REVEALED SOCIAL PREFERENCES

ARTHUR DOLGOPOLOV

Interdisciplinary Center for Economic Science, George Mason University

MIKHAIL FREER

ECARES, Université Libre de Bruxelles

Abstract. We use a revealed preference approach to develop tests for the observed behavior to be consistent with theories of social preferences. In particular, we provide nonparametric criteria for the observed set of choices to be generated by inequality averse preferences and increasing benevolence preferences. These tests can be applied to games commonly used to study social preferences: dictator, ultimatum, investment (trust) and carrot-stick games. We further apply these tests to experimental data on dictator and ultimatum games. Finally, we show how to identify the levels of altruism and fair outcomes using the developed revealed preference conditions.

1 Introduction

Various studies show that people have other-regarding preferences (see e.g. Andreoni, 1990; Andreoni and Miller, 2002; Charness and Rabin, 2002; Fisman, Kariv and Markovits, 2007; Porter and Adams, 2016; Castillo, Cross and Freer, 2017). Moreover, other-regarding preferences are widely used in the applied theory (see e.g. Dufwenberg et al., 2011; Maccheroni, Marinacci and Rustichini, 2012; Szabo and Szolnoki, 2012; Benjamin, 2015). Significant research has been devoted towards understanding the motives for the social preferences (see e.g. Charness and Rabin, 2002; Cox, 2004).

E-mail addresses: `Dolgopolov: adolgopo@gmu.edu, Freer: mfreer@ulb.ac.be`.

Date: October 25, 2018.

We would like to thank Oyvind Aas, Christian Basteck, Laurens Cherchye, Bram De Rock, Thomas Demuynck, Daniel Houser, Iris Kesternich Georg Kirchsteiger and François Maniquet for insightful comments on the earlier versions of the paper.

There are (at least) three most persistent motives: *social welfare/efficiency, fairness* and *reciprocity*. These four motives are covered by the two theories tested in this paper: *inequality aversion* and *increasing benevolence*.

Inequality aversion assumes that players extract utility from their own payoffs and encounters some disutility if payoffs are unbalanced (see e.g. Fehr and Schmidt, 1999; Bolton and Ockenfels, 2000). Hence, inequality aversion, encompasses the fairness motive. Increasing benevolence assumes that a player's willingness to pay for an additional dollar received by another player increases in the player's own payoff (see Cox, Friedman and Sadiraj, 2008). Underlying intuition implies that the payoff of another player is a normal good. Hence, increasing benevolence encompasses reciprocity motive and the social welfare considerations if these are present. Finally, let us note, that both theories are widely used in applied theory research.[1]

The paper constructs revealed preference tests for *inequality averse* and *increasing benevolence* preferences. We start with a standard choice environment over linear budgets in which a player decides how to allocate money between herself and another player (dictator game). Next, we generalize tests to other games commonly used to study social preferences: ultimatum, trust, and carrot-stick games. Note that social welfare considerations are not prevalent in these applications. In addition, we apply the tests to the experimental data on dictator and ultimatum games. There are three main empirical findings. First, both theories explain behavior better than random decision-making. Second, both inequality averse and increasing benevolence preferences are strictly nested within the other-regarding preferences. That is there is a significant share of population consistent with having other-regarding preferences, but not consistent with either of nested theories. Third, inequality aversion explains the behavior of subjects quite well in both dictator (better than increasing benevolence) and ultimatum game. However, the degree to which inequality aversion prevails over increasing benevolence different for different populations.

The revealed preference approach, pioneered by Samuelson (1938), originates in the fact that, we can only observe the choices of players but not their preference relations.

[1]Inequality aversion is popular in political economy (see e.g. Fong, 2001; Tyran and Sausgruber, 2006; Höchtl, Sausgruber and Tyran, 2012; Durante, Putterman and Van der Weele, 2014; Agranov and Palfrey, 2015). Increasing benevolence has been used by Cox, Friedman and Sadiraj (2008) to model the behavior in two-stage games and by (Benjamin, 2015) to guarantee the efficiency in the bilateral exchange with social preferences.

Revealed preference theory allows avoiding functional misspecification of preferences. Starting with Richter (1966) and Afriat (1973) the approach has been applied to construct tests of individual and collective decision-making (see Chambers and Echenique, 2016, for a comprehensive overview of the results). Revealed preference theory has been applied to other-regarding preferences starting with Andreoni and Miller (2002).

Next, we provide a connection to the previous results on revealed social preferences. Cox, Friedman and Sadiraj (2008) provides necessary revealed preferences conditions for observed choices to be consistent with increasing benevolence and provides a method of comparing subjects in terms of altruism if the demand functions are completely observed. We show that conditions proposed are also sufficient and that the comparisons in terms of altruism can be applied even if only the finite set of choices is observed.[2] Deb, Gazzale and Kotchen (2014) constructs revealed preference tests for a special case of inequality aversion (inequality aversion in differences) if budgets are linear. The test we construct does not depend on the specification of the inequality measure. That is, if a player is consistent with inequality averse preferences, she is consistent with inequality aversion preferences given any measure of inequality. Moreover, the test does not require linearity of budgets and therefore, has a larger scope of applications.

The remainder of this paper is organized as follows. Section 2 presents the general set up and the revealed preference tests as well as extensions of the test for other games. Section 3 provides empirical illustrations. Section 4 presents the partial identification of the level of altruism and notion of fair outcome using the revealed preference conditions. Section 5 provides concluding remarks. All proofs are collected in Appendix A.

2 Theoretical Framework

We consider a dictator game, which is structured as follows. A player decides how to allocate a given amount of money between herself and the other player, and the chosen allocation is implemented. This game can be written as a decision problem, in which one player chooses a two-dimensional vector allocation: payoff to self and payoff to another player.

Let $X \subseteq \mathbb{R}^2_+$ be the **set of alternatives**. For every $x \in X$ let $x = (x_s, x_o)$, where x_s is the payoff to self and x_o is the payoff to another player. Let $p \in \mathbb{R}^2_{++}$ be a price

[2]The original paper compared the altruism levels either pointwise or if the entire demand function is observed. However, we preserve the assumption of the Cox, Friedman and Sadiraj (2008) that two players had to face the same experiment (making choices over similar budgets).

vector. Income is normalized to one at every point, and the budget set is defined as, $B(p) = \{x \in X : px \leq 1\}$. Let $E = (x^t, p^t)_{t=1}^T$ be an **experiment**, which consists of T choices (x^t) at a given price vector (p^t). Moreover, we assume that chosen points x^t are such that $p^t x^t = 1$.[3] A function $u(x) : X \to \mathbb{R}$ **rationalizes** the consumption experiment E if for all $y \in B(p^t)$, $u(x^t) \geq u(y)$ for every $t \in \{1, \ldots, T\}$.

In what follows we present revealed preference tests for each of the theories of social preferences. We start with other-regarding preferences. Next, we present the test for inequality averse preferences and the test for increasing benevolence preferences. Next, we show that the latter two theories are independent. Finally, we show how to apply the tests to ultimatum, trust and carrot-stick games.

2.1 Other-Regarding Preferences (OR). Other-regarding preferences assume that a player cares about her own payoff and the payoff of the recipient. Theory does not make an explicit assumption of whether the player derives utility or disutility from x_o.

Definition 1. *An experiment $E = (x^t, p^t)_{t=1}^T$ is* **rationalizable with other-regarding preferences** *if there is a continuous and locally non-satiated utility function $u(x_s, x_o)$ that rationalizes E.*

Other-regarding preferences include utility function that is monotone in both payoffs (altruistic preferences) as a special case. Hence, rationalizability with other-regarding preferences can be deduced to the regular case of existence of locally non-satiated utility function over two-dimensional space of real outcomes.

Definition 2. *An experiment $E = (x^t, p^t)_{t=1}^T$ is consistent with* **Generalized Axiom of Revealed Preference (GARP)** *if and only if we have $p^{t_1} x^{t_n} \leq p^{t_1} x^{t_1}$ for all sequences $x^{t_1}, \ldots, x^{t_n}$, such that $p^{t_{j+1}} x^{t_j} \leq p^{t_{j+1}} x^{t_{j+1}}$, $j \in \{i, \ldots, n-1\}$.*

Figure 1 presents the violation of GARP. An allocation x^1 is chosen given prices p^1, therefore, it is better than any allocation which is available at p^1. At the same time x^2 is available at p^1, therefore, x^1 is strictly directly revealed preferred to x^2. Finally x^2 is directly revealed preferred to x^1, since x^1 is available at p^2.[4] Hence, observed choices could not be generated by maximization of utility function.

[3]This technical assumption is dictated by non-satiation of preferences. All the further reasoning can be done without this assumption using more complicated notation.

[4]Formally, this is a violation of Weak Axiom of Revealed Preferences (WARP) and in the case of two-dimensional linear budgets WARP is equivalent to GARP (see e.g. Rose, 1958). However, we

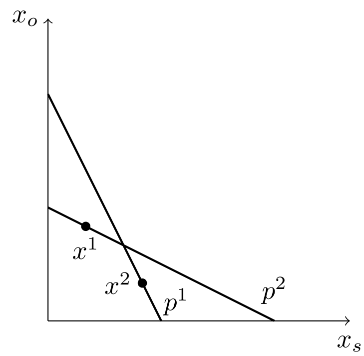


FIGURE 1. Other-Regarding Preferences and GARP

Proposition 1 (Afriat (1967); Diewert (1973); Varian (1982))**.** *An experiment is rationalizable with other-regarding preferences if and only if it satisfies GARP.*

2.2 Inequality Aversion (IA) Inequality aversion assumes that player gets utility from her own payoff and disutility if payoffs are unbalanced, In order to quantify the "unbalancedness" of the payoffs we use the *inequality measure.* Some examples of commonly used inequality measures are presented below.

– Inequality in differences (e.g. Fehr and Schmidt, 1999; Tyran and Sausgruber, 2006; Agranov and Palfrey, 2015):

$$f(x_s, x_o) = \begin{cases} x_s - x_o & \text{if } x_s \geq x_o \\ \beta(x_s - x_o) & \text{if } x_o > x_s \end{cases}$$

where $\beta \leq 1$.

– Inequality in shares or Lorenz curve[5] (e.g., Bolton and Ockenfels, 2000):

$$f(x_s, x_o) = \begin{cases} \frac{x_s}{x_s+x_o} - \frac{1}{2} & \text{if } x_s \geq x_o \\ \beta\left(\frac{x_s}{x_s+x_o} - \frac{1}{2}\right) & \text{if } x_o > x_s \end{cases}$$

where $\beta \leq 1$.

– Gini Index $f(x_s, x_o) = \frac{|x_s - x_o|}{2(x_s+x_o)}$ (e.g. Durante, Putterman and Van der Weele, 2014)

prefer to introduce the GARP, since further we deal with nonlinear budgets for which the result does not necessarily hold.

[5]Intuition for Lorenz curve is the same as for inequality in shares for the two-player case since the shape of the curve is determined by deviation of the lower payoff from equal share split.

Further we present an axiomatization of the inequality measure. Closely related axiomatization has been used by Fehr, Kirchsteiger and Riedl (1998) for the gift exchange game. This axiomatization generalizes the examples of inequality measures presented above.

Definition 3. *A continuous function $f(x_s, x_o)$ is an* **inequality measure** *if:*

- $f(x_s, x_o) \geq 0$, *for every* x_s, x_o;
- $f(x_s, x_o) = 0$ *if and only if* $x_s = x_o$;
- *if* $x_s > x_o$, *then* $f(x_s, x_o)$ *is decreasing in* x_o *and increasing in* x_s;
- *if* $x_s < x_o$, *then* $f(x_s, x_o)$ *is increasing in* x_o *and decreasing in* x_s;
- $f(\max\{x_s, x_o\}, \min\{x_s, x_o\}) \leq f(\min\{x_s, x_o\}, \max\{x_s, x_o\})$.

Further we present the definition for rationalization with inequality averse preferences. This rationalization, in general, depends on the inequality measure chosen.

Definition 4. *Let $f(x_s, x_o)$ be an inequality measure. An experiment is* **rationalizable with inequality averse preferences** *if there is a continuous utility function $u(x_s, f(x_s, x_o))$ increasing in x_s and decreasing in $f(x_s, x_o)$ that rationalizes it.*

Rationalizability with inequality averse preferences requires every player to choose to allocate to herself at least as much as to the other player. This condition is necessary, because if $x_s < x_o$, then the player could obtain greater utility by increasing x_s at the cost of x_o. Hence, player can set up $x'_s > x_s$ and $x'_o < x_o$ such that $x'_s \leq x'_o$. In this case $f(x'_s, x'_o) < f(x_s, x_o)$ and therefore, (x'_s, x'_o) should be strictly better than (x_s, x_o). That is the player has chosen a strictly dominated outcome and therefore cannot be rationalized with maximization of inequality averse utility function. This condition together with GARP is sufficient for rationalizability with inequality averse preferences.

Proposition 2. *Let $f(x_s, x_o)$ be an inequality measure. An experiment is rationalizable with inequality averse preferences if and only if it satisfies GARP and $x^t_s \geq x^t_o$ for every $t \in \{1, \dots, T\}$.*[6]

[6]The proposition is presented assuming budgets to be linear, while the proof is provided for nonlinear budgets as well. This is done to avoid further abuse of notation in the main text and state the result which can be applied to dictator as well as to other games studied further.

Condition for rationalization with inequality averse preferences does not depend on the inequality measure. That is, condition is the same for any inequality measure. Hence, the following corollary immediately follows from Proposition 2.

Corollary 1. *An experiment is rationalizable with inequality averse preferences, if and only if it is rationalizable with any inequality measure.*

The implications of Corollary 1 are two-fold. On one hand, we cannot exploit the particular structure of the inequality measure to refine the test. On another hand, we can test the *comprehensive* assumption of inequality aversion, which does not depend on the particular form of the inequality measure to be assumed.

2.3 Increasing Benevolence (IB) Increasing benevolence means that a player's willingness to pay for an additional dollar given to the other player is increasing in own payoff x_s.[7] Unlike in the preiovous cases we use the statement in terms of the demand functions. Denote the demand function for x_o by $D_o(p_s, p_o)$ and the demand for x_s by $D_s(p_s, p_o)$. Since we operate in a two-dimensional case, one demand can be immediately derived from another $D_s(p_s, p_o) = \frac{1-p_o D_o(p_s,p_o)}{p_s}$.

Definition 5. *An experiment is* ***rationalizable with increasing benevolence preferences*** *if there is a rational demand function $D_o(p_s, p_o)$ such that*

- $D_o(p_s^t, p_o^t) = x_o^t$*, and*
- $\frac{p_o}{p_s} \geq \frac{p'_o}{p'_s}$ *and* $\frac{1-p'_o D_o(p_s,p_o)}{p'_s} \geq D_s(p_s, p_o)$ *implies* $D_o(p_s, p_o) \leq D_o(p'_s, p'_o)$.

Increasing benevolence is equivalent to normality of x_o. A good is said to be normal if its demand is increasing function of income. Necessity of normality for increasing benevolence is quite obvious. Figure 2 illustrates why normality is sufficient for increasing benevolence. Assume that x^1 is a point chosen from the budget defined by p^1; then, the new budget is such that $\frac{p_s}{p_o} \geq \frac{p'_s}{p'_o}$ (x_s is relatively more expensive in the new budget) and the old bundle is attainable. The dashed line shows the parallel downward shift of the budget defined by p_2. Hence, the choice from the dashed budget should be

[7] This can be defined more formally with the marginal rate of substitution $-WTP = 1/MRS = \frac{u_{x_o}}{u_{x_s}}$ is increasing in x_s. We use the reduced form definition of this, which is necessary but not sufficient. However, it is sufficient to guarantee the empirical implications described by Cox, Friedman and Sadiraj (2008). Moreover, if we define MRS via the ratio of the inverse demand functions (to guarantee the existence of MRS), some sufficiency result can be inferred. Although, one can easily check that if we, for instance, assume that x_s and x_o are substitutes, then the demand conditions would be sufficient for the MRS version.

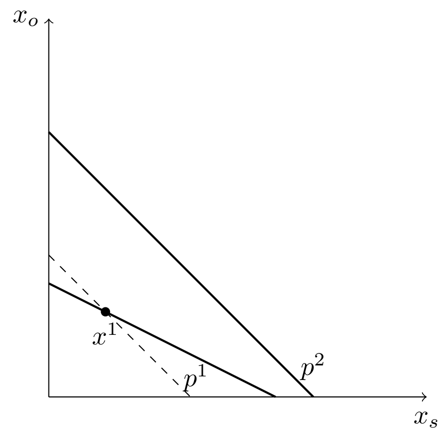


FIGURE 2. Increasing Benevolence and Normality

with at least as much x_o as from p^1 (due to the substitution effect). Furthermore, since dashed and p^2 budgets are different only in income, then normality would guarantee that the choice from p^2 would be "above" the x^1.

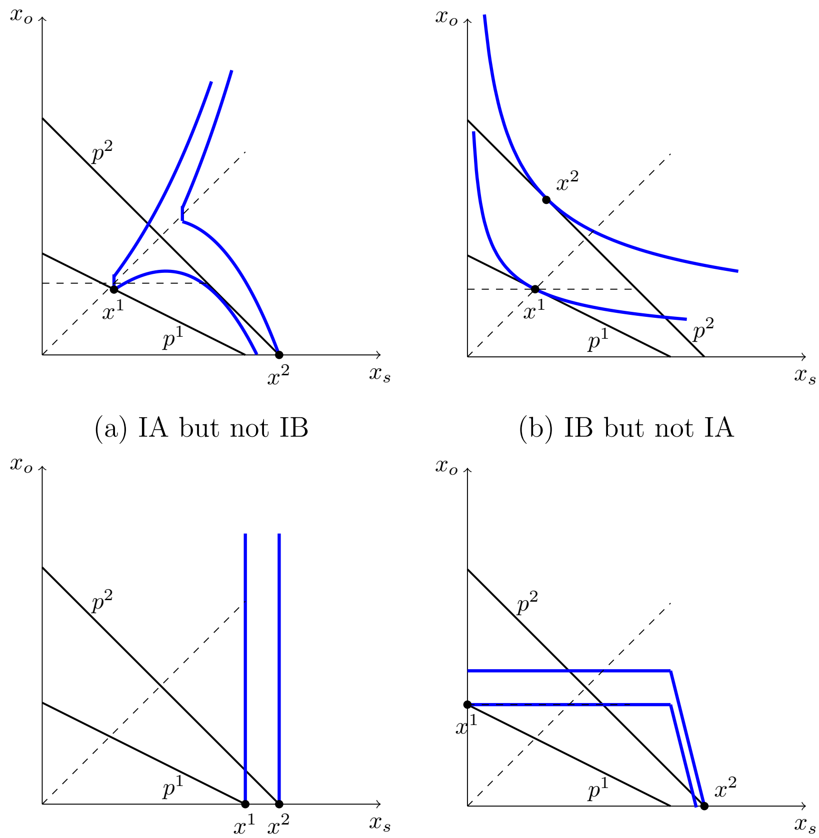
Definition 6. *An experiment* $E = (x^t, p^t)_{t=1}^T$ *is consistent with* **Normality Axiom of Revealed Preference (NARP)** *if and only if for all observations* $t, v \in \{1, \ldots, T\}$ *if* $p_o^t/p_s^t \leq p_o^v/p_s^v$ *and* $x_s^v \leq \frac{1-p_o^t x_o^v}{p_s^t}$, *then* $x_o^v \leq x_o^t$.

Equivalence between increasing benevolence and normality of demand in x_o allows us to employ the result from Cherchye, Demuynck and De Rock (2018) as the test for increasing benevolence.[8]

Proposition 3 (Cherchye, Demuynck and De Rock (2018))**.** *An experiment is rationalizable with increasing benevolence preferences if and only if it satisfies NARP.*

2.4 Independence of Nested Theories Further we show that nested theories (inequality aversion and increasing benevolence) are independent. Moreover, they are not exhaustive – there can be an other-regarding preference relation, neither inequality averse nor increasing benevolent. Hence, there are four cases: preferences consistent with both nested theories, with only one of them or with neither of them. Next we provide examples and intuition for each case.

[8]If a reader is not convinced by the equivalence argument above, please see p.375 in Cherchye, Demuynck and De Rock (2018) where it is directly proven that the increasing benevolence property is satisfied.



(a) IA but not IB

(b) IB but not IA

(c) IA and IB

(d) OR, but neither IA nor IB

FIGURE 3. Independence of Inequality Aversion and Increasing Benevolence

Consider budgets from Figure 3. Inequality aversion predicts choices to be at or below the 45 degree line from the origin. Increasing benevolence requires the choice from p^2 to have more x_o than the choice from p^1. Figure 3(a) presents the case for the preferences to be consistent with inequality averse preferences, but not increasing benevolent. Indifference curves presented could be generated by the utility function $u(x_s, x_o) = x_s^3 - \max(|x_s - x_o|, 1)$. It guarantees that for p^1 the optimal point is an allocation close to equal split, while for p^2, the optimal choice is to spend all income on x_s. Therefore, this is a violation of NARP and choices are not consistent with increasing benevolence preferences. Figure 3(b) presents the case of preferences that are increasing benevolent, but not inequality averse. Assume that player maximizes the utility function $u(x_s, x_o) = x_s x_o^2$. Then, for hight enough incomes (and low enough p_o) the choice would lie above 45 degree line ($x_s < x_o$). Hence, such preferences would not be consistent with inequality aversion. Figure 3(c) presents example of preferences consistent with both theories. Examples of such preference relations include selfish preferences ($u(x_s, x_o) = x_s$, presented on the figure) and perfect complements ($u(x_s, x_o) = \min(\alpha x_s, x_o)$ with $\alpha \geq 1$). Finally, Figure 3 presents example of other-regarding preferences not consistent with either of nested theories. Example of such preference is $u(x_s, x_o) = 4\max(x_s, 3) + x_o$. Idea behind, is that for low income, player only cares about x_o and as soon as she gets enough income, she becomes more selfish. Therefore, choice from p^1 would be above 45 degree line at the same time in the budget p^2 player would choose less of x_o then under p^1.

2.5 Revealed Social Preferences Beyond Dictator Games Extending the theory of revealed social preferences to other games is of particular importance, because different motives (that can depend on the game) can trigger different theories to perform better (see for instance Engellman and Strobel, 2004). Further we show how the revealed preference tests of social preferences can be applied for ultimatum, investment and carrot-stick games. Following Cox, Friedman and Sadiraj (2008) we consider second-movers in the two-stage games.

2.5.1 Ultimatum Game. First-mover is given an endowment m^t and asked to allocate it between herself and a second-mover, given that $p^t_o x_o + p^t_s x_s = m^t$, where x_o denotes the first-mover's earnings and x_s denotes the second-mover's earnings. Recall that we analyze the game from the point of view of the second-mover, therefore, payoff to proposer is considered to be as x_o and payoff to responder as x_s. Second-mover decides whether to accept or reject the proposed allocation. If the allocation is accepted, it is implemented; otherwise, both players get zero.

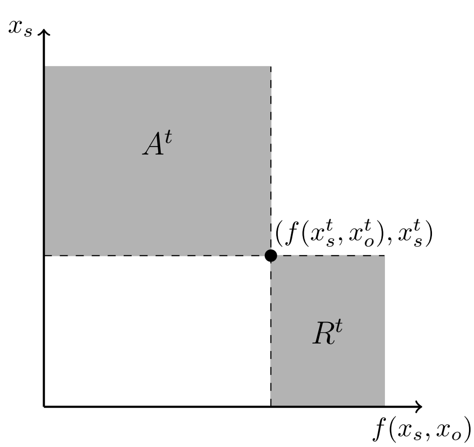


Figure 4. Acceptance and Rejection regions in Ultimatum Game

The case of other-regarding preferences is already considered in Castillo, Cross and Freer (2017). Increasing benevolence is not well-defined for the binary choices. Hence, we are left to test for inequality aversion. The experiment, on the side of the responder, is a sequence of binary decisions between proposed allocations and zero payoffs. Figure 4 presents the decision problem, as well as acceptance (A^t) and rejection (R^t) regions in $(f(x_s, x_o), x_s)$ coordinates. To be more precise, acceptance and rejection regions can be defined as follows.

$$A^t = \{(f(x_s, x_o), x_s) : x_s \geq x_s^t \text{ and } f(x_s, x_o) \leq f(x_s^t, x_o^t)\}$$

and

$$R^t = \{(f(x_s, x_o), x_s) : x_s \leq x_s^t \text{ and } f(x_s, x_o) \geq f(x_s^t, x_o^t)\}$$

If point $y^t = (f(x_s^t, x_o^t), x_s^t)$ was accepted, then it is revealed preferred to zero. Hence, every point in which is strictly better than y^t should also be better than zero (by transitivity), thereofre, should be accepted. If y^t is rejected, then zero is revealed better than y^t. Hence, every point which is strictly worse than y^t is also strictly worse than zero (by transitivity), therefore, should be rejected. Note that acceptance and rejecting regions correspond to the better than and worse than sets imputed from the partial order imposed by inequality aversion. Hence, if y^t is accepted, then every point from its acceptance region should be accepted and if y^t is rejected, then every points from its rejecting region should be rejected. Denote the set of all accepted allocations by A_x and the set of all rejected allocations by R_x.

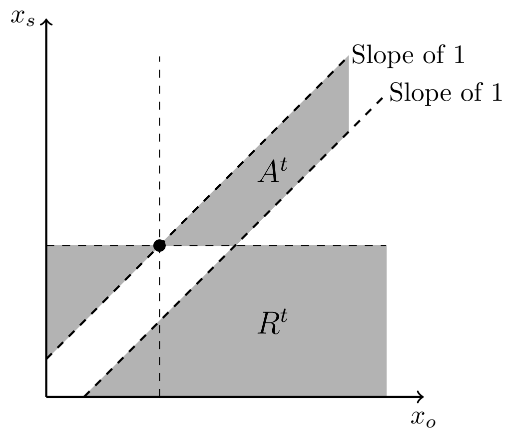
Corollary 2. *Let $f(x_s, x_o)$ be a measure of inequality. An ultimatum game experiment is rationalizable with inequality averse preferences if and only if*

$$R_x \cap \left(\bigcup_{x^t \in A_x} A^t \right) = \emptyset$$

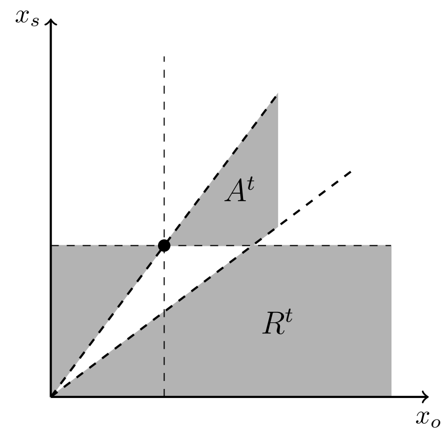
and

$$A_x \cap \left(\bigcup_{x^t \in R_x} R^t \right) = \emptyset.$$

Acceptance and rejection regions translates for different measures of inequality. Hence, performance of different measures of inequality can be distinguished. To illustrate this, we consider examples of inequality aversion in differences ($f(x_s, x_o) = |x_s - x_o|$) and inequality aversion in shares ($f(x_s, x_o) = \left|\frac{x_s}{x_s + x_o} - \frac{1}{2}\right|$). We choose this



(a) in Differences



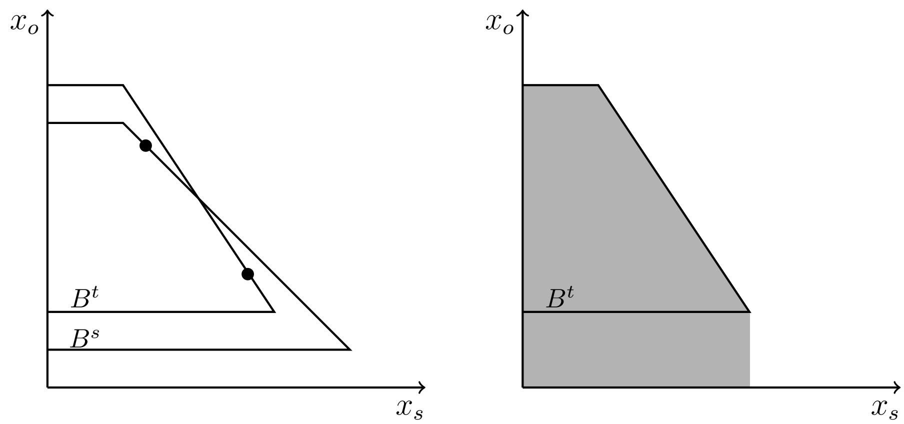
(b) in Shares

FIGURE 5. Inequality Aversion in Ultimatum Game for Different Measures of Inequality ($x_s > x_o$)

measures for the matter of illustration, since they are among the most widely applied in the literature.

Figure 5(a) shows the acceptance and rejection regions for the inequality aversion in difference. Every point on the line of slope one which goes through x has the same inequality level as x. Hence, the area between two dashed lines of slope one delivers the inequality level which is less or equal than inequality level at x. Therefore, the area between these lines and above the horizontal dashed line (current level of x_s) is strictly better than x and specifies the acceptance region. Rejection regions (shaded regions below the horizontal line) give the second-mover lower payoff and increase inequality, therefore, is strictly worse than x according to the inequality averse partial order. Figure 5(b) shows acceptance and rejection regions for inequality aversion in shares. Every point on the line that goes through zero and x has the same inequality level as x. The acceptance and rejection regions constructed by exactly the same logic as on Figure 5(a), although with different lines that preserve inequality. Comparing rejection and acceptance regions from Figures 5(a) and 5(b), we can see that they are different. Therefore, these measures of inequality have different testable implications.

2.5.2 Investment Game. Players start with an endowment of I. The first-mover sends an amount $s \in [0, I]$ to the second-mover who receives ks, for $k > 1$. Then the second-mover returns an amount of $r \in [0, ks]$, and the first-mover receives pr, where $1 \leq p \leq k$. The final payoffs are $x_o = I - s + pr$ and $x_s = I + ks - r$ for the first- and second-mover correspondingly. Hence, a family of investment games with different p and different s sufficient price generates variation to apply revealed preference tests.



(a) Violation of GARP (b) Downward closure of budgets.

FIGURE 6. Second-mover's budget set in the investment game.

Figure 6(a) presents the budget set of the second-mover and the possible violation of GARP in this case. Choices on the horizontal segments are not feasible. However, to construct the precise test we need to take the downward closures of the budget sets presented at the Figure 6(b). Denote by.

$$B^{\downarrow} = \{y : \text{ there is } x \in [0, ks] \text{ such that } x \geq y\}$$

the downward closure of B and by $B^{\downarrow\downarrow}$ the interior of the downward closure (replacing the weak inequality with strict one). Assume k to be fixed over the observations, hence, *investment game experiment* consists of observed triples of s^t (determines the income), p^t (relative price of returning) and x^t (chosen point). Hence, we can restate GARP using $x \in B^{\downarrow}$ instead of $px \leq m$ and $x \in B^{\downarrow\downarrow}$ instead of $px < m$. Using the new notation Proposition 1 can be immediately applied (using the Forges and Minelli, 2009, result) therefore, the proof is omitted.[9]

[9]Formally we also have to assume that burning money is feasible, i.e. players can choose in the interior of the budget set. Although, the necessity of GARP holds for both altruistic (player gets utility from both x_s and x_o) and spiteful (player gets utility from own payoff and disutility from x_o) preferences, while sufficiency can be inferred from Nishimura, Ok and Quah (2017) result. Idea behind is that spiteful player will always choose to return nothing and this choice pattern is consistent with GARP.

Corollary 3. *An investment game experiment $E = (x^t, B^t)_{t=1}^T$ is rationalizable with other-regarding preferences if and only it satisfies GARP.*

Next, we consider increasing benevolence preferences. If all choices are such that $x^t \in B^v$ if and only if $p^v x^t \leq s^t$ for every $t, v \in \{1, \ldots, T\}$, then Proposition 3 can be applied to test for increasing benevolence. This assumption reduces the budgets to the linear case of dictator game. Considering the inequality aversion, we can immediately apply the Proposition 2, substituting the linear definition of the budget with the general definition. The reason behind is that since $s^t \geq 0$, then $x_s = x_o$ is available even for $s = 0$ and clearly available for every $s > 0$.

Corollary 4. *Let $f(x_s, x_o)$ be an inequality measure. An investment game experiment $E = (x^t, B^t)_{t=1}^T$ is rationalizable with inequality averse preferences if and only if it satisfes GARP and $x_s^t \geq x_o^t$ for every $t \in \{1, \ldots, T\}$.*
Moreover, if an investment game experiment experiment is rationalizable with an inequality measure, then it is rationalizable with any inequality measure.

2.5.3 Carrot-Stick Game. Both players start with an endowment of I. The first-mover chooses the amount to be sent $s \in [0, I]$. Then, the second-mover can "return" the amount $r \in [-ks, ks]$ and the first-mover receives pr. The final payoffs are $x_o = I - s + pr$ and $x_s = I + ks - |r|$. Hence, the family of carrot-stick games with different different p and different s generates sufficient price variation. *Carrot-stick experiment* is defined by s^t, p^t and x^t.

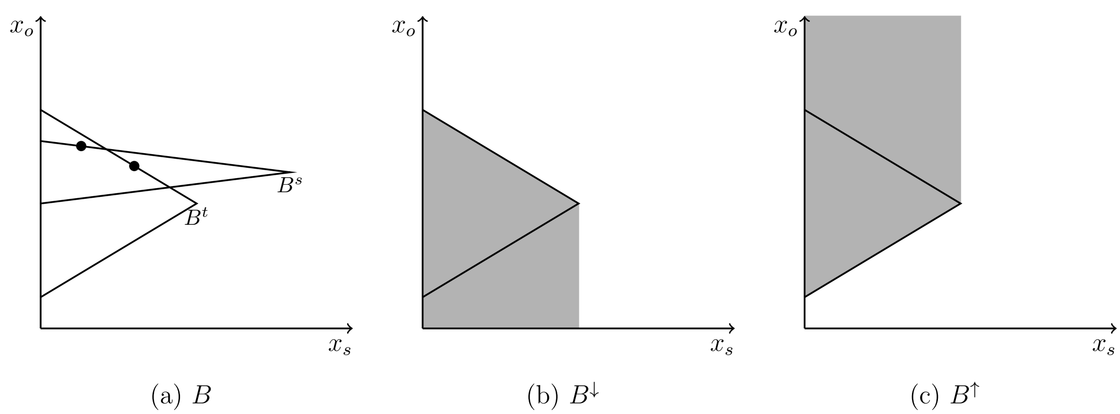


FIGURE 7. Second-mover's budget set in the carrot-stick game.

Figure 7(a) presents the budget sets that the second-mover faces. Unlike in the cases of dictator and investment games there implications are different for "altruistic" and "spiteful" preferences, because there are both "upper" and "lower" borders of the budgets. Preferences are said to be *altruistic* if utility is increasing in both x_s and x_o. Preferences are said to be *spiteful* if utility is increasing in x_s and decreasing in x_o. Therefore, the altruistic player use only carrot, while spiteful use only stick, and each of the choices is dominated for the different type of player. Denote by B^t the budget (as on Figure 7) based on which the player makes a choice. Denote by $B^{\downarrow}[^{\uparrow}] = \{(x'_s, x'_o) : (x_s, x_o) \in B$ such that $x_s \geq x'_s$ and $x'_o \geq (\leq) x_o\}$. Denote by $B^{\downarrow\downarrow}[^{\uparrow\uparrow}] = \{(x'_s, x'_o) : (x_s, x_o) \in B$ such that $x_s \geq x'_s$ and $x'_o \geq (\leq) x_o\}$ with at least one inequality being strict. Figures 7(b) and 7(c) illustrate the construction of $B^{\downarrow}$ and $B^{\uparrow}$ respectively. The shaded areas show the part of the space added by taking the closure of the budget.

Further we refer to the A-GARP as to GARP which uses $x \in B^{\downarrow}$ instead of $px \geq 1$ and $x \in B^{\downarrow\downarrow}$ instead of $px < 1$ and to S-GARP as to GARP which uses $x \in B^{\uparrow}$ instead of $px \geq 1$ and $x \in B^{\uparrow\uparrow}$ instead of $px < 1$. We als claim that a choice is a violation of A-GARP is it is in $B^{\downarrow\downarrow}$ and a choiceis a violation of S-GARP if it is in $B^{\uparrow\uparrow}$. Hence, we can immediately provide the criteria for rationalization with altruistic and spiteful preferences using the result from Nishimura, Ok and Quah (2017).

Corollary 5. *A carrot-stick experiment $E = (x^t, B^t)_{t=1}^T$ is rationalizable with altruistic [spiteful] preferences if and only if it satisfies A-GARP [S-GARP].*

Denote by p^t price vector, that corresponds to the "upper boundary" of B^t. If all choices are such that $x^t \in B^v$ if and only if $p^v x^t \leq 1$ for every $t, v \in \{1, \ldots, T\}$, then Proposition 3 can be applied to test for increasing benevolence. Recall that increasing benevolence is nested within altruistic preferences. Therefore, the stick is not consistent with increasing benevolent preferences.

Next we consider inequality-averse preferences. As in ultimatum game, in the carrot-stick game different measures of inequality have different empirical implications.[10] Figure 8(a) presents the case with an inequality averse (in differences) player using the stick. The shaded area presents the set of points better than the chosen action. None of the points that dominate the chosen one are in the budget. Hence, the choice of stick can be optimal if a player has inequality averse preferences. Figure 8(b) shows that if p is low enough, then using stick is no longer rational. Figure 8(c) shows that

[10] The test given the measure of inequality can be easily formulated following the result of Nishimura, Ok and Quah (2017) as we have done for the case of ultimatum game.

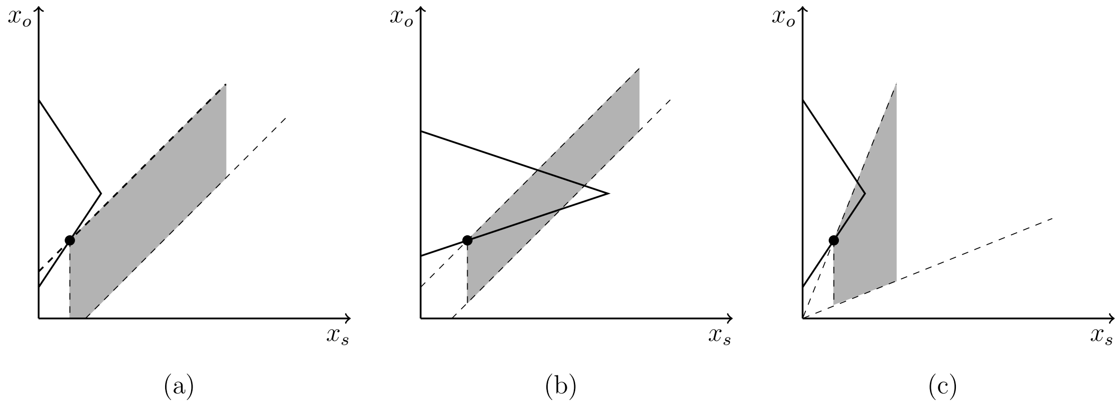


FIGURE 8. Using the stick with inequality averse preferences.

testable implications in the carrot-stick game would depend on the particular measure of inequality, because the budget set contains the points that dominate the chosen one. Hence, the same choice is consistent with inequality aversion in differences (Figure 8(a)), but not with inequality aversion in shares (Figure 8(c)). Note that inequality aversion is the only of the above-mentioned theories that can rationalize a player who uses both carrot and stick.

Further we present restrictions on the experimental design which allows us to apply test for inequality aversion without making parametric restrictions about the measure of inequality. Idea behind is that we need to restrict the experiment to the collection of budgets such that $x_s = x_o$ is available. In order to implement this, it is enough to either guarantee the second-mover the initial endowment of I. The same logic as for investment game implies that for every $s \geq 0$, the equal outcome is available. Alternatively, one can restrict the minimal amount sent by the first-mover to $s \geq \frac{I}{k+1}$ to guarantee that equal outcome is available. Hence, in this case the version of Proposition 2 can be applied to test for rationalizability with inequality aversion (using the altruistic version of GARP from Corollary 5). Finally, in this case inequality averse player would use carrot only and never use a stick.

Corollary 6. *Let $f(x_s, x_o)$ be an inequality measure and $E = (x^t, B^t)_{t=1}^T$ be carrot-stick experiment such that $x_s = x_o$ outcome is available at every budget set. A carrot-stick experiment $E = (x^t, B^t)_{t=1}^T$ is rationalizable with inequality averse preferences if and only if it satisfies A-GARP and $x_s^t \geq x_o^t$ for every $t \in \{1, \ldots, T\}$.*
Moreover, if a carrot-stick experiment is rationalizable with an inequality measure, then it is rationalizable with any inequality measure.

Let us conclude with a remark on possible experimental design in order to apply the tests. Design of experiment directly follows from the construction of the test. In order to guarantee the sufficient price variation one can use discretized first-mover's problem with a strategy method. Hence, the second-mover would have to make decisions over the budgets corresponding to every possible decision (out of the finite set) the first-mover can make for every budget proposer would face (see Castillo and Cross, 2008; Castillo, Cross and Freer, 2017, for the case of ultimatum game). Strategy method allows to avoid possibility of falling short on the power of test due to specific decisions first mover made.

3 Empirical Illustration

We present evidence from dictator and ultimatum games. While dictator game allows for comprehensive test of inequality aversion hypothesis (see Corollary 1), ultimatum game (theoretically) allows to distinguish between different measures of inequality.

3.1 Dictator Game We use data from two studies of dictator games. In both studies, subjects repeatedly played a dictator game with different relative prices and endowments. In every period subjects were asked to allocate tokens between themselves and another person, choosing a point on a linear budget $p_s^t x_s + p_o^t x_o \leq m^t$. The first study (Fisman, Kariv and Markovits, 2007) contains results of experiments with 76 undergraduates from UC Berkeley.[11] In this study, every subject faced 50 different budgets with randomly determined prices. The second study (Porter and Adams, 2016) contains results of experiments with 89 subjects recruited from the general population from the southeast region of the UK. In this study every subject faced 11 different budgets with predetermined prices.

3.1.1 Consistency Results When applied to data, notions of rationality prove to be very strict at least for the first data set: no more than 16% of subjects can be rationalized with other-regarding preferences and no more than 11% with nested theories. Therefore, it makes sense to relax the notion of rationality and allow for some probability that people make mistakes. For this purpose, we use the **Houtman-Maks index (HMI)**.[12] HMI is the maximum fraction of data that can be rationalized by a given

[11]Experiment contains two other treatments which we do not consider in our analysis. One of the treatments uses step-shaped budgets and another is a dictator game with two recipients.

[12]See Houtman and Maks (1985); Heufer and Hjertstrand (2015); Dean and Martin (2009). We use the HMI because it is the only index that can be applied to test Inequality Aversion. Critical Cost

theory. That is, if in a total of T observations, the maximum subset which is consistent with the theory is τ, then $HMI = \tau/T$. For the technical details regarding the implementation of the HMI index, see Supplementary Materials. We report results for the HMI level of .9. The results are robust to other levels of HMI (see Supplementary Materials). The HMI level of .9 allows for deviations from rationality in no more than 10% of budgets.

Next, we want to control for false positives. A false positive is the probability that a random decision making would look consistent with the test. We use two procedures which differ in the assumption about the random behavior. First is the Bronars (1987) power, conducted by generating 1000 random subjects who make decisions uniformly distributed along the budget line. Power of the test is computed as the fraction of random subjects who fail to perform consistently with the test. The second is the bootstrap power (see e.g. Cox, 1997; Harbaugh, Krause and Berry, 2001; Andreoni and Miller, 2002). This measure controls for possible behavioral rules that can cause false positive results even if people would take decisions at random. To compute the bootstrap power of the test, we calculate the empirical distribution of the shares of income spent on each commodity – in our case the subject's payoff and the other's payoff – and simulate the pseudo subjects who make their choices at random but distributed according to the empirical distribution function.

Last, to compare pass rates controlling for the power we use the **predictive success index (PSI)** introduced by Selten (1991).[13] The predictive success index is defined as the difference between the share of people that satisfies an axiom at the given level of HMI and the probability that random choices will satisfy the axiom at the same level of HMI. This index ranges between -1 and 1, with -1 meaning no subject passes while all random subjects pass and 1 meaning every subject passes while none of the random subjects do. If PSI is greater than zero, then theory describes the behavior better than random choice, and if PSI is less or equal to zero, then the random choice explains the observed behavior better.

Efficiency Index introduced by Afriat (1973) would not adequately work in the context of inequality aversion. The money pump index introduced by Echenique, Lee and Shum (2011) is defined for GARP only. The swaps index proposed by Apesteguia and Ballester (2015) can be applied only in the context of finite choice sets.

[13]Methodology of using predictive success index in the revealed preference context was introduced by Beatty and Crawford (2011). Statistical interpretation of the index which allows us to construct confidence intervals was proposed by Demuynck (2015).

Table 1 shows results of testing other-regarding preferences for both datasets. The second column presents the pass rates (share of subjects who pass the test with HMI at least .9). The third and fourth columns present the power computations according to Bronars and the bootstrap methods.[14] Last two columns present the predictive success index using Bronars and bootstrap powers.

Theory	Pass Rate	Power of Test Bronars	Power of Test Bootstrap	PSI Bronars	PSI Bootstrap
Fisman, Kariv and Markovits (2007) data					
Other-regarding	58 (76.32%)	100.00%	99.63%	0.76	0.76
95% conf. interval	(65.18% - 85.32%)	(99.99% - 100.00%)	(99.58% - 99.67%)	(0.67 - 0.86)	(0.66 - 0.86)
Porter and Adams (2016) data					
Other-regarding	81 (91.01%)	68.72%	80.01%	0.60	0.71
95% conf. interval	(83.05% - 96.04%)	(68.41% - 69.02%)	(79.75% - 80.28%)	(0.54 - 0.66)	(0.65 - 0.77)

Table 1. Results for Other-Regarding Preferences

Subjects (in both experiments) are consistent with having other-regarding preferences. In particular 76% of subjects in the first dataset and 91% in the second one are consistent with having other-regarding preferences. Results are robust to controlling for the power of test.

Inequality aversion and increasing benevolence are nested within the other-regarding preferences model. That is, a subject can only be consistent with having inequality averse and/or increasing benevolence preferences, if she is consistent with having other-regarding preferences. Hence, we report a nested theory analysis; that is, results are presented for the subexperiment, which consists only of subjects who are consistent with other-regarding preferences hypothesis (given HMI=.9).

Table 2 presents results for nested theory analysis. Structure of the table is the same to the one of Table 1. Both theories are significantly restrictive – there is significant share of population (15-79%) which is consistent with having other-regarding preferences, but not with increasing benevolence or inequality averse preferences. In addition, while 55% of subjects are consistent with inequality averse preferences in

[14] Power is different for different data sets first of all, because of the different amount of budgets: 50 vs 11. Difference in power is even larger for increasing benevolence. Experiment of Porter and Adams (2016) is aimed at testing GARP, which rather requires price variations while NARP requires rather income variation. Income variation is higher in Fisman, Kariv and Markovits (2007) data set because of the larger amount of budgets.

Theory	Pass Rate	Power of Test Bronars	Power of Test Bootstrap	PSI Bronars	PSI Bootstrap
Fisman, Kariv and Markovits (2007) data					
Inequality Aversion	32 (55.17%)	100.00%	92.58%	0.55	0.48
95% conf. interval	(41.54% - 68.26%)	(100.00% - 100.00%)	(92.39% - 92.76%)	(0.42 - 0.68)	(0.35 - 0.61)
Increasing Benevolence	12 (20.69%)	100.00%	100.00%	0.21	0.21
95% conf. interval	(11.17% - 33.35%)	(100.00% - 100.00%)	(100.00% - 100.00%)	(0.10 - 0.31)	(0.10 - 0.31)
Porter and Adams (2016) data					
Inequality Aversion	51 (62.96%)	98.62%	90.50%	0.62	0.53
95% conf. interval	(51.51% - 73.44%)	(98.55% - 98.70%)	(90.31% - 90.69%)	(0.51 - 0.72)	(0.43 - 0.64)
Increasing Benevolence	69 (85.19%)	85.68%	65.67%	0.71	0.51
95% conf. interval	(75.55% - 92.10%)	(85.44% - 85.90%)	(65.35% - 65.98%)	(0.63 - 0.79)	(0.43 - 0.59)

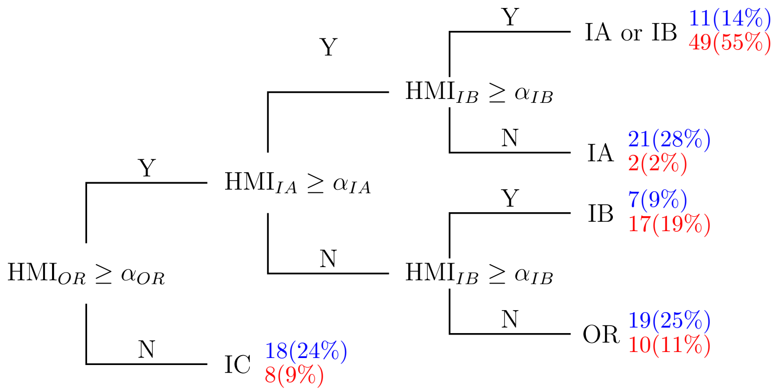
TABLE 2. Results for Nested Theories

Fisman, Kariv and Markovits (2007) data, only 21% of them is consistent with having increasing benevolence preferences. However, the results are opposite for the Porter and Adams (2016) data: 63% of subjects are consistent with having inequality averse preferences and 85% of them are consistent with having increasing benevolence preferences. To sum up, inequality aversion appears to describe data better in the first dataset; and increasing benevolence performs at least as well as inequality aversion in the second one (difference in PSIs is not statistically significant). This inconsistency between the two datasets provides evidence in line with Fehr, Naef and Schmidt (2006), who showed that social preferences may depend on the demographic characteristics of the population.

3.1.2 Mixed Types Analysis None of the nested theories can explain the behavior of the entire sample. At the same time, both theories perform well even conditioning on their power. In addition, different theories have quite different empirical implications, and the correlations between pass rates for inequality aversion and increasing benevolence are quite low: .22 (with a confidence interval of $[-.01, .42]$) for Fisman, Kariv and Markovits (2007) data and .51 (with a confidence interval of $[.34, .65]$) for Porter and Adams (2016) data.[15] This shows that there is a non-trivial probability that different

[15]Given that the tests are binary, appropriate statistic is ϕ-coefficient. It is a version of correlation coefficient for two binary variables. Both logit and probit regression coefficients are insignificant for Fisman, Kariv and Markovits (2007) data: logit regression coefficient is 1.2 (with 95% confidence interval of $[-0.06, 2.61]$) and probit regression coefficient is 0.75 (with 95% confidence interval of $[-0.04, 1.57]$). That is we can not reject that two nested theories are unrelated for Fisman, Kariv and Markovits (2007) data. For Porter and Adams (2016) data the relationship is much stronger: logit coefficient is 3.09 (with 95% confidence interval of $[1.74, 4.99]$), probit coefficient is 1.84 (with

subjects can be consistent with different notions of rationality. Therefore, we perform a mixed type analysis. Main goal of this exercise is to find out which theory is the most appropriate to describe behavior at the subject level, while the previous analysis focused at the sample level.



Top numbers are for Fisman, Kariv and Markovits (2007) data,
bottom numbers are for Porter and Adams (2016) data.

Figure 9. Classification Tree for Dictator Game

Subjects are assigned to theories according to three sequential binary classification steps presented in Figure 9. First, if a subject is not consistent with other-regarding preferences at threshold α_{OR}, she is classified as inconsistent with other-regarding preferences (IC). Next, we compare whether she is consistent with inequality aversion or increasing benevolence with thresholds α_{IA} and α_{IB} respectively. If the subject is not consistent with either, she is classified as other-regarding (OR). If the subject is consistent with both, she is assigned to a separate class of inequality averse or increasing benevolent (IA or IB). If the subject is consistent with only one theory, she is classified as inequality averse (IA) or increasing benevolent (IB).

It is still necessary to determine the thresholds for the classification tree. In order to do this, we modify the unsupervised machine learning methodology from Liu, Xia and Yu (2000). The approach maximizes the information gain from adding a particular cluster. We base this measure on HMI, but the approach is general (for more detailed explanation see Supplementary Materials). The thresholds obtained are as follows:

95% confidence interval of $[1.07, 2.72]$). That is, odds of the subject being consistent with inequality aversion are at least $e^{1.74} = 5.7$ times higher if she is also consistent with increasing benevolence than if she is not.

$\alpha_{OR} = 45/50$; $\alpha_{IA} = \alpha_{IB} = 41/50$ for Fisman, Kariv and Markovits (2007) data and $\alpha_{OR} = \alpha_{IA} = \alpha_{IB} = 10/11$ for Porter and Adams (2016) data.

In the first dataset, a large set of subjects can be described by inequality aversion but not by increasing benevolence preferences (28% against 9%). In the second experiment, the distinction is less clear, as the majority of subject (55%) can be described by IA or IB.[16] Remark that, 11-25% of the population cannot be explained by either inequality aversion or increasing benevolence, but still has other-regarding preferences. This fact also provides additional evidence for both assumptions being significantly restrictive. The difference between the two datasets in terms of classification for nested theories is consistent with the results in the previous subsection.

Given the significant share of population consistent with both: IA and IB especially in Porter and Adams (2016) data set, we conduct the cross power analysis. That is we need to simulate the random subjects which are consistent with IA but not with IB and vise versa. This allows us to construct the modified predictive success given the conditional power analysis. Using the results of cross power analysis we can construct the adjusted predictive success index (APSI). To explain the idea of APSI we provide an example of its computation for IA. We consider separate PSIs for the subsamples of IA or IB and IA. The main difference is that for IA or IB subsample we use the cross power. APSI in its order is equal to the weighted sum of the PSIs for each subsample, where weights are the ratios of corresponding subsample size to the entire sample size.

Table 3 presents the APSI results for nested theories in the dictator game. The second column presents APSI computed using the Bronars power and the third one presents APSI computed using the bootstrap power. First, we look at the results for Fisman, Kariv and Markovits (2007) dataset. APSI for inequality aversion is at least as large as one for increasing benevolence. This result holds for both ways used to compute the power. Results for Porter and Adams (2016) dataset look rather mixed. APSI is higher for increasing benevolence if Bronars power is used and APSI is higher for inequality aversion is higher if bootstrap power is used. Hence, inequality aversion is a rather prevalent theory, but it is not obviously dominant in terms of explaining

[16]However, as a caveat here, note that power of test for increasing benevolence is significantly lower than the one for inequality aversion. Moreover, in Porter and Adams (2016) experiment, three participants gave more to their counterparts than they kept for themselves in all 11 budgets. Such altruistic behavior is maximally inconsistent with inequality aversion, implying an HMI of zero (theoretically HMI for other theories starts with 1). We exclude these three subjects from the mixed type analysis without significantly affecting the results (see detailed results in Supplementary Materials).

	Bronars	Bootstrap
Fisman, Kariv and Markovits (2007) data		
Inequality Aversion	.55	.31
Increasing Benevolence	.31	.31
Porter and Adams (2016) data		
Inequality Aversion	.63	.55
Increasing Benevolence	.74	.50

Table 3. APSI for Nested Theories in Dictator Game

the observed behavior. Therefore, it is of particular importance to take both theories into account to explain the observed behavior.

3.2 Ultimatum Game We use data from Castillo, Cross and Freer (2017) who conduct an experiment with total of 123 participants (students from Georgetown and Texas A&M universities). Every subject had to make the accept/reject decision over 13 alternatives drawn from 9 different linear budgets, that adds up to 117 binary choices from every subject. See Castillo, Cross and Freer (2017) for the more detailed description of the design and the data as well as the evidence that subjects are consistent with other-regarding preferences.[17] Next, we present the results on testing inequality aversion in differences and inequality aversion in shares.

3.2.1 Consistency Results About 40-45% of the sample are consistent with either versions of inequality aversion without allowing for any decision making error. Results of the analysis from allowing for error of 5% are presented in the Table 4 (composition of the Table similar to those for dictator game). About 87% of subjects are consistent with inequality aversion in differences and 82% of subjects are consistent with inequality aversion of shares. In addition to Bronars and bootstrap power we also conduct the cutoff power analysis.

Given the specifics of the budget sets we use the cutoff rules Idea behind is that responder uses cutoff rule – everything below cutoff is rejected and everything above cutoff is accepted. This cutoff is determined randomly according to uniform distribution (Bronars cutoff) and empirical distribution functions (Bootstrap cutoff). Finally,

[17] Castillo, Cross and Freer (2017) conducted two sets of sessions, we report the results from them together. Let us note that choices are quite different between the populations, while the consistency with other-regarding preferences is quite uniform for both samples.

Theory	Pass Rate	Power of Test Bronars Cutoff	Power of Test Bootstrap Cutoff	PSI Bronars Cutoff	PSI Bootstrap Cutoff
IA in Differences	107 (86.99%)	100.00%	98.45%	0.87	0.84
95% conf. interval	(79.74% - 92.38%)	(100.00% - 100.00%)	(97.81% - 98.84%)	(0.85 - 0.89)	(0.81 - 0.86)
IA in Shares	101 (82.11%)	100.00%	99.00%	0.82	0.80
95% conf. interval	(74.18% - 88.44%)	(100.00% - 100.00%)	(98.46% - 99.39%)	(0.80 - 0.84)	(0.77 - 0.82)

TABLE 4. Results for Ultaimatum Game

the power analysis shows that no more than 5% of random subjects are consistent with either theories. Hence, both theories explain data better than the random decision making. Further analysis is aimed on distinguishing which of inequality measures explains the data better.

Given the pass rates (86% for IA in differences and 82% for IA in shares) and power of test (more than 95% of random subjects fail the test at the given HMI) both theories are valid – explain the behavior better than random. Hence, let us move on to comparing the performance of different theories. The pass rates are higher for the IA in Differences, although, the difference is not significant. The same result holds for PSI. Moreover, given that 107 out of 123 subjects are consistent with IA in differences and 101 are consistent with IA in shares, there is obviously a significant chunk of population consistent with both theories.

3.2.2 Mixed Types Analysis Both versions of IA perform better than random hypothesis. Therefore, next, we perform the mixed type analysis using the similar methodology we use for dictator game. Subjects are assigned to theories according to the decision tree presented in Figure 10. The thresholds $\alpha_S = 111/117$ and $\alpha_D = 112/117$ for IA in shares and IA in differences correspondingly.

Only 12 subjects (10%) are not consistent with either of theories (IC). Most of the sample 106 subject (86%) is consistent with both theories (S or D). At the same 4 subjects (3%) are consistent with IA in shares but not with IA in differences (S), and 1 subject (1%) is consistent with IA in differences but not IA in shares (D). Hence to further disentangle performance of the theories we conduct cross-power analysis. That is to simulate the random subjects which are consistent with IA in shares and check which share of them is consistent with IA in differences and vice versa. Using the results of cross power analysis we can construct the APSI as for the dictator game.

Table 5 presents the APSI results for IA in Differences and IA in shares. The second column presents the APSI computed using the Bronars cutoff power, and the third one present APSI computed using the bootstrap cutoff power. APSI for IA in shares is

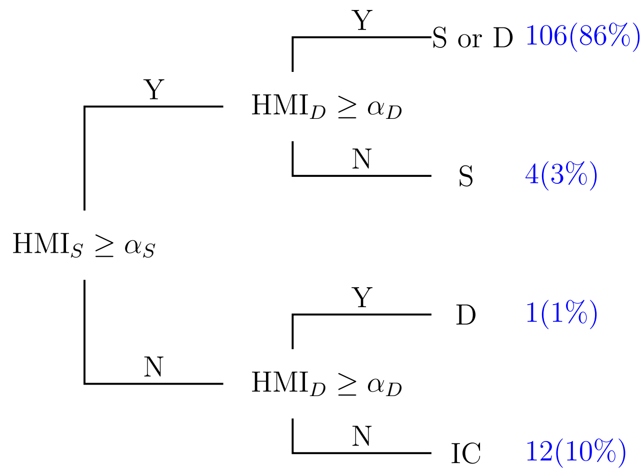


FIGURE 10. Classification Tree for Ultimatum Game

	Bronars Cutoff	Bootstrap Cutoff
IA in Differences	.64	.43
IA in Shares	.09	.09

TABLE 5. APSI for Ultimatum Game

much higher for both cases. Hence, we can conclude that a higher share of subjects is rather consistent with IA in shares, that with IA in differences. Although, this evidence is rather weak since the main driving factor is the power of the tests.

4 Revealing Altruism and Fairness

Further we present how the revealed preference conditions can be used for comparison of the level of altruism among players and partial identification of the (subjective) notion of fair outcome player may have. To classify player in terms of altruism we need to require them to be consistent with increasing benevolence preferences (consistent with NARP) and use the methodology from Cox, Friedman and Sadiraj (2008). While the original method can either compare players pointwise or to require the entire demand function to be assumed, we show that under the same comparison can be done under partial observability.

Revealation of fair outcome in refers to the genrealization of inequality aversion. While the standard inequality averse theory assumes that players assume that the fair outcome is the one which delivers equal split, this does not have to be true in general.

Hence, if players have subjective notion of fair outcome, which can deviate from equal split, but still get disutility if the outcome deviates from the fair outcome, we obtain the generalization of inequality aversion. Therefore, conditions from Proposition 2 can be generalized to identify the fair outcome.

4.1 Revealed Relative Altruism Cox, Friedman and Sadiraj (2008) provide the revealed preference–based approach to classify people in terms of altruism. A demand function $D(p_s, p_o)$ is **more altruistic than** $\tilde{D}(p_s, p_o)$ if $D_o(p_s, p_o) \geq \tilde{D}_o(p_s, p_o)$ for every $p \in \mathbb{R}_{++}$. Original conditions required to observe the whole demand function, while we show that the same method can be applied even if only finite set of choices is observed.

Corollary 7. *Consider experiments E and $\tilde{E}$ in which players faced the same prices. Moreover, assume that both experiments satisfy NARP. Experiments are rationalizable with increasing benevolence preferences such that $D(p_s, p_o)$ is more altruistic than $\tilde{D}(p_s, p_o)$ if and only if $\tilde{x}_o^t \geq x_o^s$ for all $p^s = \tilde{p}^t$.*

The necessity of this condition is quite obvious since we consider experiments with similar prices. Hence, we can reconstruct demand functions such that the first experiment will be more altruistic than the second one.

4.2 Revealed Fair Outcome Next we show how to identify the fair outcome using the revealed preference conditions. For this purpose we need formally define what is the fair outcome. Assume that $\chi^* < 1$ is the *fair ratio of payoffs*, that is, the outcome is fair if and only if $x_s/x_o = \chi^*$. We assume that $\chi^* < 1$, as otherwise every player who is consistent with GARP can be rationalized as inequality averse.

Moreover, we slightly modify the definition of the inequality measure. We assume that $f(x_s, x_o) = 0$ if and only if $x_s/x_o = \chi^*$. Moreover, $f(x_s, x_o)$ is increasing in x_o and decreasing in x_s if $x_s/x_o < \chi^*$; and $f(x_s, x_o)$ is decreasing in x_o and increasing in x_s if $x_s/x_o > \chi^*$. The last property of an inequality measure needs to be restated as follows: if $x_s/x_o = \chi < \chi^*$, then there is $x_s' \leq x_s$, such that $f(x_s, x_o) \geq f(x_o, x_s')$.

Corollary 8. *Let χ^* determine the notion of fair outcome and $f(x_s, x_o)$ be an inequality measure. An experiment is rationalizable with inequality averse preferences if and only if an experiment satisfies GARP and $x_s^t \geq \chi^* x_o^t$ for every $t \in \{1, \ldots, T\}$.*

5 Concluding Remarks

The paper presents the revealed preference tests for increasing benevolence and inequality averse preferences. Moreover, the tests can be applied (beyond the standard revealed preference framework with linear budgets) to other games used to study social preferences. Although all conditions provided in the paper are deterministic, the constraints obtained can be used as the moment inequalities. This would allow one to construct stochastic bounds that take into account decision making and/or measurement errors.[18]

In addition, we provide (the method for) mixed type analysis using only non-paramteric revealed preference approach. Several previous papers (see e.g. Andreoni and Miller, 2002; Porter and Adams, 2016) attempted to classify people into distinct types according to their giving behavior. However, in these papers particular types of preferences were characterized with a parametric specification of the utility function, while the method we offer, is completely non-parametric. Hence, the method proposed is more flexible and allows for more robust classification of subjects, which can further be used for the out-of-sample predictions.

Appendix A: Proofs

Proof of Proposition 2 We present a generalized version of the proof for Proposition 2, with not necessarily linear budgets. This allows us to get the immediate implications for the investment and carrot-stick games regardless of budgets being non-linear. Hence, before we proceed with the further proof, let us introduce the formal definition of the feasible budget sets. To the large extent we follow the definition of non-linear budgets provided by Forges and Minelli (2009).

Let $\gamma : \mathbb{R}^2_+ \to \mathbb{R}_+$ be a gauge function, if it is continuous, homogeneous of degree one, and strictly monotone. We consider the experiment that contains of the budgets described as $\gamma^t(x) = 1$, where γ is a gauge function. In addition we assume that equal outcome is available at every budget, that is for every $x_s < x_o : \ \gamma(x_s, x_o) = 1$, then $\gamma(x_s, x_s) \leq 1$. Hence, $px < 1$ corresponds to $\gamma(x) < 1$ and $px \leq 1$ corresponds to $\gamma(x) \leq 1$. Hence, experiment can be described as a collection $E = \{x^t, \gamma^t(x)\}_{t=1}^T$.

[18]See Chernozhukov, Hong and Tamer (2007) for general results on partial identification and Aguiar and Kashaev (2017) for particular applications for revealed preferences with measurement error. Moreover, methodology from the latter paper directly applies to the results we state.

Before we proceed further let us introduce the corresponding space of the inequality aversion. Let $IA = (Y, \geq_{IA})$ be a *partially ordered space*, where $Y \subseteq \mathbb{R}^2_+$, with $y = (x_s, f(x_s, x_o))$ for every $y \in Y$ and $y \geq_{IA} y'$ if $x_s \geq x'_s$ and $f(x_s, x_o) \leq f(x'_s, x'_o)$. Denote by $>_{IA}$ the strict part of $\geq_{IA}$. Note that $f(x_s, x_o)$ defines the injective mapping from X to Y. Since $f(x_s, x_o)$ is a continuous function and X is a compact set, then Y is a compact set as well.

Next step is to map the budget line from X to Y. Although, we do not map the entire budget line, but only the part of it, which corresponds to $x_s \geq x_o$. Denote by $Z = \{x \in X : \ x_s \geq x_o\}$ the half-space at which player leaves to herself at least as much as received by another player. Denote by B the budget line in IA obtained from mapping a budget $\gamma(x) = 1$ such that $x \in Z$. Denote by $B^{\downarrow} = \{y : \text{ there is } y' \in B \text{ such that } y \geq_{IA} y'\}$ the **downward closure** of budget B. Denote by $B^{\downarrow\downarrow} = \{y : \text{ there is } y' \in B \text{ such that } y' >_{IA} y$ the **interior** of budget set B. Denote by $\partial B = B^{\downarrow} \setminus B^{\downarrow\downarrow}$ the **boundary** of $B^{\downarrow}$. Then, an experiment is rationalizable with inequality averse preferences if and only if there is a continuous and monotone (with respect to $\geq_{IA}$) utility function $u(x_s, f(x_s, x_o))$, such that observed choices $x^t \in \underset{x \in (B^t)^{\downarrow} \cap \mathbb{R}^2_+}{\operatorname{argmax}} \{u(x_s, f(x_s, x_o))\}$.

Hence, to construct the inequality averse utility function we need to construct a utility function in Y. Using the result from Nishimura, Ok and Quah (2017) existence of the utility function monotone with respect to $\geq_{IA}$ is equivalent to the GARP in space Y . Formally, an experiment satisfies **Y-GARP** if for every sequence $x^{t_1}, \ldots, x^{t_n}$, such that $x^{t_j} \in (B^{t_{j+1}})^{\downarrow}$ for every $j \in \{i, \ldots, n-1\}$ implies $x^{t_n} \in (B^{t_1})^{\downarrow\downarrow}$. Hence, we can derive the following result using the main theorem from Nishimura, Ok and Quah (2017).[19]

Lemma A.1 (Nishimura, Ok and Quah (2017))**.** *An experiment satisfies Y-GARP if and only if it is rationalizable with inequality averse preferences.*

Hence to complete the proof of Proposition 2 we need to show that GARP (in space X) given that $x^t_s \geq x^t_o$ for every $t \in \{1, \ldots, T\}$ is equivalent to Y-GARP. We start with a simple supplementary Lemma which allows to simplify the further reasoning.

[19] Topological restrictions are also satisfied. Recall that X is a compact space, therefore, IA is a compact space as well, as a consequence of continuous mapping of compact space. Moreover, $\geq_{IA}$ is a continuous order, since we consider its natural topology.

Lemma A.2. *Let $x, x' \in Z$. If $(x'_s, f(x'_s, x'_o)) >_{IA} (\geq_{IA})(x_s, f(x_s, x_o))$, then $(x'_s, x'_o) > (\geq)(x_s, x_o)$.*

Proof. We only prove the case for strict inequalities. Weak inequalities can be proven in a similar fashion. If $(x'_s, f(x'_s, x'_o)) >_{IA} (x_s, f(x_s, x_o))$ then $x'_s \geq x_s$ and $f(x'_s, x'_o) \leq f(x_s, x_o)$ with at least one inequality being strict. Recall that f is increasing in x_s and decreasing in x_o, hence $x'_o > x_o$. This implies that $(x'_s, x'_o) > (x_s, x_o)$. □

For this purpose we need to show that budgets map to the space Y such that point is on the border of the budget in Z if and only if it is in the border of the budget in Y and correspondingly for the interior. We mainly need to consider points in Z, because all chosen points belong to Z (given the conditions for sufficiency) and Y-GARP as well as GARP are checked only using the chosen points.

Lemma A.3. *Let $(x_s, x_o) \in Z$. $(x_s, f(x_s, x_o)) \in B^{\downarrow}$ if and only if $\gamma(x_s, x_o) \leq 1$.*

Proof. **(⇒)** Take $(x_s, f(x_s, x_o)) \in B^{\downarrow}$. By construction of $B^{\downarrow}$ there is $x' = (x'_s, x'_o) \in Z$ such that $\gamma(x') = 1$ and $(x'_s, f(x'_s, x'_o) \geq_{IA} (x_s, f(x_s, x_o))$, then $x' \geq x$ (see Lemma A.2). This implies that $\gamma(x) \leq \gamma(x') = 1$.

(⇐) To prove the reverse implications we consider two separate cases.

Case 1: $x_s > x_o$**.** Take $x = (x_s, x_o)$ such that $\gamma(x) \leq 1$. Given that $x_s > x_o$ and that $\gamma(x)$ is continuous and strictly monotone, there is $x'_o > x_o$ such that $\gamma(x_s, x'_o) \leq 1$. This implies that $f(x_s, x'_o) \leq f(x_s, x_o)$. Therefore, $(x_s, f(x_s, x_o)) \leq_{IA} (x_s, f(x_s, x'_o)$, that in its order implies that $(x_s, f(x_s, x_o)) \in B^{\downarrow}$.

Case 2: $x_s = x_o$**.** Let $1 \geq \lambda = \gamma(x_s, x_s)$. Hence, let $x'_s = \frac{x_s}{\lambda} > x_s$. Therefore, $x'_s \geq x_s$ and $f(x'_s, x'_s) = f(x_s, x_s) = 0$, i.e. $(x'_s, f(x'_s, x'_s) \geq_{IA} (x_s, f(x_s, x_s))$. Moreover, by construction $\gamma(x'_s, x'_s) = 1$, therefore, $(x_s, f(x_s, x_s)) \in B^{\downarrow}$. □

Next we show that if $x_s < x_o$, then the corresponding point in the IA space is in the interior of the budget set. This allows us to show that all points in $X \setminus Z$ are strictly dominated. Moreover, it shows that the mapped set determined by $\gamma(x) \leq 1$ is a subset of $B^{\downarrow}$.

Lemma A.4. *If $x_s < x_o$ and $\gamma(x_s, x_o) \leq 1$, then $(x_s, f(x_s, x_o)) \in B^{\downarrow\downarrow}$.*

Proof. Recall that by construction of the budget set $\gamma(x_s, x_s) = \lambda \leq 1$. Let $x'_s = \frac{x_s}{\lambda}$, then $\gamma(x'_s, x'_s) = 1$ and $(x'_s, f(x'_s, x'_s)) >_{IA} (x_s, f(x_s, x_o))$. Hence, $(x'_s, f(x'_s, x'_s)) \in \partial B$. This implies $(x_s, f(x_s, x_o)) \in B^{\downarrow\downarrow}$ by construction. $\square$

Next we show that budget line in the space Z is mapped into the boundary of the budget in space Y and vice versa. The following result also operates over Z only, although, it also shows that neither of choices on the boundary of the budget are not dominated in IA space.

Lemma A.5. *Let $(x_s, x_o) \in Z$. $(x_s, f(x_s, x_o)) \in \partial B$ if and only if $\gamma(x_s, x_o) = 1$.*

Proof. **(⇒)** Take $(x_s, f(x_s, x_o)) \in \partial B$. On the contrary, assume that $\gamma(x_s, x_o) < 1$. Then, we can apply the construction as in the (⇐) part of the proof of Lemma A.3 to get a bundle x' such that $\gamma(x'_s, x'_o) = 1$ and $(x_s, f(x_s, x_o)) <_{IA} (x'_s, f(x'_s, x'_o))$. This implies that $(x_s, f(x_s, x_o)) \in B^{\downarrow\downarrow}$, that is a direct contradiction.

(⇐) Take x such that $\gamma(x) = 1$. On the contrary, assume that $(x_s, f(x_s, x_o)) \in B^{\downarrow\downarrow}$. Then by construction of the budget set there is $x' = (x'_s, x'_o) \in Z$ such that $(x_s, f(x_s, x_o)) <_{IA} (x'_s, f(x'_s, x'_o))$ and $\gamma(x'_s, x'_o) = 1$. At the same time Lemma A.2 implies that $x < x'$ and therefore, $\gamma(x) < \gamma(x') = 1$, that is a contradiction. $\square$

Lemmas A.3 and A.5 immediately imply the following corollary. Which would complete the mapping of the budgets between different spaces.

Corollary A.1. *Let $(x_s, f(x_s, x_o)) \in Z$. $(x_s, f(x_s, x_o)) \in B^{\downarrow\downarrow}$ if and only if $\gamma(x) < 1$.*

Hence, we can complete the proof that of equivalence between Y-GARP and GARP.

Corollary A.2. *Let $x^t \in Z$ for every $t \in \{1, \dots, T\}$. An experiment satisfies GARP then it satisfies Y-GARP.*

Proof. On the contrary, assume that there is a violation of Y-GARP. Then, there is a sequence $x^{t_1}, \dots, x^{t_n}$, such that $x^{t_j} \in (B^{t_{j+1}})^{\downarrow}$ for every $j \in \{i, \dots, n-1\}$ and $x^{t_n} \in (B^{t_1})^{\downarrow\downarrow}$. Lemma A.3 implies that $\gamma^{t_{j+1}}(x^{t_j}) \leq 1$ and Corollary A.1 implies that $\gamma^{t_1}(x^{t_n}) < 1$ that is a violation of GARP. $\square$

Using the results above we can prove that conditions stated are necessary and sufficient for the rationalization with inequality aversion preferences. We start from the proof of necessity.

Proof of Necessity. Assume that data set is rationalizable with inequality aversion preferences. First we show that $x^t \in Z$ for every $t \in \{1, \dots, T\}$ is a necessary condition. Next, we show that if $x^t \in Z$ for every $t \in \{1, \dots, T\}$, then GARP is still necessary.

Assume that at some chosen point $x_o^t > x_s^t$. Hence, $\gamma^t(x_s^t, x_s^t) = \lambda \leq 1$. Therefore, homogeneity of the gauge function can be used to obtain $x_s = \frac{x_s^t}{\lambda}$, such that $\gamma^t(x_s, x_s) = 1$. Moreover, the $x_s \geq x_s^t$ and $0 = f(x_s, x_s) < f(x_s^t, x_o^t)$. Hence, $u(x_s, 0) > u(x_s^t, f(x_s^t, x_o^t))$ that is a contradiction to the experiment being rationalizable with inequality averse preferences.

Next, we assume that $x^t \in Z$ for every $t \in \{1, \dots, T\}$. Assume there is a violation of GARP. That is, there is a sequence $x^{t_1}, \dots, x^{t_n}$, such that $\gamma^{t_{j+1}}(x^{t_j}) \leq 1$ for every $j \in \{i, \dots, n-1\}$ and $\gamma^{t_1}(x^{t_n}) < 1$. Since $\gamma^{t_{j+1}}(x^{t_j}) \leq 1$ then $u(x^{t_{j+1}}) \geq u(x^{t_j})$ (see Lemma A.3), hence $u(x^n) \geq u(x^1)$. At he same time $\gamma^{t_1}(x^{t_n}) < 1$ implies $u(x^1) > u(x^n)$ (see Corollary A.1). $\square$

Proof of Sufficiency. Suppose that $x^t \in Z$ for every $t \in \{1, \dots, T\}$ and GARP is satisfied. Corollary A.2 implies that there is a continuous utility function $u(x_s, f(x_s, x_o))$ monotone with respect to $\geq_{IA}$, such that $u(x_s^t, f(x_s^t, x_o^t)) \geq u(x_s, f(x_s, x_o))$ for every $(x_s, f(x_s, x_o)) \in B^{\downarrow}$. Moreover, Lemmas A.3 and A.4 imply that $B_x^t = \{x \in X : \gamma^t(x) \leq 1)\} \subseteq (B^t)^{\downarrow}$. Therefore, $u(x_s^t, f(x_s^t, x_o^t)) \geq u(x_s, f(x_s, x_o))$ for every $\gamma^t(x_s, x_o) \leq 1$. $\square$

Proof of Corollary 2 The budget in this case is $B^t = \{(x_s^t, f(x_f^t, x_s^t)), (0, 0)\}$. The comprehensive closure of the budget is $(B^t)^{\downarrow} = B^t \cup R^t$. The interior of the comprehensive closure of the budget is $(B^t)^{\downarrow\downarrow} = R^t$. Moreover, one can easily see that $x^s \in A^t$ if and only if $x^t \in R^t$. Hence, the proof can be concluded by applying result from Nishimura, Ok and Quah (2017).

Proof of Corollary 4 To apply the Proposition 2 we need to show that there is a continuous, strictly increasing and homogeneous gauge function that defines the budget set. Hence, the proof is nothing more than direct construction of the gauge function.

Figure A.1 presents the illustration to construct the gauge function. The original downward closure of the budget cannot be described by the strictly increasing gauge function, because it contains flat (vertical and horizontal) segments. Hence, we construct the envelope of the budget which contains only strictly sloped segments, such that GARP on the original budget is equivalent to the GARP on the envelope budgets. There are three segments (as on Figure A.1) depending on x_s: (1) $x_s \in [0, I]$ (2) $x_s \in]I, I + ks^t]$ (3) $x_s \in]I + ks^t, \infty[$.

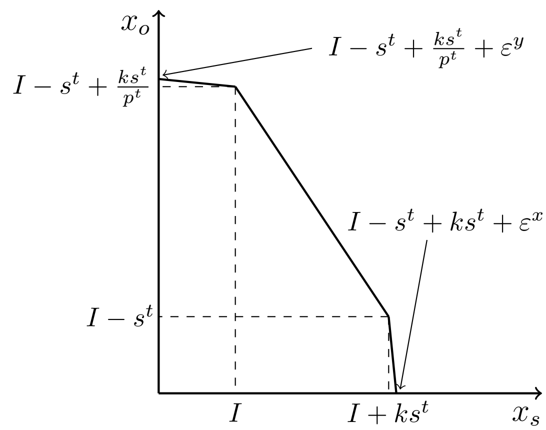


FIGURE A.1. Construction of the enveloping budget set

We start from the first segment. Take all x^r for $r \in \{1, \ldots, T\}$ such that $x_s^r < I$ and $x_o^r > I - s^t + \frac{ks^t}{p^t}$. Given the finite amount of observations, there is $0 < \varepsilon^y < x_o^r - (I - s^t + \frac{ks^t}{p^t})$ for every such point. Moreover, we assume that $\frac{\varepsilon^y}{I} \leq \frac{1}{p^t}$. Hence, let us replace the horizontal segment with the decreasing one:

$$x_o \frac{1}{\beta_1} + x_s \frac{\alpha_1}{\beta_1} = 1$$

where $\alpha_1 = \frac{\varepsilon^y}{I}$ and $\beta_1 = I - s^t + \frac{ks^t}{p^t} + \varepsilon^y$. It can be easily seen that at $x_s = 0$, $x_o = I - s^t + \frac{ks^t}{p^t} + \varepsilon^y$, and at $x_s = I$, $x_o = I - s^t + \frac{ks^t}{p^t}$. Hence, every point x^r that belongs to the original budget (interior of the downward closure) it is still inside of the budget, because the envelope budget set is a superset of the original one. Moreover, every point which is outside of the original budget it is still outside of the envelope budget, by construction (recall that $\varepsilon^y < \min\limits_{x_s^r < I,\ x_o^r > I - s^t + \frac{ks^t}{p^t}} x_o^r - (I - s^t + \frac{ks^t}{p^t})$, and maximum $x_o = I - s^t + \frac{ks^t}{p^t} + \varepsilon^y$ in this budget).

Next, we construct from the third segment. Similarly let $\varepsilon^x < \min\limits_{x_s^r > I + ks^t,\ x_o^r < I - s^t} x_o^r - (I + ks^t)$. Also, make sure that $\frac{I - s^t}{\varepsilon^x} > \frac{1}{p^t}$. Hence, let us replace the vertical segment by the following linear one.

$$x_o \frac{1}{\beta_3} + x_s \frac{\alpha_3}{\beta_3} = 1$$

where $\alpha_3 = \frac{I - s^t}{\varepsilon^x}$ and $\beta_3 = \frac{I - s^t}{\varepsilon^x}(I + ks^t + \varepsilon^x)$. By the same token as in the previous case, a point is in the same case, the point belongs to the strict interior of the original budget if and only if it belongs to the strict interior of the envelope budget.

For the second segment, we preserve the original linear segment,

$$x_o \frac{1}{\beta_2} + x_s \frac{\alpha_2}{\beta_2} = 1$$

where $\beta_2 = (I - s^t) + \frac{I + ks^t}{p^t}$ and $\alpha_2 = \frac{1}{p^t}$. Hence, the gauge function can be constructed as follows.

$$\gamma(x) = \max \left\{ x_o \frac{1}{\beta_1} + x_s \frac{\alpha_1}{\beta_1}, x_o \frac{1}{\beta_2} + x_s \frac{\alpha_2}{\beta_2}, x_o \frac{1}{\beta_3} + x_s \frac{\alpha_3}{\beta_3} \right\}$$

The gauge function is continuous, strictly monotone and homogeneous of degree one by construction. Moreover, $\gamma(x) = 1$ specifies the budget line from the Figure A.1. It can be easily checked that $\beta_1 - \alpha_1 x_s < \beta_2 - \alpha_2 x_s$ if and only if $x_s < I$, and $\beta_2 - \alpha_2 x_s < \beta_3 - \alpha_3 x_s$ if and only if $x_s < I + ks^t$.

Hence, we are left to show that at the budget line the constructed gauge function corresponds to the budget line. Take $\gamma(x) = 1$. Take $x_s < I$ and let $x_o \frac{1}{\beta_1} + x_s \frac{\alpha_1}{\beta_1} = 1$. Take the second segment

$$x_o \frac{1}{\beta_2} + x_s \frac{\alpha_2}{\beta_2} < 1$$

Hence, multiplying both side by β_2 and replacing x_o by $\beta_1 - \alpha_1 x_s$, we obtain the following equivalent inequality.

$$\beta_1 - \alpha_1 x_s < \beta_2 - \alpha_2 x_s$$

Similarly we can show that

$$x_o \frac{1}{\beta_3} + x_s \frac{\alpha_3}{\beta_3} < 1$$

and similar proof can be conducted for other segments. Hence, to complete the proof it suffices to apply Proposition 2, since the gauge function satisfies the conditions.

Proof of Corollary 6 We follow the same lines as in the proof of Corollary 4. There is vertical segment which does not allow us to have the strictly increasing gauge function directly. Hence, we need to construct the enveloping budget with only slopped segments, such that GARP on the enveloping budget is equivalent to the GARP on the original one.

Figure A.2 illustrates the idea of constructing the budget. There are two segments: (1) $x_s \in [0, ks^t]$ and (2) $x_s \in]ks^t, \infty[$. We leave the original budget for the first segment which can be defined as

$$x_o \frac{1}{\beta_1} + x_s \frac{\alpha_1}{\beta_1} = 1$$

where $\alpha_1 = \frac{1}{p^t}$ and $\beta_1 = I - s^t + \frac{ks^t}{p^t}$.

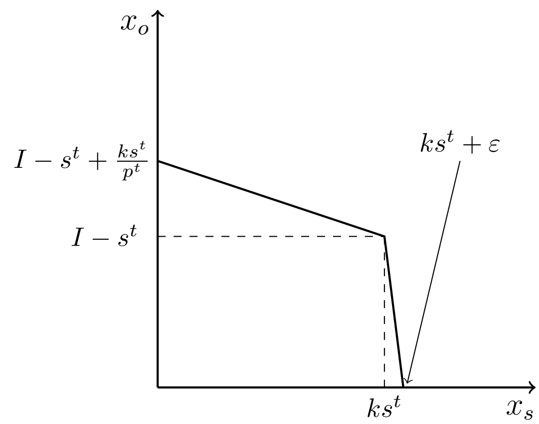


FIGURE A.2. Construction of the enveloping budget set

Next, we construct the sloped line for the second segment. Let $\varepsilon < \min_{x_s^r > ks^t,\ x_o^r < I - s^t} (x_o^r - ks^t)$. Hence, we can define the linear segment, which connects $(ks^t, I - s^t)$ and $(ks^t + \varepsilon, 0)$. Hence, the GARP on the original budget is satisfied if and only if it is satisfied on the envelope budget. Hence, we can define the linear segment of the budget as

$$x_o \frac{1}{\beta_2} + x_s \frac{\alpha_2}{\beta_2} = 1$$

where $\alpha_2 = \frac{I - s^t}{\varepsilon}$ and $\beta_1 = \frac{I - s^t}{\varepsilon}(ks^t + \varepsilon)$.

Hence, the gauge function looks as follows.

$$\gamma(x) = \max \left\{ x_o \frac{1}{\beta_1} + x_s \frac{\alpha_1}{\beta_1}, x_o \frac{1}{\beta_2} + x_s \frac{\alpha_2}{\beta_2} \right\}$$

The gauge function is continuous, strictly monotone and homogeneous of degree one by construction. Hence, we are left to show that gauge function coincides with the budget line if $\gamma(x) = 1$. To show that we use the fact that $\alpha_1 - \beta_1 x_s < \alpha_2 - \beta_2 x_s$ if and only if $x_s < ks^t$. Take the second segment

$$x_o \frac{1}{\beta_2} + x_s \frac{\alpha_2}{\beta_2} < 1$$

Hence, multiplying both side by β_2 and replacing x_o by $\beta_1 - \alpha_1 x_s$, we obtain the following equivalent inequality.

$$\beta_1 - \alpha_1 x_s < \beta_2 - \alpha_2 x_s$$

Similarly we can show the reverse for $x_s > ks^t$. Hence, the proof can be complete the proof by applying Proposition 2.

Proof of Corollary 7 Let us introduce some additional notation. We rely on the result from Cherchye, Demuynck and De Rock (2018). Let $\omega = \frac{p_o}{p_s}$ and $m = \frac{1}{p_s}$. Therefore, we can refer to the demands as functions of only ω and m. Moreover, we renumerate observations s.t. $\tilde{p}^t = p^t$.

Define $\alpha, \beta > 0$ such that

$$1 + \beta < \min \left\{ \min_{t,s} \left\{ \frac{x_o^t}{x_o^s} : x_o^t > x_o^s \right\}, \min_{t,s} \left\{ \frac{\tilde{x}_o^t}{\tilde{x}_o^s} : \tilde{x}_o^t > \tilde{x}_o^s \right\} \right\}$$

and

$$a(1+\beta) < \min \left\{ \min_{t,s} \left\{ \frac{x_o^t}{x_o^s} \right\}, \min_{t,s} \left\{ \frac{\tilde{x}_o^t}{\tilde{x}_o^s} \right\} \right\}$$

Let $\delta_{t,v} = \max\{|w^t - w^v|, |m^t - m^v + (w^t - w^v)x_o^t|, |m^t - m^v + (w^t - w^v)\tilde{x}_o^t|\}$ and let $\varepsilon < \min \delta_{t,v}$. Consider the function

$$g(z) = \begin{cases} \alpha & \text{for } z \leq -\varepsilon \\ 1 + \frac{1-\alpha}{\varepsilon} z & \text{for } -\varepsilon \leq z \leq 0 \\ 1 & \text{for } z \geq 0 \end{cases}$$

In addition, consider the function

$$h(z) = \begin{cases} \alpha \frac{1}{z+\varepsilon-1} & \text{for } z < -\varepsilon \\ 1 + \frac{1-\alpha}{\varepsilon} z & \text{for } -\varepsilon \leq z \leq 0 \\ 1 + \beta \frac{z}{z+1} & \text{for } z \geq 0 \end{cases}$$

Then, according to Cherchye, Demuynck and De Rock (2018), the rationalization of the demand can be obtained as a solution of the following program.

$$\begin{aligned} D_o(w,m) = & \max_r r \\ \text{s.t. } & g(w - w^t)h(m^t + (w - w^t)r - m)r \leq x_o^t \; \forall t \in \{1, \ldots, T\} \\ & wr \leq x \end{aligned}$$

For both experiments, the functions $g(z)$ and $h(z)$ are the same. Moreover, since both experiments are composed of the same set of prices, every left-hand side of the constraints would be the same for both experiments. In addition, if the left-hand side is decreasing in r, then constraint is not binding, hence, we need to concentrate only on increasing left-hand sides. At the same time every $\tilde{x}_o^t \geq x_o^t$, hence there is larger r and, consequently, a larger demand for x_o at given prices. Therefore, the $\tilde{D}_o(w,m) \geq D_o(w,m)$, i.e. $\tilde{E}$ is more altruistic than E.

Proof of Corollary 8 Note that the fair outcome is always available at the linear budgets. Given χ^* being a fair outcome, let $p_s x_s + p_o x_o = 1$ define the budget set. Then, in order to guarantee the fair outcome $x_s = \frac{1}{p_s + \chi^* p_o}$ and $x_o = 1 - p_o x_s$. Hence, to guarantee that fair outcome is available we need to show that $x_o > 0$, that is correct as long as $p_o \chi^* > 0$. Recall that by definition $\chi^* \geq 1$ and $p_o > 0$, hence, this condition is immediately satisfied.

The rest of the proof is same as the proof of Proposition 2, and is therefore omitted, given that fair outcome is always available on a linear budget. For the nonlinear budgets we can directly impose this requirement.

References

Afriat, Sydney N. 1967. "The construction of utility functions from expenditure data." *International economic review*, 8(1): 67–77.

Afriat, Sydney N. 1973. "On a system of inequalities in demand analysis: an extension of the classical method." *International economic review*, 460–472.

Agranov, Marina, and Thomas R Palfrey. 2015. "Equilibrium tax rates and income redistribution: A laboratory study." *Journal of Public Economics*, 130: 45–58.

Aguiar, Victor, and Nail Kashaev. 2017. "Stochastic Revealed Preferences with Measurement Error: Testing for Exponential Discounting in Survey Data." *Working Paper.*

Andreoni, James. 1990. "Impure altruism and donations to public goods: A theory of warm-glow giving." *The economic journal*, 100(401): 464–477.

Andreoni, James, and John Miller. 2002. "Giving according to GARP: An experimental test of the consistency of preferences for altruism." *Econometrica*, 70(2): 737–753.

Apesteguia, Jose, and Miguel A Ballester. 2015. "A measure of rationality and welfare." *Journal of Political Economy*, 123(6): 1278–1310.

Beatty, Timothy KM, and Ian A Crawford. 2011. "How demanding is the revealed preference approach to demand?" *The American Economic Review*, 101(6): 2782–2795.

Benjamin, Daniel J. 2015. "Distributional preferences, reciprocity-like behavior, and efficiency in bilateral exchange." *American Economic Journal: Microeconomics*, 7(1): 70–98.

Bolton, Gary E, and Axel Ockenfels. 2000. "ERC: A theory of equity, reciprocity, and competition." *American economic review*, 166–193.

Bronars, Stephen G. 1987. "The power of nonparametric tests of preference maximization." *Econometrica: Journal of the Econometric Society*, 693–698.

Castillo, Marco E, and Philip J Cross. 2008. "Of mice and men: Within gender variation in strategic behavior." *Games and Economic Behavior*, 64(2): 421–432.

Castillo, Marco E, Philip J Cross, and Mikhail Freer. 2017. "Nonparametric utility theory in strategic settings: Revealing preferences and beliefs from games of proposal and response." *Working Paper.*

Chambers, Christopher P, and Federico Echenique. 2016. *Revealed preference theory.* Vol. 56, Cambridge University Press.

Charness, Gary, and Matthew Rabin. 2002. "Understanding social preferences with simple tests." *The Quarterly Journal of Economics*, 117(3): 817–869.

Cherchye, Laurens, Thomas Demuynck, and Bram De Rock. 2018. "Normality of demand in a two-goods setting." *Journal of Economic Theory*, 173: 361–382.

Chernozhukov, Victor, Han Hong, and Elie Tamer. 2007. "Estimation and confidence regions for parameter sets in econometric models." *Econometrica*, 75(5): 1243–1284.

Choi, Syngjoo, Shachar Kariv, Wieland Müller, and Dan Silverman. 2014. "Who is (more) rational?" *The American Economic Review*, 104(6): 1518–1550.

Cox, James C. 1997. "On testing the utility hypothesis." *The Economic Journal*, 107(443): 1054–1078.

Cox, James C. 2004. "How to identify trust and reciprocity." *Games and Economic Behavior*, 46(2): 260–281.

Cox, James C, Daniel Friedman, and Vjollca Sadiraj. 2008. "Revealed altruism." *Econometrica*, 76(1): 31–69.

Dean, Mark, and Daniel Martin. 2009. "How consistent are your choice data?"

Dean, Mark, and Daniel Martin. 2016. "Measuring rationality with the minimum cost of revealed preference violations." *Review of Economics and Statistics*, 98(3): 524–534.

Deb, Rahul, Robert S Gazzale, and Matthew J Kotchen. 2014. "Testing motives for charitable giving: A revealed-preference methodology with experimental evidence." *Journal of Public Economics*, 120: 181–192.

Demuynck, Thomas. 2015. "Statistical inference for measures of predictive success."

Theory and Decision, 79(4): 689–699.

Diewert, W Erwin. 1973. "Afriat and revealed preference theory." *The Review of Economic Studies*, 40(3): 419–425.

Dufwenberg, Martin, Paul Heidhues, Georg Kirchsteiger, Frank Riedel, and Joel Sobel. 2011. "Other-regarding preferences in general equilibrium." *The Review of Economic Studies*, 78(2): 613–639.

Durante, Ruben, Louis Putterman, and Joël Van der Weele. 2014. "Preferences for redistribution and perception of fairness: An experimental study." *Journal of the European Economic Association*, 12(4): 1059–1086.

Echenique, Federico, Sangmok Lee, and Matthew Shum. 2011. "The money pump as a measure of revealed preference violations." *Journal of Political Economy*, 119(6): 1201–1223.

Engellman, Dirk, and Martin Strobel. 2004. "Inequality aversion, efficiency, and maximin preferences in simple distribution experiments." *The American Economic Review*, 94(4): 857–869.

Fehr, Ernst, and Klaus M Schmidt. 1999. "A theory of fairness, competition, and cooperation." *The quarterly journal of economics*, 114(3): 817–868.

Fehr, Ernst, Georg Kirchsteiger, and Arno Riedl. 1998. "Gift exchange and reciprocity in competitive experimental markets." *European Economic Review*, 42(1): 1–34.

Fehr, Ernst, Michael Naef, and Klaus M Schmidt. 2006. "Inequality aversion, efficiency, and maximin preferences in simple distribution experiments: Comment." *The American economic review*, 96(5): 1912–1917.

Fisman, Raymond, Shachar Kariv, and Daniel Markovits. 2007. "Individual preferences for giving." *The American Economic Review*, 97(5): 1858–1876.

Fong, Christina. 2001. "Social preferences, self-interest, and the demand for redistribution." *Journal of Public economics*, 82(2): 225–246.

Forges, Francoise, and Enrico Minelli. 2009. "Afriat's theorem for general budget sets." *Journal of Economic Theory*, 144(1): 135–145.

Harbaugh, William T, Kate Krause, and Timothy R Berry. 2001. "GARP for kids: On the development of rational choice behavior." *The American Economic Review*, 91(5): 1539–1545.

Heufer, Jan. 2014. "Generating random optimising choices." *Computational Economics*, 44(3): 295–305.

Heufer, Jan, and Per Hjertstrand. 2015. "Consistent subsets: Computationally feasible methods to compute the Houtman–Maks-index." *Economics Letters*, 128: 87–89.

Höchtl, Wolfgang, Rupert Sausgruber, and Jean-Robert Tyran. 2012. "Inequality aversion and voting on redistribution." *European economic review*, 56(7): 1406–1421.

Houtman, Martijn, and J Maks. 1985. "Determining all maximal data subsets consistent with revealed preference." *Kwantitatieve methoden*, 19(1): 89–104.

Liu, Bing, Yiyuan Xia, and Philip S Yu. 2000. "Clustering through decision tree construction." 20–29, ACM.

Maccheroni, Fabio, Massimo Marinacci, and Aldo Rustichini. 2012. "Social decision theory: Choosing within and between groups." *Review of Economic Studies*, 79(4): 1591–1636.

Nishimura, Hiroki, Efe A Ok, and John K-H Quah. 2017. "A Comprehensive Approach to Revealed Preference Theory." *The American Economic Review*, 107(4): 1239–1263.

Porter, Maria, and Abi Adams. 2016. "For love or reward? Characterising preferences for giving to parents in an experimental setting." *The Economic Journal*, 126(598): 2424–2445.

Richter, Marcel K. 1966. "Revealed preference theory." *Econometrica: Journal of the Econometric Society*, 635–645.

Rose, Hugh. 1958. "Consistency of preference: the two-commodity case." *The Review of Economic Studies*, 25(2): 124–125.

Samuelson, Paul A. 1938. "A note on the pure theory of consumer's behaviour." *Economica*, 5(17): 61–71.

Selten, Reinhard. 1991. "Properties of a measure of predictive success." *Mathematical Social Sciences*, 21(2): 153–167.

Szabo, Gyoergy, and Attila Szolnoki. 2012. "Selfishness, fraternity, and other-regarding preference in spatial evolutionary games." *Journal of theoretical biology*, 299: 81–87.

Tyran, Jean-Robert, and Rupert Sausgruber. 2006. "A little fairness may induce a lot of redistribution in democracy." *European Economic Review*, 50(2): 469–485.

Varian, Hal R. 1982. "The nonparametric approach to demand analysis." *Econometrica: Journal of the Econometric Society*, 945–973.

Supplementary Materials for "Revealed Social Preferences"

by Artur Dolgopolov and Mikhail Freer

This supplemenemntary material is organized as follows. Section A presents the mixed integer program used to compute the Houtman-Maks index. Section B provides detailed description of the methodology used to classify subjects as well as comparison to the minimum-sum-of-squares classification. Section C provides additional empirical analysis and robustness checks.

A Computing Houtman-Maks index (HMI)

Multiple approaches to the problem of calculating HMI have been taken in the literature (Choi et al. (2014), Heufer and Hjertstrand (2015)). Choi et al. (2014) and Dean and Martin (2016) used a set cover problem approach to calculate HMI, and we follow in a similar vein. The program below calculates HMI, but does not rely on the linearity of budgets.

We first discuss the calculation of HMI for GARP, which allows us to test for other-regarding preferences and inequality aversion. We will then discuss HMI for NARP, necessary for testing increasing benevolence and other normality-related theories. We require two constants to implement the method, and use the big-M method to selectively activate constraints for a subset of data. Let $M > 1$ be the big-M. Moreover, since strict constraints do not make sense for practical optimization, we introduce an infinitesimal tolerance term $\epsilon < \frac{1}{n}$.

We take as given preference relation $\geq$ with strict part $>$ on space X with $|X| = n$. The (mixed integer) linear program is then to find such $u_i \in [0, 1]$ and $\delta \in \{0, 1\}$ for all elements in X, indexed by $i \leq n$ that minimize $\sum_{i=1}^{n} \delta_i$, so that

$$u_i \geq u_j + \epsilon - M(\delta_i + \delta_j) \text{ for } \{(x_i, x_j) \in X^2 : x_i > x_j\} \tag{1a}$$

$$u_i \geq u_j - M(\delta_i + \delta_j) \text{ for } \{(x_i, x_j) \in X^2 : x_i \geq x_j\} \tag{1b}$$

Binary variables δ in the linear program make constraints active only for the chosen subset of observations, and we thus ensure that this subset is minimal. Then we can simply calculate HMI as $1 - \frac{\sum_{i=1}^{n} \delta_i}{n}$.

To calculate HMI for NARP, we only need to adjust the constraints in the program to Definition 6. We take all pairs of observations $t, v \in \{1, \dots, T\}$ for which $p_o^t/p_s^t \leq p_o^v/p_s^v$ and $x_s^v \leq \frac{1-p_o^t x_o^v}{p_s^t}$. These are the observations for which NARP has implications. The (mixed integer) linear program is then to find such $\delta \in \{0,1\}$ for all t, v above that minimize $\sum_{i=1}^{n} \delta_i$, so that

$$x_o^v \leq x_o^t + M(\delta_t + \delta_v) \tag{2}$$

HMI for JNARP, required for rationalization with both x_s and x_o normal, follows in the same way, but with conditions replaced with those from Definition A.1. We therefore omit it here.

B Classification

This section discusses our classification methodology and results in more detail. We use the clustering technique from Liu, Xia and Yu (2000), who developed a method to apply decision trees to the problem of organizing unlabeled data.[20] Decision trees are appropriate for our data due to the nested nature of theories.

To select HMI thresholds for the classification rule we use the information gain purity function from Liu, Xia and Yu (2000). Unlike usual distance-based measures (e.g. sum of squares) it can potentially be interpreted regardless of the environment. Information gain is the difference in the expected information needed to identify observed data points against uniform distribution before and after the test. In other words, we select the test that minimizes the weighted entropy for all classes of players. The intuition behind this approach is the following. We apply sequential binary tests for different theories, checking if each data point passes the test at a given threshold level or not. All of these binary tests convey one bit of information about each data point: whether it passes or not. If the performance of the test is indistinguishable from testing uniformly distributed data, then the test conveys no information. If, however, the performance on real data is clearly different from the random data, we would suspect that the test conveys some information about the population, and we would like to maximize this information. Information theory suggests that information in bits conveyed by such tests can be measured as the negative logarithm to the base 2 of the number of possible outcomes described by the test.

To calculate the information gain for a group of n data points we introduce n additional fictional points that have uniformly distributed HMI. We then calculate the expected amount of information needed to classify real points against these uniformly

[20] Classification trees are widely applied, although mostly as supervised learning technique. That is, it requires having "training" dataset which is already categorized.

distributed points before and after every binary test. Formally, the information gain from clustering with some threshold α is:

$$1-\frac{1}{2}\left(\left(\alpha+\frac{N_F}{n}\right)E_F+\left((1-\alpha)+\frac{N_P}{n}\right)E_P\right), \tag{3}$$

where n - number of subjects, N_F (N_P) - number of subjects who fail (pass) the test at $HMI \geq \alpha$, E_F (E_P) - entropy for the class of data that passes (fails) the test. Then $(1-\alpha)$ and α are the fractions of points with uniformly distributed HMI that would respectively pass and fail the test.

Information required to identify a data point against a uniform random draw before clustering is 1 bit. After clustering this information is the weighted sum of entropy in each cluster, which in turn is calculated for the points failing the test as

$$E_F=-D_F^R log_2(D_F^R)-D_F^D log_2(D_F^D),$$

where $D_F^R=\frac{\alpha n}{\alpha n+N_F}$ and $D_F^D=\frac{N_F}{\alpha n+N_F}$. These are the fractions of random and real data points in the cluster that fails the test. The entropy for the cluster that passes the test is calculated in the same manner with fractions $D_P^R=\frac{(1-\alpha)n}{(1-\alpha)n+N_P}$ and $D_P^D=\frac{N_P}{(1-\alpha)n+N_P}$.

By substituting expressions for E_F and E_P in (3), we obtain a simplified expression:

$$1-\frac{1}{2}\left(\alpha I_P^R+(1-\alpha)I_F^R+\frac{N_P}{n}I_P^D+\frac{N_F}{n}I_F^D\right),$$

where

$$I_P^R=-log_2\left(D_P^R\right),\ I_F^R=-log_2\left(D_F^R\right),$$

$$I_P^D=-log_2\left(D_P^D\right),\ I_F^D=-log_2\left(D_F^D\right),$$

These four terms represent the information from identifying a point as a data point (D) or as a random point (R) for points that pass the test (P) and fail the test (F). Recall that entropy is the expected amount of information required to decide if some point is an observed data-point or a uniformly-generated random point given the result of a binary test.

We apply this procedure sequentially, first separating the inconsistent cluster by applying the test for other-regarding preferences and then clustering the remaining data according to nested theories. However, we omit the inconsistent points in the figure below.

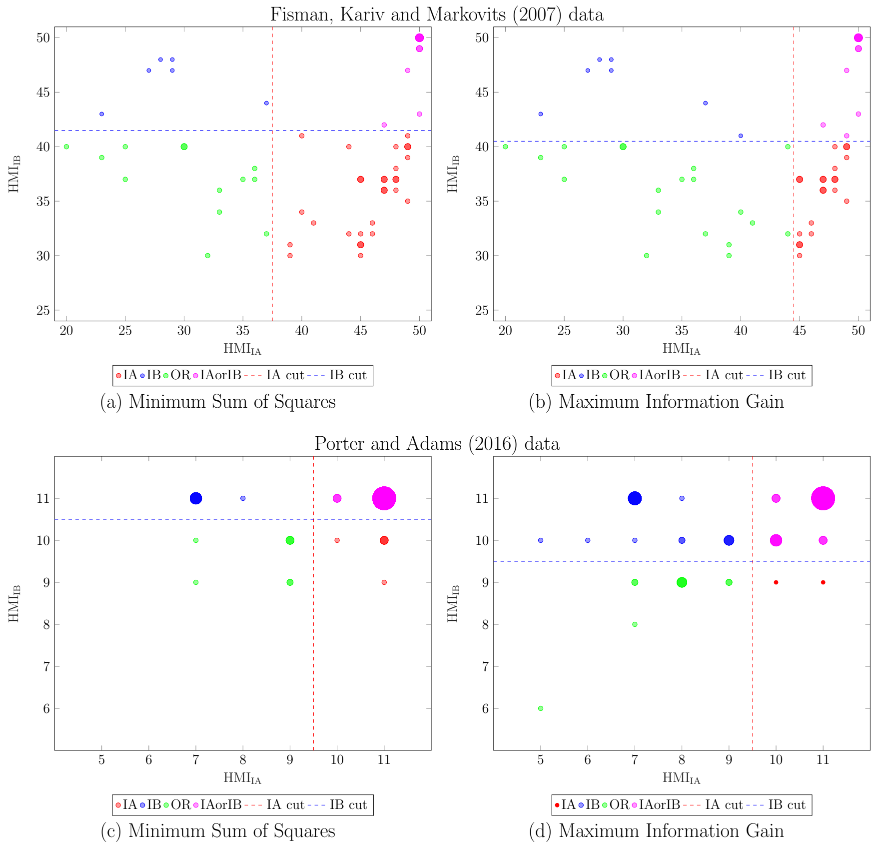


FIGURE B.1. Mixed Types Analysis

Classification thresholds for nested theories and classified points are presented in Figure B.1 along with the alternative classification based on minimizing within-cluster sums of square distances from cluster means.

Fisman, Kariv and Markovits (2007) data				
IA	IB	IA or IB	OR	IC
29 (38%)	6 (8%)	10 (13%)	13 (17%)	18 (24%)
Porter and Adams (2016) data				
IA	IB	IA or IB	OR	IC
5 (6%)	8 (9%)	40 (45%)	7 (8%)	26 (29%)

TABLE B.1. Classification of Subjects (Minimal sum of squares)

The latter largely agrees with our information gain measure, as can be seen from comparing classification results in Figure 9 and Table B.1. The classification is fairly robust to other approaches: 4-means clustering of nested theories agrees with our classification only for half of the data, but qualitatively the results are similar.

C Additional Empirical Analysis

C.1 Additional Theories As an alternative assumption to the increasing benevolence Cox, Friedman and Sadiraj (2008) offered a similar condition, but for one's own payoff. Moreover, it would also be a legitimate assumption to claim normality of both goods. These are two additional theories we are going to test.

Normality of keeping (x_s) may organize the data better, as has been partially shown by Cherchye, Demuynck and De Rock (2018). While the normality of x_s can be checked by applying the permuted version of NARP, the normality in both giving and keeping needs a different test called Joint Normality Axiom of Revealed Preferences.

Definition A.1. *An experiment* $E = (x^t, p^t)_{t=1}^T$ *is consistent with* **Joint Normality Axiom of Revealed Preference (JNARP)** *if and only if for all observations* $t, v \in \{1, \ldots, T\}$ *if* $p_o^t/p_s^t \leq p_o^v/p_s^v$ *and* $x_o^t < x_o^v$*, then* $x_s^t \leq x_s^v$*.*

Both x_s and x_o are normal goods if and only if an experiment satisfies JNARP. Proof of this fact uses the same logic as proof of Proposition 3 and Theorem 2 in Cherchye, Demuynck and De Rock (2018) and is omitted.

C.2 Fisman, Kariv and Markovits (2007) Data

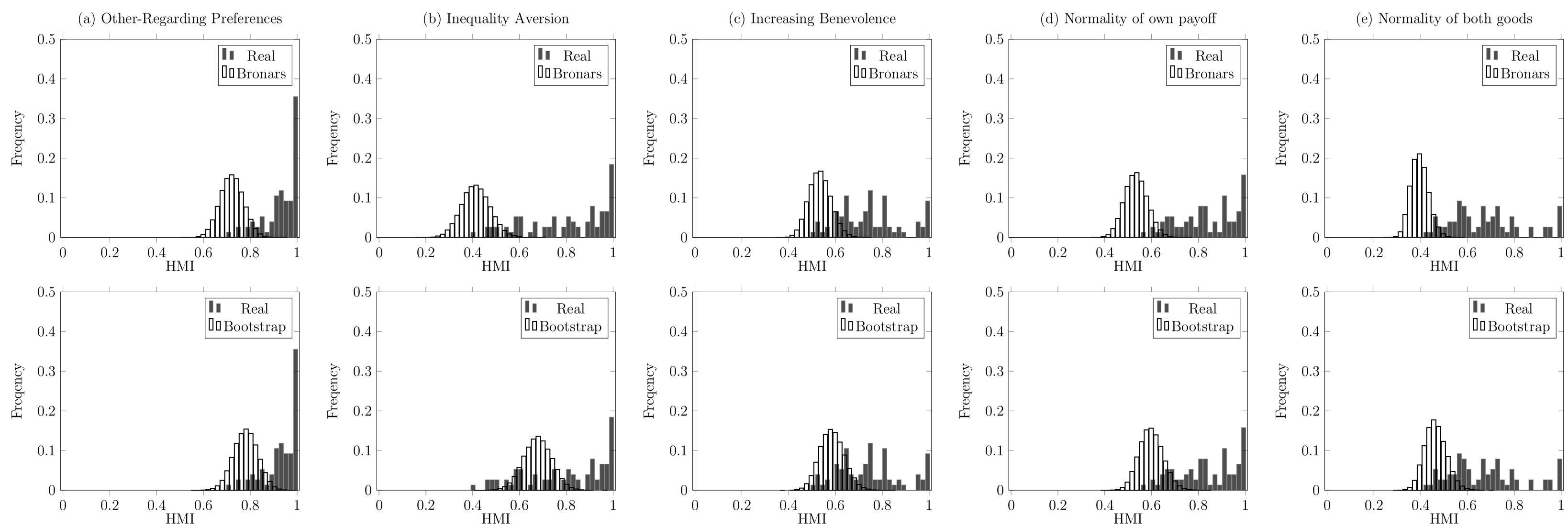


Figure C.2. Distributions of HMI for Fisman, Kariv and Markovits (2007) Data

Figure C.2 presents the distributions of HMI indexes for the theories that we are testing. The first row demonstrates the distribution of the HMI for the real subjects in comparison to the distribution of the HMI for the Bronars' power test. The second row presents the distribution of the HMI for the real subjects in comparison to the distribution of the HMI for the bootstrap power test. In order to test the theory, we compare the distribution of its HMI to the distribution of powers of the test. For all five theories, we see that the real subjects pass both the Bronars' and the bootstrap tests; that is, they perform better than random subjects.[21] We confirm that all five theories have empirical support, and at most a quarter of the data needs to be dropped to rationalize an average subject.

Further, we present comparisons of the theories. For this part of the analysis, we restrict our attention to the HMI levels of .8, .9, .95 and 1 (no deviations).

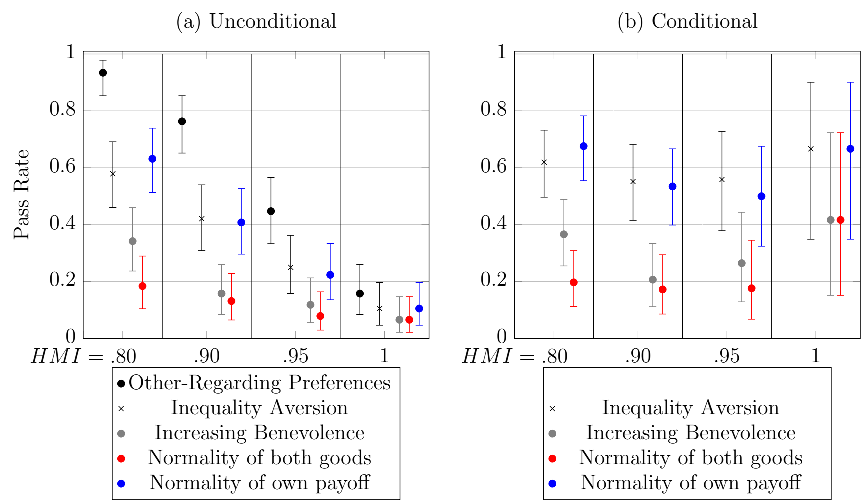


FIGURE C.3. Pass Rates for Fisman, Kariv and Markovits (2007) Data

[21]For other-regarding preferences the mean HMI for real subjects is .92; for Bronars subjects it is .7; for bootstrap subjects it is .76 (p-values$<$ .001 for both comparisons using Wilcoxon test and t-tests). For inequality aversion the mean HMI for real subjects is .79; for Bronars subjects it is .4; for bootstrap subjects it is .66 (p-values$<$ .001 for both comparisons using Wilcoxon test and t-tests). For increasing benevolence preferences the mean HMI for real subjects is .74; for Bronars subjects it is .52; for bootstrap subjects it is .57 (p-values$<$ .001 for both comparisons using Wilcoxon test and t-tests). For normality of x_s the mean HMI for real subjects is .83; for Bronars subjects it is .52; for bootstrap subjects it is .58 (p-values$<$ .001 for both comparisons using Wilcoxon test and t-tests). For normality of both x_s and x_o the mean HMI for real subjects is .67; for Bronars subjects it is .38; for bootstrap subjects it is .45 (p-values$<$ .001 for both comparisons using Wilcoxon test and t-tests).

Figure C.3 presents the pass rates with a confidence interval for every theory.[22] We can see that other-regarding preferences demonstrate higher pass rates for all given levels of HMI.

Figure C.3(a) shows that increasing benevolence preferences perform significantly worse than other-regarding preferences. Inequality aversion does better than increasing benevolence (the difference is significant for the HMI levels of .8, .9) and worse than other-regarding preferences (the difference is significant for the HMI levels of $.8, .9$). Figure C.3(b) presents the conditional pass rates. In particular, it shows that inequality aversion still outperforms the increasing benevolence preferences (the difference is significant for the HMI levels of $.8, .9$). Moreover, if we assume the inequality aversion preferences, then at least 20% of population who have other-regarding preferences are not behaving as if they have inequality aversion preferences. Assuming increasing benevolence preferences would cost us about 50% of population. This shows that all nested theories are significantly restrictive. Furthermore, the normality of x_s organizes data better than increasing benevolence and joint normality. This result confirms the findings of Cherchye, Demuynck and De Rock (2018) who applied these tests to the Andreoni and Miller (2002) data. Finally, the normality in the own payoff performs as successfully as inequality aversion in this data.

The top row in Figure C.4 shows the predictive success levels with confidence intervals with both Bronars and bootstrap as the control. First of all, we see that the lower bounds of the confidence intervals for the predictive success of all the theories are above zero. Therefore, all of the presented theories predicts the observed behavior better than random (Bronars or bootstrap) decision making. Comparing the predictive success of other-regarding and inequality aversion preferences we see mixed evidence. While the predictive success is always higher for other-regarding preferences, the difference is not always significant. We also see that other-regarding preferences outperform the increasing benevolence preferences at every level of HMI for both Bronars and bootstrap random controls.

In order to compare the predictive success of inequality aversion and increasing benevolence preferences, we take into account the fact that theories are nested. This requires us to not only use the subset of subjects who are consistent with the other-regarding preferences at the given HMI, but to also use random subjects who are also

[22] Confidence intervals are computed using the Clopper-Pearson procedure, since the pass rate can be perceived as a binomial variable.

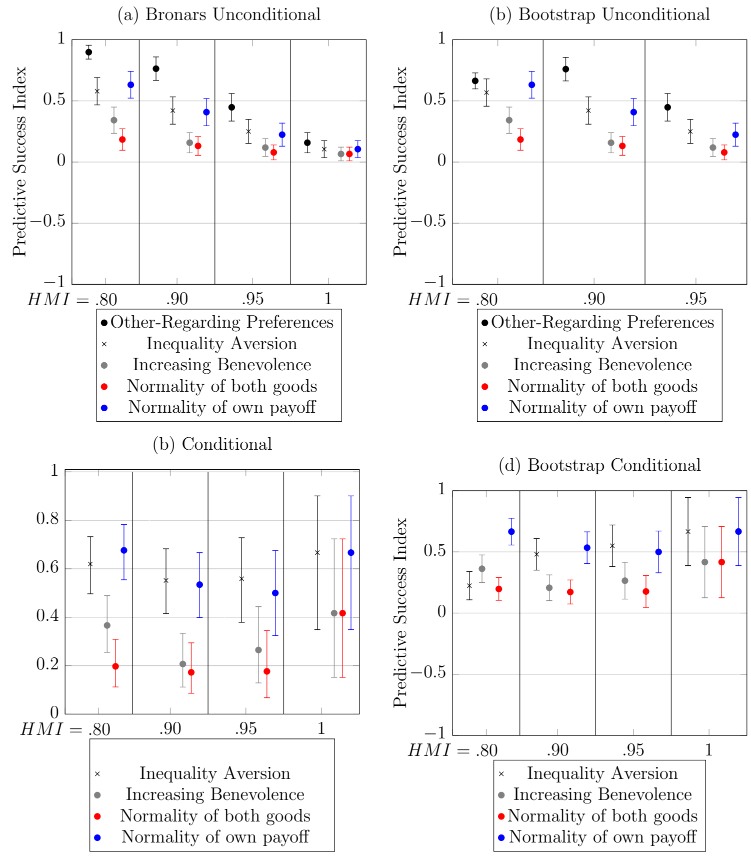


FIGURE C.4. Predictive Success Index for Fisman, Kariv and Markovits (2007) Data

consistent with other-regarding preferences rationalization at the given level of HMI. In particular, if we consider the conditional predictive success for HMI=90%, we take only the subsample of subjects who are consistent with other-regarding preferences rationalization with the HMI of 90%. We then generate for every set of budgets a 1000 random pseudo-subjects who are consistent with other-regarding preferences rationalization with the HMI of 90%. We then compute their HMIs for inequality aversion and increasing benevolence preferences to use those as *random pass rates* for corresponding predictive success indexes. In order to generate random choices that are consistent with other-regarding preferences rationalization at a given HMI, we use the following procedure. We take the random subsample of the experiment that contains 80%, 90% or 95% of budgets and generate the random choices which are consistent with other-regarding preferences rationalization using the Heufer (2014) procedure. We unconditionally place the random choices for the remaining budgets. We calculate this both for the Bronars' and bootstrap tests. The first case follows Heufer (2014) exactly, generating choices that approximate a uniform distribution on each budget, while satisfying GARP. With bootstrap we only need to truncate the empirical distribution at each step to the admissible region, and draw choice points from the resulting distribution. This step is trivial for the Bronars case, since conditional distribution is also a uniform distribution.

The bottom row in Figure C.4 presents the conditional predictive success index. Under the Bronars test, inequality averse preferences theory outperforms increasing benevolence preferences at every level of HMI, and difference is significant at $HMI = .8$ and $HMI = .9$. Under the bootstrap test, we see that for higher levels of HMI, inequality aversion performs better than increasing benevolence, while difference is only significant at $HMI = .9$.

C.3 Porter and Adams (2016) Data In this experiment every subject has played two sets of budgets in a row. One of them giving to strangers and the other one giving to parents, while the order differs between treatments. We only consider giving to strangers since we want to remain consistent with the analysis we conducted for Fisman, Kariv and Markovits (2007) data.[23] We only consider treatments in which subjects started with a dictator game with strangers to guarantee comparability with the other dataset. Moreover, the second part was a surprise for subjects (it was not announced before the end of the first part), so we can consider the games as comparable.

However, there are some differences in design. The first difference is the population. Fisman, Kariv and Markovits (2007) conducted an experiment with undergraduates from UC Berkley, while Porter and Adams (2016) used a sample of the adults from the southeast region of the UK. Another important difference is that Fisman, Kariv and Markovits (2007) used a constant exchange rate of tokens (experimental currency) to dollars, while Porter and Adams (2016) had a changing exchange rate, through which the price variation was implemented. Let us illustrate this with an example of a decision problem. The subject is given 40 tokens and can decide how much to pass and to hold, while every token she holds converts into 10 pence and every token she passes converts into 30 pence. If one wants to get an equal allocation of tokens (20 pass and 20 hold), then the allocation of real world currency will not be equal (6 pounds pass and 2 pounds hold). One the other hand, if one wants to keep an equal allocation of

[23]Porter and Adams (2016) show that preferences of giving to strangers and parents are significantly different.

real world currency (3 pounds pass and 3 pounds hold), then the allocation of tokens will not be equal (10 tokens pass and 30 tokens hold).

This design feature is important, as the inequality measure for Fisman, Kariv and Markovits (2007) data would be similar whether we think about endowments in tokens or dollars. For Porter and Adams (2016), it would be different. Therefore, we look at both inequality aversion in real currency and in experimental currency. Remark 8 allows us to test for inequality aversion in experimental currency in the same manner as for inequality aversion in real currency. We simply set the equal allocation of tokens as the fair outcome x^*, while the inequality measure is still in terms of real currency payoffs.

We present an analysis similar to one we conducted for Fisman, Kariv and Markovits (2007) data with the only difference that we have two separate versions of inequality aversion. We also report tests for normality of own payoff and normality of both goods. This brings the total number of theories to six. In addition, since this experiment has fewer budgets, we use the following levels of HMI$= 9/11, 10/11, 11/11$.

Figure C.5 presents the distribution of the HMI for all theories. As before, we use the Bronars and bootstrap tests to estimate power. Figure C.5 consists of six panels: (a) for other-regarding preferences; (b) for inequality aversion in real currency; (c) for inequality aversion in experimental currency; (d) for increasing benevolence preferences; (e) for normality of own payoff and (f) for normality of both goods. Most theories outperform random decision making for this data as well.[24] The exception is

[24] For other-regarding preferences, the mean HMI for real subjects is .96; for Bronars subjects it is .82; for bootstrap subjects it is .78 (p-values$< .001$ for both comparisons using Wilcoxon test and t-tests). For inequality aversion in real currency, the mean HMI for real subjects is .84; for Bronars subjects it is .46; for bootstrap subjects it is .59 (p-values$< .001$ for both comparisons using Wilcoxon test and t-tests). For increasing benevolence preferences, the mean HMI for real subjects is .93; for Bronars subjects it is .68; for bootstrap subjects it is .7 (p-values$< .001$ for both comparisons using Wilcoxon test and t-tests). For normality of x_s, the mean HMI for real subjects is .95; for Bronars subjects it is .68; for bootstrap subjects it is .68 (p-values$< .001$ for both comparisons using Wilcoxon test and t-tests). For normality of both x_s and x_o, the mean HMI for real subjects is .92; for Bronars subjects it is .57; for bootstrap subjects it is .6 (p-values$< .001$ for both comparisons using Wilcoxon test and t-tests).

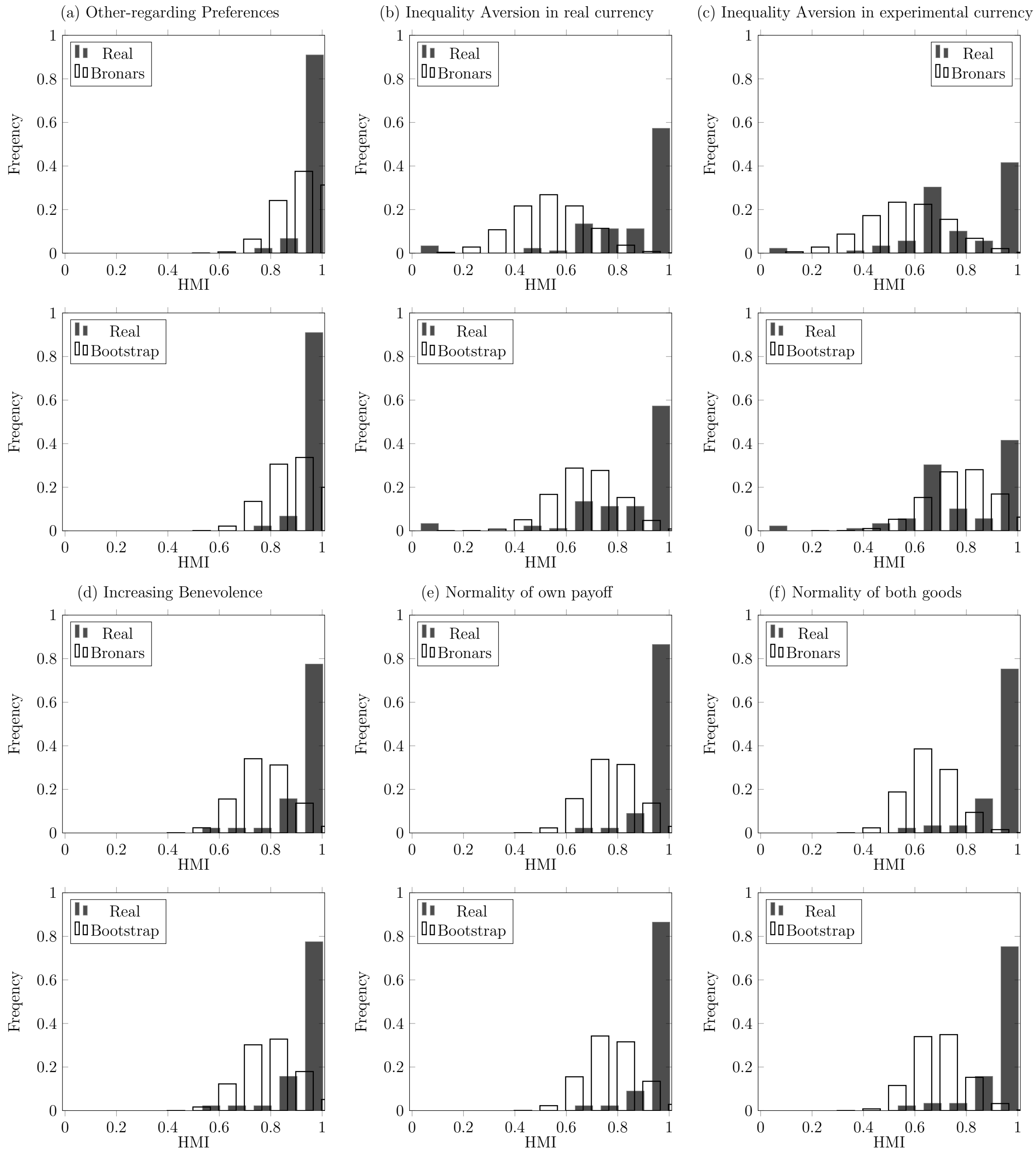


Figure C.5. Distributions of HMI for Porter and Adams (2016) Data

inequality aversion in experimental currency. Although it performs better under the Bronars test, it shows almost the same levels of HMI as bootstrap subjects.[25]

[25]For inequality aversion in experimental currency the mean HMI for real subjects is .77; for Bronars subjects it is .49; for bootstrap subjects it is .68 (p-values$< .001$ for both comparisons using Wilcoxon test and t-tests).

Figure C.2 shows that regardless of framing, subjects are more prone to be inequality averse in real currency than in experimental one. Moreover, power for increasing benevolence is lower in this experiment. Therefore, further comparison should be done based on the predictive success index.

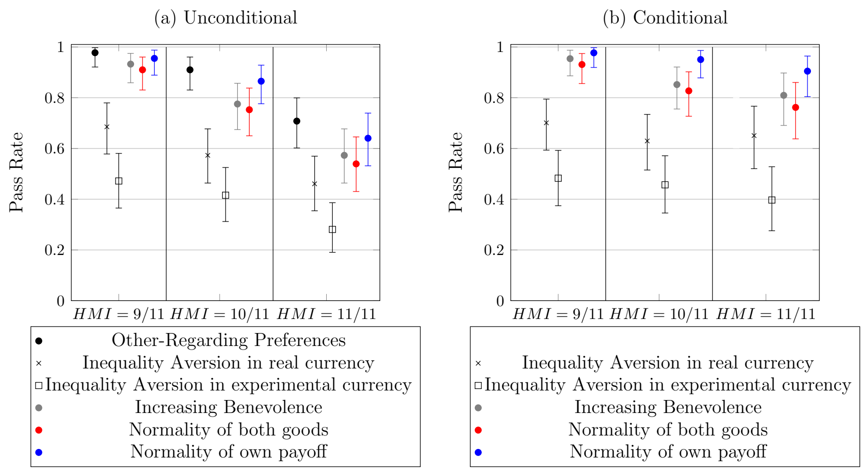


FIGURE C.6. Pass Rates for Porter and Adams (2016) Data

Figure C.6 presents the pass rates for all theories. Since the latter five theories are nested within the other-regarding preferences, we also present the pass rates conditional on a subject being consistent with other-regarding preferences at a given level of HMI. All nested theories are significantly restrictive, moreover, we observe the ordering of nested theories which is reverse from the one obtained using Fisman, Kariv and Markovits (2007) data. Increasing benevolence preferences tend to be more consistent with the data than inequality averse preferences. Moreover, the difference is statistically significant for $HMI = 9/11$ and $HMI = 10/11$. Let us move on to the predictive success in order to further investigate this, while controlling for the power of the test.

Figure C.7 presents the value of predictive success indexes. As before, we use the Bronars and bootstrap tests to control for both conditional and unconditional predictive success. Ordering of the theories is preserved controlling for power of the test if we restrict HMI for a high enough level ($\geq 10/11$). Observation that the subject's own payoff appears to act as a normal good carries on to this dataset as well. Normality of x_s organizes data better than normality of x_o. Moreover the difference is statistically significant for the bootstrap test and $HMI \leq 10/11$. Additionally, due to the small

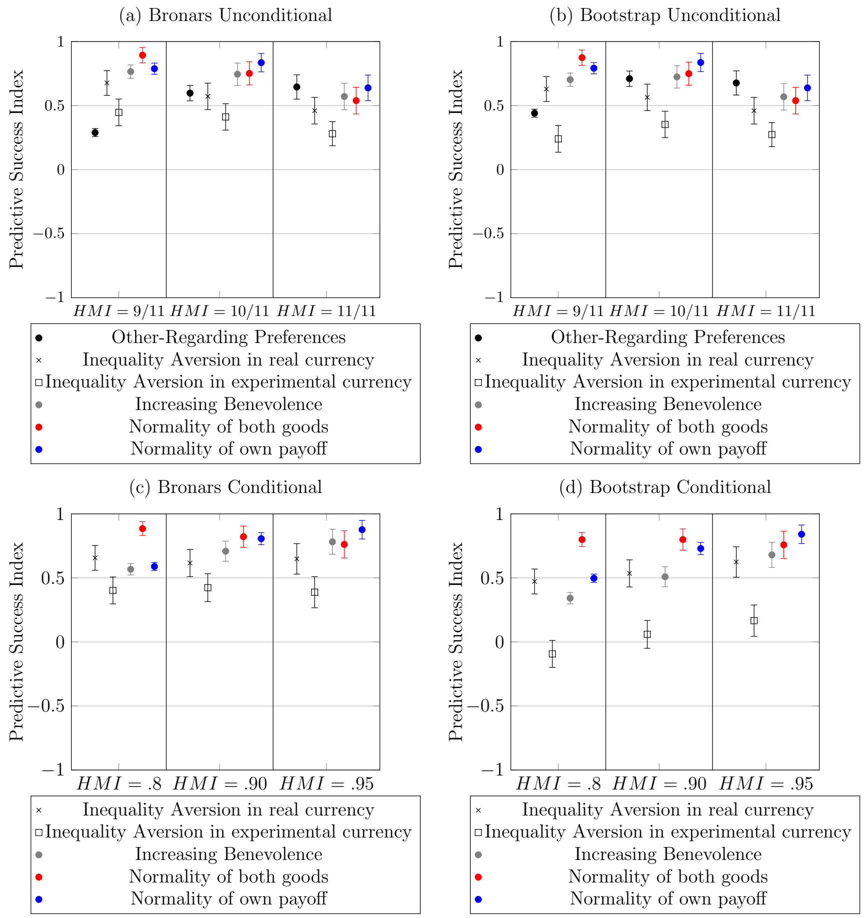


FIGURE C.7. Predictive Success Index for Porter and Adams (2016) Data

number of budgets for the low levels of HMI, normality in both goods looks rather favorable, since it has the higher power. However, this effect disappears at high enough levels of HMI.