Measuring Hearts and Minds: A Validated Survey Module on Inequality Aversion and Altruism

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Abstract

Social preferences are widely studied in behavioral economics, with some validated survey modules to measure trust, altruism and reciprocity. Despite growing interest in inequality aversion—defined as an individual's dislike of disparities in outcomes—there is, however, no dedicated and validated module to assess this specific social preference. Moreover, inequality aversion and altruism are often hard to disentangle, which points to the need for a unified module that incorporates both preferences. To bridge these gaps, we introduce a novel survey module that captures general attitudes toward inequality aversion and altruism. This module was developed and validated through an experimental study with a representative U.S. population sample. Our results demonstrate that the proposed module effectively captures variations in both inequality aversion and altruism, with consistent reliability across individual heterogeneity. This tool offers researchers a standardized and generalizable approach for measuring inequality aversion and altruism, paving the way for future studies and across diverse contexts.

Keywords. *inequality — altruism — redistribution — social preferences — survey instrument*
JEL codes. D63, D91

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1 Introduction

Incentivized experiments have long been the preferred approach for measuring preferences. By offering real stakes, such experiments help mitigate issues such as inattention and hypothetical bias that may affect survey responses. However, they are resource-intensive, requiring significant time and financial investment. This makes it challenging to implement them on a large scale, particularly in fieldwork or broad population studies. On the other hand, qualitative self-assessments of preferences have gained increasing interest in recent years. These assessments typically take the form of (non-incentivized) Likert scale items such as, *"Are you generally willing to share with others without expecting something in return, or are you not willing to do so?"* and are intended to be used as a substitute to the behavior observed in incentivized experiments. Major studies have shown a notable empirical relationship between preferences elicited in incentivized lab settings, on the one hand, and qualitative self-assessments of preferences, on the other hand. These include validated survey modules, providing a proxy of risk aversion, time discounting, trust, altruism, positive and negative reciprocity (Falk et al., 2018, 2023), ambiguity (Cavatorta et al., 2019) and competition (Fallucchi et al., 2020).

Yet there is no study addressing the preference of *inequality aversion*, defined as individuals' dislike of disparities in outcomes. Inequality aversion has been a cornerstone of theoretical models (Fehr and Schmidt, 1999) and extensively examined in research on preferences for redistribution (Fong, 2001; Alesina and Angeletos, 2005; Alesina and Giuliano, 2011).[1] Other studies investigate redistribution in specific policy domains (Corneo and Grüner, 2002; Guillaud, 2013; Hvidberg et al., 2023), in connection with welfare (Decancq et al., 2017, 2019; Fleurbaey and Zuber, 2024), or within macroeconomic contexts (Piketty and Saez, 2003, 2014). Despite both interests in validated survey modules and inequality measurement, there are, however, no standardized instruments for measuring inequality aversion at the individual level using survey methods.

We aim to address this gap by proposing a parsimonious survey module that jointly measures inequality aversion and altruism.[2] The proposed instrument is designed to serve three distinct objectives. First, it functions as a cost-effective *substitute* for incentivized experimental tasks, while preserving their predictive validity. Second, it can be used as a right-hand side variable, where the instrument serves as an *explanatory or control* variable for predicting real-world behaviors and choices, particularly in settings where experimental elicitation is infeasible. Third, it can serve as a left-hand side variable, allowing researchers to explain heterogeneity in the instrument using other variables—that is, to treat it as an *outcome* whose variation warrants empirical investigation. To achieve these objectives, we conduct an online experimental study with a U.S. general population sample. We calibrate and validate the survey module by selecting items based on their ability to predict choices in an incentivized preference elicitation task. To identify the most predictive items, we evaluate a broad pool of candidate items using a gradient boosting algorithm. We then interpret the model's predictions using SHapley Additive exPlanations (SHAP).[3] We eventually identify a restricted set of sur-

[1] For a recent literature review on preferences for redistribution, see Mengel and Weidenholzer (2023). For an introduction to the concept of economic inequality, see Cowell (2011).

[2] We add *altruism*, as inequality aversion and altruism are often difficult to dissociate, both in incentivized experiments and survey questions.

[3] SHAP provide a method for interpreting machine learning models by attributing the contribution of

vey items that, when appropriately weighted, explain a reasonably large proportion of behavioral type and parameter variation we observe in the sample and its subsets. Although our proposed module is validated using a general population sample (with various subsets of the data used for training and validation), we anticipate that it will serve as a useful measure of inequality aversion and altruism across various populations. Additionally, the module can be applied to a range of contexts in which a relationship exists between preferences for inequality and altruism, on the one hand, and specific behaviors toward a given application, such as pro-environmental behavior, on the other.

The remainder of the paper is structured as follows. Section 2 describes the research design, with the characterization of the sample, the description of the preference elicitation method used in the experiment, the tested survey items, as well as the hypothetical choices and real-world behavior. Section 3 presents the method and results to infer preference types and parameter from the incentivized preference elicitation task. Section 4 develops a predictive model that uses a concise subset of survey responses to predict both type assignment and differences in inequality aversion. Section 5 outlines the structure of the *"Hearts-and-Minds"* module, which constitutes the core of our contribution. In Section 6 we evaluate the model's performance in predicting self-reported real-world social actions and compare its predictive accuracy to that of the more resource-intensive incentivized measures. Section 7 concludes with an overview of potential applications and future research directions.[4]

2 Research Design

This section provides an overview of the sample and study design. In Section 2.1, we describe the sample's characteristics and evaluate its representativeness of the U.S. adult population. Section 2.2 outlines the incentivized preference elicitation task, which serves as the core of our analysis. Section 2.3 details the comprehensive set of survey items included in the study. Finally, Section 2.4 introduces a series of hypothetical questions and real-world behavior used to assess external validity.

2.1 Setup and Sample

The study was conducted online using a representative sample of the U.S. adult population. A total of 536 participants, recruited *via* Prolific in autumn 2024, completed the study. The online sessions lasted 40 minutes on average. Participants received a fixed completion fee of £4, along with a variable bonus payment based on one randomly selected decision from the preference elicitation task.[5] The variable bonus payments ranged from £2.70 to £7.05. Our analysis focuses on participants who successfully passed three attention checks administered throughout the study. Details of the attention

each feature (variable) to a model's predictions. This approach is based on the Shapley value concept from cooperative game theory (Shapley, 1953).

[4]The Appendix A contains additional material, such as the full list of candidate survey items, descriptive analyses on the survey responses, and further results on feature importance. The Online Appendix B presents detailed sample statistics, additional type characterizations, and additional results on the external validity of the survey module.

[5]The British Pound (£) is the default currency used by Prolific, regardless of the participant's country of residence.

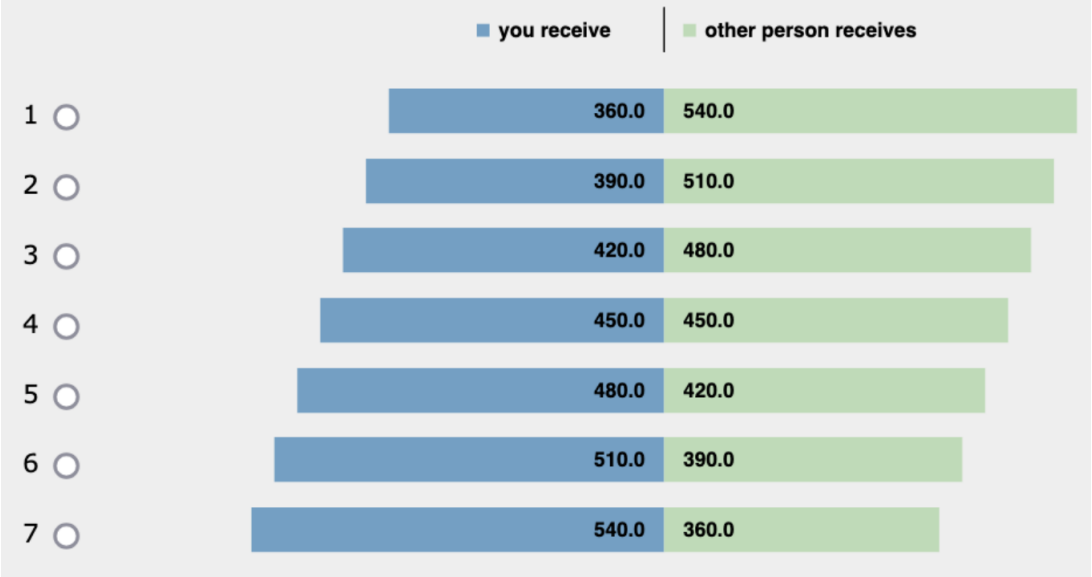
checks are provided in Appendix B.1. Of those completing the study, a high proportion of 93.7% met this criterion, yielding a final dataset of 502 participants. As shown in Appendix B.2, this restricted sample remains broadly representative of the U.S. adult population across three key stratification criteria: age group, gender and ethnicity.

2.2 Preference Elicitation

To measure respondents' social preferences, we employ a series of 20 money allocation tasks. The task design is adapted from Fehr et al. (2024) and Epper et al. (2024).[6] Calibration follows Fehr et al. (2023), who elicited distributional preferences from a Swiss representative sample (referring to their 2020 wave). The primary modification in our study is a scaling of the payoffs, with 100 ECU (experimental currency units) equivalent to £1. The 20 choice situations are listed in Table 1.

In each choice situation, respondents chose one option from a set of seven possible bilateral distributions. Each option represented a distribution of monetary payoffs between the respondent (`self`) and an anonymous counterpart (`other`). The counterpart did not participate in the same allocation decisions, and both parties remained fully anonymous throughout the study. An example choice situation corresponding to $j = 4$ in Table 1 is depicted in Figure 1, as shown on respondents' screens.

Figure 1: Choice interface



Note. In each choice situation (here $j = 4$), respondents were confronted with seven possible distributions between themselves and another person. They were asked to choose the one they preferred.

Choice situations vary in their marginal return (MR) of redistribution. Specifically, for each choice situation involving a trade-off between `self` and `other` (as in the example shown in Figure 1), the MR represents the amount `self` has to give up to increase the payoff of `other` by 1 ECU. Symmetrically, for each choice situation involving a mutual

[6]Fehr et al. (2024) elicit social preferences of a Swiss broad population sample using a larger set of (64) choice situations. Epper et al. (2024) elicit social preferences of a Danish broad population sample using 11 (instead of 7) choice options per situation and a slightly different configuration.

Table 1: Choice situations

j	y^s	x^s	y^o	x^o	domain	MR	α_{crit}	β_{crit}
1	270.0	630.0	450.0	450.0	mixed	Inf	0.00	0.00
2	300.0	600.0	480.0	420.0	mixed	-5.00	-0.83	0.83
3	330.0	570.0	510.0	390.0	mixed	-2.00	-0.67	0.67
4	360.0	540.0	540.0	360.0	mixed	-1.00	-0.50	0.50
5	390.0	510.0	570.0	330.0	mixed	-0.50	-0.33	0.33
6	420.0	480.0	600.0	300.0	mixed	-0.20	-0.17	0.17
7	450.0	450.0	630.0	270.0	mixed	0.00	-0.00	0.00
8	420.0	480.0	300.0	600.0	mixed	0.20	0.25	-0.25
9	390.0	510.0	330.0	570.0	mixed	0.50	1.00	-1.00
10	360.0	540.0	360.0	540.0	mixed	1.00	Inf	-Inf
11	330.0	570.0	390.0	510.0	mixed	2.00	-2.00	2.00
12	300.0	600.0	420.0	480.0	mixed	5.00	-1.25	1.25
13	420.0	460.2	480.0	679.8	behind	0.20	0.25	-
14	480.0	570.0	420.0	150.0	ahead	-0.33	-	0.25
15	420.0	480.0	480.0	660.0	behind	0.33	0.50	-
16	480.0	660.0	420.0	240.0	ahead	-1.00	-	0.50
17	420.0	492.0	480.0	648.0	behind	0.43	0.75	-
18	480.0	705.0	420.0	345.0	ahead	-3.00	-	0.75
19	420.0	430.8	480.0	711.0	behind	0.05	0.05	-
20	480.0	498.0	420.0	78.0	ahead	-0.05	-	0.05

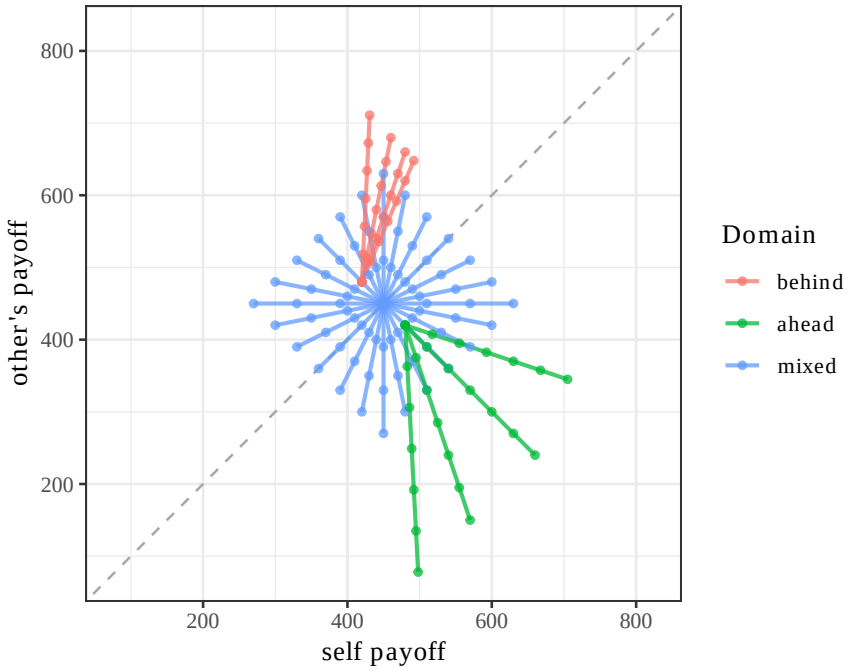
Note. j indexes the choice situation. Outcomes x and y are expressed in ECUs (experimental currency units), where superscript s refers to `self` and o to `other`. The points (x^s, x^o) and (y^s, y^o) represent the endpoints of the allocation lines shown in Figure 2, with $x^s \geq y^s$. The *domain* categorizes choice situations by the `self` and `other`'s relative standing (see main text). MR is the marginal return of redistribution. In choice situations with a *negative* MR (e.g. $j = 4$), redistribution comes at a *cost* for `self`, i.e there is a trade-off between achieving more equality and maximizing one's own outcome. In this case, MR expresses the marginal cost of redistribution the respondent has to bear when increasing the other's outcome. In choice situations with a *positive* MR (e.g. $j = 10$), there is a mutual *benefit* in increasing one's own outcome, as it also increases the others'. In this case, MR expresses the marginal benefit of redistribution of the respondent when increasing the other's outcome. α_{crit} and β_{crit} are the critical values for Fehr and Schmidt (1999) inequality aversion parameters (defined below).

benefit between `self` and `other`, the MR represents the amount `self` benefits from increasing the payoff of `other` by 1 ECU. The MR can thus be interpreted as the marginal *cost* (when negative) or marginal *benefit* (when positive) of redistribution. Table 1 details the values of the MR associated with each choice situation. It also details the critical values of the Fehr and Schmidt (1999) inequality aversion parameters α and β. α represents the aversion to disadvantageous inequality—capturing the individual's disutility when she/he receives less than the other—and β represents the aversion to advantageous inequality—capturing the individual's disutility when she/he receives more than the other. Higher values of α and β imply a stronger aversion to being at a disadvantage and advantage, respectively. The critical values are calculated as follows.

$$\alpha_{\text{crit}} = \frac{1}{\text{MR} - 1} \quad \text{and} \quad \beta_{\text{crit}} = -\frac{1}{\text{MR} - 1}$$

Each choice situation is characterized by two allocation endpoints (x^s, x^o) and (y^s, y^o) where $x^s \geq y^s$, and s and o refer to the payoffs for the `self` and the `other`, respectively. The endpoints define a line in the self-other payoff space, as illustrated in Figure 2.

Figure 2: Self-other payoff space



Note. Each (allocation) line corresponds to a choice situation listed in Table 1, with the seven dots indicating the choice options displayed on screen. The choice situations (allocation lines) are defined by their endpoints (x^s, x^o) and (y^s, y^o), where $x^s \geq y^s$. The marginal returns (MR) in Table 1 correspond to the reciprocal of the slope of the allocation lines. The 45-degree line indicates the set of distributions where both individuals are equally as well off (equality line). The lower and upper triangular regions specify the set of distributions where the respondent *(self)* is better and worse off, respectively.

We consider three different choice domains: *mixed* (blue lines), where options allow for higher payoffs to either the self or the other person, *ahead* (green lines), where the respondent is always better off than the counterpart, and *behind* (red lines), where the respondent is always worse off. In each scenario, respondents were presented with seven equally spaced convex combinations of the two endpoints:

$$(w^s, w^o) = \left(z_{ij}x_j^s + (1 - z_{ij})y_j^s, z_{ij}x_j^o + (1 - z_{ij})y_j^o\right) ,$$

with $z_{ij} \in \{0, 1/6, 1/3, 1/2, 2/3, 5/6, 1\}$ denoting the possible allocation choices, and i denoting the individual index. Higher values of z_{ij} indicate an increase in the respondent's (`self`) payoff.[7] The choice situations appeared in randomized order for each respondent.

2.3 Survey Item Candidates

We test a total of 34 items organized in three sets: *altruism* (11 items), *comparison* (12 items), and *inequality aversion* (11 items). Each of the items within these sets is structured symmetrically, including (i) a general question about the attitude in focus, labeled as `General`, (ii) a question addressing the attitude toward strangers, labeled as `Stranger`, and (iii) nine to ten questions describing specific aspects of the attitude. We refer to these as *tailored* items. The full list of items are in Appendix A.1 and the labeling structure is as follows. The first three letters refer to the specific social domain: `alt` for altruism, `cmp` for comparison, and `inq` for inequality aversion. Then follows the source, i.e. the motivation, explanation, or principle involved in the specific social domain. For example, the item `altWellBeing` means *"altruism motivated by increasing social well-being"*, `cmpEnvy` means *"comparison explained by envy"* and `inqSelfishness` means *"inequality seeking motivated by selfishness"*.[8]

Following Falk et al. (2023), we use their general altruism item as well as their item on altruism toward a specific group—in our case, strangers. Since their altruism survey module was validated using choice tasks, where participants selected their preferred donation amount to a charity of their choice, their altruism items related to charity were not applicable to our study. Instead, our experimental study involves the distribution of monetary payoffs between the respondent (`self`) and an anonymous counterpart (`other`). As the guidelines of Falk et al. (2023) suggest that it is more relevant to tailor the items to the targeted population (p. 1944), we do so by proposing our own list of altruism items that apply in most real-life circumstances—i.e., beyond charitable donations. In particular, our tailored items are inspired from what we believe to be heterogeneous sources that trigger altruistic behavior in daily life, such as concern for the well-being of others *("I value the well-being of others more than maximizing my own personal benefit")*, moral obligation *("I believe that sharing with others, even when not required, is the right thing to do")*, or personal satisfaction from donating *("I feel fulfilled when I can give something to others, even if it costs me personally")*.

One limitation we see with the altruism items is that they are primarily applicable to situations involving a trade-off between the self's payoff and the other's payoff.[9] That

[7] For the choice situation with MR $= 0$ (vertical line in Figure 2, corresponding to $j = 7$ in Table 1), $z = 1$ refers, by convention, to the distribution at the very bottom.

[8] Note that some inequality aversion items are intimately linked with altruism items, as the last example shows. We come back to this point in Section 5. Our study also included a set of additional survey items (available upon request) that are unrelated to this paper.

[9] Note that altruistic and inequality-averse motives cannot be disentangled in the ahead domain. In this domain, both altruistic and inequality-averse individuals will give up their own payoff to increase the other's payoff at some cost. The Fehr and Schmidt (1999) model captures this with a positive β parameter. However, the two concepts have very different implications in the behind domain. In this domain, altruism and inequality aversion make opposite predictions: An inequality averse individual would still aim to

is, they concern choice situations with a MR < 0, as depicted by the negatively-sloped choice situations in the *mixed* and *ahead* domain of Figure 2. To propose items that capture additional considerations for redistribution (including implicit emotions related to such choices), and that are applicable to choice situations where both self's and other's payoff increase or decrease simultaneously (that is, choice situations with a MR > 0, as depicted by the positively-sloped choice situations in the *mixed* and *ahead* domain of Figure 2), we include *comparison* and *inequality aversion* items described as follows.

The comparison items are characterized by the subject's tendency to compare their own situation with that of others. They apply to all domains, although they are particularly relevant for reflecting subjects' behavior in choice situations involving a MR > 0 (Figure 2), i.e., cases where both the self's and the other's payoff increase or decrease simultaneously. For example, while the item *"Whether others have more or less than I do is irrelevant to me"* can refer to all domains, it is specifically designed to capture behavior in the *behind* domain and to assess efficiency (maximizing both payoffs, regardless of the other's payoff). Like the altruism items, we aim at measuring general attitudes toward comparison *("Do you generally compare what you have with others or not?")* and comparison between the self and the other in anonymous contexts *("Do you generally compare what you have with strangers or not?")*. We then propose a set of ten tailored items to relate to scenarios of specific comparison involving some common emotions, like injustice *("Overall, I feel a sense of injustice when others have more than I do")*, superiority *("I particularly enjoy situations where I am better off than others")* and envy *("When I see someone enjoying more resources, I feel a desire to have the same")*.

The inequality aversion items are characterized by the subject's dislike to unequal distributions between herself/himself and the other. Similarly, we include one item that captures general preference for inequality aversion (*"Are you generally willing to redistribute resources with others to reduce inequality, or are you not inclined to do so?"*), while tailoring other items to specific cases. On the one hand, we proposed items to capture individuals' tendencies toward reducing inequality in advantageous situations, such as *"In situations where I would earn more than others for the same effort, I would feel the need to limit my income at a certain point, even if I could earn more"* and *"I would be willing to sacrifice a large part of my income to slightly reduce that of those less well off than me"*. On the other hand, we proposed items that specifically represent choice situations in the *behind* domain, where individuals are always worse off than others: *"In situations where others would earn more than me for the same effort, I would be willing to set an income limit for everyone"* and *"I would be willing to sacrifice a little of my income to drastically reduce that of the most fortunate"*.

2.4 Hypothetical Choices and Real-World Behavior

Building on the Global Preference Survey (GPS) module by Falk et al. (2023), which included hypothetical questions to measure people's attitudes toward risk, time, and altruism (charity), we incorporated a hypothetical version of the incentivized choice experiment. This was done across all domains, i.e., *mixed*, *ahead*, and *behind*, although

minimize the dispersion of payoffs between `self` and `other` (positive α). An altruistic individual, however, may be willing to give more to the other person, despite ending up in an even worse position (negative α).

here we use only the item related to situations involving a trade-off between the self's payoff and the other's payoff. This choice was motivated by its simplicity compared to other scenarios in our set, where the formulation of situations involving simultaneous increases or decreases in both payoffs is more cognitively demanding and complex to articulate.[10] We also used the hypothetical question from Falk et al. (2023) related to charity, which assumes the participant has won $1,000 in a lottery and must decide whether she/he would donate a portion of this amount to charity and, if so, in what proportion (Appendix A.2).

Moreover, we included the set of real-world behavior questions of Falk et al. (2023) in the altruism domain, asking about association/volunteering community membership, monthly hours spent volunteering, the number of people the participant knows she/he commits to volunteering, actual donations (whether regular or not), and, if applicable, the amount donated. Lastly, we included a question regarding participants' general support for redistributive policies—see Appendix A.3 and Epper et al. (2024) for a related item administered to a broad Danish population. These real-world behavior questions are particularly useful to test the external validity of our survey module, which is our endeavor in Section 6.[11]

3 Preference Measurement

In this section we present our findings from the incentivized preference elicitation task. We start with a descriptive analysis of the results (Section 3.1). We then explore preference types with a qualitative characterization of heterogeneity within our broad population sample (Section 3.2). Then, we examine the distribution of inequality aversion parameters in our data (Section 3.3).

3.1 Descriptive Results

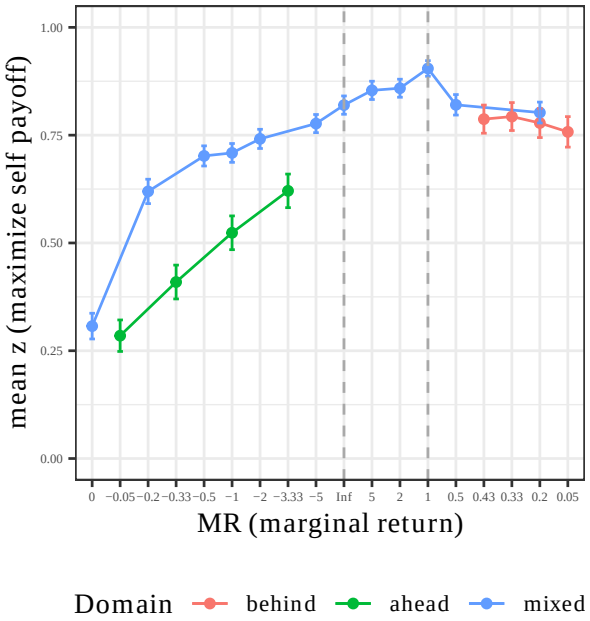
We begin by examining aggregate response patterns within our sample. To do this, we plot the mean z_{ij}-values—where higher z_{ij} indicates a greater propensity to maximize self-payoff—as a function of the marginal return (MR) of redistribution. Recall that the MR represents the amount of self-payoff that is incurred (MR < 0) or gained (MR > 0) from increasing the other person's payoff by one currency unit. It also represents the slope of the allocation lines in Figure 2.

[10] These additional items with the associated data may be provided upon request.

[11] Self-reported real-world behaviors collected within the same survey are frequently used in the literature to assess the external validity of preference measures, despite possible concerns such as social desirability bias. See for example Falk et al. (2023) and Fehr and Charness (2025). Nonetheless, empirical evidence suggests that associations between preferences and behaviors prevail, even when measured at different points in time or sourced from independent data sets. For instance, using the same preference elicitation task, the data of Fehr et al. (2024) indicates comparable links between preferences and incentivized donation behavior elicited two years apart. Similarly, and also employing the same elicitation method, Epper et al. (2024) report an even stronger association between inequality aversion parameters and third-party-recorded charitable donations in a Danish sample. These findings suggest that other factors—beyond the method of behavior elicitation—may influence the strength of observed preference-behavior associations.

Figure 3 illustrates the mean responses across the three domains: *mixed* (blue), *behind* (red) and *ahead* (green). In the *mixed* domain, the progression starts with the vertical line in Figure 2 (MR $= 0$) and moves counterclockwise, transitioning from steeper to flatter negatively sloped lines. As the transition occurs, redistribution becomes progressively more costly, meaning the self-payoff sacrifice required to increase the other's payoff by one currency unit grows. This trend continues until reaching the choice situation represented by a horizontal line, where the cost of redistribution becomes infinite (first vertical dashed line in Figure 3). Beyond this point, the lines have a positive slope. Initially, increasing the other's payoff by one unit provides a significant benefit to self, but this benefit diminishes as the slope steepens. At the MR $= 1$ (second vertical dashed line in Figure 3), increasing the other's payoff by one unit results in an equivalent benefit for self, maintaining equality. After this threshold, the self-benefit associated with increasing the other's payoff decreases further as the slope continues to steepen. For the *behind* and *ahead* domains, the progression similarly moves from steeper to flatter lines. Figure 3 presents domain-specific responses alongside 95% confidence intervals.

Figure 3: Aggregate response by domain



Note. The figure depicts mean z-values for different marginal returns (MR) of redistribution. The whiskers indicate 95% confidence intervals. The choice situations with MR < 0 are represented by the negative sloped lines, and the choice situations with MR > 0 are represented by the positive sloped lines in Figure 2. An infinite MR indicates a horizontal line in the figure, and a MR $= 1$ (both persons benefit the same) indicates a line with unit slope.

The results are as follows. In the *mixed* domain (blue curve), participants, on average, start off generously, allocating more to the other person than to themselves (mean $z < 0.5$ between MR $= 0$ and MR $= -0.05$). However, as the cost of redistribution increases, participants tend to retain more for themselves, reducing the amount given to the other. Conversely, with increasing benefits of redistribution, they allocate more to themselves, peaking at the point where the total payoff is maximized while maintaining equality. Notably, aggregate behavior does not exhibit perfect maximization of

the sum of payoffs at this point. When the other person stands to benefit more than the decision-making participant, individuals demonstrate a willingness to allocate additional resources to the other. In the *ahead* domain (green curve), where participants are always better off than the other person, they initially exhibit a willingness to move closer toward equal allocations. However, as the cost of redistribution rises, their willingness to give diminishes, eventually leading them to move more toward self-payoff maximization. In the *behind* domain (red curve), where participants are always worse off than the other person, they generally move toward self-payoff maximization. This behavior aligns with both selfish and efficiency-maximizing motives. As the personal benefit decreases, participants slightly reduce the proportion they retain, but this adjustment is minimal.

Given these aggregate-level results, we now examine behavioral heterogeneity to explain it through variation in survey responses. To achieve this, we adopt two complementary approaches. First, we investigate qualitative differences between participants by identifying preference types based on their response patterns. Second, we explore quantitative differences by estimating individual-level inequality (aheadness and behindness) aversion parameters.

3.2 Type Characterization

To identify preference types in our data, we follow Fehr et al. (2024) and search for clusters in the 12-dimensional allocation space. Specifically, each individual is represented as a point in the $z_{.j}$-space, where the allocation in each of the 12 choice situations within the *mixed* domain corresponds to one dimension. We employ the Dirichlet Process (DP) means algorithm (Kulis and Jordan, 2012) with various penalization terms. The penalization term λ punishes for the addition of new clusters to the model.[12]

Using this algorithm on the raw data offers several advantages over alternative methods. First, there is no need to commit to a specific behavioral and error model. Clusters can be identified directly in the allocation space without assuming specific behavioral structures or error models. Second, there is no need to presume the existence of predefined preference types. The algorithm starts with all individuals assigned to a single cluster, represented by the centroid of the mean allocations across all individuals. It iteratively identifies outliers—data points that exceed a predefined threshold (in terms of Euclidean distance)—and creates new clusters as needed. Third, this is a hard clustering algorithm where each individual is assigned to a specific type, producing distinct type labels. This is simpler to interpret compared to probabilistic assignments, as seen in mixture models or related approaches. However, the algorithm does not inherently add interpretation to the resulting clusters. To address this, Fehr et al. (2023) and Fehr et al. (2024) propose three complementary approaches to justify the emergence of three types in their data.

First, the resulting types should exhibit clear qualitative meaning. Fehr et al. (2023, 2024) identify three primary types in Swiss representative samples: one predominantly selfish, one primarily inequality-averse, and one largely altruistic.[13] In this study, we an-

[12] The algorithm and the objective function it minimizes are thoroughly described in Fehr et al. (2023).

[13] Similar results emerge when adopting the algorithm to a Danish representative data set. See in particular Fehr and Charness (2025).

alyze type-specific response signatures to determine whether our results align with these established interpretations. Second, parsimony is a key consideration. A small number of types should explain a large proportion of the heterogeneity in the data. Fehr et al. (2023) find that allowing for a small number of preference types significantly increases precision and out-of-sample predictive ability, while further gains diminish when additional types are introduced. Their findings suggest that three types represent a "sweet spot" in existing datasets. Third, robustness can be assessed by analyzing how types transition when moving from e.g., two to three, or from three to four clusters. Meaningful types should remain stable within the relevant range of clusters and only lose interpretability when the number of clusters becomes excessively high or low. We confirm this intuition in a robustness exercise detailed in Appendix B.3.[14] These approaches ensure that the preference types identified are both rigorous and interpretable, offering valuable insights into the heterogeneity of preferences in the population.

Building on previous work, we focus on the three-type clustering presented in Table 2. Figure 4 shows that these three types have a clear and unambiguous interpretation. This interpretation aligns with the findings of Fehr et al. (2024) for Switzerland and those reported in Fehr and Charness (2025), based on the data from Epper et al. (2020) for Denmark.

Table 2: Distribution of preference types

Type	Proportion
1	36.25%
2	32.27%
3	31.47%

Note. Proportion of subjects assigned to the three types resulting from employing the DP-means algorithm.

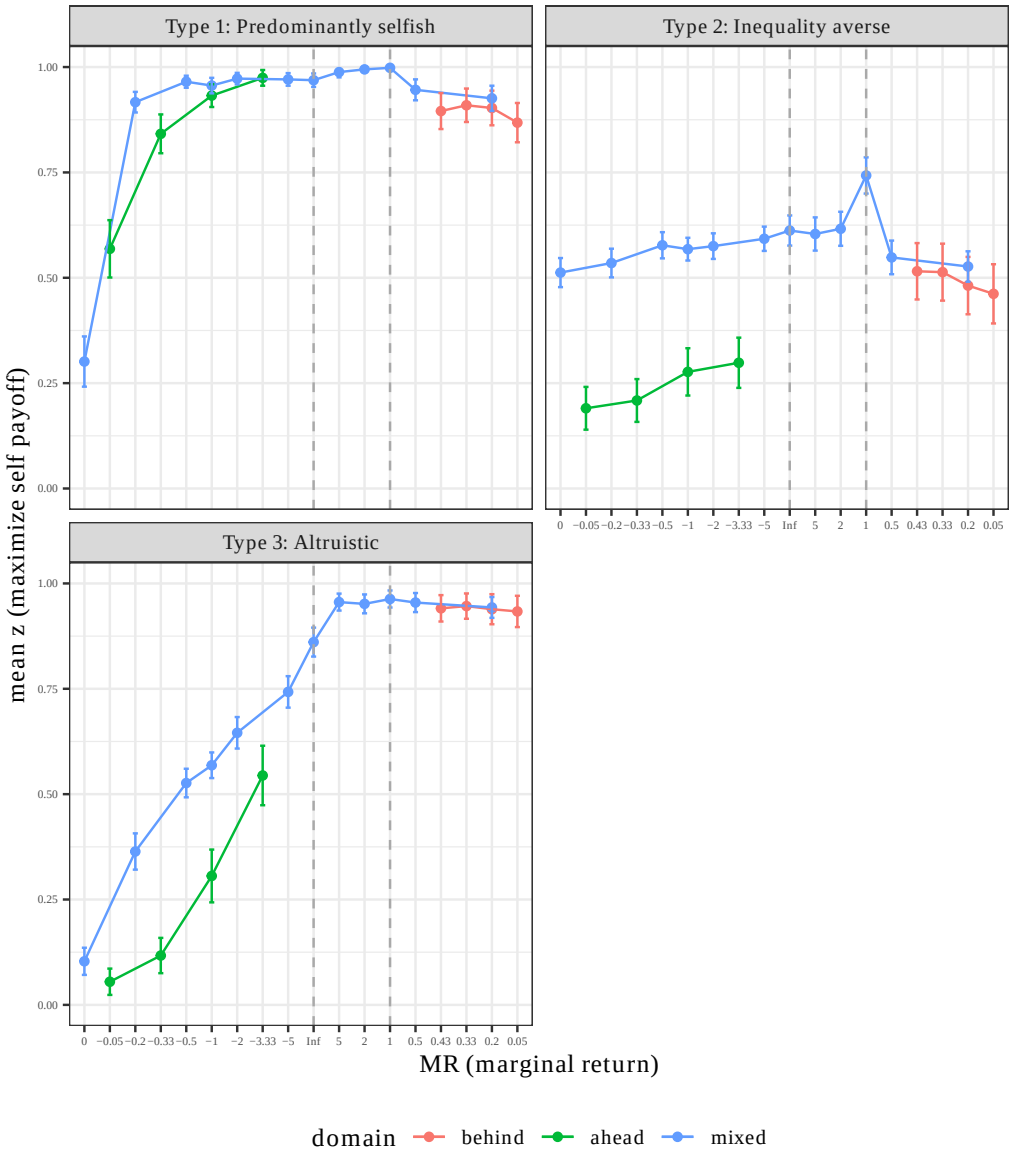
Approximately 36% of the sample can be classified as the *predominantly selfish* type, around 32% as the *inequality-averse* type, and roughly 31% as the *altruistic* type. The type-specific response patterns, illustrated in Figure 4, provide clear interpretations.

The predominantly selfish type (Type 1) is characterized by consistently maximizing their own payoff across nearly all choice situations, displaying minimal sensitivity to the cost of redistribution. Notably, a perfectly selfish individual would remain indifferent to all allocations when the cost of redistribution is zero. In our findings, individuals of this type exhibit this behavior even when the cost is only marginally above zero. In the *behind* domain, this type retains as much as possible, with negligible variation in their responses.

The inequality-averse type (Type 2) predominantly selects approximately equal allocations across the board, showing limited sensitivity to the cost of redistribution. For the case where $\text{MR} = 1$, this type should theoretically be indifferent among allocations, unless they also value the sum of the self's and other's payoff. In our results, this type moves toward more equal allocations in the *ahead* domain, though the tendency is slightly less pronounced compared to other domains.

[14] See in particular Figure 17, which depicts type transitions when increasing the number of types.

Figure 4: Type-specific response signatures



Note. The three panels depict mean z-values for different marginal returns (MR) of redistribution conditional on the preference type. The whiskers indicate 95% confidence intervals.

The altruistic type (Type 3) exhibits a strong inclination to allocate substantial resources to the other person, both when they are ahead and when given the opportunity to prioritize the other's payoff over their own. However, in situations where redistribution yields mutual benefits (choice situations with MR > 0, where increasing the other's payoff simultaneously increases the self's payoff), this type displays behavior that aligns more closely with selfishness, focusing on maximizing their own gains as well.

Our clustering approach successfully identifies three preference types with interpretations that are consistent with previous findings (Epper et al., 2024; Fehr et al., 2024; Fehr and Charness, 2025). The most notable difference from earlier studies is that the selfish type constitutes the largest proportion of our sample (36.3%), whereas it constitutes a minority in the Swiss samples (between 9.9% and 24%), and a slightly smaller proportion in the Danish sample (32.5%)—see also Fehr et al. (2023).[15]

3.3 Inequality Aversion Parameters

We estimate individual-level parameters of the Fehr and Schmidt (1999) inequality aversion model. When applied to bilateral distributions (which is the object of choice in our setting), the valuation depends on an individual's own payoff and her/his relative standing compared to the other person's payoff. The subject's valuation is expressed as:

$$V((w^s, w^o)) = w^s - \alpha_i \max(0, w^o - w^s) - \beta_i \max(0, w^s - w^o)\,,$$

where w^s denotes the individual's own payoff, defined as $w^s = z_{ij}x_j^s + (1 - z_{ij})y_j^s$, and w^o represents the other person's payoff, defined as $w^o = z_{ij}x_j^o + (1 - z_{ij})y_j^o$. The parameters α_i and β_i are individual-specific preference parameters. The parameter α_i measures inequality aversion when the individual is behind the other person (disadvantageous inequality, or, simply, behindness aversion), while β_i measures inequality aversion when the individual is ahead (advantageous inequality, or, simply, aheadness aversion). The Fehr and Schmidt (1999) model produces piecewise linear indifference curves in the space depicted in Figure 2. The slopes of these curves is closely tied to β_i in the domain where the individual is ahead and α_i where the individual is behind.[16] Table 1 provides the critical values for these preference parameters for each choice situation.

To estimate the model, we assume a random-utility error structure and adopt an estimation approach that permits for individual-level heterogeneity. For the error structure, we employ a random-utility framework as introduced by McFadden (1981). Under this model, the probability that individual i chooses alternative k is given by:

$$P_i(k) = \frac{e^{V_{ik}/\lambda_i}}{\sum_m e^{V_{im}/\lambda_i}}\,,$$

where λ_i is an individual-level error parameter representing noise. A smaller λ_i implies more deterministic choice. To model heterogeneity, we use a hierarchical Bayesian

[15] A recent study (Fehr et al., 2025) investigating the effect of incentives on inequality averse preferences also based on a representative U.S. sample documents very similar type distributions and inequality aversion parameters.

[16] In this model, global inequality aversion implies $\alpha_i, \beta_i > 0$. Global altruism, on the other hand, implies $\beta_i > 0$ but $\alpha_i < 0$.

modeling approach. This approach allows individuals to vary in their preference parameters α_i and β_i, as well as their error parameter λ_i. The model constrains individuals with outlier behavior toward the group mean while maintaining flexibility to capture individual differences (partial pooling). Technical details of the estimation procedure are provided in Epper et al. (2024) and Fehr et al. (2023), which estimate such a model to broad population samples from Denmark and Switzerland.

Table 3 presents the Bayesian posterior summary statistics of the estimated parameters. The results indicate that the posterior mean of β exceeds the posterior mean of α. This suggests that aversion to being ahead (advantageous inequality aversion) is stronger than aversion to being behind (disadvantageous inequality aversion). This finding contrasts with the conjecture of Fehr and Schmidt (1999), who proposed $\alpha > \beta$ for their original model. The central 95% credible intervals for both parameters include zero, highlighting substantial variability in inequality aversion across individuals.

Table 3: Posterior summary statistics

	Estimate	StdDev	2.5%	97.5%
α	0.090	0.634	-0.772	1.698
β	0.636	0.901	-0.851	2.797
λ	0.117	0.122	0.005	0.411

Note. The table lists the posterior means (Estimate), the posterior standard deviation (StdDev) and the central 95% credible interval of the posterior. α and β denote behindness and aheadness aversion, respectively, according to Fehr and Schmidt (1999). λ is the error term in the random-utility specification.

Figure 5 illustrates the distribution of individual-level inequality aversion parameters. The results reveal substantial heterogeneity, with both parameters ranging widely, from slightly negative values to more substantial positive ones.

Table 4 reports the correlations of the parameters across the posterior samples, showing a strong correlation between aheadness and behindness aversion. This relationship is further illustrated in Figure 9 (Appendix A.4), which presents a scatter plot of the two inequality aversion parameters.

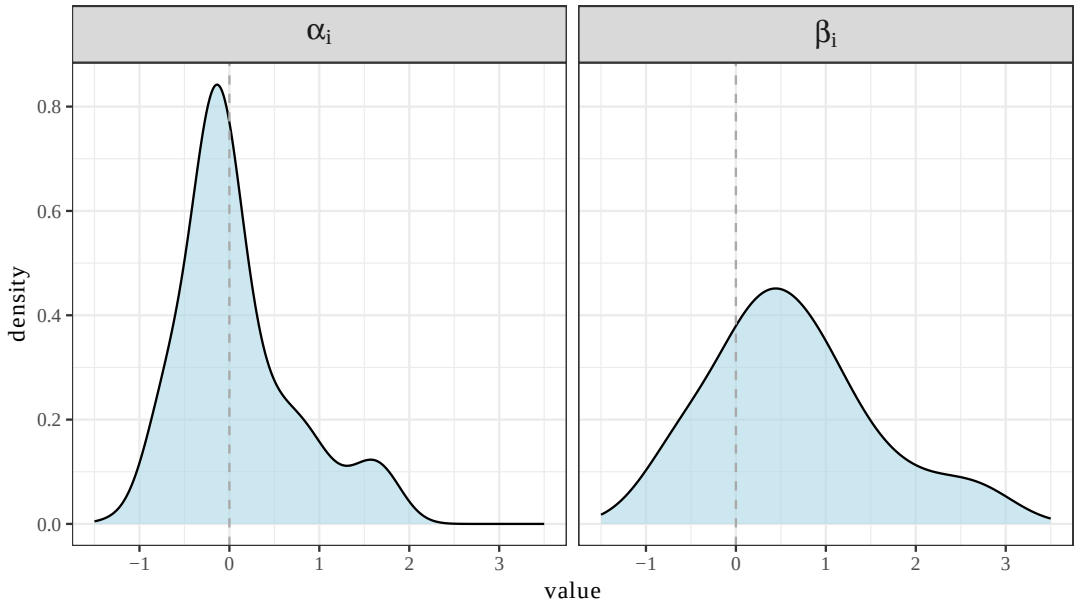
Table 4: Posterior sample correlation matrix

	α_i	β_i	λ_i
α_i	1.000	0.797	-0.382
β_i	0.797	1.000	-0.308
λ_i	-0.382	-0.308	1.000

Note. The numbers are Pearson correlations between the three individual-level parameters, α_i (behindness aversion), β_i (aheadness aversion) and λ_i (error term). There is a strong individual-level correlation between inequality aversion in the ahead and the behind domain.

Figure 6 illustrates the distribution of aheadness (β_i) and behindness (α_i) aversion parameters conditional on type assignment (see Section 3.2). We also provide the scatter plot of the two inequality aversion parameters conditioned by types in Figure 10 (Ap-

Figure 5: Distribution of individual inequality aversion parameters



Note. The panels illustrate the distribution of behindness aversion (α_i) and aheadness (β_i) in our sample. There is vast heterogeneity in these parameters with an overall tendency toward inequality aversion in both domains.

pendix A.4).

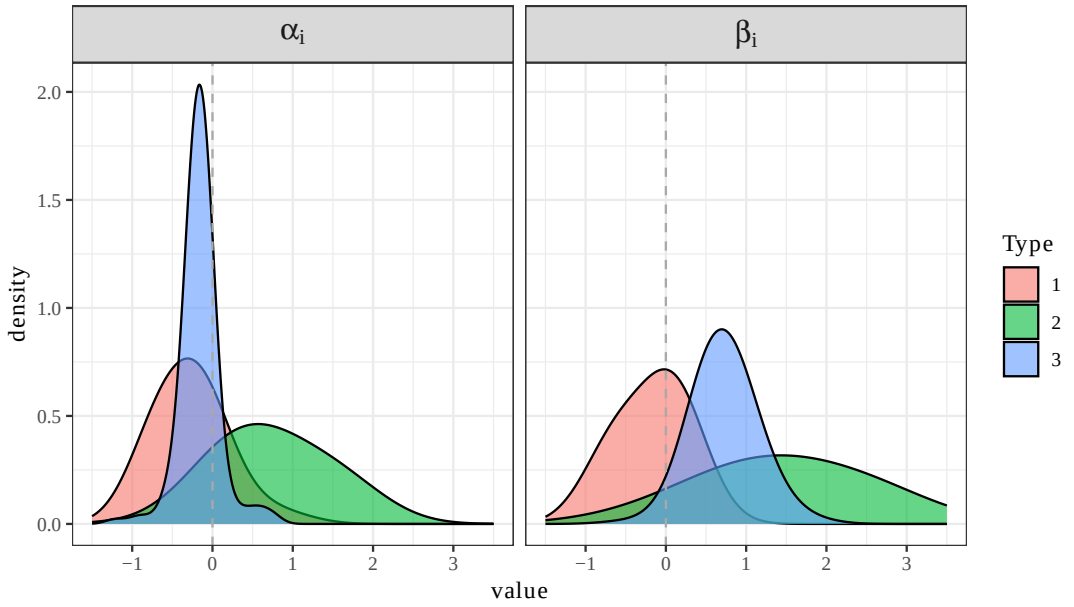
The results confirm that our interpretation of the response signatures (Figure 4) aligns closely with the structural findings. Type 1 is best described by an average β_i close to zero, but a slightly negative α_i. In other words, this type is selfish and even a bit spiteful when being behind. Type 2 is characterized by largely positive inequality aversion in both the ahead and the behind domain. We therefore label this type as inequality averse. Type 3 exhibits a more asymmetric behavior with mostly positive β_i (aheadness aversion), but α_i close to zero (selfishness in the behindness domain). Consistent with this, we coin this type "altruistic".

In Appendix A.5 we examine the structural model's ability to capture individual-level features of the data. The analysis demonstrates that the model effectively characterizes heterogeneity across individuals and provides accurate predictions of the observed behavioral responses. In Appendix A.6 we descriptively analyze key survey responses and their association with the behavioral types. We also analyze their correlation with inequality aversion parameters, which are derived from the incentivized preference elicitation task.

4 Prediction

In this section we develop models to predict type associations and domain-specific inequality aversion parameters. To this end, we tune and train a gradient boosting algorithm on a subset of our data and use it to predict types and inequality aversion pa-

Figure 6: Within-type distribution of aheadness and behindness aversion parameters



Note. The panels illustrate the distribution of behindness aversion (α_i) and aheadness (β_i) conditioned by types, where 1: predominantly selfish, 2: inequality averse, and 3: altruistic.

rameters for the remaining data.[17] We then evaluate the predictive ability of the large set of survey items using SHapley Additive exPlanations (SHAP values).[18] Our approach identifies six survey items that, when appropriately weighted, explain a reasonably large proportion of behavioral variation we observe in the sample and its subsets.

In what follows, we first develop a classification model to predict assignment to the three preference types identified earlier (Section 4.1). Next, we address the regression problem of predicting aheadness and behindness aversion parameters, estimated from choice data (Section 4.2). Section 5 proposes the final survey module items and the scoring method to aggregate the measures, enabling prediction of both types and inequality aversion. We assess the predictive performance of our module using a holdout test set that was not used for any model training and tuning. In Section 6, we demonstrate that our proposition is able to explain variation in stated hypothetical and real-world settings where inequality aversion and altruism are expected to play a role.

[17] We utilize the XGBoost (eXtreme Gradient Boosting) algorithm (Chen and Guestrin, 2016), which is a regularized gradient boosting algorithm. We perform a grid search on a wide array of hyperparameters combined with 5-fold cross-validation. This approach minimizes the risk of overfitting while ensuring the model's generalizability and validity.

[18] We deliberately exclude other variables, such as socioeconomic or political background, as potential predictors. Our primary objective is to develop a module that serves as a substitute for incentivized preference measures with relatively high accuracy, rather than to construct a predictive model that leverages all available data to forecast preference types or inequality aversion. In Section 6 we demonstrate a typical application of our approach. In regression analyses, we replace the preference measures with an index measure, while still controlling for socioeconomic and other explanatory variables.

4.1 Predicting Types

Our first primary objective is to develop a model that is capable of predicting whether an individual exhibits a preference type classified as *selfish*, *inequality averse*, or *altruistic*. This prediction relies on a comprehensive set of survey items designed to capture relevant dimensions of social attitudes. Specifically, we utilize survey items assessing *altruism*, *social comparison*, and *inequality aversion*, all of which were included in our survey. We also incorporate responses to the hypothetical version of the incentivized choice experiment. We construct a binary variable, `hypGeneralSelfish`, which indicates whether a participant selected a selfish strategy or not (see Appendix A.6 for details).

We proceed as follows. We split our data into a training set of 402 respondents (roughly 80% of the full sample) and a holdout test set of 100 observations (roughly 20%). As its name suggest, the training set is used for the training and tuning of the model. We make use of the holdout test set later, where we use it to assess the model's performance on data it has not seen before. To optimize the predictive performance of our model and make efficient use of our (training) data, we further employ a 5-fold cross-validation. In this procedure, the dataset (the 80% of the full sample) is partitioned into five approximately equal subsets, or "folds". The model is then iteratively trained on four folds (the training set of a fold) and tested on the remaining fold (the validation set of a fold). This process is repeated five times, with each fold serving as the validation set exactly once. Based on these five iterations, we compute performance metric as an average of the individual metrics. In the classification problem we study in this part, our performance metric is the *accuracy*, i.e., the proportion of correctly predicted type labels, and our objective is a softmax function.

We use this cross-validation procedure to tune the gradient boosting model's hyperparameters, i.e., parameters that specify the way the model learns from the data, using a grid search over a wide set of tuning parameters. Specifically, these parameters contain the number of trees, their depth, the learning rate, the minimum loss reduction, the fraction of features (variables), the minimum sum of weights, and the fraction of data used for the boosting. For each hyperparameter combination, we perform the 5-fold cross validation and compute the average accuracy. We then select the best set of parameters for our final model. This selection procedure minimizes the risk of overfitting and ensures a balanced evaluation of model performance. Importantly, it enhances the model's generalizability by enabling robust predictions on data it has not encountered during the training steps.

To assess our final model's performance, we make use of our holdout test set. Table 5 shows the confusion matrix for these out-of-training-set predictions. It compares the predicted type assignment with the actual (reference) type assignment we obtained *via* the clustering exercise. Note that we have exactly 100 respondents in this sample. Hence, the numbers can be directly interpreted as percentages.

With 57% of correctly predicted classifications, the accuracy of our model is relatively high. This accuracy represents a substantial and significant improvement over the no-information rate (NIR), which simply uses the largest preference type in the holdout set as the prediction (43%). A statistical test confirms the significance of this improvement. The p-value for comparisons of the accuracy with the NIR lies below 0.01, indicating

Table 5: Confusion matrix for holdout test set | Full model

Predicted	Actual	Type 1 Selfish	Type 2 Ineq. Av.	Type 3 Altruistic
Type 1	Selfish	27	4	5
Type 2	Ineq. Av.	9	14	8
Type 3	Altruistic	7	10	16

Note. The contingency table (or confusion matrix) reports on how many respondents were correctly or incorrectly assigned to one of the types in the holdout test set. Note that we have exactly 100 respondents in the holdout test set, such that the numbers can be interpreted as proportions. Perfect prediction would mean that all 100 respondents are located on the diagonal of the matrix.

strong evidence of the model's predictive capability. To evaluate misclassification patterns, we employ McNemar's test, which assesses whether significant differences exist between false assignments. The high p-value of 0.48 suggest that misclassification patterns are stable, further supporting the model's reliability. We complement our analysis by predictive value-based diagnostics. These diagnostics tell us how much predictions improve by type over the base rate prior. Table 6 presents the results. The information contained in the survey items yields a substantial gain in confidence for all three types, with the strongest diagnostic gain for predictions of Type 1 (Selfish). Diagnosticity ratios indicate that the improvement in confidence ranges from 61% (Altruistic) to 74% (Selfish). The model thus significantly improves confidence in predictions across all three types.

Table 6: Predictive value-based diagnostics | Full model

Type	Base Rate (Prior)	PPV (Posterior)	Gain	Ratio
Selfish	0.43	0.75	+0.32	1.74
Ineq. Av.	0.28	0.45	+0.17	1.61
Altruistic	0.29	0.48	+0.20	1.67

Note. The table compares model-based predictions (i.e., predictions with inclusion of all survey items) to prior expectations based on type prevalence (i.e., predictions without inclusion of survey items). *Base Rate (Prior)* refers to the proportion of the types in the population. *PPV (Posterior)* indicates the probability than an individual truly belongs to a type, conditional on the model predicting that type (i.e., the Positive Predictive Value). *Gain* in confidence is the absolute increase in probability from prior to posterior. Diagnosticity *Ratio* is the ratio of posterior to prior probability, capturing how much more confident the model allows us to be in its predictions compared to chance-level expectations. Overall, the model meaningfully improves classification confidence across all types, with gains ranging from 61% to 74% relative to base rates.

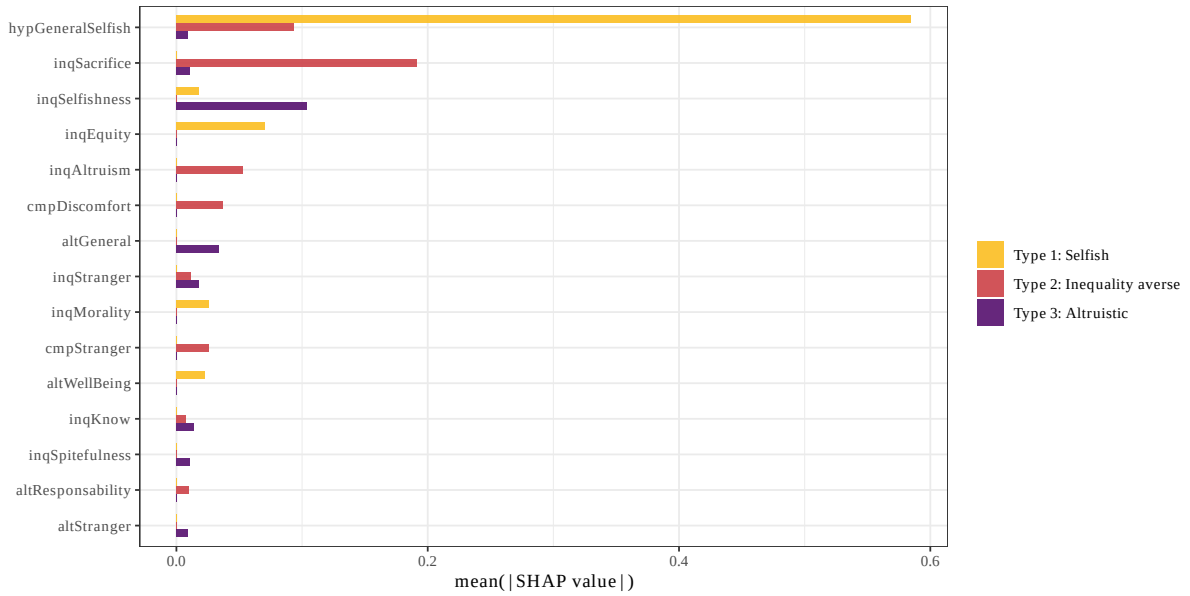
The model performs particularly well in distinguishing *selfish* individuals from *non-selfish* individuals, exhibiting high sensitivity, detection rates and precision for the *selfish* type (Type 1). This result aligns with expectations, as *selfishness* tends to correspond to more distinct and measurable patterns in survey responses. In contrast, differentiating *inequality averse* individuals from *altruistic* individuals presents greater challenges. This difficulty likely stems from the nuanced and overlapping characteristics of these preference types, which may be driven by similar underlying motivations and reflected in comparable survey response patterns.[19] To further investigate these challenges and

[19]Albeit far from perfect, the reduced model we propose later performs slightly better in this regard.

gain a deeper understanding of the importance and discriminatory ability of variables, we analyze SHAP values derived from the calibrated model. They quantify the contribution of each variable (feature) to the model's type predictions, providing both global and local interpretability. These values are particularly useful for identifying key predictors and understanding how individual survey items impact the classification of preference types—which is the main objective in this exercise.

As a reference, Figure 7 presents the mean absolute SHAP value for the three types.[20] This figure gives a quick indication on the importance of different variables (features) in predicting assignment to the different types, with higher mean absolute SHAP values indicating higher importance (predictive ability). If the ordering of the values is unbalanced across types, this suggests that a variable has discriminatory power to separate between preference types. This is of particular relevance to disentangle the two (harder to distinguish) non-selfish types (Type 2 and 3).

Figure 7: Mean absolute SHAP values by type



Note. The figure lists the top 15 predictors ranked by their importance computed from mean absolute SHAP values. The variables (features) work differently well in predicting type assignment. For instance, `hypGeneralSelfish` is highly predictive for Type 1 (selfish), and to some extent for Type 2 (inequality averse). However, it has little to contribute for identifying Type 3 (altruistic). `inqSacrifice` and `inqSelfishness`, on the other hand, perform comparatively well in predicting Type 2 (inequality averse) and Type 3 (altruistic), respectively. The full wording of all items can be found in Appendix A.1.

The figure provides key insights into how individual variables contribute to type assignment in our model. Notably, the strategy variable `hypGeneralSelfish` stands out as one of the top predictors. This variable plays a crucial role in distinguishing between the selfish and the inequality averse type. In particular, endorsing a selfish strategy sig-

Also, the models predicting inequality aversion parameters provide further insights on domain heterogeneity, and, thus, variation of altruism across individuals.

[20] We show the SHAP values for each of the three preference types as computed from the full dataset in Figure 15 (Appendix A.7).

nificantly increases the probability of being classified as the selfish type (Type 1), while simultaneously reducing the likelihood of being categorized as the inequality-averse type (Type 2). Although its predictive power for the altruistic type (Type 3) is less pronounced compared to the other two types, it still exhibits clear, albeit relatively weak, discriminatory power (it is the 7th most important predictor for this type only). These findings are consistent with intuitive expectations. Analyzing the mean response patterns of the altruistic type (see Figure 4) reveals that altruistic individuals demonstrate cost-sensitive giving when they are ahead of others, while their behavior aligns more closely with selfishness when they are behind others.[21]

Survey variables capturing respondents' willingness to distribute money between themselves and another person across various scenarios (the tailored items) also rank prominently among the top predictors. These variables, while to some extent related to the hypothetical question, provide more detailed insights due to their framing and use of an 11-point Likert scale (see, for example, `inqSelfishness`, `inqSacrifice`, and `inqEquity`). Interestingly, responses to the general altruism item (`altGeneral`) stands out for its contribution to distinguishing altruists (Type 3) from non-altruists (Type 1 and 2). This suggests that certain survey items capture essential behavioral nuances specific to altruistic tendencies, reinforcing the value of these variables in enhancing the model's classification accuracy.

Despite the strong predictive performance of the aforementioned variables, a considerable subset of the survey items contributes minimally to the model's predictive ability. These low-impact variables can be identified and excluded from the model without compromising much of its predictive power. We discuss this point in more detail in Section 5.

4.2 Predicting the Degree of Inequality Aversion

In this section, we extend our analysis by studying the prediction of inequality aversion parameters α_i (behindness aversion) and β_i (aheadness aversion) as conceptualized in Fehr and Schmidt (1999). These parameters are estimated for each respondent in our dataset. Our objective is to explore the extent to which variation in these parameters can be explained by the comprehensive set of survey items included in our study. Specifically, we aim to identify survey items that are most predictive of higher values in the sample distributions of α_i and β_i.

This regression-based analysis represents a more complex task compared to the classification problem explored earlier. Here, the goal is not to precisely predict the numerical values of the inequality aversion parameters but rather to determine whether variation in these parameter values can be systematically predicted using the available survey data. Additionally, we aim to evaluate whether predictability differs across domains, as different variables may have bite in predicting people's dislike of being behind (α_i) or being ahead (β_i). As previously observed, the distribution of α_i is more concentrated compared to that of β_i, indicating less heterogeneity in behindness aversion (see Figure 5). This reduced variability likely makes it more challenging to explain differences in α_i,

[21] As a matter of fact, it is thus harder to distinguish between the two social preference types using survey information alone.

whereas the greater heterogeneity observed in β_i should facilitate better predictability in the domain of aheadness aversion. Using the same methodological framework as in the classification analysis—a 5-fold cross-validation jointly with a grid search for the hyperparameter tuning—we train a separate model for each inequality aversion parameter. As these are regression models, our objective function has to be adopted to a squared error. Moreover, we use the root mean square error as our metric for choosing the best set of hyperparameters. To evaluate our models, we again assess their performance in predicting outside of the training sample, i.e., in the holdout test set. Table 7 describes the results of the model performance.

Table 7: Model performance in the holdout test set using different metrics | Full models

Model	RMSE	R^2	MAE	ρ (p-value)
α_i (behindness aversion)	0.646	7.77%	0.501	0.242 (0.015)
β_i (aheadness aversion)	0.866	22.67%	0.661	0.511 (≈ 0)

Note. The table reports several metrics on the performance of the regression models when predicting the inequality aversion parameters in the holdout test set. RMSE is the root mean square error. The coefficient of determination R^2 has the usual interpretation. It states how much of the total variance is explained by the model. MAE is the mean absolute error. The last column lists the Spearman rank correlation coefficients (ρ) and the p-values of the corresponding test on the association between predicted *vs.* observed parameter values. What is striking is the better performance of the model aimed at predicting aheadness aversion (β_i) as opposed to the model aimed at predicting behindness aversion (α_i).

In line with our expectation, the performance of the model differs substantially between the two inequality aversion domains. The model aimed at predicting β_i (aheadness aversion) performs substantially better than the model aimed at predicting α_i (behindness aversion). The proportion of the variation in β_i that is predicable from the variables (22.67%) is considerably higher than the proportion of the variation in α_i (7.77%). However, we see a significant association between the ranks of predicted inequality aversion parameters and those we observe in our data. This is the case for both models (domains), albeit the association is arguably stronger for β_i than for α_i.

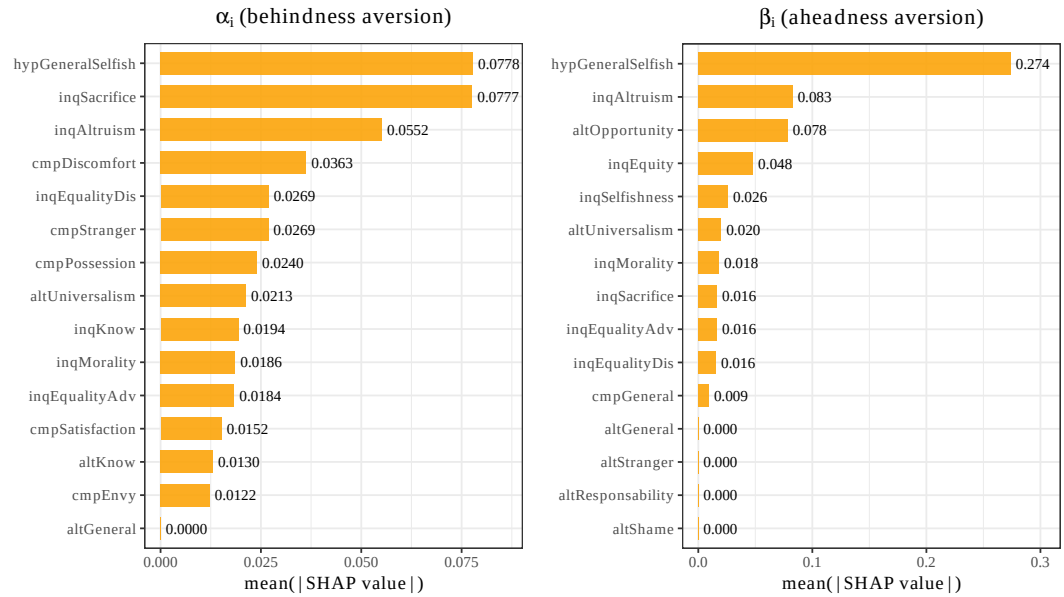
As a reference, we provide the figures listing the mean absolute SHAP values for the top predictors in the models.[22] Figure 8 shows that the hypothetical question `hypGeneralSelfish` stands out in the aheadness aversion model. The remaining predictors have mean absolute SHAP values that are in the ballpark of those in the behindness aversion model, however. Only 14 variables feature positive mean contributions for α_i, and 11 for β_i.

5 The *"Hearts-and-Minds"* Module

Using the importance rankings of the predictors identified in the previous sections, we can now select a concise set of survey items that, when appropriately weighted, provide reasonably good quality predictions for type assignment and individual heterogeneity in inequality aversion. We do this with the objective to identify a set of items that suits well

[22] To interpret the contributions of individual variables to the models, we examine the SHAP values computed from the full dataset in Figure 16 (Appendix A.7), which reveals that similar variables are among the top predictors for both α_i and β_i.

Figure 8: Mean absolute SHAP values by inequality aversion parameter



Note. The two panels list the top predictors, ranked by their importance based on mean absolute SHAP values, computed separately for the two-parameter regression models. `hypGeneralSelfish` is the best predictor in both models. However, in terms of quantitative contribution it does much better in the β_i (aheadness aversion) model. This variable is followed by some key variables we already identified in the classification exercise (in particular, `inqAltruism` and `inqSacrifice`). The full wording of all items is provided in Appendix A.1.

to identify both type *and* parameter heterogeneity. To maintain brevity and focus, we select the top two predictors (features with the highest SHAP values) from each of the three models with outcome variables *type assignment*, *aheadness aversion*, and *behindness aversion*. For the classification model, we include the two top predictors across all three preference types. This approach results in a total of six survey items, which, we argue, strike an effective balance between brevity and predictive validity. These six items take less than two minutes to administer, making the module practical for integration into larger surveys or field studies.

Table 8 presents the full set of six survey items that constitutes the *"Hearts-and-Minds"* module. All items have high feature importance (in terms of SHAP values) in our original models and/or they provide good discriminatory power between preference types or parameters.

From the response to `hypGeneral`, we construct an indicator variable for selfishness. This indicator variable, `hypGeneralSelfish`, is 1 if the respondent chose one of the selfish categories, i.e. *"keep everything for myself"* or *"take a larger portion for myself and leave a smaller portion for the other"*, and 0 otherwise. The `hypGeneralSelfish` item acts as a clear indicator of selfish behavior, functioning as a dummy variable that strongly associates with Type 1 (selfish) and decreases the likelihood of being classified as Type 2 (inequality averse) or Type 3 (altruistic). Similarly, this variable effectively predicts low values of both behindness and aheadness aversion parameters. The `inqSelfishness` and `inqAltruism` items are identical in terms of consequences but are framed differently.

Table 8: The *"Hearts-and-Minds"* 6-item survey module

Item	Description
`hypGeneral`	Imagine you are in a situation where you have to distribute money between yourself and an anonymous person. Neither of you will see or interact with the other. You have absolutely no information about the other person's circumstances (such as his/her wealth). The only thing you know is that nobody, except you and the other person, will ever know your choice. What would you do? I would...
`inqSacrifice`	I would be willing to sacrifice a large part of my income to slightly reduce that of those less well off than me.
`inqSelfishness`	If I have the choice to distribute resources with strangers, I would rather keep more for myself and give less to others.
`inqEquity`	I would prioritize equity over maximizing my own benefits if I were in a situation where I had to distribute resources with others.
`inqAltruism`	If I have the choice to distribute resources with strangers, I would rather give more to others and keep less for myself.
`altGeneral`	Are you generally willing to share with others without expecting something in return, or are you not willing to do so?

Note. For the `hypGeneral` item the answer categories are: (i) *"keep everything for myself"*, (ii) *"take a larger portion for myself and leave a smaller portion for the other"*, (iii) *"make an approximately equal distribution between myself and the other person"*, (iv) *"take a smaller portion for myself and leave a larger portion to the other person"*, (v) *"give everything to the other person"*, (vi) *"do something else (see below)"*. A single option must be selected. The last option of the hypothetical question is followed by an open text field. The `hypGeneralSelfish` variable we use is a dummy variable, which is 1 if option (i) or (ii) was selected and 0 otherwise. The 11-point Likert scales are as follows. For the tailored items: *"0: does not describe me at all"* to *"10: describes me perfectly."* Note that we intentionally reverse-coded `inqSelfishness` to check participants' consistency in responses. For the `altGeneral` item: *"0: completely unwilling to do so"* to *"10: very willing to do so."*

While `inqSelfishness` adopts a rather self-interested approach, focusing on personal endowment *("keep more to myself")*, `inqAltruism` emphasizes the other *("give more to others")*. This dual framing—focusing on "keeping" *versus* "giving"—ensures that the module does not overlook individuals who may express different preferences depending on how the situation is framed.[23]

`inqSacrifice` encapsulate the willingness to sacrifice one's income to reduce inequality, but in a peculiar way. This item stands at the opposite of Pareto-efficiency or maximization, capturing whether one would prefer to reduce the income of both parts but in difference proportion—large for *self*, small for *other*—out of, e.g., solidarity. For real-world cases where individuals have political opinions about whether they should "sacrifice" themselves for the community or not to reduce inequalities, this item can be particularly useful.

A notable remark is that, while we aim to test the predictive ability of three different categories of survey items—*altruism*, *comparison*, and *inequality aversion*—some

[23]This duality addresses a known issue in decision making under framing (Tversky and Kahneman, 1981), allowing participants to more clearly articulate a "reflective" preference when they are aware of both frames (Lecouteux and Mitrouchev, 2024).

inequality aversion items, in particular `inqSelfishness` and `inqAltruism`, are difficult to dissociate from altruism items. In theory, the concepts of inequality aversion and altruism are distinct, where all cases are possible (inequality averse and altruistic, inequality averse and selfish, inequality seeking and altruistic, inequality seeking and selfish). Yet, in practice, both concepts appear to be intimately linked, as an inequality-averse person is more likely to exhibit moderate altruism, aiming for an equal split between oneself and the other person.[24]

`inqEquity` prompts respondents to consider how they balance their own personal benefits with a concern for fairness and equality when allocating resources. This item captures the underlying tension that individuals might feel between self-interest and the desire to ensure equal opportunities or outcomes for others. By addressing this cognitive *trade-off*, the item helps to gauge whether individuals prioritize social equity over their personal advantage in decision-making scenarios. As for `altGeneral`, it is Falk et al. (2018, 2023)'s simple item, which performs well in their GPS module. They find a coefficient weight resulting from their OLS regressions of 0.635 (Falk et al., 2018) and 0.321 (Falk et al., 2023), although with a different social preference elicitation than ours (charity donation in their case). Note also that we modified their phrasing to better fit with one's general (i.e., a-contextual) tendency to give.[25] This item particularly captures altruism in a disinterested sense *("without expecting something in return")*, aligning with the common understanding of *pure* altruism.

Note that none of the `comparison` items are retained in our final survey module due to their poor predictive ability. This contrasts with our prior intuitions, as α and β parameters are inherently dependent on a *comparison* between one's payoff and that of the other person. This relationship is notably emphasized in Fehr and Schmidt (1999). In their words: "fairness judgments are inevitably based on a kind of neutral reference outcome" (p. 820).[26]

In summary, our module is constituted by one hypothetical item (`hypGeneral`), one trade-off item (`inqEquity`), one simple and powerful item (`altGeneral`) that has already proven effective in prior studies (Falk et al., 2018, 2023), two "dual framing" items (`inqSelfishness` and `inqAltruism`), and one additional item that explores attitudes against social welfare maximization (`inqSacrifice`). We can categorize these items in terms of their specific domain: `hypGeneral`, `inqSelfishness`, and `inqAltruism` are primarily related to altruism, while `inqSacrifice`, `inqEquity`, and `inqSacrifice` are more closely associated with inequality aversion. However, it is essential to empha-

[24] Several interpretations can be made regarding the different possible sources of inequality aversion and altruism. One possibility is that, on the one hand, inequality aversion may reflect political ideologies—e.g., left-oriented individuals emphasizing egalitarian and collective values, while right-oriented individuals prioritize individual values such as meritocracy and freedom. On the other hand, altruism appears to be more of a moral concept shaped by religion and education—focusing on interpersonal rather than social considerations. For example, a Republican might be strongly inequality-seeking due to libertarian political beliefs while simultaneously being highly altruistic due to Christian values. Understanding the psychological factors that could separate inequality aversion and altruism would be valuable, but goes beyond the present study.

[25] The original phrasing in Falk et al. (2023) is: *"How willing are you to give to good causes without expecting anything in return?"*.

[26] The reference point in the social domain could be elicited in further research, if not already undertaken. See Baillon et al. (2019) for an attempt to elicit the reference point in the risk domain.

size that none of these items are exclusively about either altruism or inequality aversion. Rather, they exist on a spectrum where some items lean more toward altruism and others toward inequality aversion. This categorization reveals a notable symmetry within our module: three items capture altruism, and three items capture inequality aversion.

Based on our proposed module, we now train and fine-tune three *reduced* models: one with the aim to predicting preference types, and two with the aim to predicting aheadness and behindness aversion, respectively. We again train these models on our testing dataset to ensure robust performance, and then document these reduced models' ability to predict types and parameters within the holdout test set. Table 9 illustrates that the reduced model is performing slightly better than the full model (see the confusion matrix in Table 5). Thus, reducing the item set from 34 to 6 does not compromise our model's predictive accuracy.

Table 9: Confusion matrix for holdout test set | Reduced model

Actual / Predicted	Type 1	Type 2	Type 3
Type 1	31	4	5
Type 2	3	15	10
Type 3	9	9	14

Note. The contingency table (confusion matrix) reports on how many respondents were correctly or incorrectly assigned to one of the types. Note that we have exactly 100 respondents in the holdout test set, such that the numbers can be interpreted as proportions of correct/incorrect predictions per bin.

The accuracy of the reduced model is with 60% about 3 percentage points higher than in the full model. Again, this is substantially and significantly higher than the no-information rate (NIR) of 43%. With 0.72, the p-value of a McNemar's test is far beyond any level of significance. Furthermore, Table 10 shows substantial improvements in confidence across all three types. The diagnosticity ratios indicate gains between 51% (Altruistic) to 91% (Inequality Averse) relative to base rates. Moreover, the model has discriminatory power between Type 2 (Inequality Averse) and Type 3 (Altruistic), albeit its ability to distinguish these types is—not surprisingly—imperfect. We conclude that—even with our relatively compact survey module—we are able to predict preference types with an accuracy far beyond chance and at a much improved level of confidence.

Examining the inequality aversion parameters, the reduced model benefits from its smaller set of predictors, potentially mitigating some overfitting challenge we faced in the full model. It demonstrates superior generalizability and portability in predicting considerably better in the holdout test set. Table 11 reports the different metrics.

The coefficients of determination (R^2) are better for both reduced models as compared to their full model counterparts. Most strikingly, however, the behindness aversion model features a substantially better ability in predicting out of sample, indicated by an enhanced R^2 and higher rank correlations (coefficients of 0.403 and 0.591, respectively, and p-values of ≈ 0). Importantly, the correlation between our survey-based scores and estimated preference lies above what is typically found in the literature. See for instance Chapman et al. (2025), who employ questions from the Falk et al. (2023) GPS module.

Table 10: Predictive value-based diagnostics | Reduced model

Type	Base Rate (Prior)	PPV (Posterior)	Gain	Ratio
Selfish	0.43	0.78	+0.34	1.80
Ineq. Av.	0.28	0.54	+0.26	1.91
Altruistic	0.29	0.44	+0.15	1.51

Note. The table compares model-based predictions (i.e., predictions with inclusion of the *"Heart-and-Minds"* survey module items) to prior expectations based on class prevalence (i.e., predictions without inclusion of survey items). *Base Rate (Prior)* refers to the proportion of each type in the data. *PPV (Posterior)* indicates the probability than an individual truly belongs to a type, conditional on the model predicting that type (i.e., the Positive Predictive Value). *Gain* in confidence is the absolute increase in probability from prior to posterior. Diagnosticity *Ratio* is the ratio of posterior to prior probability, capturing how much more confident the model allows us to be in its predictions compared to chance-level expectations. Overall, the model meaningfully improves classification confidence across all types, with gains ranging from 51% to 91% relative to base rates.

Table 11: Model performance in the holdout test set using different metrics | Reduced models

Model	RMSE	R^2	MAE	ρ (p-value)
α_i (behindness aversion)	0.621	18.54%	0.496	0.403 (≈ 0.000)
β_i (aheadness aversion)	0.835	30.10%	0.641	0.591 (≈ 0.000)

Note. The table reports several metrics on the performance of the regression models when predicting the inequality aversion parameters in the holdout test set. RMSE is the root mean square error. The coefficient of determination R^2 has the usual interpretation. It states how much of the total variance is explained by the model. MAE is the mean absolute error. The last column lists the Spearman rank correlation coefficients (ρ) and the p-values of the corresponding test on the association between predicted *vs.* observed parameter values. For the reduced models, the model aimed at predicting aheadness aversion (β_i) only performs similarly well as than the model aimed at predicting behindness aversion (α_i).

We hypothesize that this may stem from our more sophisticated scoring procedure and the richer set of survey items we include in our module.

Our reduced models thus perform well in predicting both preference types and differences in inequality aversion, even though they are based on a relatively concise survey module with only six items. Practitioners who incorporate our module in their survey can use the boosting weights of our three models to obtain predictions. Instructions on how to load the model and predict types and individual heterogeneity is available here: `https://gitlab.com/thomasepper/repl-MEL-surveyModule`.[27]

In some applications, researchers may be interested in only one objective: either uncovering *type heterogeneity* or identifying *heterogeneity in inequality aversion parameters*.[28] In such cases, a reduced set of module items may suffice, keeping the module even more concise. While the importance rankings show considerable overlap (see Figure 7 and 8, items `hypGeneralSelfish` and `inqSacrifice`), some items are more effective at distinguishing between types, whereas others better capture variation in aheadness and behindness aversion. Specifically, `inqEquity`, `inqSelfishness`, and `altGeneral` are among the strongest predictors for being classified as a selfish or altruistic type. How-

[27]Note that the predictive performance of our models may be further improved by retraining the model on more diverse data sets that include our survey module and real-incentivized preference elicitation tasks.

[28]The same reasoning applies if a researcher is interested in a single domain (ahead or behind) only.

ever, these items do not rank among the top predictors in the aheadness and behindness aversion models. Instead, `inqAltruism` emerges as a key contributor to heterogeneity in aheadness aversion. Depending on the objective, items may be chosen based on their feature importance (see the mean absolute SHAP values in Figures 7 and 8).

6 External Validity

We eventually examine the predictive power of our scores in relation to both stated actual and hypothetical behaviors that are expected to be associated with inequality aversion and altruism. To this end, we present the results of a selected set of regressions. Additional details, including the bivariate associations between these variables and our preference measures, as well as results from a series of supplementary regressions, are provided in Appendix B.4.

To assess the explanatory and predictive capabilities of our module scores for behavior, we first compute these scores across the full dataset. Subsequently, we regress the stated behavioral variables on the scores and, for reference, on the estimated aheadness and behindness aversion parameters from the incentivized preference elicitation task. Our analysis focuses on four key behavioral variables: (i) support for redistributive policies, (ii) engagement in volunteering, (iii) hours spent volunteering, and (iv) willingness to donate to charity following a windfall. Motivated by Fehr et al. (2024), we begin by examining support for redistributive policies. Similar regression analyses have been conducted by Epper et al. (2024), who investigated the relationship between inequality aversion parameters—estimated from an incentivized preference elicitation task—and support for public policies and charitable giving. Their study also incorporates a comparable set of control variables to assess the robustness of their findings. However, it is important to note that differences in their outcome scale and control variable specifications limit direct comparability of coefficients between their results and ours.

Table 12 presents the key regression results for our policy support variable, `policy`. It is measured on an 11-point Likert scale, where higher values indicate greater support for redistribution (for the exact wording of the question, see Appendix A.3). The table reports results for four models. Model (1) and Model (1c) use the individual behindness aversion (α_i) and aheadness aversion (β_i) parameters estimated from the incentivized preference elicitation task, without and with the inclusion of a comprehensive set of control variables, respectively. Model (2) and Model (2c) follow the same structure but replace the estimated parameters with scores derived from our survey module. In all models, we use percentile ranks of the preference parameters as regressors. The control variables include indicators for income class, education level, age, gender, immigration status, marital status, and the presence of children living in the household. Specifically, marital status is captured using dummies for being married, divorced, separated, or widowed. The intercept represents the baseline support for redistribution for an 18-year-old, non-immigrant male with median income, a high school degree, no marital history (neither married, divorced, separated, nor widowed), and no children living in the household.

The regression results reveal a significant positive association between aheadness

Table 12: Regression Results for Redistributive Policies Support (`policy`)

Variable	(1) estimated	(1c) estimated	(2) score	(2c) score
behindness av.	-0.293 (0.667)	-0.06 (0.672)	-0.084 (0.759)	0.014 (0.784)
aheadness av.	1.52 (0.667)**	1.214 (0.669)*	2.324 (0.735)***	2.029 (0.762)***
Intercept	6.237 (0.292)***	7.823 (0.731)***	5.794 (0.274)***	7.372 (0.735)***
Controls	no	yes	no	yes
R^2	0.015	0.117	0.048	0.141

Note. The response variable is measured on an 11-point Likert scale ranging from 0 to 10, with 10 indicating the highest support. Model (1) and (1c) use the inequality aversion parameters *estimated* from the incentivized preference elicitation task without and with controls, respectively. Model (2) and (2c) substitute the inequality aversion parameters with our survey module-based *scores*. The controls include age, immigrant status, income class, highest degree of education, civil status and a dummy for children in the household. The intercept (baseline level) refers to an 18 year old, non-immigrant male with median income and a high school degree who is neither married, nor divorced, separated or widowed, and has no dependent children. p-values: $0 \leq^{***} < 0.01 \leq^{**} < 0.05 \leq^{*} < 0.1$.

aversion (as reflected by β_i and the related survey module-based score) and support for redistributive policies. The coefficients remain relatively robust when the full set of control variables is included. Notably, the relationship between preferences and policy support is moderately stronger when using the survey module based scores compared to the estimated parameters. This is possibly due to lower measurement error in the survey-based scores, or because the scores more directly capture self-reported normative attitudes.[29] This suggests that while both behavioral and attitudinal measures are informative, self-assessed fairness concerns may be more salient predictors of redistributive preferences in a policy context. Epper et al. (2024) report similar findings regarding aheadness aversion. However, their analysis also identifies a significant association between behindness aversion and policy support, a relationship we do not observe in our data. Given the use of similar elicitation methods and the same estimation protocol in both studies, this discrepancy is likely attributable to difference in sample characteristics (U.S. representative *vs.* Danish representative sample).[30]

To further assess the external validity of our survey module-based scores, we analyze a set of survey questions proposed by Falk et al. (2023), in which respondents report their volunteering activities. Table 13 presents the results from a linear probability model where a binary variable indicating volunteering is regressed on the preference parameters, both without and with the inclusion of control variables.

All regressions reveal a positive and significant association between behindness aversion and volunteering, with slightly stronger effects observed for the survey module-

[29] It is noteworthy that all choice situations in the incentivized elicitation task were presented within a uniform context. By contrast, our survey module may be regarded as richer due to its more diverse set of questions. There are various possible strategies for improving the external validity of incentivized preference measures. One involves exploiting variation within the choice set to account for measurement error. Another entails enriching the task by systematically varying contextual parameters, such as whether the recipient is (*ex-ante*) poorer or richer. However, to preserve comparability with earlier studies, we deliberately chose not to implement such modifications.

[30] We also observe the expected ordering of support for redistribution across the three preference types discussed earlier, with individuals assigned to the selfish type showing less support compared to those with social preferences. However, this difference is not statistically significant in our data.

Table 13: Regression Results for Volunteering (`member`)

Variable	(1) estimated	(1c) estimated	(2) score	(2c) score
behindness av.	0.257 (0.096)***	0.209 (0.095)**	0.355 (0.109)***	0.259 (0.111)**
aheadness av.	-0.058 (0.096)	-0.015 (0.095)	-0.008 (0.106)	0.057 (0.108)
Intercept	0.175 (0.042)***	0.22 (0.103)**	0.101 (0.04)**	0.132 (0.104)
Controls	no	yes	no	yes
R^2	0.02	0.159	0.051	0.180

Note. The response variable is binary. The reported results are for a linear probability model. Model (1) and (1c) use the inequality aversion parameters *estimated* from the incentivized preference elicitation task without and with controls, respectively. Model (2) and (2c) substitute the inequality aversion parameters with our survey module-based *scores*. The controls include age, immigrant status, income class, highest degree of education, civil status and a dummy for children in the household. The intercept (baseline level) refers to an 18 year old, non-immigrant male with median income and a high school degree who is neither married, nor divorced, separated or widowed, and has no dependent children. p-values: $0 \leq^{***} < 0.01 \leq^{**} < 0.05 \leq^{*} < 0.1$.

based score. This finding aligns with the intuitive notion that individuals who are more concerned about being left behind are more motivated to engage in volunteering activities.

In Table 14 we analyze the intensive margin of volunteering, focusing on the number of hours spent in volunteering activities per month. The results indicate a positive (though less statistically significant) association between behindness aversion and time investment in volunteering. This is consistent with our expectations. Notably, our survey module-based score demonstrates a stronger ability to detect this relationship compared to the parameters estimated from the incentivized preference elicitation task. The reason for this may be the apparent contextual mismatch. The incentivized elicitation task involves a sequence of single-context money allocation decisions, whereas the target behavior concerns time investment in a real-world activity.

Table 14: Regression Results for Hours Spent in Volunteering (`hours`)

Variable	(1) estimated	(1c) estimated	(2) score	(2c) score
behindness av.	4.309 (2.743)	5.284 (2.831)*	6.472 (3.153)**	6.886 (3.338)**
aheadness av.	-2.524 (2.743)	-3.057 (2.82)	-0.802 (3.055)	-1.663 (3.243)
Intercept	2.801 (1.199)**	11.009 (3.081)***	0.838 (1.139)	8.936 (3.126)***
Controls	no	yes	no	yes
R^2	0.005	0.073	0.018	0.081

Note. The response variable are hours per month spent in volunteering activities. Model (1) and (1c) use the inequality aversion parameters *estimated* from the incentivized preference elicitation task without and with controls, respectively. Model (2) and (2c) substitute the inequality aversion parameters with our survey module-based *scores*. The controls include age, immigrant status, income class, highest degree of education, civil status and a dummy for children in the household. The intercept (baseline level) refers to an 18 year old, non-immigrant male with median income and a high school degree who is neither married, nor divorced, separated or widowed, and has no dependent children. p-values: $0 \leq^{***} < 0.01 \leq^{**} < 0.05 \leq^{*} < 0.1$.

Finally, we present the results for the hypothetical donation question proposed by

Falk et al. (2023). In this scenario, respondents were asked to imagine winning $1,000 in a lottery and to decide whether (and how much) they would donate to charity. Table 15 reports the results for the extensive margin, focusing on whether respondents would choose to donate. Further analysis on the intensive margin, examining the amount they would donate, are deferred to Appendix B.4.

Table 15: Regression Results for Participation in Giving after Lottery Win (`hypLottery`)

Variable	(1) estimated	(1c) estimated	(2) score	(2c) score
behindness av.	0.129 (0.108)	0.061 (0.109)	0.234 (0.12)*	0.217 (0.124)*
aheadness av.	0.119 (0.108)	0.188 (0.109)*	0.293 (0.116)**	0.33 (0.12)***
Intercept	0.402 (0.047)***	0.166 (0.119)	0.27 (0.043)***	0.008 (0.116)
Controls	no	yes	no	yes
R^2	0.018	0.113	0.087	0.182

Note. The response variable is binary. The reported results are for a linear probability model. Model (1) and (1c) use the inequality aversion parameters *estimated* from the incentivized preference elicitation task without and with controls, respectively. Model (2) and (2c) substitute the inequality aversion parameters with our survey module-based *scores*. The controls include age, immigrant status, income class, highest degree of education, civil status and a dummy for children in the household. The intercept (baseline level) refers to an 18 year old, non-immigrant male with median income and a high school degree who is neither married, nor divorced, separated or widowed, and has no dependent children. p-values: $0 \leq^{***} < 0.01 \leq^{**} < 0.05 \leq^{*} < 0.1$.

We would expect that, upon receiving a (hypothetical) windfall, individuals perceive themselves to be in the ahead domain, and consequently become more willing to give. This expectation is confirmed by the regressions that use our survey-based score as a predictor variable. In contrast, we do not observe a similarly strong relationship between estimated preferences and giving behavior. One possible explanation lies in the design of the incentivized elicitation task. Unlike typical dictator games, respondents were not endowed with an initial amount but instead faced a full menu of choices from the outset. A detailed examination of this discrepancy is beyond the scope of the present study and is left for future research.

Overall, our findings highlight the external validity of the survey module-based scores across multiple domains. Appendix B.4 provides further evidence by reporting bivariate associations between our preference measures and the survey responses, along with analyses of additional survey questions to extend the robustness of our conclusions.

7 Conclusion

This study introduces a novel survey module designed to measure inequality aversion and altruism, with an emphasis on simplicity, scalability, and broad applicability. By leveraging data from a representative U.S. population sample, we demonstrate our survey module's capacity to capture behavioral variation in incentivized experiments while maintaining practicality for use in diverse settings. The *"Hearts-and-Minds"* module is specifically crafted for use across a wide range of contexts, from controlled laboratory studies to large-scale population surveys, particularly when resources are limited or rapid

assessment is needed. The six survey items can be administered in approximately two minutes, imposing minimal burden on respondents and enabling efficient large-scale deployment. The module provides reliable and externally valid measures of inequality aversion and altruism, offering a practical tool for examining responses to unequal resource distributions in various economic and social environments. Through a data-driven item-selection process grounded in machine learning, the module remains both parsimonious and predictive. This approach enables researchers to study inequality aversion and altruism effectively in diverse contexts without the costs and logistical challenges of incentivized experiments. Notably, the module's performance on new data—as tested on a holdout set—confirms strong applicability and predictive value. Our external validation exercises further show that the module-based scores correspond meaningfully to real-world social behavior.

The module may support various applications, including the study of pro-environmental behavior. For example, inequality-averse and altruistic individuals—motivated by empathic concern—may be more inclined to adopt conservation practices and sustainable lifestyles (Tam, 2013). Social signaling may also play a role, as some individuals engage in environmentally friendly behavior to convey status (Griskevicius et al., 2010). Applying our framework to such domains can enhance understanding of how social preferences influence sustainable decision-making and policy support, thereby informing strategies to promote environmental responsibility. Our findings underscore the module's broader potential to capture real-world social behaviors, namely attitudes toward inequality and altruistic actions. The transparency of our methodology enhances its adaptability to specific research aims, making it a flexible tool for future studies. However, since validation to date has focused on a U.S. population sample, further testing across countries, cultures, and socioeconomic groups is essential. Such work is key to strengthening the generalizability of our approach and the robustness of the item selection process. Expanding data collection to include more diverse populations will also provide a foundation for model refinement. In particular, we aim to build a comprehensive database that future versions of the module can leverage to better capture heterogeneity and reflect cultural variation. As part of this effort, identifying survey items that are especially well-suited to specific cultural settings will be important for enhancing the module's relevance and applicability.

Future research should therefore prioritize cross-cultural validation and iterative refinement of the module. Additionally, integrating other social preferences to the module, such as trust and reciprocity, could yield a richer understanding of the drivers of social behavior. In doing so, we aim to support deeper insights into social preferences and their implications for economic behavior and policy. This work lays the groundwork for accessible and broadly applicable tools to measure inequality aversion and altruism.

A Appendix

A.1 Survey Items

Table 16: Altruism items

Item	Description
altGeneral	Are you generally willing to share with others without expecting something in return, or are you not willing to do so?
altStranger	Are you generally willing to share with strangers, or are you not willing to do so?
altResponsability	I feel personally responsible for helping others when I am in a position to do so.
altShame	I would feel uncomfortable keeping all available resources for myself while others have less.
altWellBeing	I value the well-being of others more than maximizing my own personal benefit.
altGoodness	I would rather give to others than see them go without, even if it means I have less.
altMorality	I believe that sharing with others, even when not required, is the right thing to do.
altUniversalism	When I have the chance to give, I do so willingly, regardless of who benefits.
altSatisfaction	I feel fulfilled when I can give something to others, even if it costs me personally.
altKnow	I am willing to share what I have with others, whether I know them well or not.
altOpportunity	If I had the opportunity to help someone financially, I would, even if it is a complete stranger.

Note. The scale is as follows. For altGeneral item: *"0: completely unwilling to do so"* to *"10: very willing to do so."* For altStranger item: *"0: completely unwilling to share with strangers"* to *"10: very willing to share with strangers."* For tailored items: *"0: does not describe me at all"* to *"10: describes me perfectly."* The items altGeneral and altStranger are adapted from Falk et al. (2023) and have been rephrased in what we believe to be a simpler and more accessible form.

Table 17: Comparison items

Item	Description
cmpGeneral	Do you generally compare what you have with others or not?
cmpStranger	Do you generally compare what you have with strangers or not?
cmpPossession	Overall, I am affected by what others have compared to what I have.
cmpInjusticeDis	Overall, I feel a sense of injustice when others have more than I do.
cmpInjusticeAdv	I feel a sense of injustice when some people have significantly less than what I have.
cmpIndifference	Whether others have more or less than I do is irrelevant to me.
cmpIndifferenceAdv	It does not affect me if I am better off than someone else.
cmpUnease	Overall, I am uneasy when I am better off than others.
cmpSatisfaction	In a situation where wealth is redistributed, I am satisfied as long as I get something, even if someone else gets much more.
cmpSuperiority	I particularly enjoy situations where I am better off than others.
cmpEnvy	When I see someone enjoying more resources, I feel a desire to have the same.
cmpDiscomfort	I would feel uncomfortable if I perceive advantages or privileges that are not perceived by others.

Note. The scale is as follows. For cmpGeneral item: *"0: I absolutely do not compare what I have with others"* to *"10: I absolutely compare what I have with others."* For cmpStranger item: *"0: I absolutely do not compare what I have with strangers"* to *"10: I absolutely compare what I have with strangers."* For tailored items: *"0: does not describe me at all"* to *"10: describes me perfectly."*

Table 18: Inequality aversion items

Item	Description
inqGeneral	Are you generally willing to redistribute resources with others to reduce inequality, or are you not inclined to do so?
inqStranger	Are you generally willing to redistribute resources with strangers to reduce inequality, or are you not inclined to do so?
inqKnow	I believe it's important to share equally with others, even if I don't know them personally.
inqEqualityDis	In situations where others would earn more than me for the same effort, I would be willing to set an income limit for everyone.
inqEqualityAdv	In situations where I would earn more than others for the same effort, I would feel the need to limit my income at a certain point, even if I could earn more.
inqEquity	I would prioritize equity over maximizing my own benefits if I were in a situation where I had to distribute resources with others.
inqSelfishness	If I have the choice to distribute resources with strangers, I would rather keep more for myself and give less to others.
inqAltruism	If I have the choice to distribute resources with strangers, I would rather give more to others and keep less for myself.
inqMorality	When I have more than someone else, I feel like I should share what I have.
inqSacrifice	I would be willing to sacrifice a large part of my income to slightly reduce that of those less well off than me.
inqSpitefulness	I would be willing to sacrifice a little of my income to drastically reduce that of the most fortunate.

Note. The scale is as follows. For inqGeneral item: *"0: completely unwilling to do so"* to *"10: very willing to do so."* For inqStranger item: *"0: completely unwilling to redistribute resources with strangers to reduce inequality"* to *"10: very willing to redistribute resources with strangers to reduce inequality."* For tailored items: *"0: does not describe me at all"* to *"10: describes me perfectly."* We intentionally reverse-coded inqSelfishness to check participants' consistency in responses, although this item is not intended to serve as a screener. We do observe consistency in responses, as the α and β parameter values are positively correlated when the scale is adjusted (see Figure 13).

A.2 Hypothetical Questions

The first question (hypGeneral) is a hypothetical version of the incentivized choice tasks, involving a trade-off between the self's payoff and the other's payoff. The other questions (hypLottery and hypAmount) are adapted from Falk et al. (2023), but decomposed into two parts: the subject first indicates whether he/she would donate to charity, and only then specifies the amount (we believe this slight modification reduces priming).

Table 19: Hypothetical questions

Item	Description
hypGeneral	Imagine you are in a situation where you have to distribute money between yourself and an anonymous person. Neither of you will ever see or interact with the other. You have absolutely no information about the other person's circumstances (such as his/her wealth). The only thing you know is that nobody, except you and the other person, will ever know your choice. What would you do? I would...
hypLottery	Imagine the following situation: you won $1,000 in a lottery. Considering your current situation, would you donate a part of your gains to charity?
hypAmount	If you would, how much would you donate to charity? (Please indicate '0' if you would not.)

Note. The alternatives are as follows (with the associated strategy in parentheses). For hypGeneral: *"keep everything for myself"* (selfish), *"take a larger portion for myself and leave a smaller portion for the other"* (ineqselfish), *"make an approximately equal distribution between myself and the other person"* (egalitarian), *"take a smaller portion for myself and leave a larger portion to the other person"* (ineqaltruism), *"give everything to the other person"* (altruism), *"do something else"* (see below) (other: open text field). For hypLottery: Yes/No. For hypAmount: open text field.

Table 20 documents the number of respondents that chose one of the six possible strategies in the hypothetical survey question. 187 respondents (37.3%) stated the selfish or the mainly selfish (ineqselfish) strategy. 301 respondents (60%) stated the egalitarian strategy. Only a few subjects chose one of the other strategies.

Table 20: Number of respondents' strategies in the hypothetical question hypGeneral

Variable	Count
selfish	72
ineqselfish	115
egalitarian	301
altruism	1
ineqaltruism	4
other	9

A.3 Real-World Behavior

We adapted the real-world behavior questions from Falk et al. (2023) by replacing references to "charity" with "association/volunteering community" to make them more general, except for one question, which specifically addressed donations. We also included one item assessing people's support for policies aimed at reducing inequality.

Table 21: Real-world behavior

Item	Description
`member`	I am a member of an association/volunteering community.
`hours`	Please specify as precisely as possible how many hours per month you volunteer for an association/volunteering community. (If you do not, simply indicate '0'.)
`relatives`	How many people (approximately) know that you commit time to an association/volunteering community? (If you do not, simply indicate '0'.)
`donor`	I am a donor to an association/volunteering community (regular or not).
`amount`	Please specify as precisely as possible what amount you have given to charity over the past year. (If you have not, please enter '0'.)
`policy`	I support policies aimed at reducing inequality, such as taxing the rich to help the poor.

Note. The alternatives are as follows. For `member` and `donor`: Yes/No. For `hours`, `relatives` and `amount`: open text field. For `policy`: *"0: does not describe me at all"* to *"10: describes me perfectly"*.

A.4 Structural Estimation Results

Figure 9 depicts the association between individual aheadness and behindness aversion parameters. The positive correlation between domain-specific inequality aversion discussed in the main text is clearly visible.

Figure 9: Association between aheadness and behindness aversion parameters

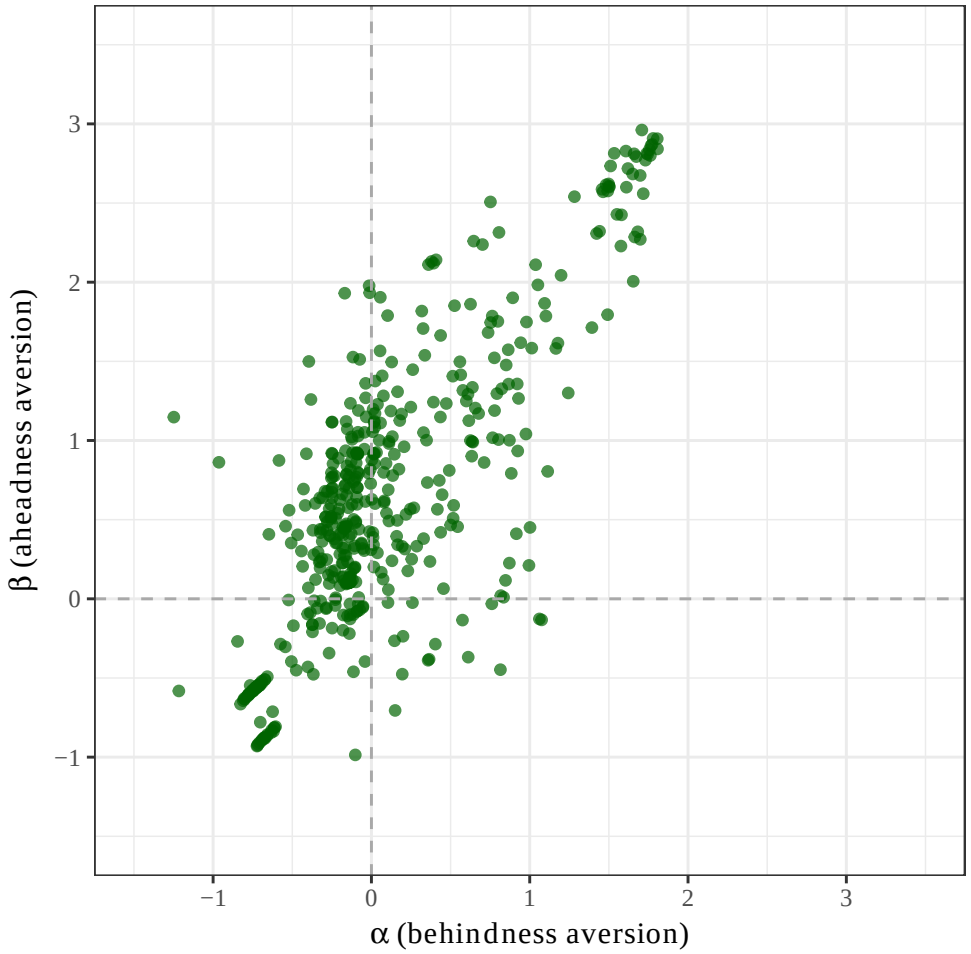
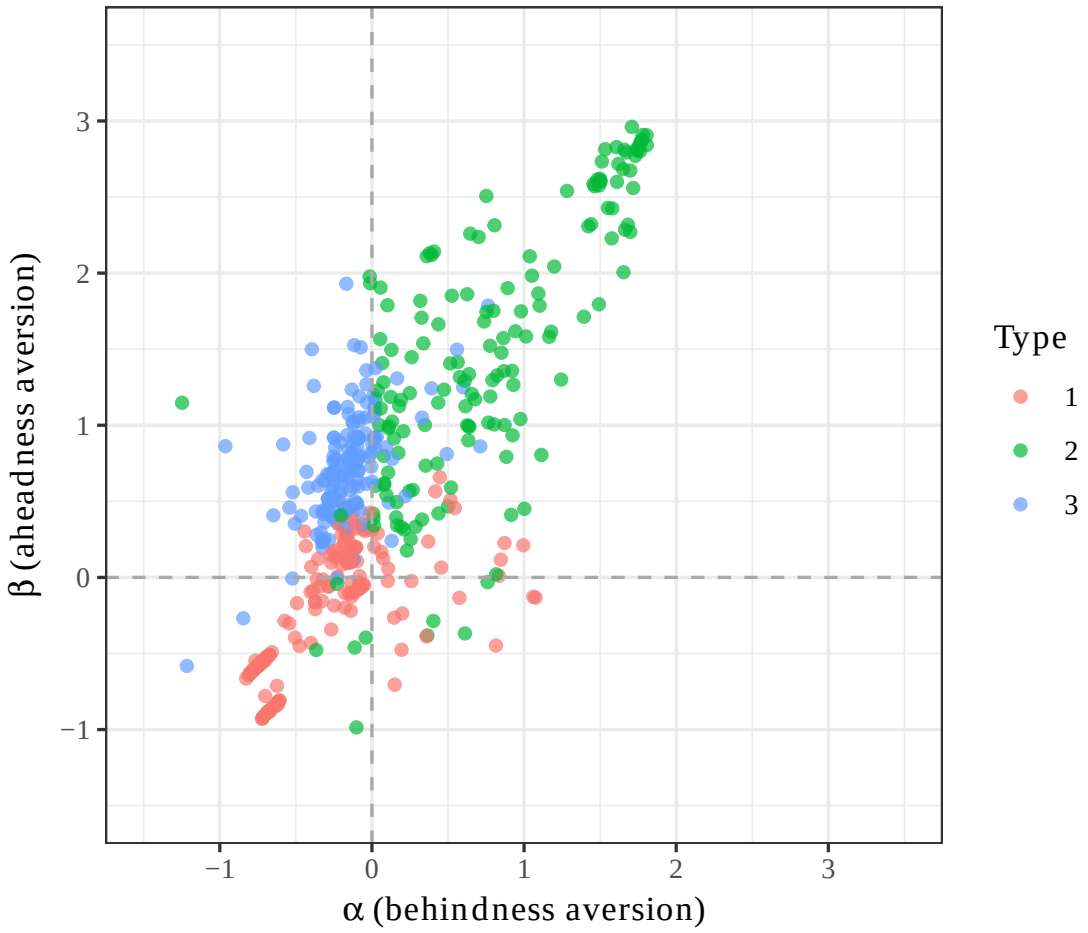


Figure 10 makes the results of Figure 6 visible in the scatter plot. The selfish type's parameters scatter around zero. The inequality averse type shows a more heterogeneous distribution with largely positive inequality aversion in the aheadness and behindness domain. Lastly, the altruistic type's parameters lie mostly in the upper left quadrant of the figure.

Figure 10: Association between aheadness and behindness aversion parameters by type



A.5 Ability of the Structural Model to Capture Features of the Data

Figures 11 and 12 split the α_i and β_i parameters into deciles labeled as D1 (low value) to D10 (high value). As the figures illustrate, subjects who got estimated a high value of the parameters indeed exhibit more inequality aversion in the respective domain. Thereby, α_i seems to more clearly separate the deciles in the behindness domain, whereas β_i seems to more clearly separate the deciles in the aheadness domain. Note, however, that the two parameters are highly correlated in our data.

Figure 11: Deciles α_i (behindness aversion)

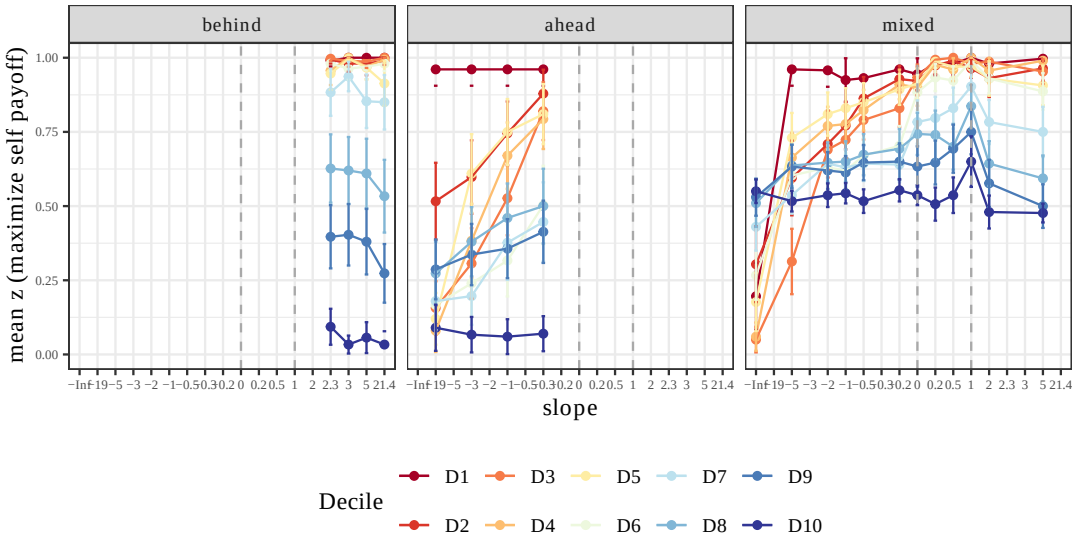
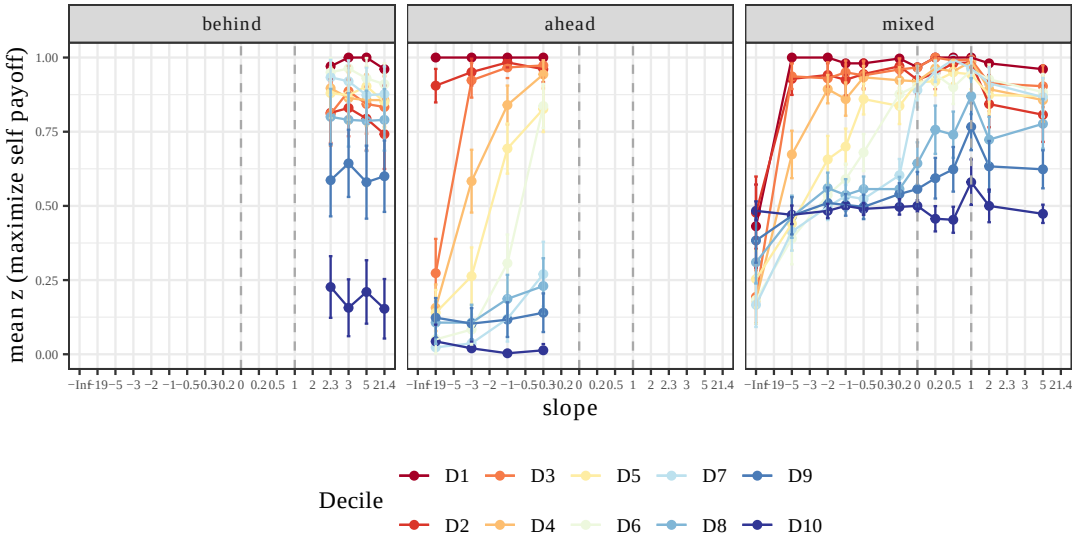


Figure 12: Deciles β_i (aheadness aversion)



A.6 Survey Responses

The responses to the survey items exhibit substantial heterogeneity, reflecting the diverse perspectives of participants. Figure 13 provides an initial exploration of the relationship between survey responses and the inequality aversion parameters estimated from the incentivized choice task. For each candidate variable, the figure presents a heat map illustrating the association with the two inequality aversion parameters α_i and β_i. Although the associations are not unequivocal for every individual variable, a general pattern emerges: higher levels of inequality aversion (depicted by darker tones in the heat map) tend to correspond to higher response values on the survey items. This suggests a meaningful relationship between self-reported attitudes and the estimated preference parameters we obtained from our incentivized elicitation task.

In addition to the survey items, we also included a question about preferred strategies in a hypothetical scenario where participants were asked to decide between the following six options when faced with another participant: (i) take the entire stake (`selfish`), (ii) take more for themselves, but leave some to the other person (`ineqselfish`), (iii) choose an equal allocation (`egalitarian`), (iv) give more to the other person, but keep some to oneself (`inequaltruism`), (v) give the entire stake to the other person (`altruism`), or (vi) select another strategy (`other`) (see Appendix A.2 for the detailed wording).[31] The distribution of responses across these six options was highly uneven, with some strategies (`altruism`, `ineqaltruism`, and `other`) being only rarely chosen (see Table 20 for details). To simplify the analysis, we constructed a binary variable, `hypGeneralSelfish`, which indicates whether a participant selected a selfish strategy. Overall, 37.3% of participants opted for a selfish strategy, aligning closely with the proportion of selfish types identified in our clustering exercise.

As shown in Table 22, while these responses contain some predictive signal regarding participants' actual choices, the signal is imperfect, reflecting a notable discrepancy between stated preferences and revealed preferences. Consequently, this survey question appears to offer limited discriminatory power for distinguishing between the two social preference types.

Table 22: Contingency table of subjects stating any selfish strategy *vs.* the three types identified *via* clustering

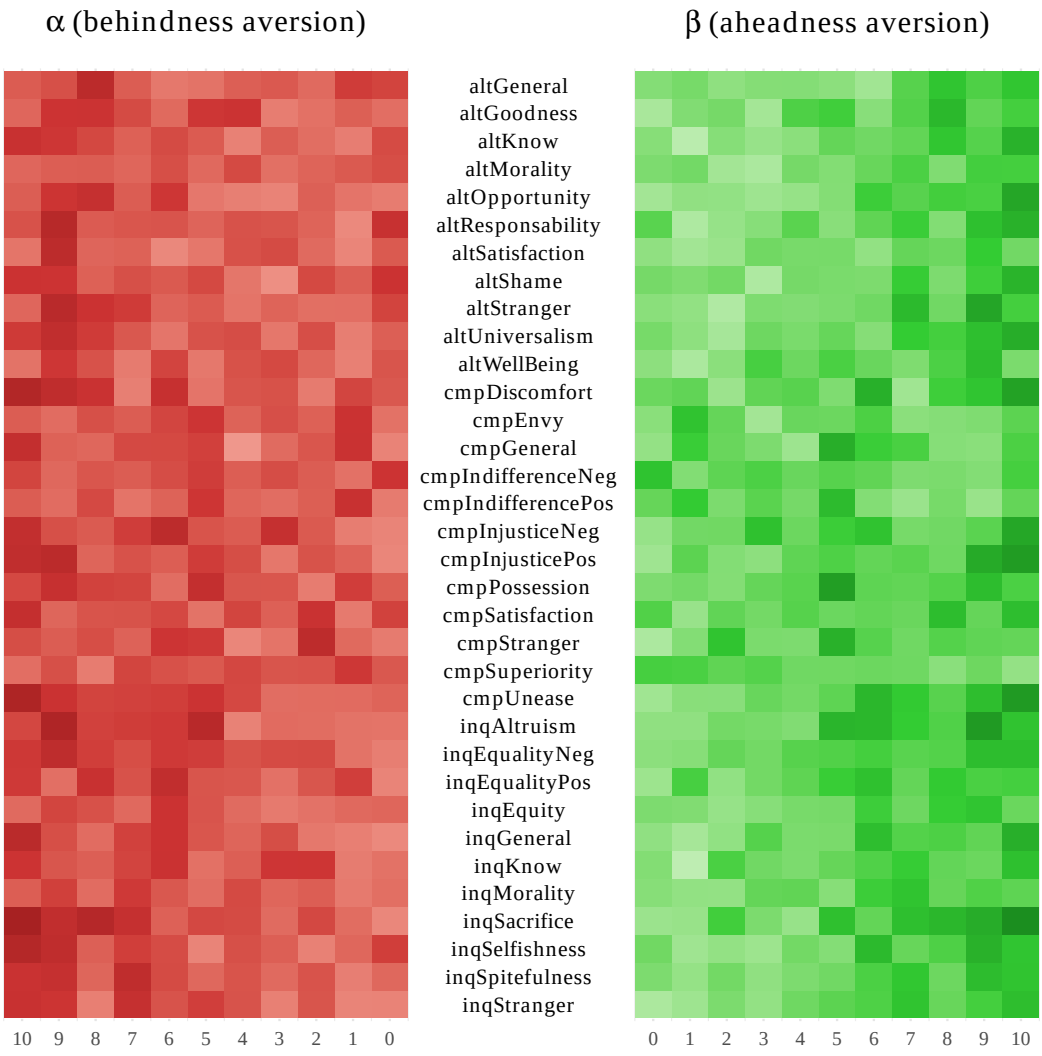
	Type 1: Selfish	Type 2: Inequality averse	Type 3: Altruistic
any selfish strategy	**24.9%**	5.4%	7.0%
other strategy	11.4%	**26.9%**	**24.5%**

Note. The table reports proportions. Stated selfish strategies are indicative for being a selfish preference type as inferred from revealed preference data. However, this signal is far from perfect.

To further assess the effectiveness of strategy responses in predicting allocation choices, consider Figure 14. This figure illustrates the response patterns for four strategy types:

[31] This survey question appeared at a random point in the survey, either early on, preceding the choice task, or later, following the choice task. We find no evidence that the position of this survey question influenced participants' responses to the task, nor that task responses affected how participants answered the survey question.

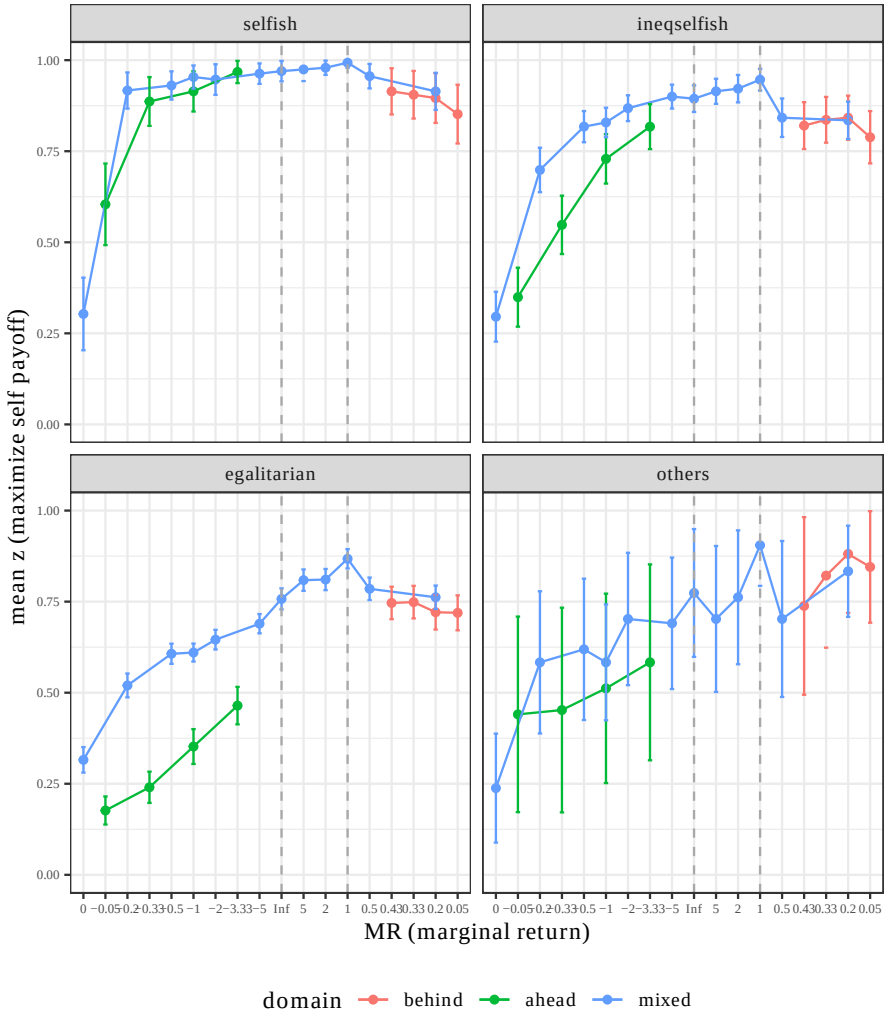
Figure 13: Association between 11-point Likert-scale responses and inequality aversion parameters in the 34 survey items



Note. The heat maps illustrate the association between Likert-scale responses and inequality aversion in the *behind* (α) and the *ahead* (β) domain. Darker tones indicate higher degrees of inequality aversion. A smoothing of the parameter values has been applied since some variable feature bins with only a few observations. Overall, there is a tendency of higher degrees of inequality aversion toward higher Likert-scale responses (10). However, there are vast differences across variables.

(i) participants who chose the fully selfish strategy (`selfish`), (ii) those who selected a more balanced selfish strategy, taking more for themselves but leaving some for the other participant (`ineqselfish`), (iii) participants who stated an egalitarian strategy (`egalitarian`), and (iv) a residual group encompassing other or unspecified strategies (`others`). Stated strategies are roughly in line with the responses we expect in the different settings of the elicitation task (see also the figure notes).

Figure 14: Strategy response signatures



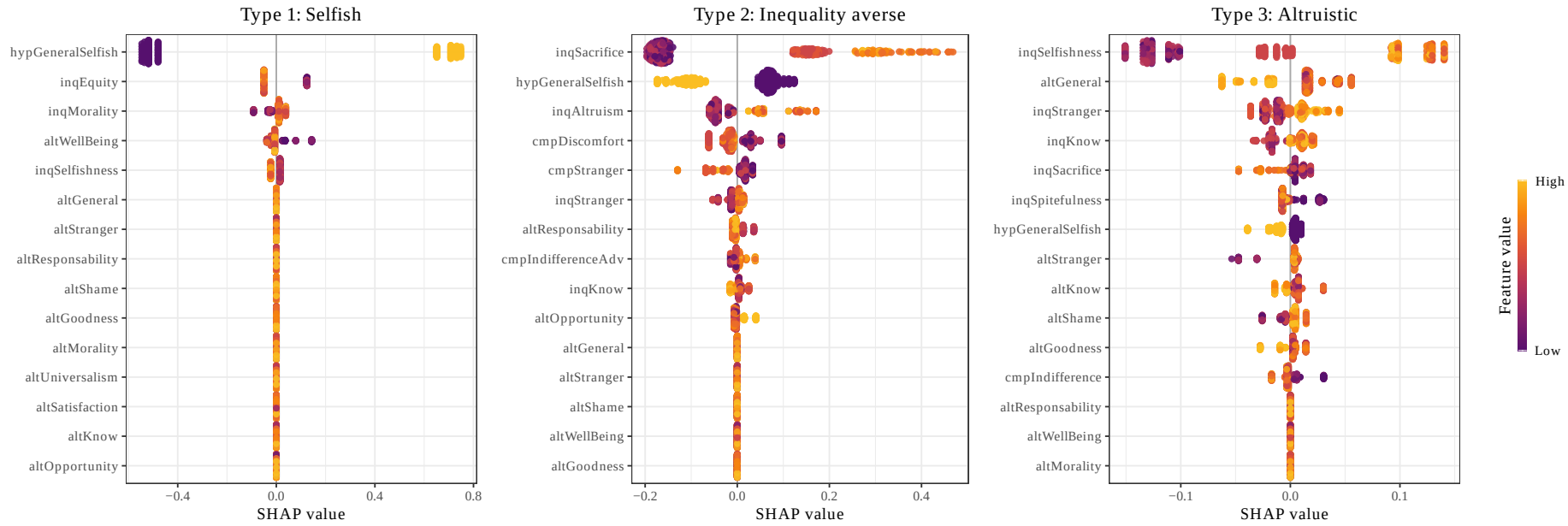
Note. Stated strategies are broadly in line with expected (revealed) behaviors. Respondents who stated the purely selfish strategy (`selfish`) exhibit selfish behavior across the board. The only exception is the area where the cost of redistribution is negligible. Respondents who stated the more balanced strategy of taking more for themselves, but still allocating a smaller part to the other person (`ineqselfish`), reveal a cost-sensitive response pattern. Respondents who stated the `egalitarian` strategy reveal a behavior that is closer to equal allocations, albeit only imperfectly. Finally, respondents who stated one of the other strategies reveal a wide variety of behaviors.

A.7 SHAP Values

Figure 15 below displays SHAP values by type. For each type, the most predictive variables (features) are listed from top to bottom in order of their overall importance (computed as the mean absolute SHAP value). Positive SHAP values indicate a contribution toward predicting assignment to that type, while negative values indicate a contribution away from predicting that preference type. Each point represents an individual data point for a specific variable. The color of the points (heat) correspond to the variable value (yellow for high values, purple for low values).[32] Looking at the points, we can see how variables affect SHAP contribution. A wider spread of the data points for a given variable indicates that the variable's impact on the prediction varies significantly across observations.

[32] Recall that our strategy variable `hypGeneralSelfish` is a binary variable with a value of 1 indicating a *selfish* strategy and a value of 0 indicating a *non-selfish* strategy.

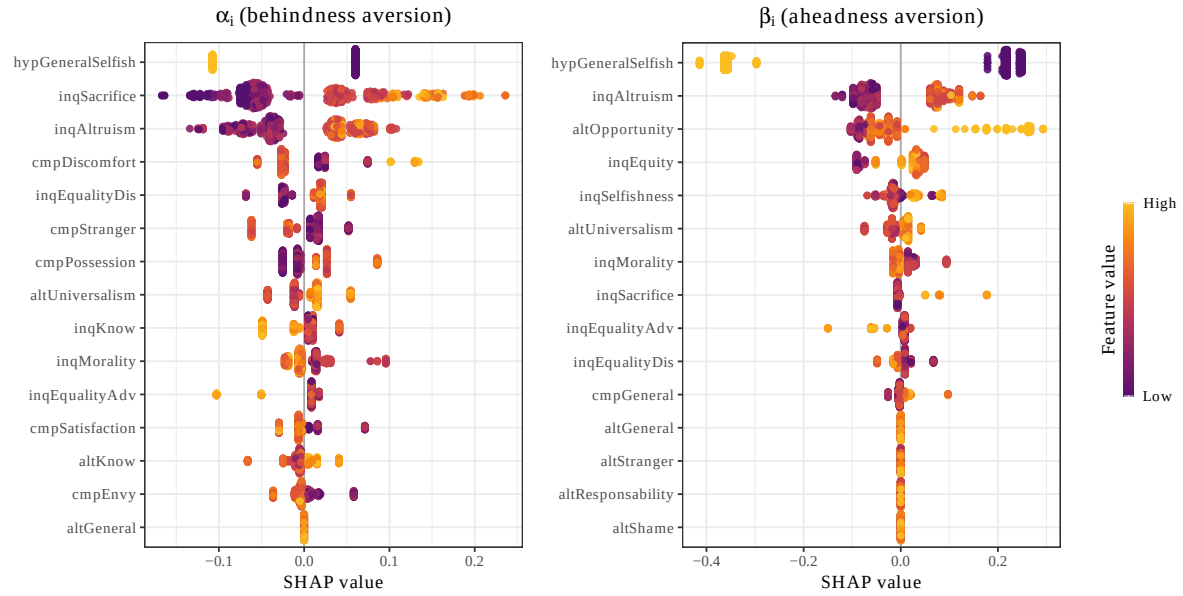
Figure 15: SHAP values by type



Note. The beeswarm plots show the SHAP values for the variables (features) of highest importance separately by preference type. The hypothetical strategy question (`hypGeneralSelfish`) discriminates well between selfish (Type 1) and inequality aversion (Type 2). However, it is less powerful in identifying altruistic types (Type 3). The survey item `inqSelfishness` performs particularly well in identifying altruism (Type 3), followed by `altGeneral`. Variables that have little to no predictive power are omitted.

Figure 16 shows the SHAP values by inequality aversion parameter (α and β). Respondents who indicated a selfish strategy in the hypothetical scenario are systematically predicted to have lower values for both α_i and β_i, suggesting that selfish strategies are associated with reduced concern to inequality in both domains. Among the survey variables, the inequality tailored items (particularly `inqAltruism`, `inqSacrifice`, and `inqSpitefulness`) again emerge as important predictors on our list. These variables provide valuable insights into respondents' attitudes toward inequality and their sensitivity to distributional preferences, making them central to the predictive models for both α_i and β_i.

Figure 16: SHAP values by inequality aversion parameter



Note. The beeswarm plots show the SHAP values by inequality aversion parameter based on two separate models. Stating a selfish strategy is associated with lower α_i and β_i values. The survey item `inqAltruism`—which is a similar type of question as `inqSelfishness` (see the type SHAP plots)—is the next best predictor for both aheadness and behindness aversion. Only the top 15 predictors are displayed.

B Online Appendix

B.1 Attention Checks

We used three attention checks, also referred to as "screeners," adapted from Berinsky et al. (2021). These asked respondents about the most important problems facing the country, their favorite colors, and news websites. We positioned the screeners so that they were equally spaced throughout the whole experiment. Specifically, `screener1` appeared before the choice tasks, `screener2` after the choice tasks, and `screener3` midway through the survey items. The screeners were presented as follows and in the following order.

Table 23: Attention check items

Item	Description
`screener1`	Research shows that questions considered important by some people can influence their opinions on other topics. We also want to know if you are paying attention to the survey. If you do, please ignore the question below and select 'Crime'. Which of the following issues faced by the nation do you think is the most important?
`screener2`	Some research has shown that individual preferences and knowledge, as well as external factors, can have a significant impact on the decision-making process. To show that you have read carefully, choose 'Pink' from the options below, regardless of your favorite color. Yes, in order to show us that you are paying attention to this survey, please select 'Pink'. What is your favorite color?
`screener3`	When major news breaks, people often go online to find up-to-the-minute details on current events. We also want to know if you are paying attention to the survey. To show us that you do, please ignore the following question and select 'ABC News' as your answer. When major news breaks, which news website do you visit first?

Note. The alternative are as follows. For `screener1`: Health care, Unemployment, Public debt, War, Crime, Education, International relations. For `screener2`: White, Black, Red, Pink, Green, Blue. For `screener3`: The New York Times, The Washington Post, CNN, NBC, USA Today, ABC News, CBS News.

B.2 Representativeness

We targeted a sample of approximately 500 individuals from the U.S. adult population, aiming for representativeness based on three stratification criteria: age group, gender, and ethnicity. The following three tables illustrate that, after excluding participants who failed the three attention checks, the actual proportions in our sample closely align with the target quotas. Deviations per category are generally within ± 1 percentage point, demonstrating that we come very close to the targeted values.

Table 24: Age group

Age group	Target proportion	Actual proportion	Deviation
18 to 24	0.120	0.116	-0.004
25 to 34	0.173	0.172	-0.002
35 to 44	0.169	0.174	0.004
45 to 54	0.159	0.166	0.006
55 to 100	0.378	0.373	-0.005

Table 25: Gender

Gender	Target proportion	Actual proportion	Deviation
Female	0.508	0.499	-0.009
Male	0.492	0.501	0.009

Table 26: Ethnicity

Ethnicity	Target proportion	Actual proportion	Deviation
Asian	0.062	0.070	0.008
Black	0.118	0.116	-0.002
Mixed	0.104	0.116	0.012
Other	0.080	0.076	-0.004
White	0.637	0.623	-0.015

B.3 Type Characterization: Results for Two and Four Types

Table 27 and 28 show the proportions of subjects assigned to the emerging types. The Alluvial plot in Figure 17 depicts how subjects transition between assigned types when enforcing two, three, four and five types. As argued in the main text, the three type clustering yields a clear interpretation of the types. However, it appears that parts of this interpretation gets lost when forcing the algorithm to return only two types. In the 2-type clustering, the first type (Type 1) is an amalgam of selfish (red for three types) and altruistic (green for three types). The second type (Type 2) of the 2-type clustering contains nearly all inequality averse subjects from the three type clustering, but also a substantial portion of the altruists that we found there. Similarly, going from three to four and more types yields smaller types with less clear interpretation.

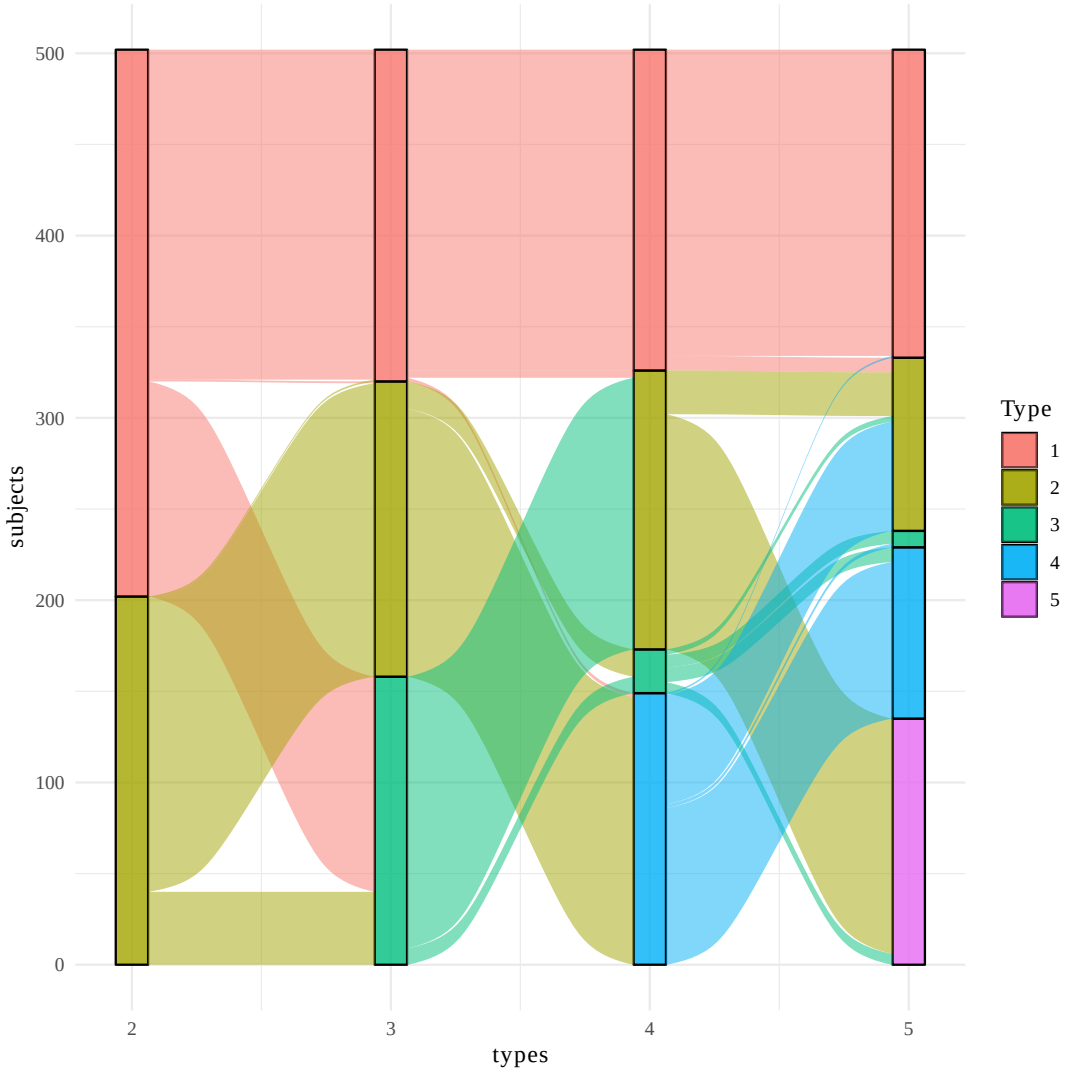
Table 27: Distribution of preference types | $k = 2$

Type	Proportion
1	59.76%
2	40.24%

Table 28: Distribution of preference types | $k = 4$

Type	Proportion
1	35.06%
2	30.48%
3	4.78%
4	29.68%

Figure 17: Alluvial plot



B.4 Additional Results on External Validity

Tables 29 and 30 document the bivariate relationships between our real-world and hypothetical survey items, and the estimated inequality aversion parameters and our module-based scores.

Table 29 presents results for Spearman rank correlation tests on the association between the continuous variables and the preference measures. Our module-based score is more strongly and significantly associated with the different stated behaviors than the preference parameters obtained from estimation.

Table 29: Bivariate associations between estimated preference parameters/module score and continuous real-world behaviors

Variable	(i) behind estim.	(ii) behind score	(iii) ahead estim.	(iv) ahead score
`hours`	0.127 (0.004)	0.222 (0.000)	0.069 (0.124)	0.180 (0.000)
`relatives`	0.105 (0.018)	0.213 (0.000)	0.081 (0.070)	0.182 (0.000)
`amount`	0.064 (0.152)	0.120 (0.007)	0.061 (0.169)	0.143 (0.001)
`hypAmount`	0.191 (0.000)	0.359 (0.000)	0.183 (0.000)	0.335 (0.000)
`policy`	0.055 (0.223)	0.149 (0.001)	0.125 (0.005)	0.240 (0.000)

Note. `behind` and ahead refer to the behindness aversion (α_i or score) and aheadness aversion (β_i or score) parameters, respectively. The table reports Spearman rank correlations between preference parameters obtained from the incentivized elicitation task, α_i and β_i (see columns i and iii), and a series of self-stated behaviors. It reports the same for our behindness aversion index prediction (column iii) and our aheadness aversion index prediction (column iv). p-values are stated in parentheses.

Table 30 reports results of Mann-Whitney U tests. More specifically, we test whether inequality aversion is higher for those who are participating in volunteering and donate to charities (one-sided test). As we see, this is indeed the case for all variables, with our scores performing better than estimated parameters.

Table 30: Bivariate associations between estimated preference parameters/module score and binary real-world behaviors

Variable	(i) behind estim.	(ii) behind score	(iii) ahead estim.	(iv) ahead score
`member`	0.180 (0.001)	0.105 (0.000)	0.158 (0.037)	0.150 (0.000)
`donor`	0.056 (0.098)	0.059 (0.001)	0.027 (0.232)	0.118 (0.000)
`hypLottery`	0.133 (0.003)	0.110 (0.000)	0.187 (0.003)	0.215 (0.000)

Note. `behind` and ahead refer to the behindness aversion (α_i or score) and aheadness aversion (β_i or score) parameters, respectively. The table reports differences in the means of the parameters for Variable=1 - Variable=0. The p-values are for one-sided Mann-Whitney U tests.

Table 31 presents regression results on the intensive margin of charitable giving after a hypothetical lottery win. The results here are a bit less clear, but according to our scores, there is evidence that behindness aversion is associated positively with the donated amount.

Similar results emerge for monetary donations to a volunteering community (see Table 32). Here it is the aheadness aversion that is positively associated with donations. Once again, it is our score that picks up this association, while estimated parameters do

Table 31: Regression Results for Amount of Donations after Windfall `hypAmount`

Variable	(1) estimated	(1c) estimated	(2) score	(2c) score
behindness av.	116.176 (78.104)	102.922 (80.552)	214.293 (89.938)**	206.777 (95.159)**
aheadness av.	120.767 (78.104)	142.933 (80.251)*	40.825 (87.148)	44.342 (92.457)
Intercept	9.688 (34.151)	14.307 (87.681)	1.764 (32.488)	-16.9 (89.131)
Controls	no	yes	no	yes
R^2	0.030	0.096	0.039	0.100

Note. The response variable is the amount donated after a hypothetical lottery win. Model (1) and (1c) use the inequality aversion parameters *estimated* from the incentivized preference elicitation task without and with controls, respectively. Model (2) and (2c) substitute the inequality aversion parameters with our survey module-based *scores*. The controls include age, immigrant status, income class, highest degree of education, civil status and a dummy for children in the household. p-values: $0 \leq^{***} < 0.01 \leq^{**} < 0.05 \leq^{*} < 0.1$.

not.

Table 32: Regression Results for Donations to Volunteering Community `donor`

Variable	(1) estimated	(1c) estimated	(2) score	(2c) score
behindness av.	0.114 (0.104)	0.07 (0.105)	0.052 (0.12)	0.009 (0.123)
aheadness av.	-0.025 (0.104)	0.022 (0.105)	0.213 (0.116)*	0.272 (0.12)**
Intercept	0.320 (0.046)***	0.209 (0.115)*	0.238 (0.043)***	0.116 (0.115)
Controls	no	yes	no	yes
R^2	0.003	0.11	0.025	0.135

Note. The response variable is a binary variable for whether the respondent donates to a volunteering community. We estimate a linear probability model. Model (1) and (1c) use the inequality aversion parameters *estimated* from the incentivized preference elicitation task without and with controls, respectively. Model (2) and (2c) substitute the inequality aversion parameters with our survey module-based *scores*. The controls include age, immigrant status, income class, highest degree of education, civil status and a dummy for children in the household. p-values: $0 \leq^{***} < 0.01 \leq^{**} < 0.05 \leq^{*} < 0.1$.

Tables 33 and 34 show two instances where we fail to detect any association with aheadness and behindness aversion. The results are consistent between estimated parameters and scores. While we find clear bivariate associations between these variables and our score (see Table 29), we do not find any support for such associations in the regressions. This results is not particularly surprising, however. The `relatives` item should possibly only be weakly related to own preferences. The number of people knowing about respondents' volunteering activities may crucially depend on other factors (social network and nature of the association, etc.), factors we cannot control for. Similarly, the amount donated to charities (`amount`) is heavily influenced by wealth and income. We have a rough measure for the latter and control for it in the regressions. However, there are likely more complex interactions at play here. For a discussion, see in particular Epper et al. (2024), who use third-party registered data on charitable donations.

Lastly, Table 35 presents results on the predictive power of estimated and scored inequality aversion measures on the extensive margin of charitable giving. We find an association of aheadness aversion and giving at the 5% significance level for our score.

Table 33: Regression Results for People Knowing about Volunteering `relatives`

Variable	(1) estimated	(1c) estimated	(2) score	(2c) score
Intercept	4.849 (4.16)	-2.753 (10.68)	0.956 (3.962)	-5.988 (10.867)
behindness av.	5.012 (9.514)	4.644 (9.812)	11.321 (10.969)	10.586 (11.602)
aheadness av.	1.306 (9.514)	-0.972 (9.775)	2.95 (10.628)	-1.766 (11.273)
Controls	no	yes	no	yes
R^2	0.002	0.072	0.008	0.074

Note. The response variable is the number of people the respondent knows that he/she commit time in volunteering. Model (1) and (1c) use the inequality aversion parameters *estimated* from the incentivized preference elicitation task without and with controls, respectively. Model (2) and (2c) substitute the inequality aversion parameters with our survey module-based *scores*. The controls include age, immigrant status, income class, highest degree of education, civil status and a dummy for children in the household. p-values: $0 \leq^{***} < 0.01 \leq^{**} < 0.05 \leq^{*} < 0.1$.

Table 34: Regression Results for Donations to Charities `amount` (Intensive Margin)

Variable	(1) estimated	(1c) estimated	(2) score	(2c) score
behindness av.	2329.22 (1960.58)	2021.83 (1921.79)	1882.88 (2267.08)	1424.00 (2275.26)
aheadness av.	-2361.19 (1960.58)	-2074.42 (1914.59)	154.37 (2196.77)	363.53 (2210.64)
Intercept	825.61 (857.25)	1204.29 (2091.87)	-204.36 (818.93)	210.10 (2131.13)
Controls	no	yes	no	yes
R^2	0.003	0.163	0.004	0.163

Note. The response variable is the (self-reported) amount of U.S. dollars donated to charities over the past year. Model (1) and (1c) use the inequality aversion parameters *estimated* from the incentivized preference elicitation task without and with controls, respectively. Model (2) and (2c) substitute the inequality aversion parameters with our survey module-based *scores*. The controls include age, immigrant status, income class, highest degree of education, civil status and a dummy for children in the household. p-values: $0 \leq^{***} < 0.01 \leq^{**} < 0.05 \leq^{*} < 0.1$.

However, estimated preferences fail to establish such a relationship (possibly due to reasons highlighted earlier).

Table 35: Regression Results for Donations to Charities `amount`>0 (Extensive Margin)

Variable	(1) estimated	(1c) estimated	(2) score	(2c) score
behindness av.	0.067 (0.108)	0.006 (0.107)	-0.017 (0.124)	-0.042 (0.126)
aheadness av.	0.098 (0.108)	0.155 (0.107)	0.278 (0.12)**	0.311 (0.122)**
Intercept	0.394 (0.047)***	0.152 (0.117)	0.353 (0.045)***	0.097 (0.118)
Controls	no	yes	no	yes
R^2	0.008	0.138	0.025	0.155

Note. The (binary) response variable is whether the (self-reported) amount of U.S. dollars donated to charities over the past year is positive. Model (1) and (1c) use the inequality aversion parameters *estimated* from the incentivized preference elicitation task without and with controls, respectively. Model (2) and (2c) substitute the inequality aversion parameters with our survey module-based *scores*. The controls include age, immigrant status, income class, highest degree of education, civil status and a dummy for children in the household. p-values: $0 \leq^{***} < 0.01 \leq^{**} < 0.05 \leq^{*} < 0.1$.

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