using the unconditional expectation of d or conditional on the MAP of γ.

	(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.3: 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.4: 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.

	(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 A.5: 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] 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 Online Appendix A.2.2, Table A.15.

[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.

	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.6: 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.7: 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.10: 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.

	WTP	
LOC	9.23	1.71
	(11.994)	(12.589)
IA	1.778	2.442
	(7.686)	(8.167)
GSE	10.518	5.293
	(7.660)	(8.743)
DC	15.94	8.527
	(9.245)	(10.309)
WVS	7.328	5.463
	(4.486)	(4.738)
Controls	no	yes
Observations	791	782

Table A.8: Each cell shows the coefficient of one OLS regression (with robust standard errors in parentheses) with willingness to pay as the dependent variable. Constants are omitted. Independent variables in the 10 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). The five regressions in column (2) include controls for age, gender, income, education, risk_taking, nationality, highly_inconsistent_part1, highly_inconsistent_part2, prolific_score and not_failed. June 2021 wave.

	WTP	
LOC	7.311	6.173
	(12.550)	(9.596)
IA	-12.825	-10.165
	(8.420)	(6.621)
GSE	10.165	4.698
	(8.174)	(6.158)
DC	23.284	10.748
	(10.218)	(9.113)
WVS	4.611	-.640
	(4.037)	(3.842)
Controls	no	yes
Observations	791	782

Table A.9: Each cell shows the coefficient of one Median regression (with robust standard errors in parentheses) with willingness to pay as the dependent variable. Constants are omitted. Independent variables in the 10 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). The five regressions in column (2) include controls for age, gender, income, education, risk_taking, nationality, highly_inconsistent_part1, highly_inconsistent_part2, prolific_score and not_failed. June 2021 wave.

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

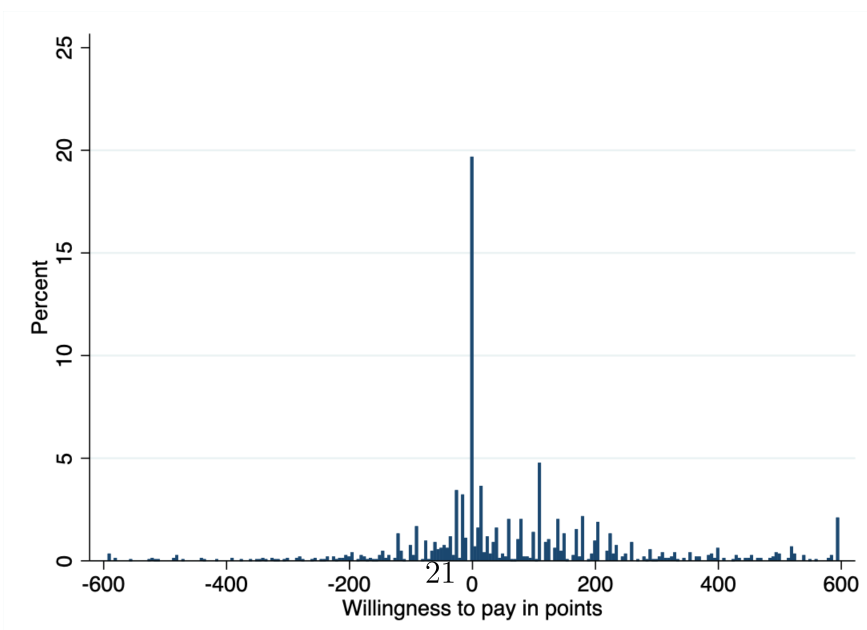

Figure A.5: Distribution of the willingness to pay, calculated using the unconditional expectation, June 2021 and January 2022, $N = 1422$.

	(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.12: 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)	(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.11: 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) **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.13: 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.14: 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

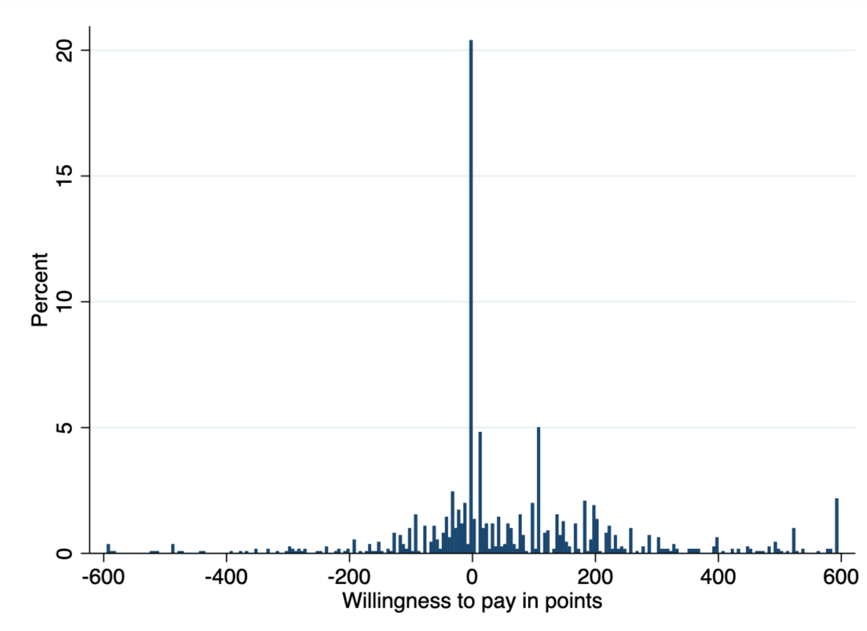

Figure A.6: Distribution of the willingness to pay among subjects with $\hat{\mu} > 30$, June 2021 and January 2022, $N = 1098$.

	(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.15: 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.16: 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)	(2)	(3)	(4)
	Trust (General)	**Trust in Intentions**	**Trust in Expertise**	**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.17: 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.18: 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.2.3 Additional analyses using the entire sample without exclusions

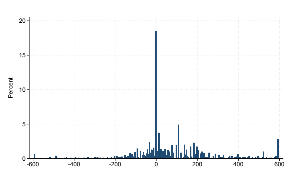

Figure A.7: Distribution of the willingness to pay, all subjects without exclusions, $N = 1792$.

We re-run the main analyses using data from all 1792 subjects, including the 370 subjects (see Section 3.3 in the main paper for details) who are excluded in the main analyses because of low data quality. Please note that the inclusion of these observations may bias the results because we cannot credibly claim to have identified an indifference choice set. In particular, their WTP may contain substantial instrumental value.

The median value is 18.76 points, the mean at 74.15 points. The distribution is shown in Figure A.7. The willingness to pay is significantly different from zero (t-test: $p<0.001$, WSR: $p<0.001$, $N=1792$). This amounts to 5% of the expected value of lottery A. The mean and median values are somewhat inflated compared to the mean and median with the restricted sample containing only subjects for whom we know that our identification works (12 and 67 points respectively). This is driven by significantly higher willingness to pay among the excluded subjects (101 vs. 67 points, p¡0.01, ttest), consistent with the interpretation that their choice set in step 2 contains instrumental value.

Regarding individual heterogeneity, 18.47% have a WTP of zero, 26.06% a negative WTP and 55.47% exhibit a positive WTP. This is very close to the shares reported in the main text (19.1%, 27.1%, 53.8%).

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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.8: Screenshot: Consent form

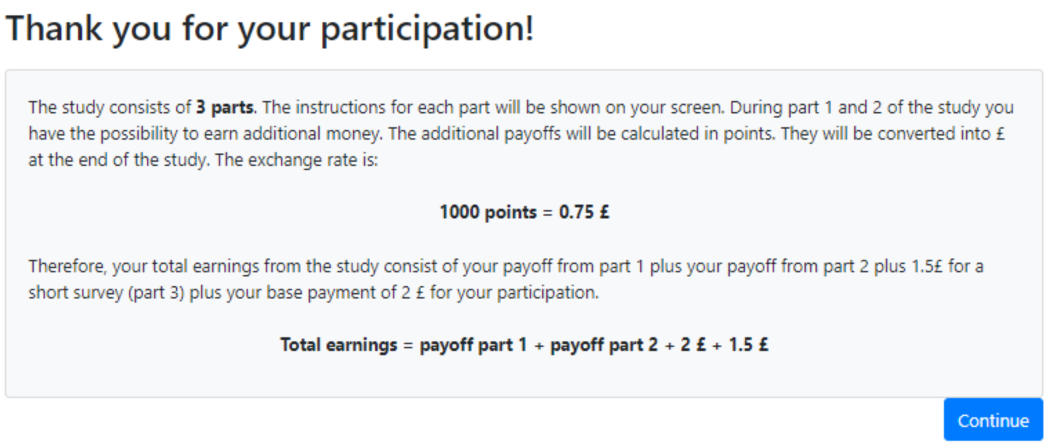


Figure A.9: Screenshot: Payoffs and exchange rate

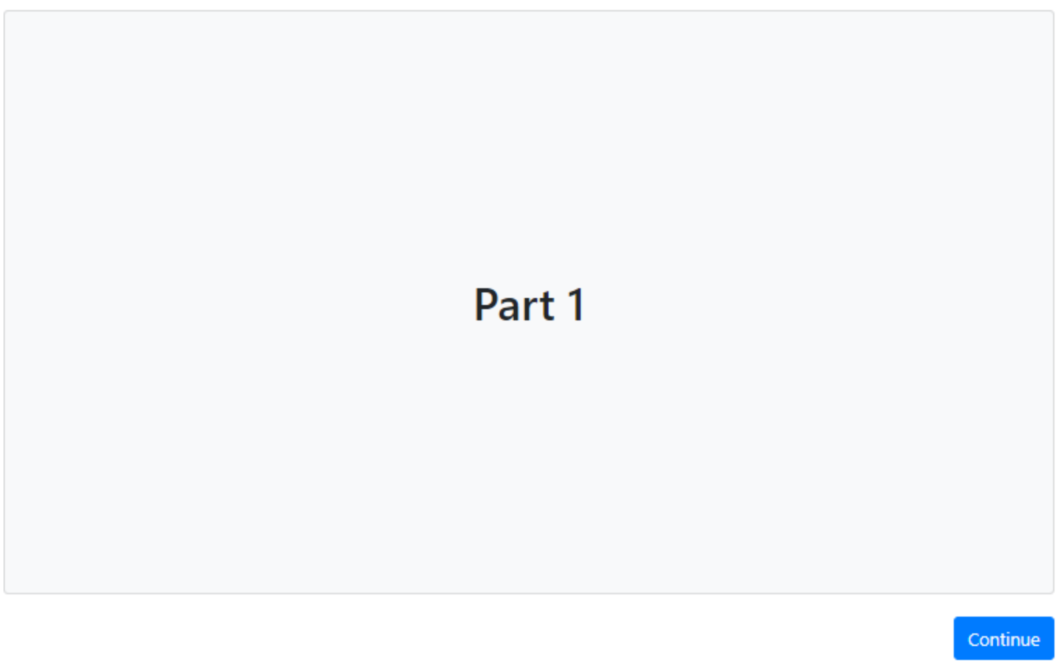
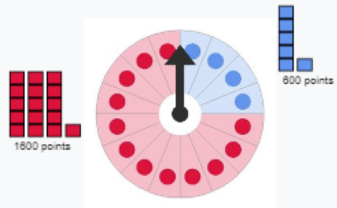


Figure A.10: Screenshot: Begin of part 1

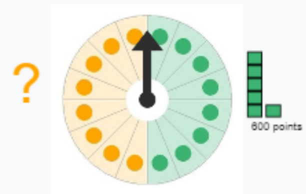
Figure A.11: Screenshot: Description of the lotteries (Elements of the screen appear sequentially. When the participant clicks "continue", the next picture and description appears.)

The outcome of lottery A is determined by wheel A. On wheel A, 12 of the 16 segments (75%) are **red**, 4 segments (25%) are **blue**.



If the arrow stops on a **red segment** you receive **1600 points.**
If the arrow stops on a **blue segment** you receive **600 points.**

The outcome of lottery B is determined by wheel B. On wheel B, 8 of the 16 segments (50%) are **yellow**, 8 segments (50%) are **green.**



If the arrow stops on a **yellow segment** you receive the **high outcome**
If the arrow stops on a **green segment** you receive **600 points.**

☑ I understood the instructions

Continue to control questions

Control Questions

The following questions ensure that you have understood the instructions. Once you have answered all 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.

Which of the following is correct?	Wrong	Correct
If a participant chooses lottery B...		
it is equally likely that he or she receives the high or the low outcome.	○	●
If a participant chooses lottery A...		
he or she always gets a payout of 1600 points.	●	○
the computer spins a wheel of fortune which determines if he or she receives 1600 or 600 points.	○	●
he or she gets a payoff of 600 points with a likelihood of 25%.	○	●

Confirm my answers

Figure A.12: Screenshot: Description of the lotteries continued and control questions part 1

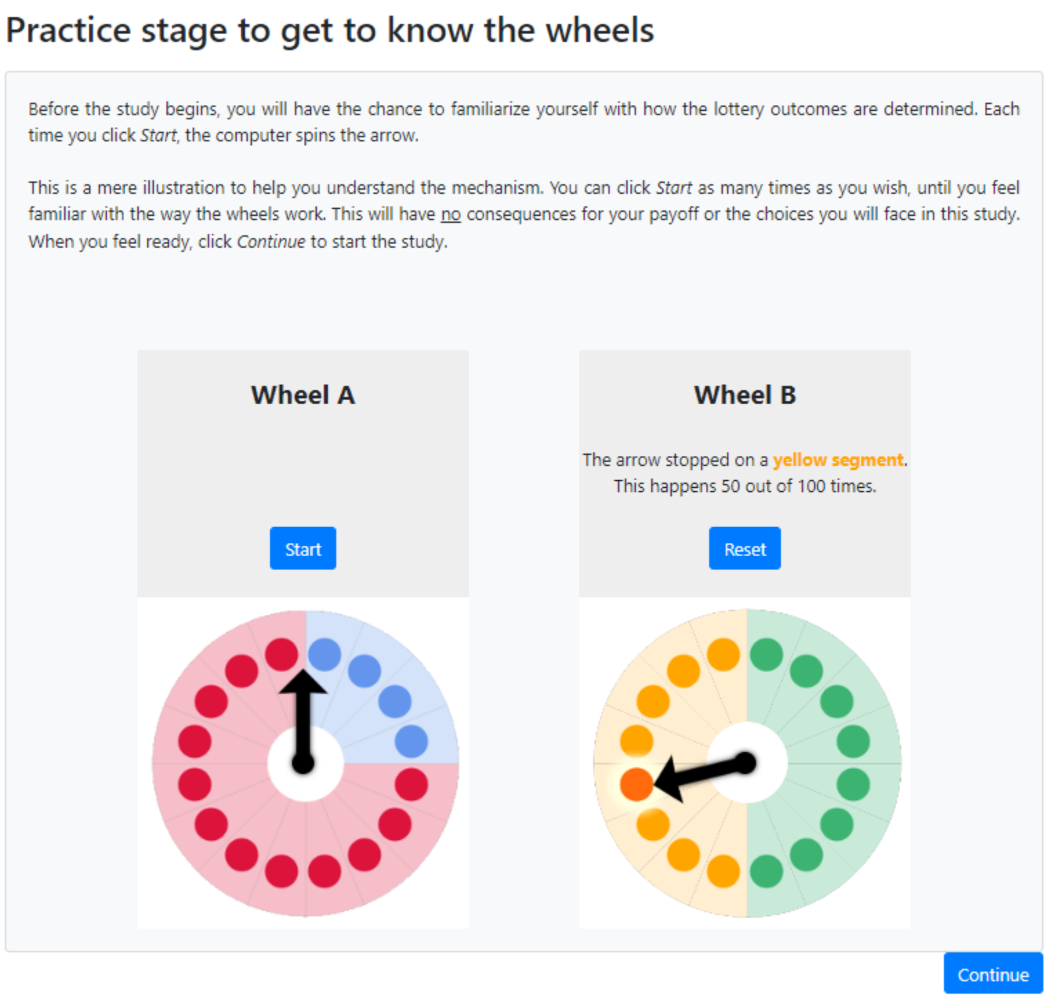


Figure A.13: Screenshot: Practice wheels (The participant can spin each wheel as often as she wishes. After each spin, the outcome is displayed together with an explanation how often this happens to prevent biases.)

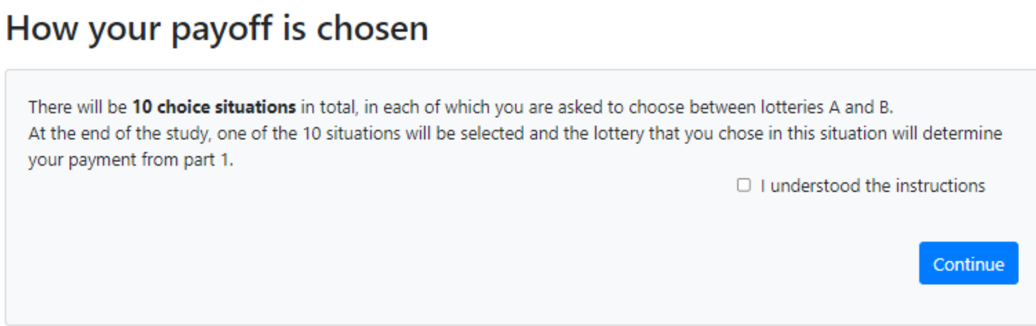


Figure A.14: Screenshot: Procedure part 1

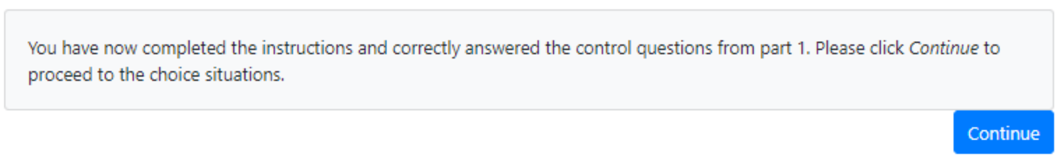


Figure A.15: Screenshot: Transition to choice situations part 1

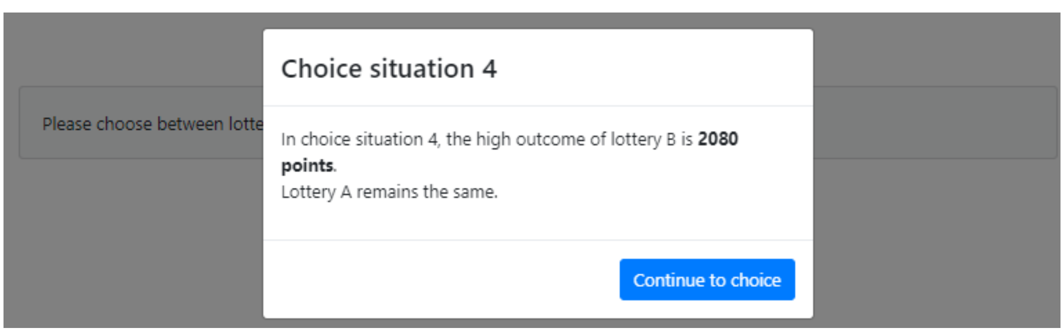


Figure A.16: Screenshot: Announcement of the next choice situation in part 1 (same for choice situations 1 to 10)

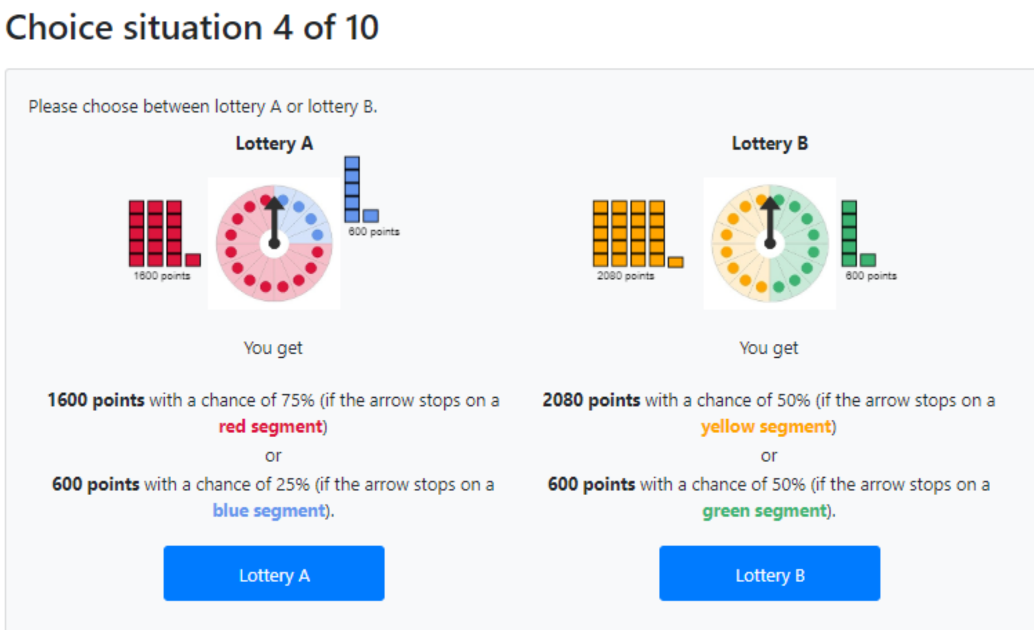


Figure A.17: Screenshot: Choice situation 4 in part 1 (same for choice situations 1 to 10)

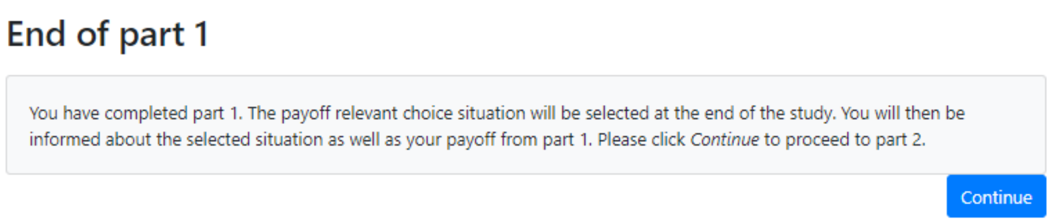


Figure A.18: Screenshot: End of part 1

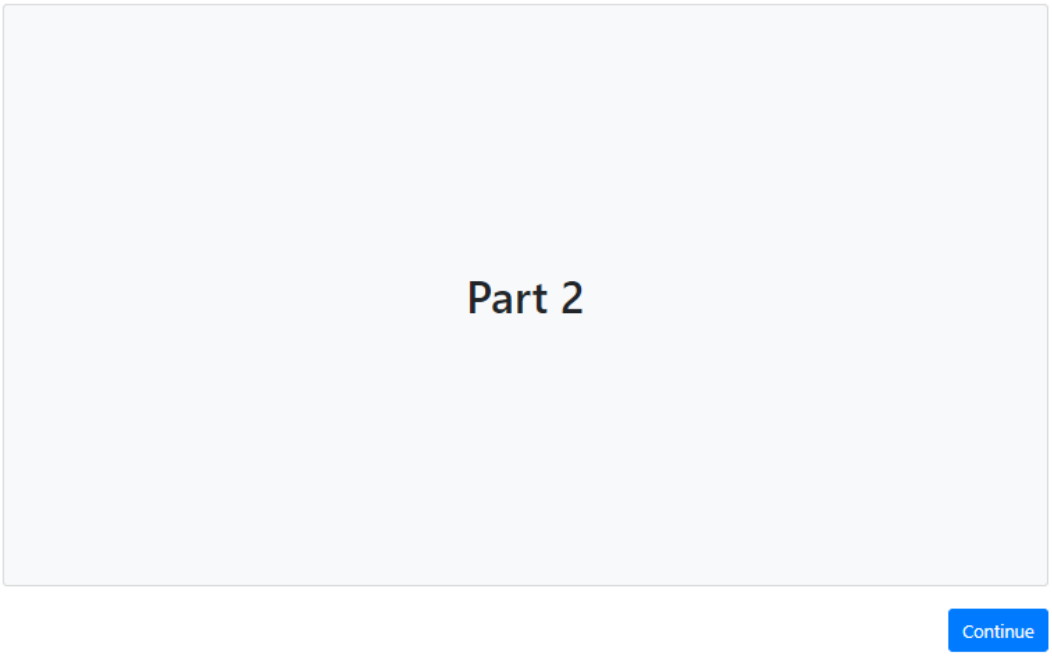


Figure A.19: Screenshot: Begin of part 2

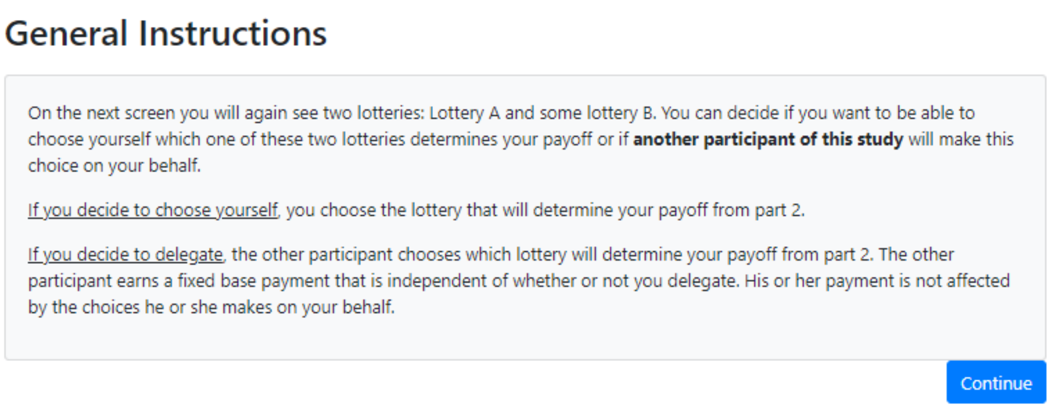


Figure A.20: Screenshot: General instructions for part 2

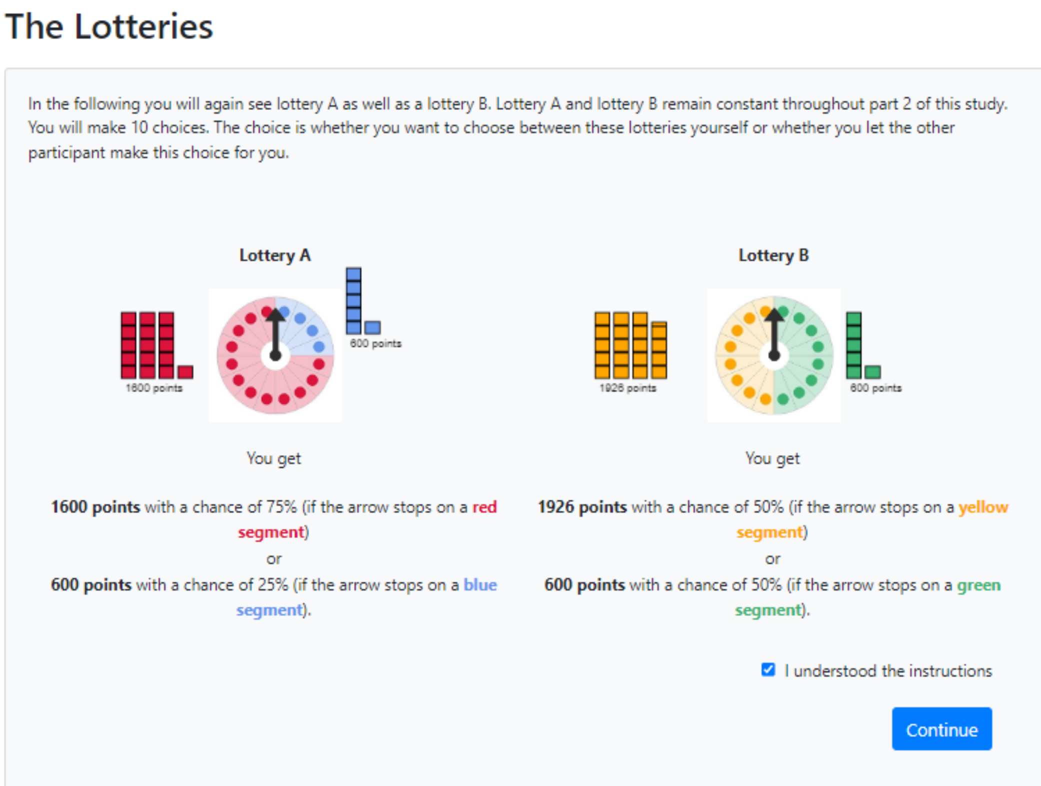


Figure A.21: Screenshot: Choice set for part 2

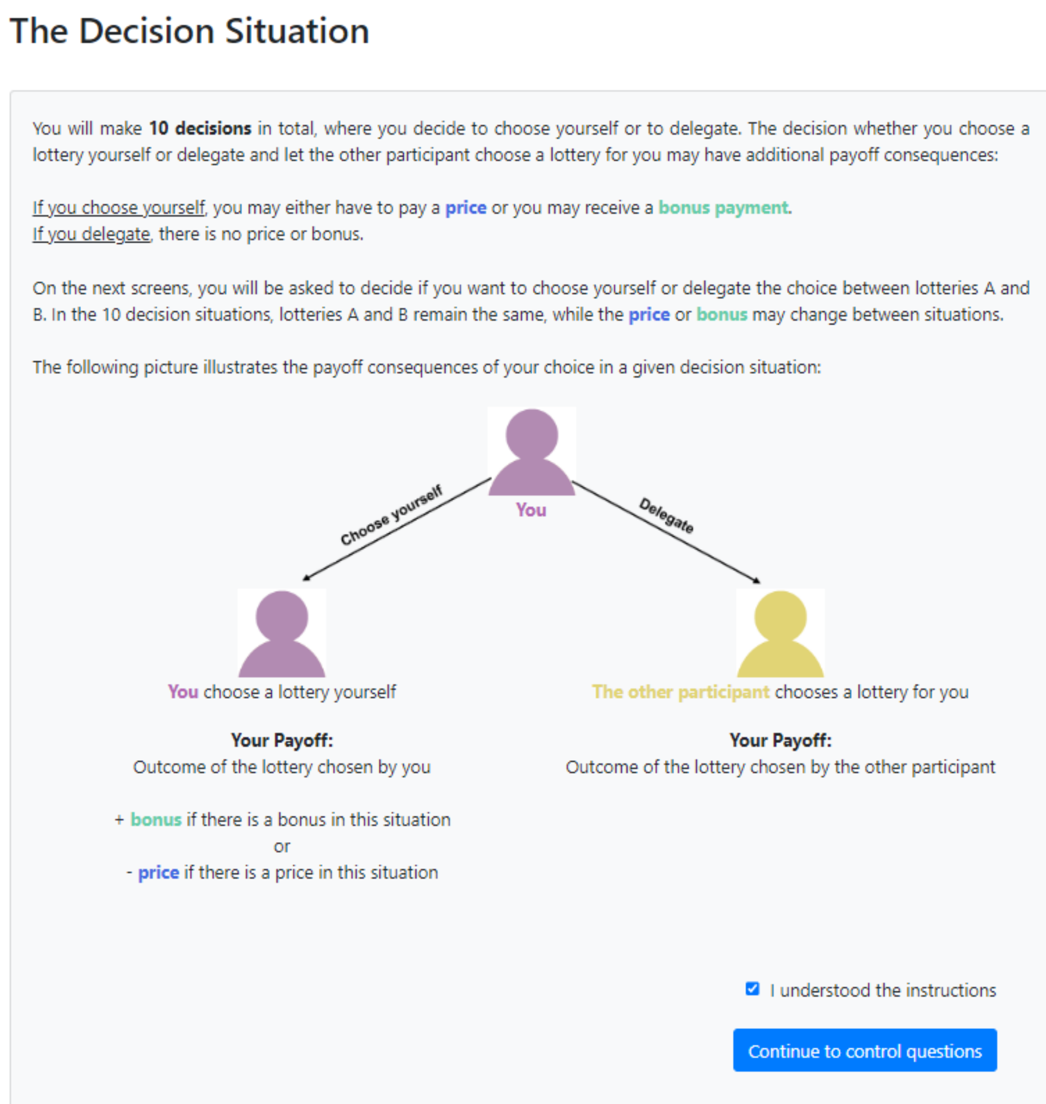


Figure A.22: Screenshot: Description of the delegation decision

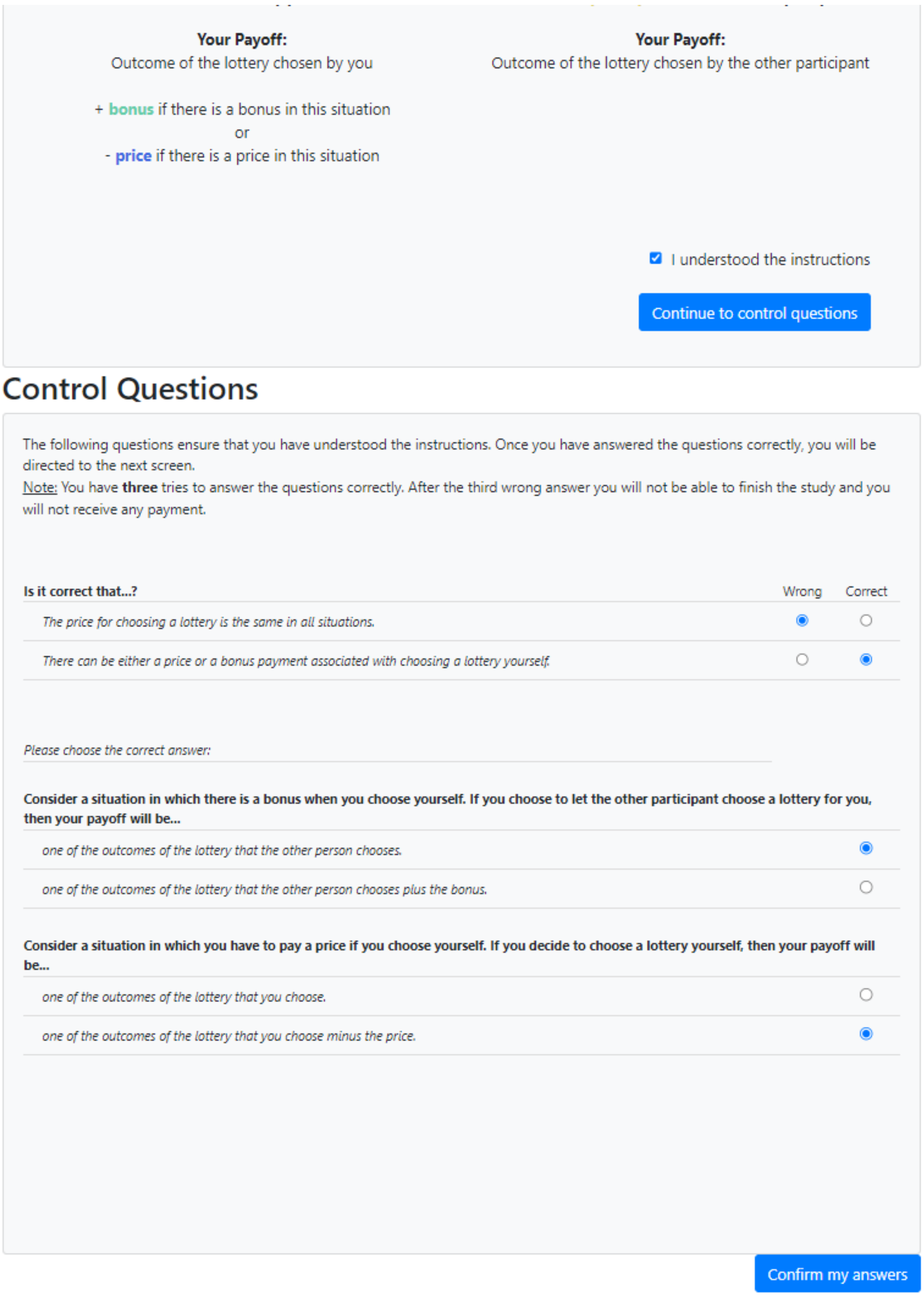


Figure A.23: Screenshot: Control questions part 2

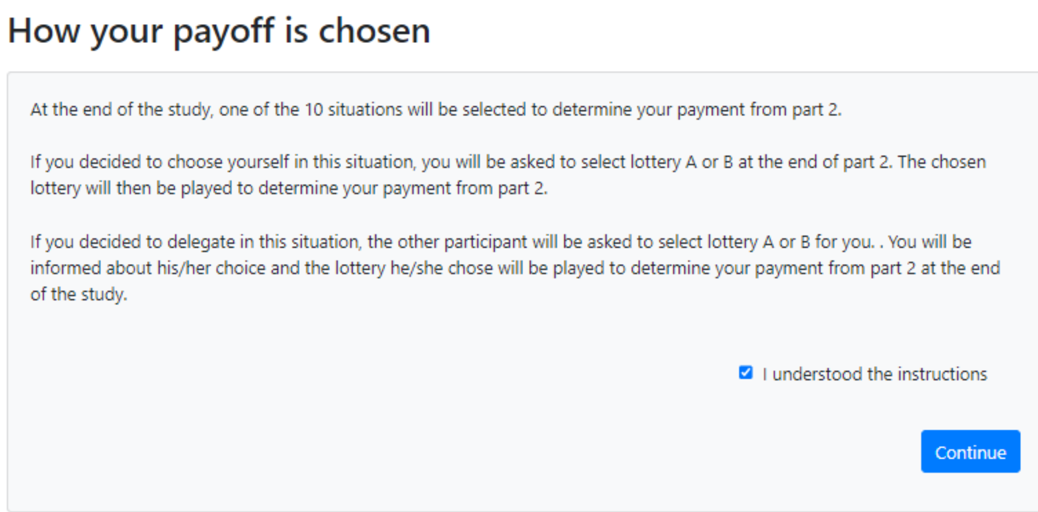


Figure A.24: Screenshot: Payoffs in part 2

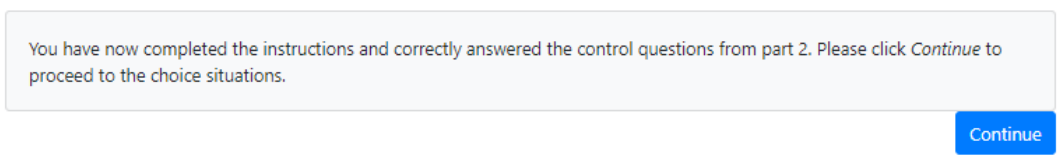


Figure A.25: Screenshot: Transition to choice situations part 1

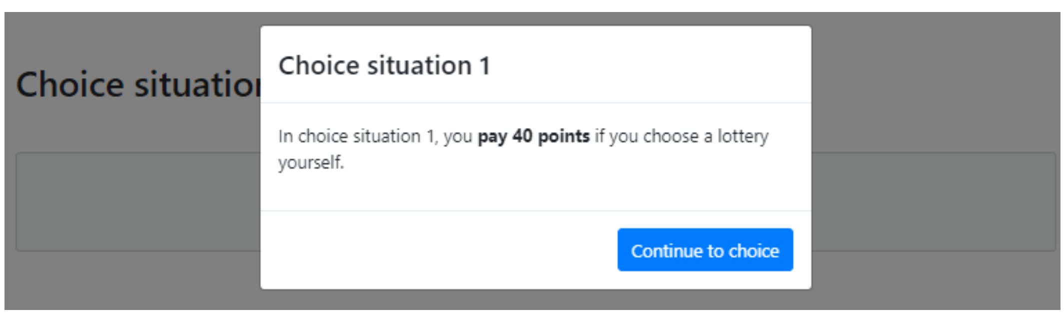


Figure A.26: Screenshot: Announcement of the next choice situation in part 2 (same for choice situations 1 to 10)

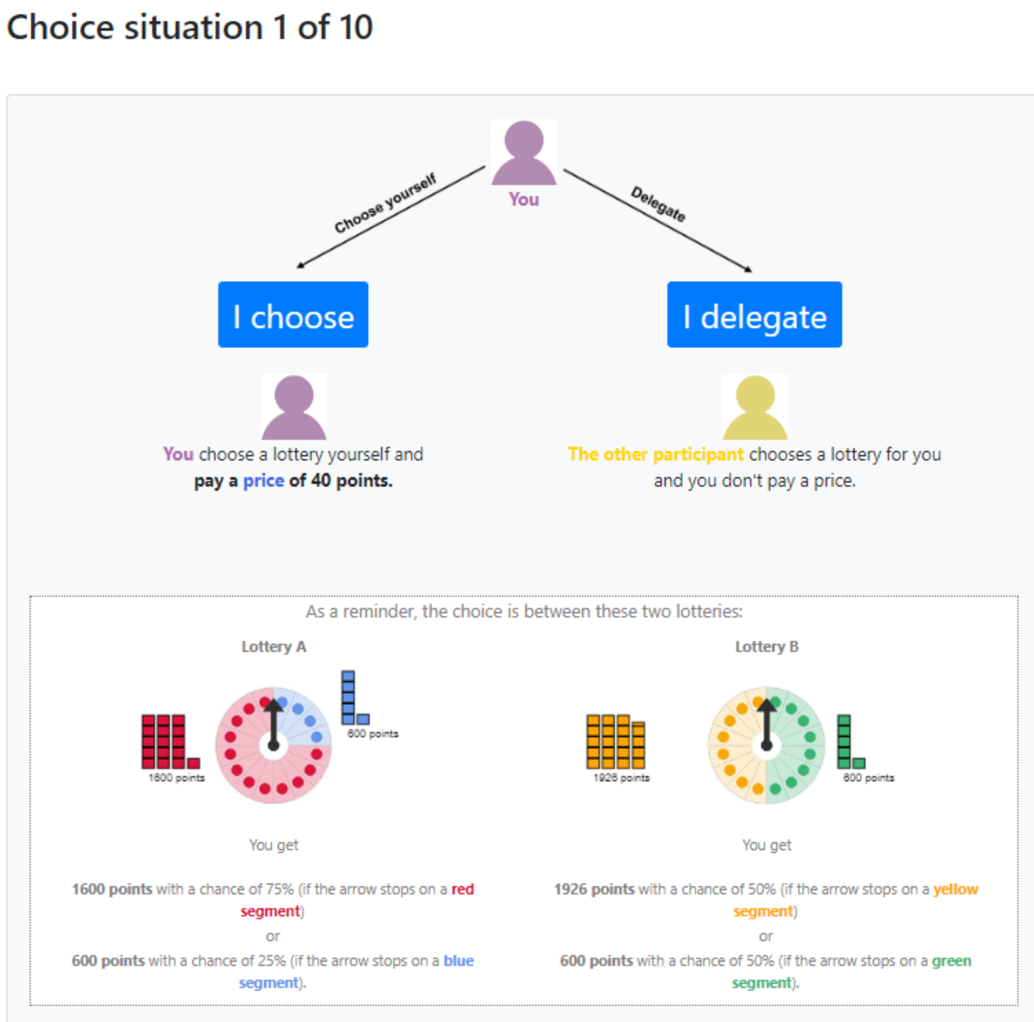


Figure A.27: Screenshot: Choice situation 1 in part 2 (same for choice situations 1 to 10)

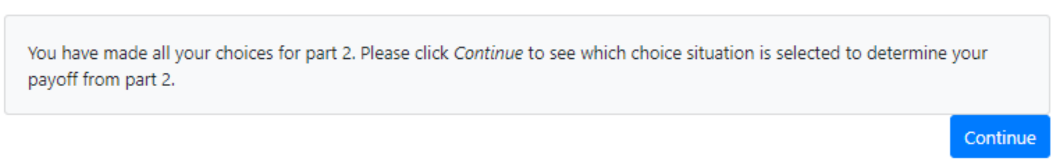


Figure A.28: Screenshot: Transition part 2

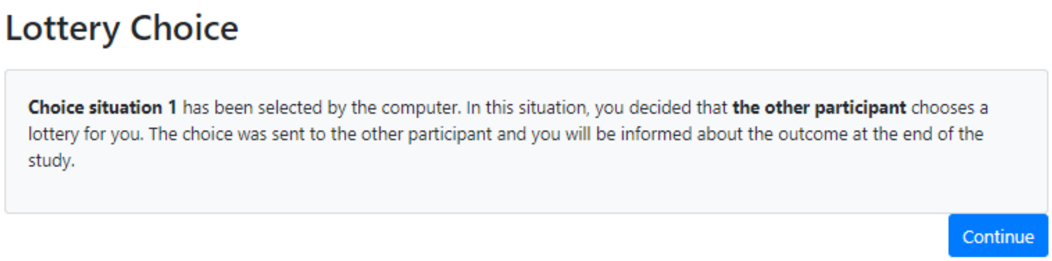


Figure A.29: Screenshot: Information about delegation of the lottery choice in case of delegation

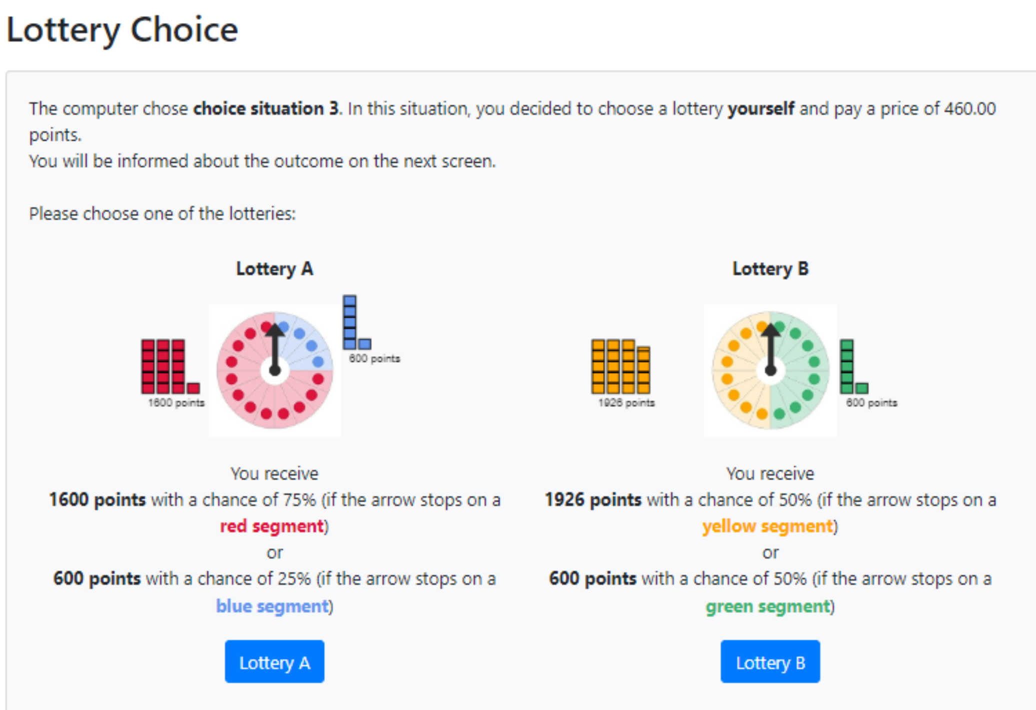


Figure A.30: Screenshot: Information and own lottery choice in case of choosing oneself

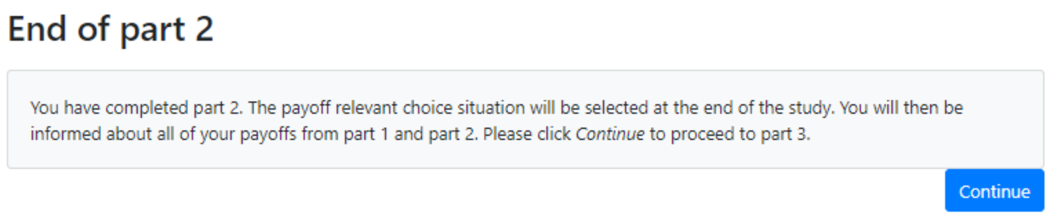


Figure A.31: Screenshot: End of part 2

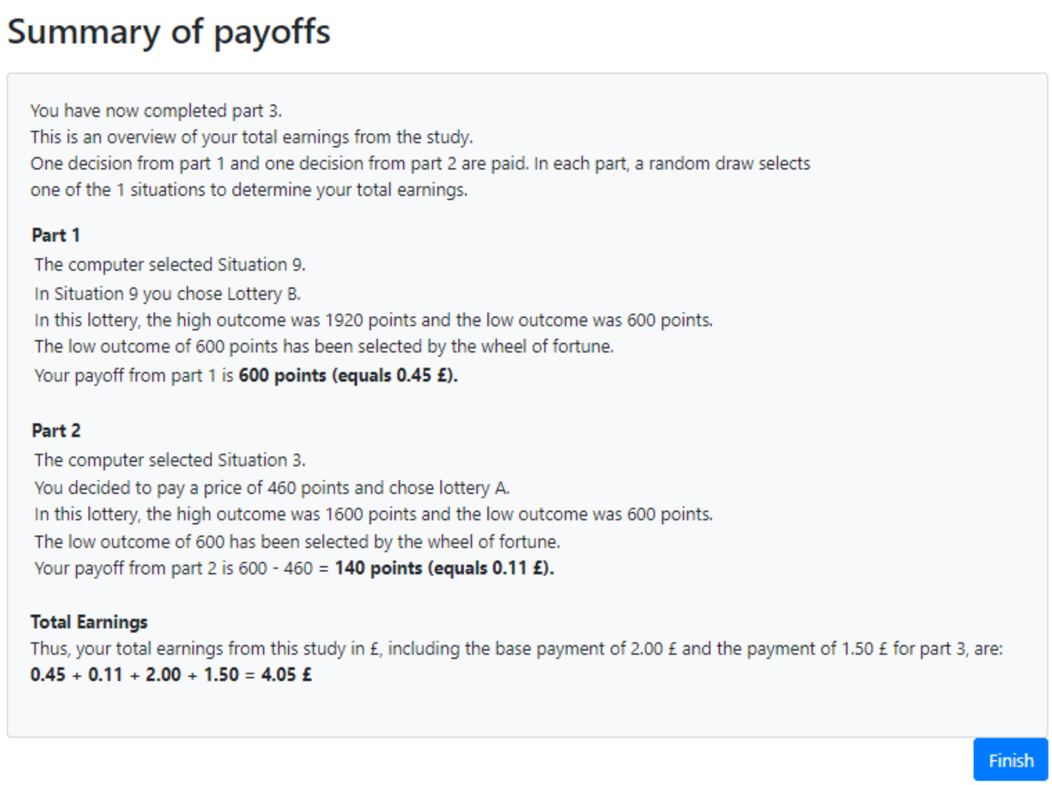


Figure A.32: Screenshot: Summary of payoffs

A.4 Questionnaires

We show the questionnaire of the June 2021 data collection here. Questions in the January 2022 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.