ONLINE APPENDIX

How do Monetary Incentives Affect the Measurement of Social Preferences?

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A.1.1 Center bundle

Table A.1 provides further details on these choice situations. The meaning of the list of variables displayed in the Table is as follows:

- 'choiceId': the unique identifier for each choice situation.
- $(own1, other1)$: represents the payoff combination at the lower end of the budget line (in points).
- $(own2, other2)$: represents the payoff combination at the upper end of the budget line (in points).
- 'bundle': indicates to which bundle the respective choice situation belongs to.
- 'slope': the slope of the budget line in the "own payoff – other payoff" space.

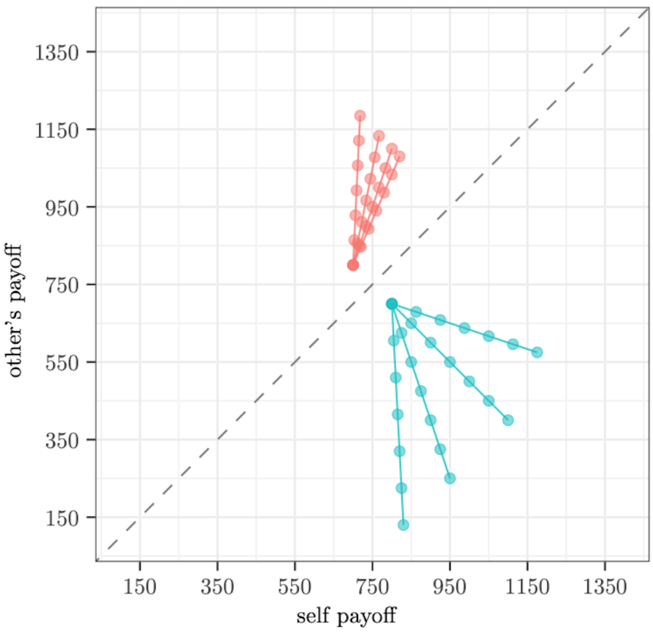
Table A.1: Choice situations in the money allocation task

choiceId	own1	own2	other1	other2	slope
1	450	1050	750	750	0.0
2	500	1000	800	700	-0.2
3	550	950	850	650	-0.5
4	600	900	900	600	-1.0
5	650	850	950	550	-2.0
6	700	800	1000	500	-5.0
7	750	750	1050	450	-Inf
8	700	800	500	1000	5.0
9	650	850	550	950	2.0
10	600	900	600	900	1.0
11	550	950	650	850	0.5
12	500	1000	700	800	0.2

A.1.2 Displaced bundles

Following Fehr ⓡ al. (2023, forthcoming), our design also includes additional choice situations that we do *not* use for type identification. Four of these choice situations lie *above* the 45 degree line (depicted in red) and thus inform us further on the decision maker's willingess to pay to *decrease* the other's payoff. The remaining four choice situations lie *below* the 45 degree line (depicted in blue) and therefore provide us further information on the decision maker's willingness to pay to *increase* the other's payoff. We include these additional budget lines as they can help us validate the behavioral interpretation of the types identified using the center bundle. They can also be used to fine-tune the structural estimation of a model of inequality aversion.

Figure A.1: Additional budget lines



A.2 Instructions

In the following, we reproduce the instructions of the money allocation task for the *Low-Incentives* and the *Hypothetical* treatments. Note that all the instructions were displayed directly on participants' computer screens.

[Social preference task – Low Incentives]

[Instructions]

We now proceed with a task in which you have to take decisions on how to allocate points between yourself and another participant of the study.

In what follows, we describe the instructions for this task. Please read them carefully.

What will you have to do in the following task?

You will be asked to take decisions in different choice situations. In each of these choice situations, you will have to decide how to allocate points between yourself and another participant.

Who is the other participant?

The other participant will take part in another part of the study. Anonymity between yourself and the other participant is guaranteed, i.e. that neither you nor the other person will ever learn about each other's identity.

Moreover, the other participant will not take decisions that affect you, i.e. you will not be affected in any way by the decisions of the other participant.

What will be the consequences of your decisions?

The points gathered during this study will be **converted into US dollars** at the following exchange rate

500 points = $ 1

At the end of this study, the computer will randomly select one of the choice situations **and pay you according to your decision in that choice situation.** This decision-dependent payment will be added to your fixed payment of $3. The other participant will also be paid according to **your** decision in that choice situation.

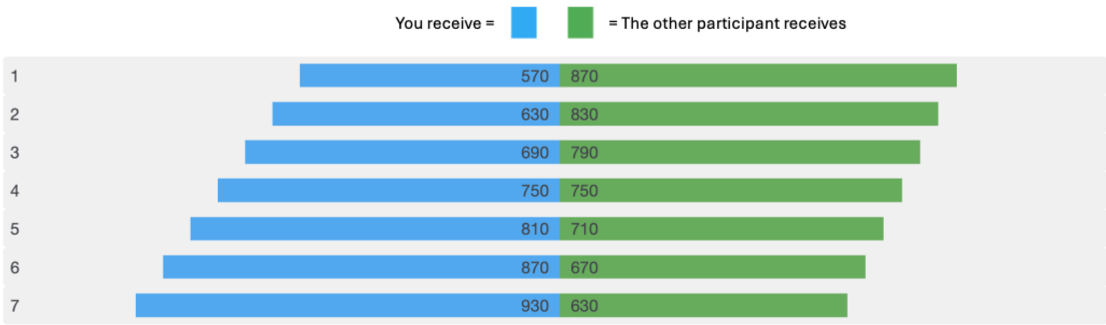
Since every choice situation has an equal chance of being drawn for payment, it is important that you think carefully about each decision.

What kind of decisions will you have to take?

In each choice situation you will be asked to allocate points between yourself and another participant of the study. You will always have the choice between seven different alternatives, numbered from 1 to 7. Each alternative consists of a distribution of points between you and the other participant.

Example

The figure below illustrates a typical choice situation as it will appear on your screen.



In this example,

- choosing alternative 1 yields you 570 points and the other participant 870 points.
- choosing alternative 7 yields you 930 points and the other participant 630 points.
- the total amount of points to be distributed varies from one alternative to another.

How do you make a choice?

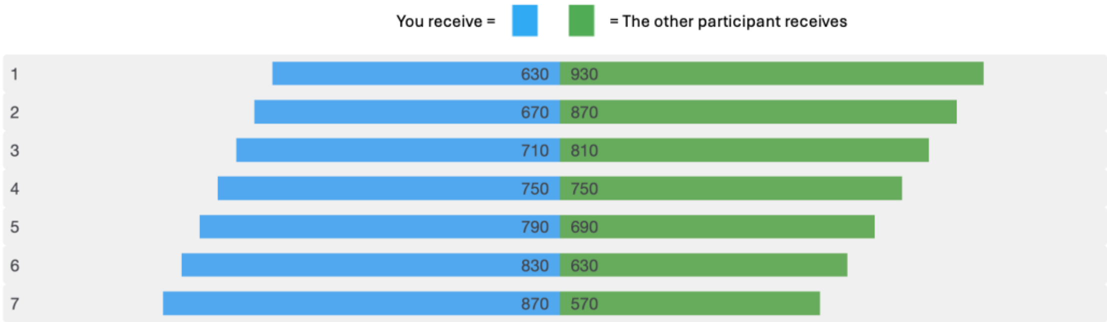
You make your choice by clicking on your preferred alternative. You can change your choice as many times as you want. Once you press the 'Next' button at the bottom right of the screen, your choice is validated and can no longer be reverted. Directly after you press "Next", the next choice situation will appear on the screen. This will be repeated until all the choices have been made.

[Control questions]

Before you start with the task, we would like to make sure that you understand what is asked from you in this task, and what the consequences from your choices are.

To show us that you understand the task, please answer the comprehension questions below. Participants who do not correctly respond to these questions will not be allowed to proceed with the study.

Consider the following example.



1. How many points do you get if you chose alternative 5? [790]

2. How many points does the other participant obtain if you chose alternative 6? [630]

3. What is the total number of points that you and the other participant receive together if you chose alternative 3? Is it 710, 810, or 1520 points? [1520]

4. Do your choices have real monetary consequences for you and the other participant? [yes, no]

[Success control questions]

You have successfully answered all the control questions. You will now start with the decision task. As of now, your decisions matter for your payment, and for the payment of another participant.

Please think carefully before taking a decision in each choice situation.

[Social preference task: decision screens]

Please choose your preferred alternative.

[DISPLAY CHOICE SITUATIONS]

[Social preference task – Hypothetical]

[Instructions]

We now proceed with a task in which you have to take decisions on how to allocate points between yourself and another participant.

In what follows, we describe the instructions for this task. Please read them carefully.

What will you have to do in the following task?

You will be asked to take decisions in different **hypothetical** choice situations. In each of these choice situations, you will have to decide how to allocate points between yourself and another hypothetical participant.

Who is the other participant?

Imagine that you are paired with a hypothetical participant that participates in another part of the study, and that anonymity between yourself and the other participant is guaranteed, i.e. that neither you nor the other person will ever learn about each other's identity.

Moreover, imagine that the other (hypothetical) participant will not take decisions that affect you, i.e. that you will not be affected in any way by the decisions of the other participant.

What will be the consequences of your decisions?

Your choices will have **no real monetary consequences** for you nor the other participant, but please imagine that you are allocating points that have monetary value between yourself and the other participant.

Imagine, in particular, that the points gathered during this study are converted into US dollars at the following exchange rate:

500 points = $ 1.

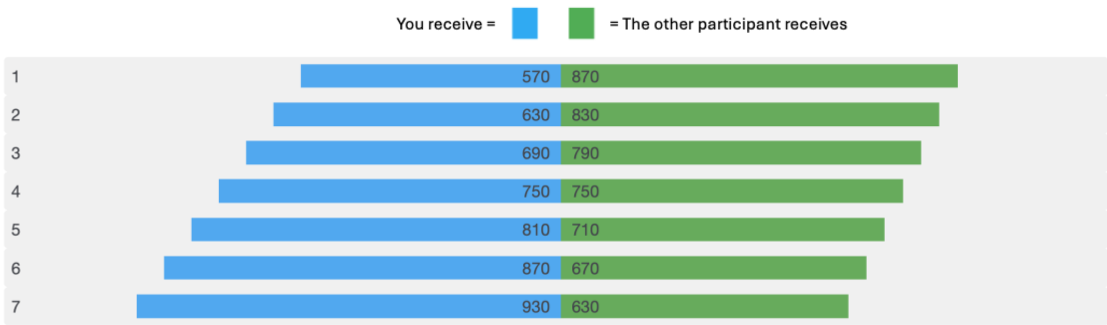
Thus, although your choices will have no real monetary consequences for you nor the other participant, please make your choices as if you and the other participant were paid accordingly.

What kind of decisions will you have to take?

In each choice situation you will be asked to allocate points between yourself and another participant of the study. You will always have the choice between seven different alternatives, numbered from 1 to 7. Each alternative consists of a distribution of points between you and the other participant.

Example

The figure below illustrates a typical choice situation as it will appear on your screen.



In this example,

- choosing alternative 1 yields you 570 points and the other participant 870 points.
- choosing alternative 7 yields you 930 points and the other participant 630 points.
- the total amount of points to be distributed varies from one alternative to another.

How do you make a choice?

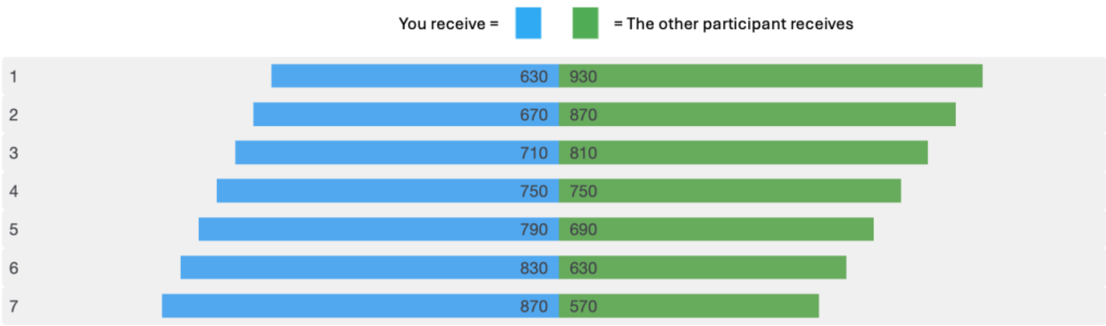
You make your choice by clicking on your preferred alternative. You can change your choice as many times as you want. Once you press the ‘Next’ button at the bottom right of the screen, your choice is validated and can no longer be reverted. Directly after you press “Next”, the next choice situation will appear on the screen. This will be repeated until all the choices have been made.

[Control questions]

Before you start with the task, we would like to make sure that you understand what is asked from you in this task, and what the consequences from your choices are.

To show us that you understand the task, please answer the comprehension questions below. Participants who do not correctly respond to these questions will not be allowed to proceed with the study.

Consider the following example.



1. How many points do you get if you chose alternative 5? [790]

2. How many points does the other participant obtain if you chose alternative 6? [630]

3. What is the total number of points that you and the other participant receive together if you chose alternative 3? Is it 710, 810, or 1520 points? [1520]

4. Do your choices have real monetary consequences for you and the other participant? [yes, no]

[Success control questions]

You have successfully answered all the control questions. You will now start with the decision task.

Please think carefully before taking a decision in each choice situation.

[Social preference task: decision screens]

Please choose your preferred alternative.

[DISPLAY CHOICE SITUATIONS]

B Demographic characteristics of sample population

We depict the main descriptive statistics in Table B.1, separately for the Low-Incentives, High-Incentives, and Hypothetical treatment. The last column indicates that our treatment is generally well balanced across the main observable characteristics. The table also indicates that our sample is broadly representative of the US population with respect to age, gender, and political affiliation.

Table B.1: Descriptive statistics and balance checks

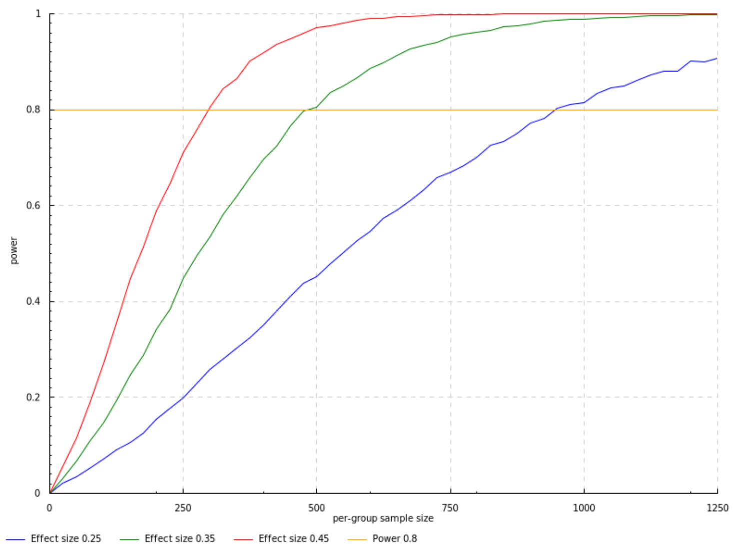
	Population	Low-Incentives	High-Incentives	Hypothetical	p-value (F-test)
Age (mean)	48.2	46.7	46.7	45.4	.918
18-25 y.o.	0.13	0.12	0.14	0.13	.098
26-35 y.o.	0.17	0.18	0.20	0.15	.001
36-45 y.o.	0.17	0.16	0.16	0.18	.185
46-55 y.o.	0.15	0.17	0.17	0.18	.733
56-65 y.o.	0.16	0.24	0.22	0.24	.385
> 65 y.o.	0.21	0.12	0.11	0.12	.268
Male	0.49	0.47	0.49	0.48	.999
Political spectrum (1 left - 10 right)	-	5.10	5.25	4.99	.186
Leaning towards Republican party	0.28	0.34	0.34	0.31	.663
Leaning towards Democratic party	0.28	0.41	0.38	0.43	.820
Income bracket : ≤ $ 20k	0.08	0.09	0.10	0.10	.263
Income bracket : $ 20-40k	0.11	0.15	0.16	0.15	.298
Income bracket : $ 40-60k	0.12	0.16	0.17	0.17	.614
Income bracket : $ 60-80k	0.11	0.16	0.13	0.16	.016
Income bracket : $ 80-100k	0.10	0.12	0.11	0.10	.124
Income bracket : $ 100-150k	0.19	0.20	0.19	0.18	.245
Income bracket : ≥ $ 150k	0.25	0.10	0.13	0.12	.005
Income bracket : NA	0.03	0.02	0.01	0.01	.000
Have been unemployed in the past	-	0.74	0.76	0.79	.105
Occupation: Full-time worker	0.44	0.43	0.41	0.43	.984
Occupation: Part-time worker	0.19	0.17	0.17	0.15	.079
Occupation: Student	0.08	0.14	0.15	0.15	.373
Occupation: Pensioner	0.14	0.08	0.07	0.08	.052
Occupation: Unemployed	0.03	0.11	0.11	0.14	.001
Occupation: Other	0.12	0.07	0.08	0.05	.000
Education: High school	0.23	0.19	0.23	0.19	.022
Education: Technical college	0.24	0.23	0.21	0.22	.656
Education: Undergraduate degree	0.29	0.35	0.35	0.36	.958
Education: Graduate or doctorate degree	0.13	0.19	0.18	0.19	.619
Education: Other	0.10	0.04	0.03	0.04	.000
Religiosity (0 - 10)	-	4.63	4.60	4.35	.826
Observations		1002	1023	1007	

Note: The table displays descriptive statistics of the US population and of our sample, separately for the Low-Incentives, High-Incentives, and Hypothetical treatment. The descriptive statistics include age (mean), the shares of people falling into each age bracket, and the share of male people. Moreover, they include subjects' political leaning (mean), the shares of people leaning towards the Republican and Democratic parties, and the shares of people falling into each yearly household income bracket. In addition, they include the share of people that have been unemployed in the past, the shares of people falling into each occupation category, as well as the shares of shares of people falling into each highest educational degree category. Lastly, the descriptive statistics include subjects' religiosity (mean). Statistics of the US population were obtained from IPUMS data (Ruggles et al., 2024) from the American Community Survey 2023 and are restricted to the adult US population (i.e., individuals who are at least 18 years old). The proportions of workers who work full-time (part-time) among the working population stem from U.S. Bureau of Labor Statistics (2025). Political affiliation comes from Gallup (2024).

C Power analysis

Prior to the start of the study, we assessed sample size requirements for our main analysis with the general population sample by considering the statistical power of our main hypotheses tests. Specifically, we looked at a two-sided Welch t-test on the difference between inequality aversion parameters α or β between two treatments (e.g., Hypothetical and Low-Incentives). We set the probability of a Type I error to 1%, and the standard deviations of the parameters in the two samples to the values we obtained from a previous (incentivized) study conducted in Switzerland using a similar experimental design. The sample size depicted on the x-axis refers to the per-group sample size (e.g. the Hypothetical treatment). We computed the power of the test under the assumption that the number of participants is identical in both treatments. Thus, a specific number X on the x-axis means that both the hypothetical and the incentivized (e.g. Low-Incentives) treatments contain X participants. The blue curve shows, for different per-group sample sizes, the power we have to detect a difference of 0.25 (using the above assumptions) between the parameters of the two treatments. With a sample size of 1,000 participants per group, we obtain a power which is slightly higher than 80 percent to detect a difference in the parameters α or β of 0.25, i.e., an effect size of about 15 percent of a standard deviation of the structural parameters in the Swiss broad population sample. The green curve depicts the power curve for a larger effect size of 0.35, and the red curve depicts the power curve for an effect size of 0.45.

Figure C.1: Power vs. per-group sample size for various effect sizes



Note: The figure depicts power curves for various effect sizes. The horizontal line indicates a power of 80%.

D Additional tables and figures

D.1 Additional analyses

The analyses and results presented in Section 4 closely follow the analysis plan that we pre-registered. In some instances, we also provide additional analyses that were not pre-registered but that are useful to further clarify our findings. For transparency, we list all these additional analyses below:

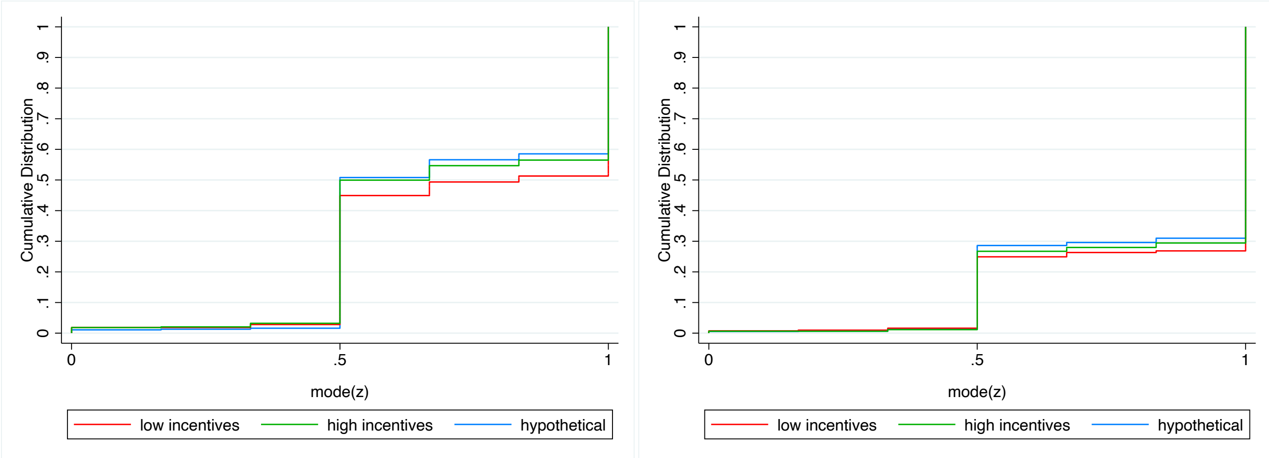
- Figure D.1: ”Cumulative distribution of modal choices”
- Figure D.2: ”Average choices”
- Table D.1: ”χ^2-test of independence by choice situation (Holm (1979) corrected)”
- Figure 5: ”The distribution of choices for positively and negatively sloped budget lines in each cluster and each treatment”
- Figure D.3: ”CDFs of structurally estimated parameters”
- Figure D.4: ”CDFs of structurally estimated parameters by social preference type”

D.2 Descriptive analysis

Figure D.1 plots the cumulative distributions of modal choices, separately for negatively sloped budget lines (Figure D.1a) and positively sloped budget lines (Figure D.1b). The Figure confirms the similarity of modal choices across treatments for both types of budget lines.

Figure D.1: Cumulative distribution of modal choices

(a) Negatively sloped budget lines (b) Positively sloped budget lines



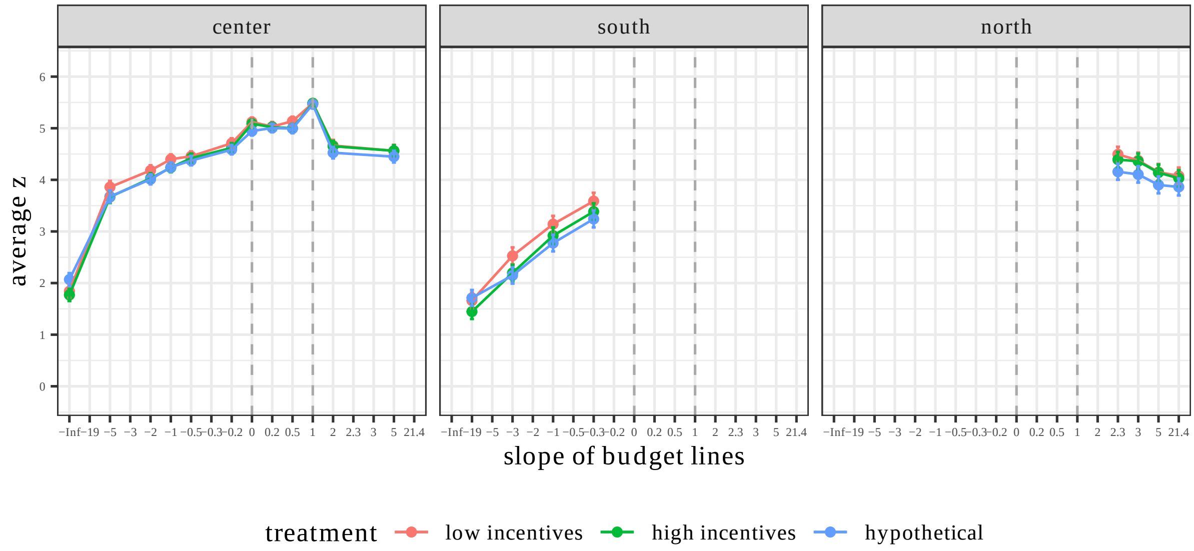
Notes: The figure shows the cumulative distribution of individuals' modal choices among negatively sloped and among positively sloped budget lines. For each budget line, $z = 1$ indicates an own-payoff maximizing choice, $z = 0$ indicates an own-payoff minimizing choice, $z = 0.5$ indicates a payoff-equalizing choice.

Figure D.2 displays the average behavior across the different treatments, separately for each budget line (x-axis) and bundle of budget lines (panels). In line with the results for the modal choices, we do not find any meaningful differences in average behavior across treatments, neither for the twelve budget lines that are centered around the 45-degree line nor for the budget lines that are fully in the disadvantageous domain (”north bundle”) or the budget lines that are fully in the advantageous domain (”south bundle”).[1] Table D.1 shows the χ^2-test of independence by choice situation, corrected for multiple testing (Holm, 1979).[2] The table further supports the conclusion that average behavior is similar across treatments in each choice situation.

[1]For details on the budget lines, see Appendix A.1.

[2]In other words, the table provides the results of a series of tests (Holm (1979) corrected) of equality in distributions of implemented choices z (where z ranges from 0 to 1) across the three treatments, by decision situation (choice ID).

Figure D.2: Average choices



Notes: The figure shows the average implemented choice (z) on the y-axis, by budget line (ordered by their slopes) and by bundle of choice situations (3 panel). For each budget line, $z = 6$ indicates an own-payoff maximizing choice, $z = 0$ indicates an own-payoff minimizing choice, $z = 3$ indicates a payoff-equalizing choice. Budget lines are sorted by slope on the x-axis.

Table D.1: χ^2-test of independence by choice situation (Holm (1979) corrected)

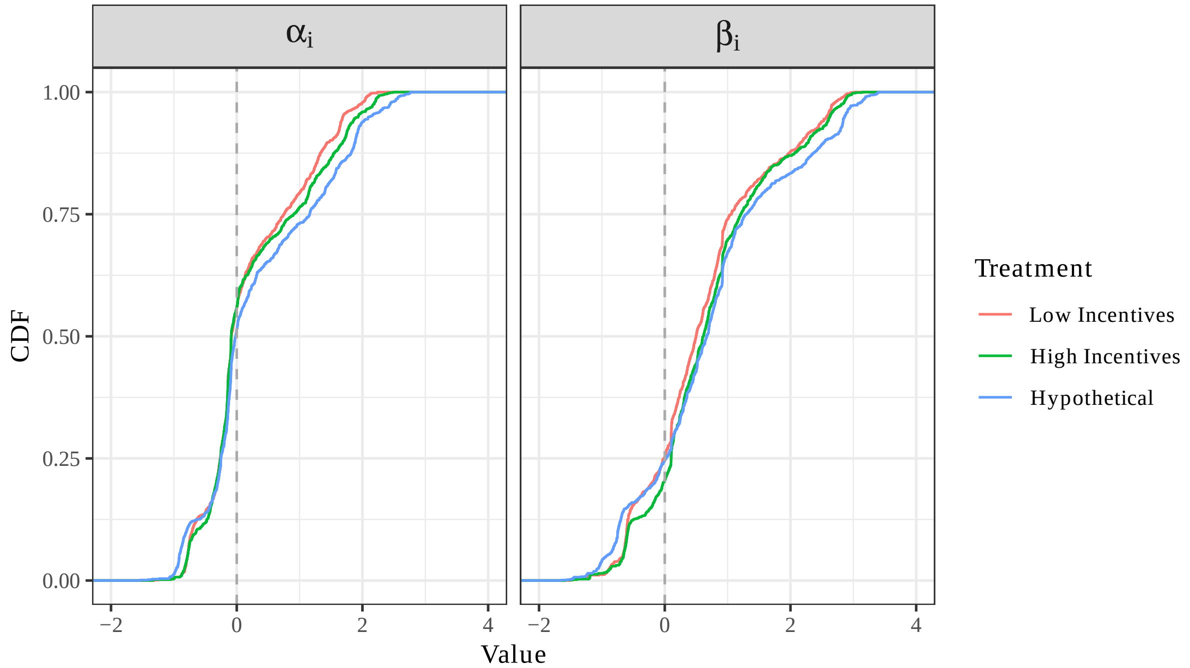
	choiceId	statistic	p-value
1	1	33.701	0.020
2	2	17.469	1.000
3	3	12.390	1.000
4	4	18.452	1.000
5	5	14.208	1.000
6	6	18.342	1.000
7	7	25.198	0.340
8	8	9.077	1.000
9	9	22.015	0.600
10	10	6.113	1.000
11	11	21.908	0.700
12	12	27.474	0.170
13	13	17.523	1.000
14	14	26.380	0.270
15	15	10.807	1.000
16	16	21.617	0.870
17	17	31.368	0.030
18	18	13.772	1.000
19	19	15.658	1.000
20	20	30.969	0.060

Notes: This table shows the χ^2-test of independence by choice situation, corrected for multiple testing (Holm, 1979). It provides the results of a series of tests of equality in distributions of implemented choices z (where z ranges from 0 to 1) across the three treatments, by decision situation (choice ID).

D.3 Structural analysis

Figure D.3 depicts the cumulative distribution functions (CDFs) of α and β by treatment. Consistent with the PDFs depicted in the main text, this analysis reveals that the distributions under Low and High-Incentives are relatively similar, but that distributions in the Hypothetical treatment are shifted to the right.

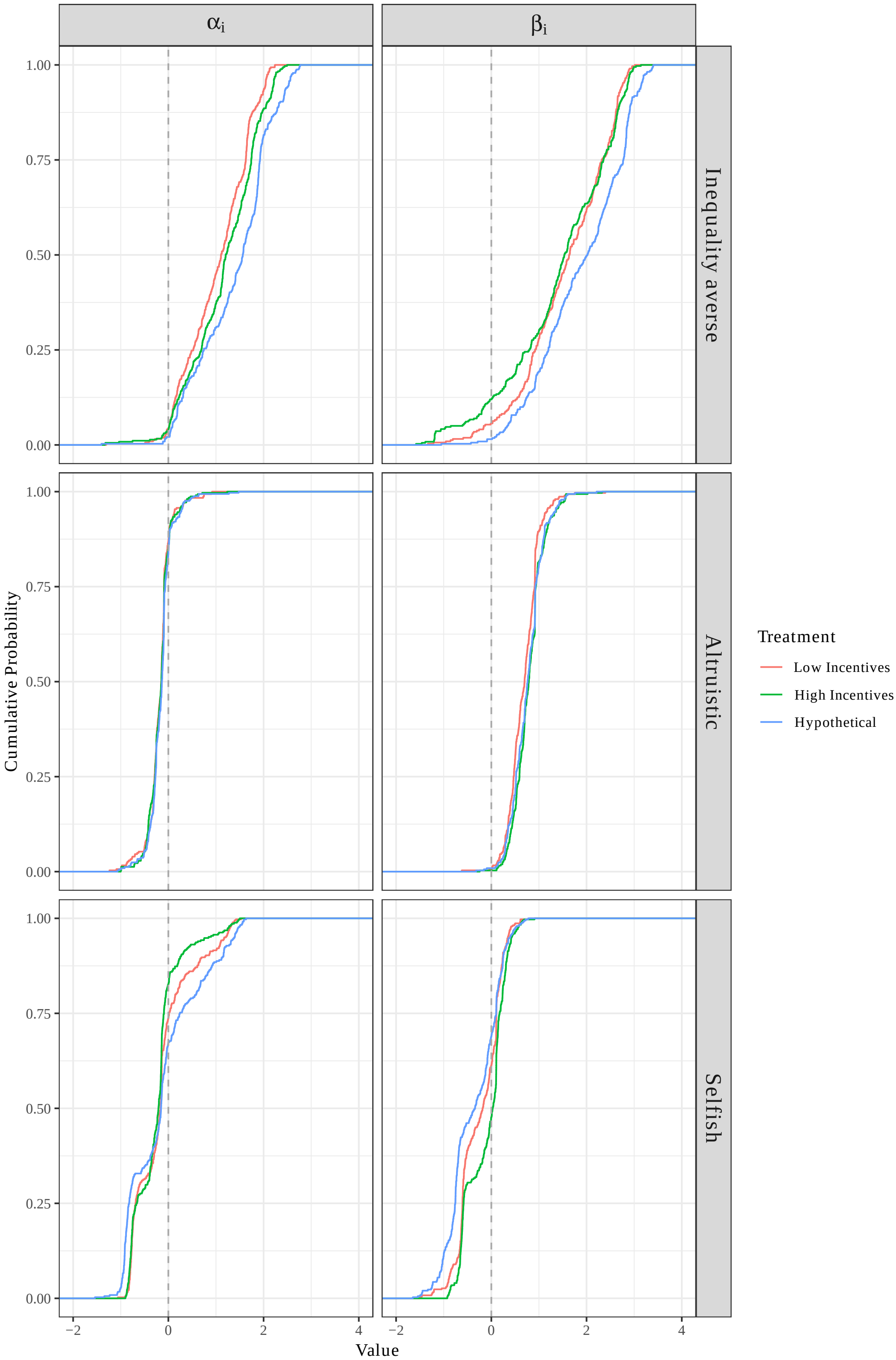
Figure D.3: CDFs of structurally estimated parameters



Notes: The CDFs on the left side depict subjects' structurally estimated α-parameters by treatment. The CDFs on the right side depict subjects' structurally estimated β-parameters by treatment.

We break down these distributions by social preference type (as identified using the clustering algorithm) in Figure D.4. This analysis shows that treatment differences are mainly driven by the inequality-averse subjects (Type 1; upper panel). It is for these subjects the distributions of social preferences parameters shifts the most to the right in the Hypothetical treatment. For the other two types, we do not find such strong treatment differences.

Figure D.4: CDFs of structurally estimated parameters by social preference type



Notes: The CDFs on the left side depict subjects' structurally estimated α-parameters by treatment, separately for each social preference type. The CDFs on the right side depict subjects' structurally estimated β-parameters by treatment, separately for each social preference type.

E Identifying preference types using Dirichlet Process Means

E.1 The method

This appendix provides an overview of the clustering algorithm used to identify the preference types and their distribution in the population. For a more detailed description of the DP-means algorithm and for a discussion of its key differences with other clustering methods such a k-means, see Fehr ⓡ al. (forthcoming, 2023).

Our implementation of the algorithm is based on an iterative refinement. We first span an m-dimensional space, with m denoting the number of budget lines used for the clustering algorithm (in our case, $m = 12$, the twelve budget lines presented in Table 1 in the main paper). Consequently, each individual's choices are represented by a single point in the 12-dimensional space. We then ask how subjects populate this space. Specifically, we are interested in the number of clusters (i.e. types) that emerge and individuals' assignment to clusters. A cluster is characterized by the set of the individuals assigned to the cluster and the associated mean vector of observations (the "centroid"), which – in our case – represents the mean (cluster- representative) behavior of all individuals in m-dimensional space that belong to the cluster.

We initialize the algorithm with a single centroid specified as the global mean vector. At this stage, all data points are assigned to this single centroid. We then refine by iterating over the following two steps: First, we sequentially go through the list of data points in m-dimensional space (i.e. subjects), and check for each subject whether any of the squared Euclidean distances to the centroid exceeds the cluster penalty parameter λ. If this is the case, we open up a new cluster with the actual data point's location vector as the centroid. Otherwise, we assign the data point to its nearest cluster. Second, we collect the subjects assigned to the same clusters and update the centroids by computing the mean vector for each cluster. These two steps are repeated until convergence is reached, i.e. until there is no change in subjects' assignments.

As Kulis and Jordan (2012) demonstrate, this iterative procedure is equivalent to minimizing the objective

$$\min_{\{g_c\}_{c=1}^{k}} \sum_{c=1}^{k} \sum_{\boldsymbol{x} \in g_c} \|\boldsymbol{x} - \boldsymbol{\mu}_c\|^2 + \lambda k \,,$$

where $\boldsymbol{x}$ denotes the vector of observations, $\boldsymbol{\mu}$ the vector of centroids, and g the cluster partitioning of $\boldsymbol{x}$. It is straightforward to see that this objective is equivalent to the k-means objective except for the additional penalty term λk.

An important aspect of the DP-means approach is that it enables the identification of preference types without committing to a pre-specified number of different preference types. Moreover, this approach does neither require an ex-ante specification or parameterization of types, nor does it presume a specific error structure. This means that it remains ex-ante agnostic about key distributional assumptions, and it does not constrain heterogeneity to lie within a predetermined set of models or parameter space.[3] The DP-means algorithm allows for all possible type partitions of the data spanning from a representative agent (i.e. a single data-generating process) up to as many types as there are individuals in the population (i.e. n data-generating processes), i.e., it determines the number of preferences types endogenously. Thus, (i) the actual number of types, (ii) the assignment of each individual to one of the types and (iii) the behavioral (preference) properties of the types emerge endogenously.[4]

[3]In this regard, our approach differs from previous work (e.g. Bellemare et al., 2008; Fisman et al., 2015, 2017; Bruhin et al., 2018) that characterized preference heterogeneity on the basis of structural assumptions on preferences and error terms.

[4]The fact that the number of types adapts to the data has important benefits (see Kulis and Jordan, 2012). Most notably, as previous work has shown (see Comiter et al., 2016), this feature of the algorithm yields higher quality type-separation than methods that specify the number of types prior to clustering (such as k-means).

F Student sample

In this Appendix, we present the results for the student sample.

F.1 Demographic characteristics of the student sample

We depict the main descriptive statistics of the student sample in Table F.1, separately for the Low-Incentives, High-Incentives, and Hypothetical groups. The last column indicates that our treatments are generally well balanced across the main observable characteristics.

Table F.1: Descriptive statistics and balance checks

	Low-Incentives	High-Incentives	Hypothetical	p-value (F-test)
Age (mean)	23.1	22.8	22.8	.649
18-25 y.o.	0.75	0.82	0.80	.246
26-30 y.o.	0.25	0.18	0.20	.246
Male	0.52	0.50	0.50	1.000
Political spectrum (1 left - 10 right)	5.46	5.21	5.18	.504
Leaning towards Republican party	0.35	0.34	0.36	.987
Leaning towards Democratic party	0.37	0.41	0.38	.977
Income bracket : ≤ $ 20k	0.16	0.20	0.10	.002
Income bracket : $ 20-40k	0.13	0.10	0.14	.125
Income bracket : $ 40-60k	0.18	0.18	0.24	.283
Income bracket : $ 60-80k	0.15	0.09	0.10	.004
Income bracket : $ 80-100k	0.11	0.10	0.11	.875
Income bracket : $ 100-150k	0.13	0.21	0.13	.011
Income bracket : ≥ $ 150k	0.13	0.10	0.14	.248
Income bracket : NA	0.02	0.02	0.04	.000
Have been unemployed in the past	0.77	0.77	0.74	.801
Education: Technical college	0.74	0.74	0.79	.610
Education: Undergraduate degree	0.26	0.26	0.21	.610
Religiosity (0 - 10)	5.47	5.10	5.27	.918
Observations	158	173	164	

Note: The table displays descriptive statistics of the student sample, separately for the Low-Incentives, High-Incentives, and Hypothetical group. The descriptive statistics include age (mean), the shares of people falling into each age bracket, and the share of male people. Moreover, they include subjects' political leaning (mean), the shares of people leaning towards the Republican and Democratic parties, and the shares of people falling into each yearly household income bracket. In addition, they include the share of people that have been unemployed in the past, as well as the shares of shares of people falling into each highest educational degree category. Lastly, the descriptive statistics include subjects' religiosity (mean).

F.2 Descriptive analysis of students

For the descriptive analysis, we examine whether the treatments affect the distribution of subjects' *modal* choice separately for negatively sloped and for positively sloped budget lines (Figure 1). We depict the results of this analysis in Figure F.1. The Figure reveals that, among the negatively sloped budget lines, the distributions of modal choices are comparable across treatments. While we do see slightly more own payoff maximizing choices in the Low-Incentives treatment, the overall pattern is similar across experimental conditions as the modal choice of the vast majority of individuals is located at either $z = 0.5$ or $z = 1$. Turning to behavior on positively sloped budget lines, own payoff maximization ($z = 1$) is the modal choice for the majority of the individuals, while the share of people predominantly implementing payoff equality ($z = 0.5$) is much smaller. This pattern is similar across treatments, with slightly more payoff-equalizing choices in the High-Incentives treatment. Figure F.2 plots the cumulative distributions and confirms the similarity of modal choices across treatments, both for negatively and positively sloped budget lines. Kolmogorov-Smirnov tests for pairwise comparisons of distributions of modal choices confirm the conclusion that monetary incentives do *not* affect subjects' willingness to pay to increase and decrease others' payoffs.[5,6]

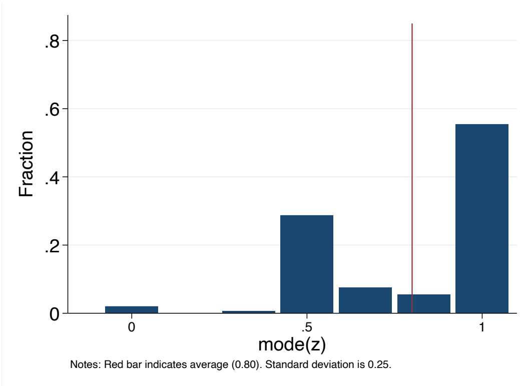
[5]For these tests, we apply Holm (1979) correction to account for multiple hypothesis testing.

[6]Kolmogorov-Smirnov test p-values for *negatively* sloped budget lines: Low-Incentives vs. High-Incentives ($p = 0.253$), Low-Incentives vs. Hypothetical ($p = 0.488$), High-Incentives vs. Hypothetical ($p = 0.951$). Kolmogorov-Smirnov test p-values for *positively* sloped budget lines: Low-Incentives vs. High-Incentives ($p = 1.000$), Low-Incentives vs. Hypothetical ($p = 1.000$), High-Incentives vs. Hypothetical ($p = 0.974$).

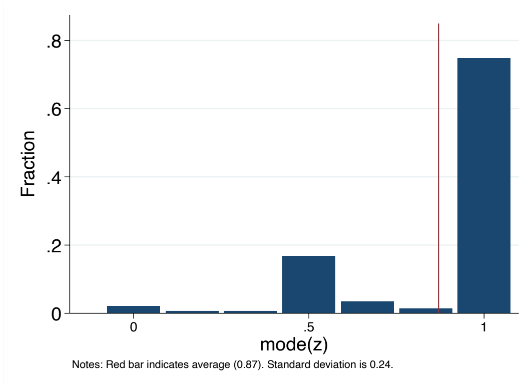
Figure F.1: Distribution of modal choices of students

Low-Incentives treatment

(a) Negatively sloped budget lines

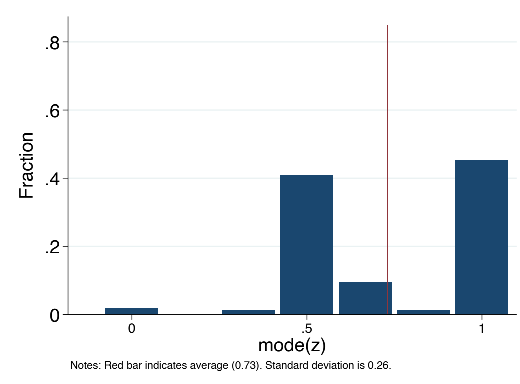


(b) Positively sloped budget lines

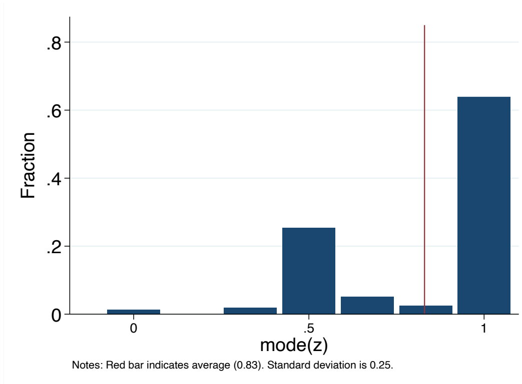


High-Incentives treatment

(c) Negatively sloped budget lines

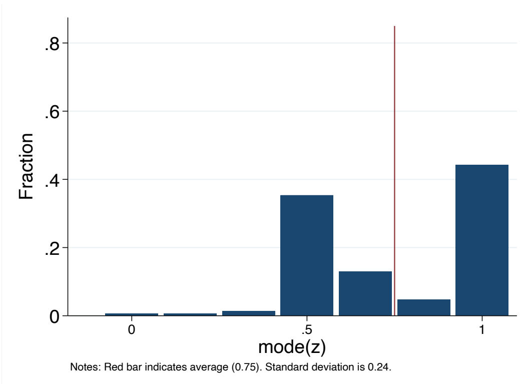


(d) Positively sloped budget lines

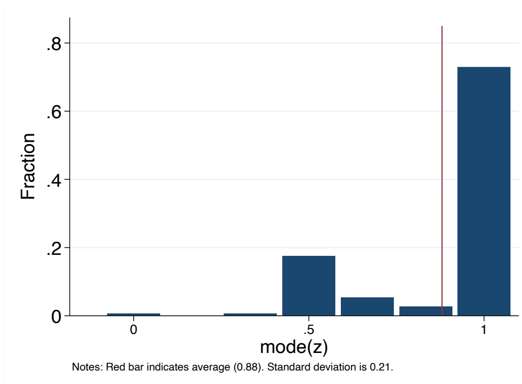


Hypothetical treatment

(e) Negatively sloped budget lines



(f) Positively sloped budget lines

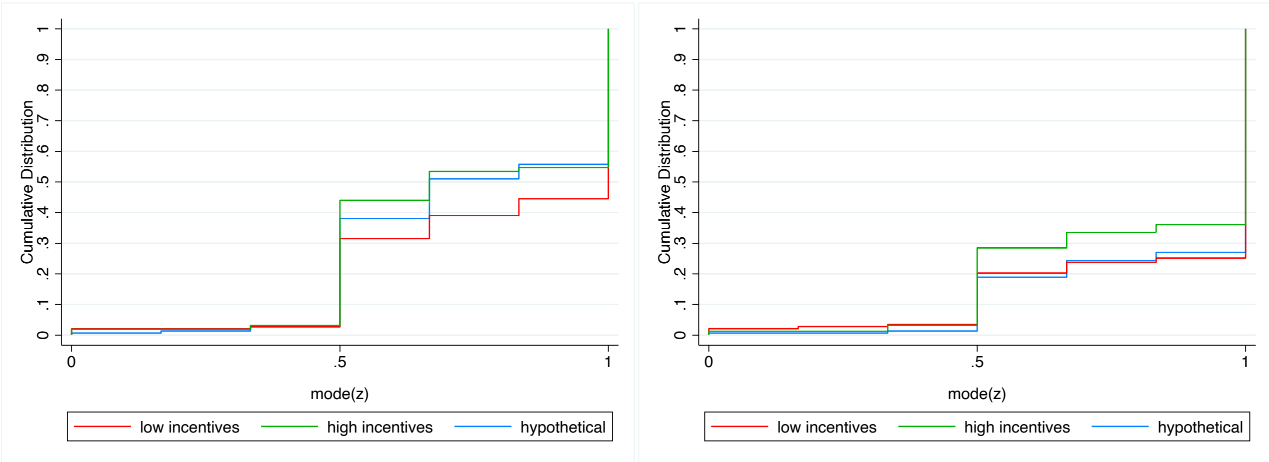


Notes: The figure shows the distribution of individuals' modal choices among negatively sloped and among positively sloped budget lines. For each budget line, $z = 6$ indicates an own-payoff maximizing choice, $z = 0$ indicates an own-payoff minimizing choice, $z = 3$ indicates a payoff-equalizing choice. The red vertical line indicates always the average over all modal choices. Panels (a) and (b) are constructed using subjects randomized into the *Low-Incentives* treatment. Panels (c) and (d) are constructed using subjects randomized into the *High-Incentives* treatment. Panels (e) and (f) are constructed using subjects randomized into the *Hypothetical* treatment.

Figure F.2: Cumulative distribution of modal choices of students

(a) Negatively sloped budget lines

(b) Positively sloped budget lines

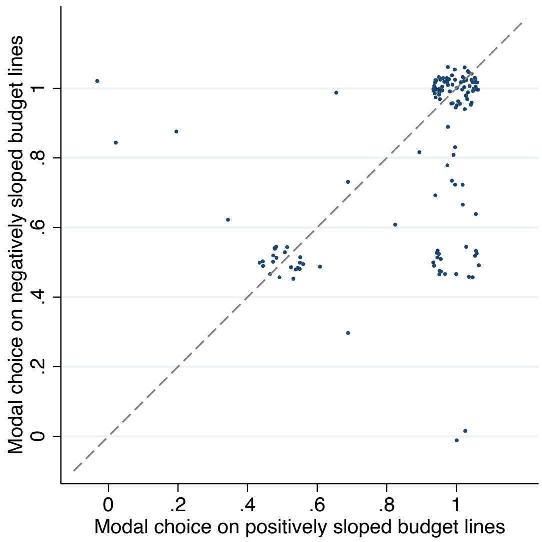


Notes: The figure shows the cumulative distribution of individuals' modal choices among negatively sloped and among positively sloped budget lines. For each budget line, $z = 1$ indicates an own-payoff maximizing choice, $z = 0$ indicates an own-payoff minimizing choice, $z = 0.5$ indicates a payoff-equalizing choice.

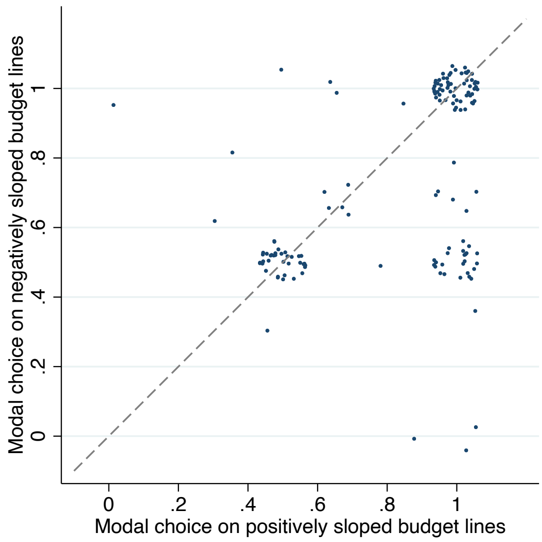
We depict subjects' modal choice on *both* positively sloped (x-axis) *and* negatively sloped (y-axis) budget in each treatment in Figure F.3. The Figure reveals the existence of the same three behavioral agglomerations across all three treatments: (i) A first agglomeration located at $z = 0.5$ for both positively and negatively sloped budget lines, i.e., a behavioral pattern suggestive of a preference for equality. (ii) A second agglomeration located at $z = 1$ for positively sloped budget lines and $z = 0.5$ for negatively sloped budget lines, i.e., a behavioral pattern suggestive of altruistic concerns for the worse off but no willingness to reduce the payoff of others for the sake of equality. (iii) A third agglomeration located at $z = 1$ for both positively and negatively sloped budget lines, i.e., a behavioral pattern suggestive of own payoff maximization.

Figure F.3: Descriptive evidence on students' modal choices

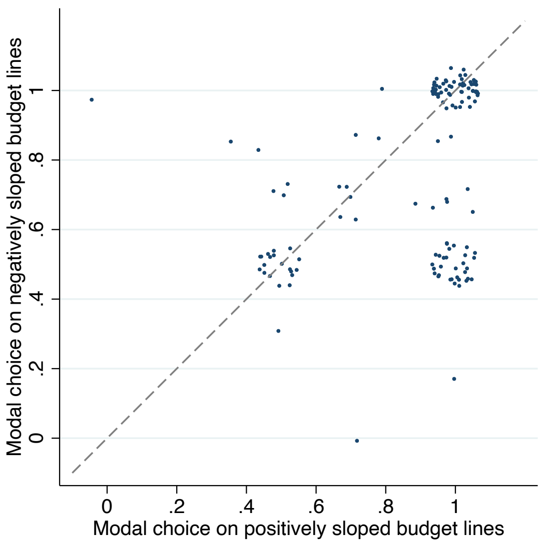
(a) *Low-Incentives* treatment



(b) *High-Incentives* treatment



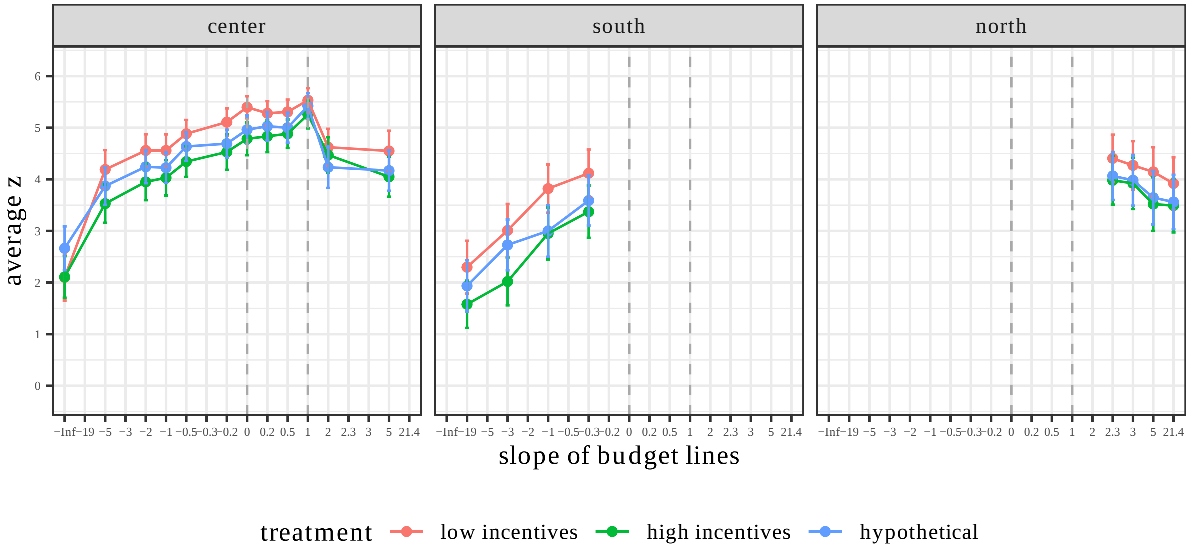
(c) *Hypothetical* treatment



Notes: In all figures, we depict subjects' modal choices among negatively sloped budget lines and among positively sloped budget lines. Each dot represents one individual. Dots are jittered in order to make identical modal choices of individuals visible. For each budget line, $z = 1$ indicates an own-payoff maximizing choice, $z = 0$ indicates an own-payoff minimizing choice, and $z = 0.5$ indicates a payoff-equalizing choice. Panel (a) is constructed using subjects randomized into the *Low-Incentives* treatment. Panel (b) is constructed using subjects randomized into the *High-Incentives* treatment. Panel (c) is constructed using subjects randomized into the *Hypothetical* treatment. Note that if we replace individuals' modal choices by their median choices, very similar behavioral agglomerations emerge.

Figure F.4 displays the average behavior across the different treatments, separately for each budget line. While those in the Low-Incentives appear to chose slightly more often the own payoff maximizing allocation, overall we do not find any meaningful differences in the average behavior across treatments. This holds for the twelve budget lines that are centered around the 45-degree line (”center bundle”, see Figure 1) as well as for the budget lines in the advantageous domain (”south bundle”) and the disadvantageous domain (”north bundle”). For details on the budget lines, see Appendix A.1. Table F.2 shows the χ^2-test of independence by choice situation, corrected for multiple testing using Holm (1979). It further supports the notion of similar average behavior across treatments in the different budget lines.

Figure F.4: Average choices of students



Notes: The figure shows the average implemented choice (z) on the y-axis, by budget line (ordered by their slopes) and by bundle of choice situations (3 panel). For each budget line, $z = 6$ indicates an own-payoff maximizing choice, $z = 0$ indicates an own-payoff minimizing choice, $z = 3$ indicates a payoff-equalizing choice. Budget lines are sorted by slope on the x-axis.

In sum, the descriptive results suggests that students’ choices are strikingly similar at the descriptive level, irrespective of whether their choices in the money allocation task are incentivized, and irrespective of the size of the financial stakes.

Table F.2: χ^2-test of independence by choice situation (Holm (1979) corrected) of students

	choiceId	statistic	p-value
1	1	18.380	1.000
2	2	22.898	0.440
3	3	11.305	1.000
4	4	17.223	1.000
5	5	19.227	1.000
6	6	13.692	1.000
7	7	24.084	0.320
8	8	17.138	1.000
9	9	20.836	0.830
10	10	11.672	1.000
11	11	15.497	1.000
12	12	14.022	1.000
13	13	12.388	1.000
14	14	25.278	0.290
15	15	9.640	1.000
16	16	18.964	1.000
17	17	19.565	1.000
18	18	15.888	1.000
19	19	22.321	0.580
20	20	21.831	0.650

Notes: This table shows the χ^2-test of independence by choice situation, corrected for multiple testing (Holm, 1979). It provides the results of a series of tests of equality in distributions of implemented choices z (where z ranges from 0 to 1) across the three treatments, by decision situation (choice ID).

F.3 Cluster analysis of students

To study whether incentives affect the distribution of social preferences in the student sample, we use the same approach as for the general population. To that end, we again apply a Bayesian nonparametric approach—the Dirichlet Process (DP) means clustering algorithm (Kulis and Jordan, 2012).

We run the DP-means algorithm separately on each treatment. We display the distribution of clusters identified by the DPM in the Table F.3. In order to assign labels to the identified clusters, we examine the behavioral characteristics of each cluster in Figure F.5, Figure F.6, and Figure F.7.

Like for the general population sample, we find that three clusters with a clear behavioral interpretation emerge in the Low-Incentives and in the Hypothetical treatments: a cluster comprising individuals predominantly equalizing payoffs[7], a cluster of subjects making altru-

[7] For example, in the Low Incentives Treatment (Figure F.5) these subjects equalize payoffs by predominantly picking the center allocation ($z = 3$) for the budget lines centered around the 45-degree line. In the North Bundle, which comprises four budget lines with a positive slope above the 45 degree line (where the decision maker is always better off than the other—see Figure A.1), they tend to give up a large portion of their payoff ($z < 3$) in order to decrease the payoff of those better off–thereby achieving greater equality. In the South bundle, which comprises four budget lines with a negative slope under the 45 degree line–see Figure A.1, they implement allocations in which they have to give up a substantial portion of their endowment in order to achieve greater inequality ($z < 3$).

istic choices towards those worse off, and a cluster comprising subjects making predominantly selfish choices. Importantly, however, note that the clustering algorithm does *not* identify a stable 3-types clustering in the High-Incentives treatment.[8] Interestingly, the assignment of students to types seems more responsive to incentives: in the hypothetical treatment, 76.83% of the subjects are assigned to a one of the other-regarding clusters (i.e., either altruistic or inequality averse), whereas only 55.07% are assigned to such a cluster when money is at stake (Low-Incentives treatment). In other words, students are more likely to be assigned to the selfish type when monetary incentives are used.

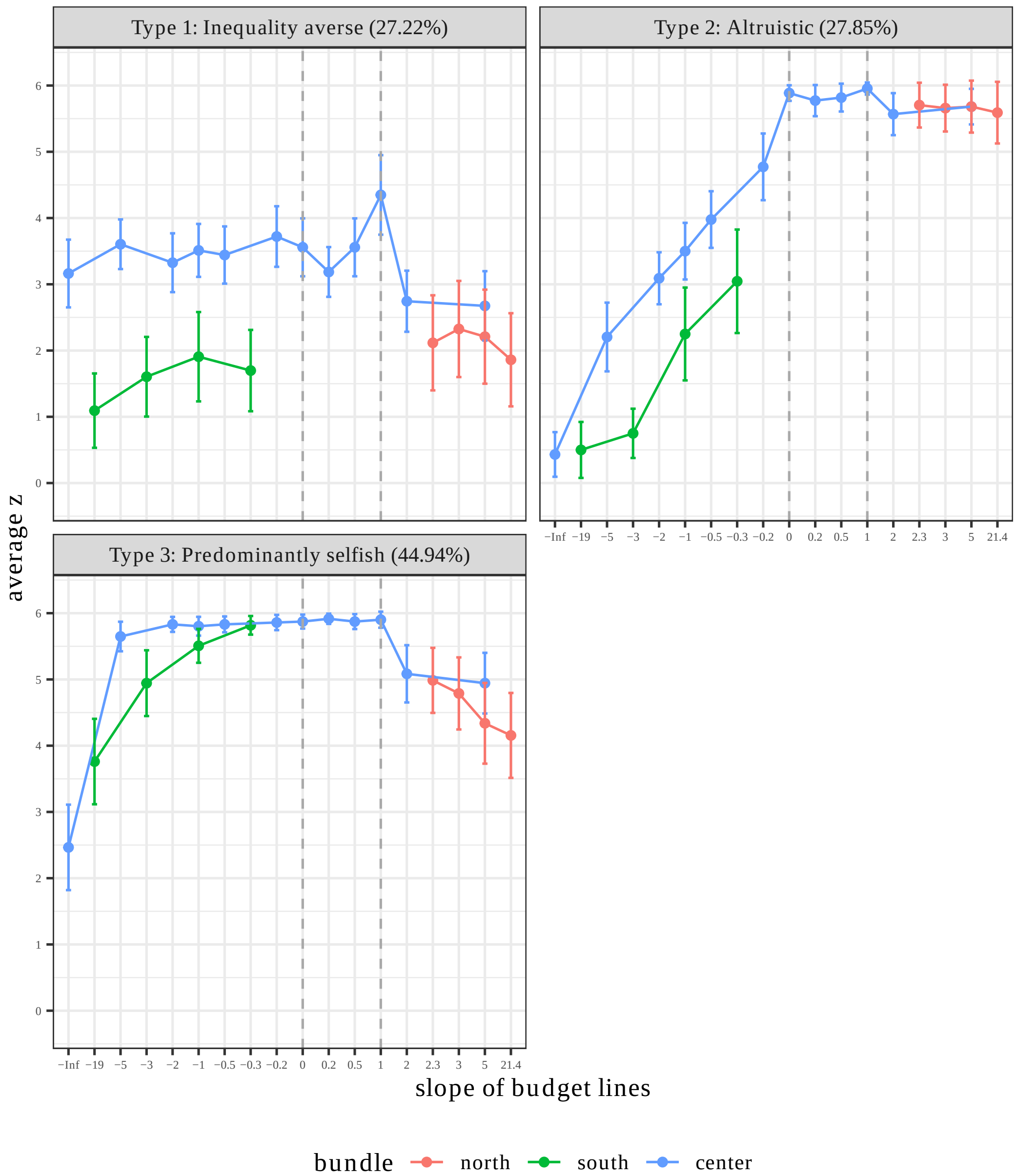
Table F.3: Type distributions of students identified using clustering analysis

	Low-Incentives	**High-Incentives**	**Hypothetical**
Cluster 1 (Inequality averse)	27.22%	N.A.	32.93%
Cluster 2 (Altruistic)	27.85%	N.A.	43.90%
Cluster 3 (Selfish)	44.94%	N.A.	23.17%

Notes: The table displays the distribution of individuals to the three clusters (in percent) that emerge in our dataset, separately for each treatment. The behavioral interpretation of the clusters (indicated in the left column) is based on the interpretation of each cluster's typical behavior.

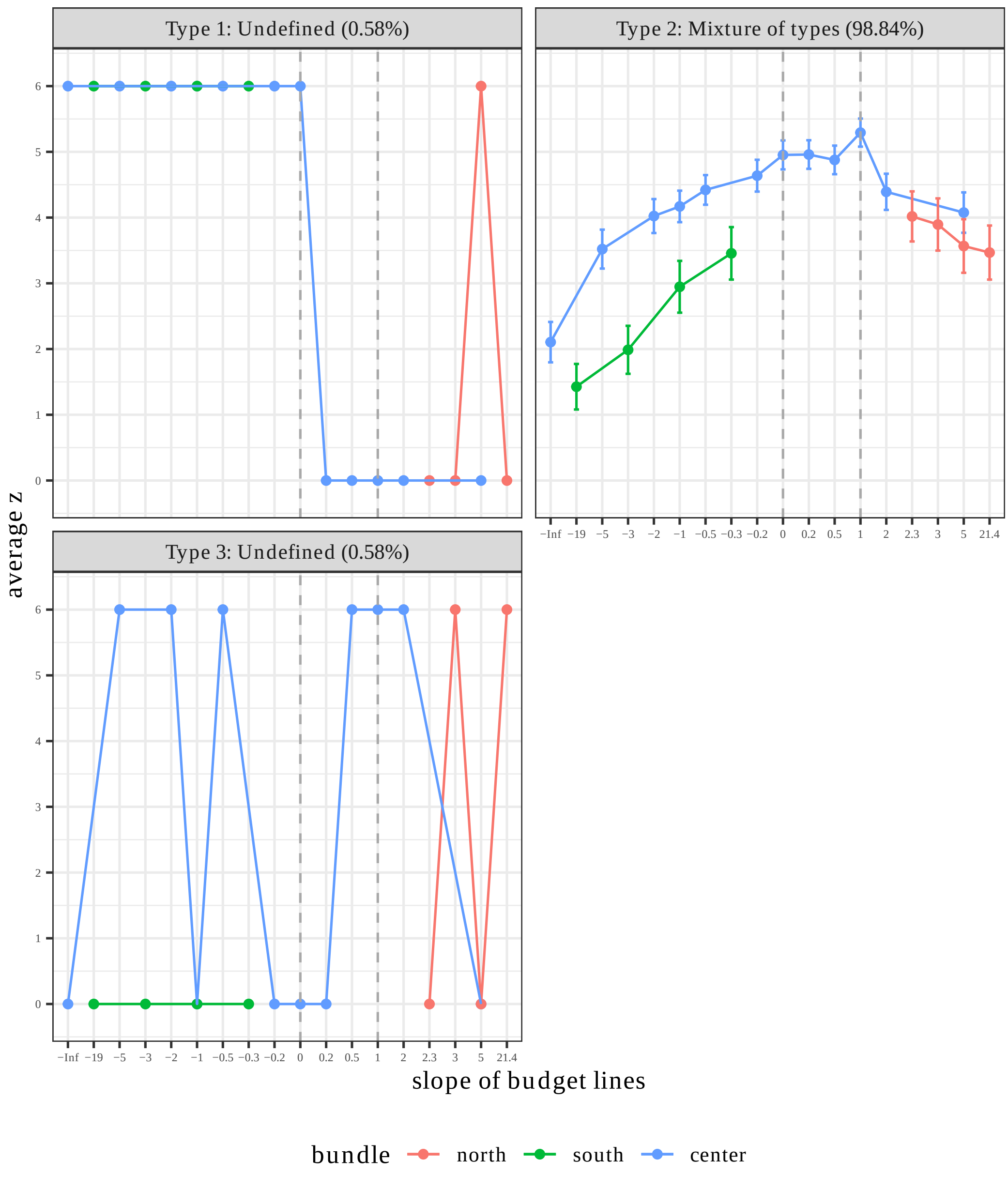
[8]More precisely, it pools almost all subjects into a single cluster that therefore contains a mixture of types, and assigns only one subject into each of the remaining two clusters (for details, see Figure F.6).

Figure F.5: Average choices of students: Low-Incentives



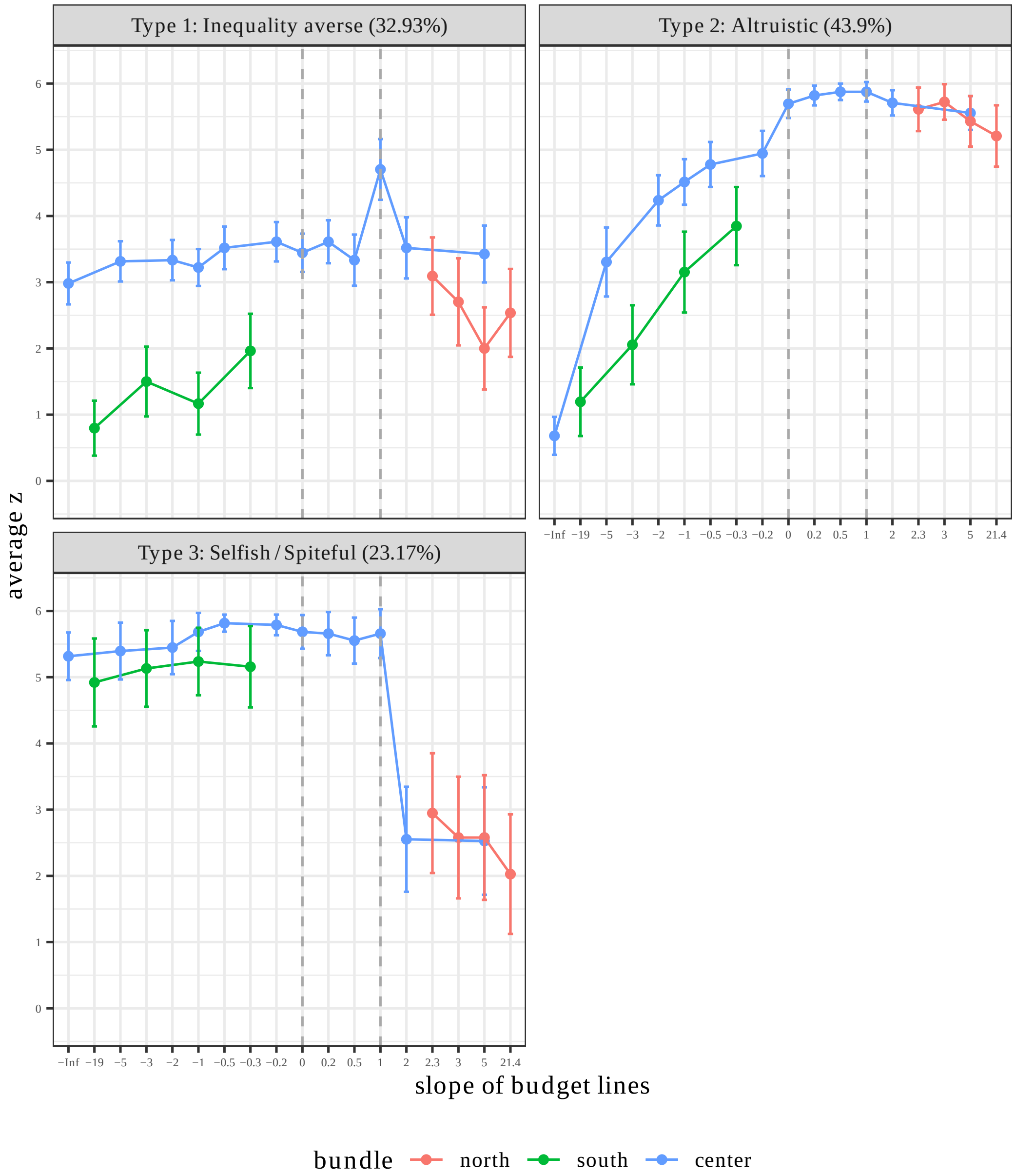
Notes: The figure shows the mean z of students' choices in the Low-Incentives treatment on the y-axis. For each budget line, $z = 6$ indicates an own-payoff maximizing choice, $z = 0$ indicates an own-payoff minimizing choice, $z = 3$ indicates a payoff-equalizing choice. Budget lines are sorted by slope on the x-axis.

Figure F.6: Average choices of students: High-Incentives



Notes: The figure shows the mean z of students' choices in the High-Incentives treatment on the y-axis. For each budget line, $z = 6$ indicates an own-payoff maximizing choice, $z = 0$ indicates an own-payoff minimizing choice, $z = 3$ indicates a payoff-equalizing choice. Budget lines are sorted by slope on the x-axis. The clustering algorithm does not identify a stable 3-types clustering in the High-Incentives treatment. It pools almost all subjects into a single cluster (Type 2) that therefore contains a mixture of types. It assigns only one subject into the Type 1 cluster and only one subject into the Type 3 cluster. Thus, the subfigures for Type 1 and Type 3 provide no statistically reliable type information.

Figure F.7: Average choices of students: Hypothetical



Notes: The figure shows the mean z of students' choices in the Hypothetical treatment on the y-axis. For each budget line, $z = 6$ indicates an own-payoff maximizing choice, $z = 0$ indicates an own-payoff minimizing choice, $z = 3$ indicates a payoff-equalizing choice. Budget lines are sorted by slope on the x-axis.

F.4 Structural analysis of students

We depict the mean values and standard deviations of the estimated structural parameters, separately by treatment, in Table F.4. Surprisingly, and in contrast with our results from the general population, we find the highest estimated parameters of inequality aversion in the High-Incentives treatment.

Table F.4: Summary statistics across treatment of students

	Low-Incentives		High-Incentives		Hypothetical	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
α	0.216	0.752	0.544	1.010	0.426	0.764
β	0.393	0.871	0.675	0.959	0.522	0.945

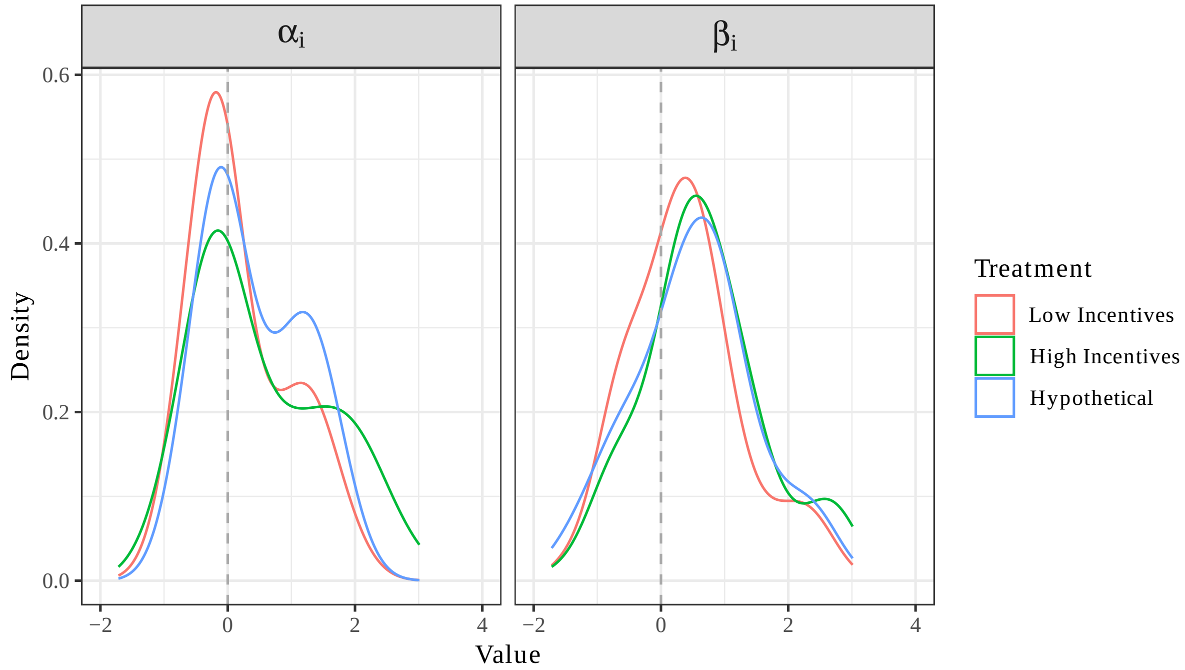
To study whether the distributions of α and β differ accross treatments, we depict their probability density function in Figure F.8, their cumulative distribution functions (CDFs) in Figure F.9, and a series of pairwise Kolmogorov-Smirnov (KS) tests of equality in distributions in Table F.5.[9] Figure F.8 and Figure F.9 indicate slight differences across treatments that are consistent with the results of the average values discussed above. Again, we find that – compared to the Low-Incentives treatment – the Hypothetical and High-Incentives treatments shift the distributions of α and β-parameters to the right, with the shift being more pronounced for the latter. Despite these slightly visible differences, Table F.5 reveals that stake sizes only significantly affect the distribution of individuals' estimated α-parameters (Low vs. High-Incentives: $p = 0.024$). On the contrary, we find no significant differences between the α-parameter distributions of the Hypothetical treatment and the two incentivized treatments. Moreover, we do not find any significant differences between the distributions of the β-parameters.

Turning to the precision of the estimates, we find that precision is the lowest in the High-Incentives treatment (see Table F.6), which is also in contrast with our results from the general population sample.

Overall, these results are slightly less consistent than those established in the general population sample. However, it is important to note that these results might have to be taken with a grain of salt since our student sample is much less well powered than our general population sample.

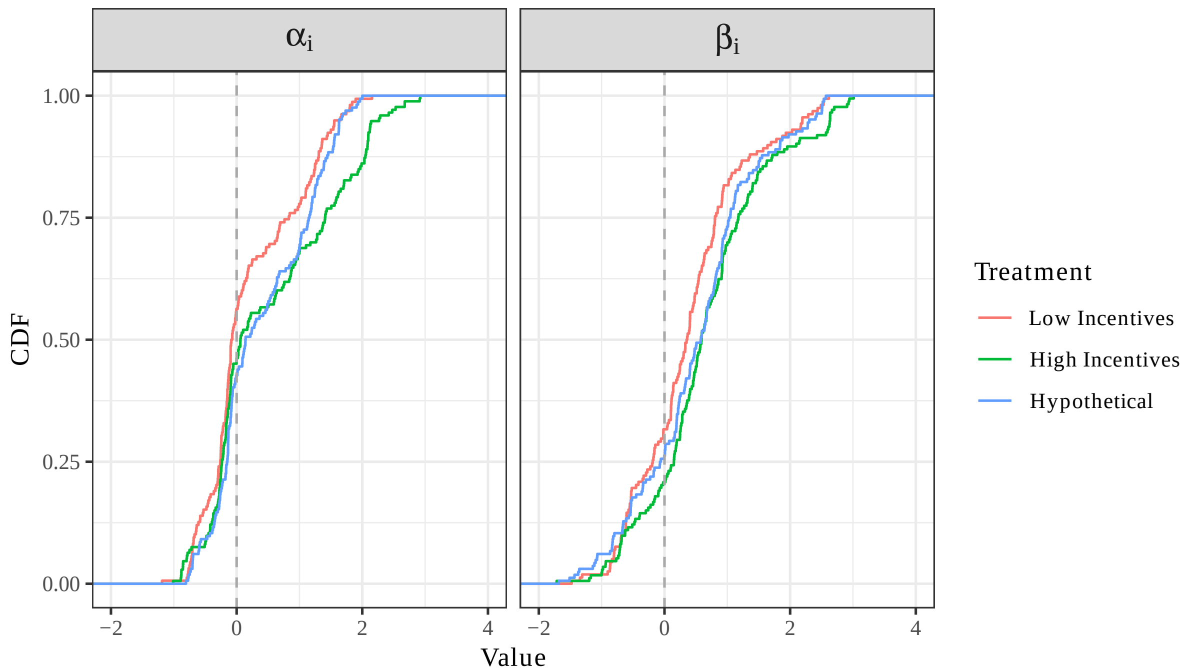
[9] For these tests, we apply Holm (1979) correction to account for multiple hypothesis testing.

Figure F.8: Distribution of students' structurally estimated parameters



Notes: The distribution on the left side depicts subjects' structurally estimated alpha parameters by treatment. The distribution on the right side depicts subjects' structurally estimated beta parameters by treatment.

Figure F.9: CDFs of students' structurally estimated parameters



Notes: The CDFs on the left side depicts subjects' structurally estimated α-parameters by treatment. The CDFs on the right side depicts subjects' structurally estimated β-parameters by treatment.

Table F.5: Kolmogorov-Smirnov Test p-values with Holm (1979) correction of students

Comparison	α-parameter p-value	β-parameter p-value
Low-Incentives vs. High-Incentives	0.024	0.055
Low-Incentives vs. Hypothetical	0.073	0.093
High-Incentives vs. Hypothetical	0.073	0.512

Table F.6: Median posterior standard deviation by treatment condition of students

Treatment	α	β
Low-Incentives	0.238	0.241
High-Incentives	0.441	0.319
Hypothetical	0.341	0.308

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