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Distributional Preferences Explain Individual Behavior Across Games and Time

Morten Hedegaard, Rudolf Kerschbamer, Daniel Müller and Jean-Robert Tyran*

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Abstract

We use a large and heterogeneous sample of the Danish population to investigate the importance of distributional preferences for behavior in a trust game and a public good game. We find robust evidence for the significant explanatory power of distributional preferences. In fact, compared to twenty-one covariates, distributional preferences turn out to be the single most important predictor of behavior. Specifically, subjects who reveal benevolence in the domain of advantageous inequality are more likely to pick the trustworthy action in the trust game and contribute more to the public good than other subjects. Since the experiments were spread out more than one year, our results suggest that there is a component of distributional preferences that is stable across games and over time.

Keywords: Distributional preferences, social preferences, Equality-Equivalence Test, representative online experiment, trust game, public goods game, dictator game.
JEL classification: C72, C91, D64.

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1 Introduction

While standard economic theory typically assumes that agents care solely about their own material payoff, there is by now ample evidence that the payoff of other people matters to decision makers as well. This finding has important implications for both economic theory and policy. For example, to evaluate the acceptance of tax policy, distributional preferences have to be taken into account. The emerging empirical evidence led to the development of new models of social preferences that aim at improving the predictive power of standard economic theory.[1] These models have subsequently become highly influential. While in general there is mounting evidence that distributional preferences matter in specific contexts, less is known about their predictive power across games and their stability across time. The current paper sheds new light on this open question.

In this paper, we elicit distributional preferences using the Equality-Equivalence Test (EET; Kerschbamer, 2015) in a large and heterogeneous sample of the Danish population. The experiment is conducted online using the Internet Laboratory for Experimental Economics (iLEE) based at the University of Copenhagen. In this panel, participants take part in several online experiments in four different waves. We exploit this rich source of experimental and survey data to make two contributions to the literature.

First, and most importantly, we investigate the predictive power of distributional preferences for behavior in two games – a binary trust game (TG) and a linear public goods game (PGG). All our empirical tests for the explanatory power of distributional preferences follow the same general structure: We first derive individual-level point predictions from elicited preferences (and the beliefs about the contributions of others in case of the PGG) using a social utility function along the lines of Fehr and Schmidt (1999) and Charness and Rabin (2002). In addition, we derive necessary conditions for the choices of subjects to depart from the selfish benchmark. In particular, we find that benevolence in the domain of advantageous inequality is a necessary (but not sufficient) condition for the trustworthy choice in the TG and a positive contribution in the PGG. We then show that (i) actual behavior correlates with point predictions and (ii) subjects classified as benevolent when ahead are more likely to pick the trustworthy option in the TG and contribute more in the PGG, even after controlling for detailed measures of socio-economics, personality, cognitive ability and attitudes. A dominance analysis (Azen and Budescu, 2003) shows that distributional preferences are the single most important predictor of behavior across games. Our results highlight that taking distributional preferences into account improves the predictive power of economic theory.

Second, we provide evidence on the distribution of social preferences in the Danish population and hence contribute to the discussion on the heterogeneity of these preferences. We document that the empirically most frequent preference type is (with roughly a third of the population) altruistic. Subjects are classified as altruistic if they are willing to give up own income to increase another

[1] See for example Fehr and Schmidt (1999), Bolton and Ockenfels (2000), Fehr and Fischbacher (2002), Charness and Rabin (2002) and Engelmann and Strobel (2004). We use the terms "distributional" and "social" preferences interchangeably. Distributional preferences explain, for instance, bargaining behavior (De Bruyn and Bolton, 2008), donations to charities (Derin-Güre and Uler, 2010; Kamas and Preston, 2015), voting decisions (Tyran and Sausgruber, 2006; Höchtl, Sausgruber, and Tyran, 2012; Paetzel, Sausgruber, and Traub, 2014; Fisman, Jakiela, and Kariv, 2017; Kerschbamer and Müller, 2020), as well as competitive behavior (Balafoutas, Kerschbamer, and Sutter, 2012).

person's income both when their income is higher and when it is lower than that of another person. Around a quarter of subjects (23 percent) act in a way that is consistent with inequality aversion – they reveal benevolence when ahead and malevolence when behind; a fifth (20 percent) behaves in a selfish manner; and 14 percent are classified as having maximin preferences – they reveal benevolence when ahead and neutrality when behind. In total, these four types make up 90 percent of our sample. Thus, while the EET provides a comprehensive framework with nine social preference types, only four of these are empirically relevant in our sample.[2]

We make these two advances by using state-of-the-art experimental methodology and high-quality empirical data. Concerning methodology, we use the EET which delivers a parsimonious, nonparametric, comprehensive and mutually exclusive classification of individuals into distributional preference types. Intuitively speaking, the test elicits the slope of an indifference curve when trading off income for oneself versus income for another person. The EET delivers two measures of preference intensity – the x-score and the y-score – which can easily be mapped into the two parameters of a piecewise-linear utility function à la Fehr and Schmidt (1999) or Charness and Rabin (2002). This mapping – plus the fact that we elicit beliefs about the contributions of others in the case of the PGG – allows us to calculate individual-level predictions of behavior for both the TG and the PGG. Moreover, the EET allows us to elicit the benevolence of the decision maker in the domain of advantageous as well as disadvantageous inequality in a straightforward manner in one experimental framework. We consider this property a distinct advantage relative to previous studies as in the EET preferences are unlikely to be contaminated by strategic motives such as reciprocity. Moreover, our empirical implementation of the EET delivers a credible measure of confusion (more than one switching point in the X- or the Y-list) that most existing studies do not deliver (an exception is Blanco, Engelmann and Normann, 2011, who also observe multiple switch points and perform various robustness checks for different ways of dealing with multiple switchers). We conduct several robustness checks to ensure that our results are not driven by errors in decision making.[3] In particular, we estimate a finite-mixture model of the four most prevalent types and use posterior probabilities to classify the inconsistent participants into their most likely types. Our conclusions remain unchallenged by this exercise.

Overall, our findings demonstrate that distributional preferences matter for behavior in experimental games and that taking them into account is important to improve the empirical realism of economic models. The results in this paper contrasts with previous experimental evidence that questioned the predictive power of social preference models (Blanco, Engelmann, and Normann, 2011). Our paper also highlights the advantages of using the EET over a standard dictator game (DG), which has frequently been used as a proxy for distributional preferences, in interpreting strategic decision making. The reason is that behavior in the games studied here does not correlate well with behavior in the DG, see Appendix A.2 for details, but does correlate well with decisions in the EET.

The paper is organized as follows. Section 2 discusses related literature. Section 3 provides a short introduction to the EET and informs about the online experiments conducted in the iLEE.

[2]This finding resonates well with that of Kerschbamer and Müller (2020) who reach similar conclusions in a sample of the German population. However, they find a larger proportion of inequality-averse subjects than in Denmark. This raises intriguing questions about the origins and international differences of social preferences.

[3]Andersson, Holm, Tyran, and Wengström (2016), for example, find evidence that errors in decision making can lead to a spurious correlation between cognitive ability and risk preferences.

Section 4 discusses the distribution of social preferences in Denmark. Sections 5 and 6 present the evidence for the predictive power of distributional preferences for behavior in the TG and the PGG, respectively. Section 7 concludes. In the appendix we present additional descriptive statistics, several robustness checks including a finite-mixture model, and a detailed description of the experiment including instructions.

2 Related Literature

Our paper contributes to an ongoing debate on the relevance of social preferences for behavior in experimental games. In general, it is fair to say that the literature has not yet reached a clear verdict on this question.

One of the most prominent contributions is Blanco, Engelmann, and Normann (2011). The authors study behavior in four games – an ultimatum game (UG), a modified dictator game (DG), a sequential prisoner's dilemma game (PDG) and a public goods game (PGG) – with the aim of testing the Fehr and Schmidt (1999) model of inequality aversion. They use responder data from the UG to estimate aversion to disadvantageous inequality and the data from the modified DG to estimate aversion to advantageous inequality. The resulting measures are used to predict decisions in the other two games. The authors find that the Fehr and Schmidt (1999) model has considerable predictive power at the aggregate level but performs less well at the individual level.

There are other studies that reach similar conclusions to Blanco et al. (2011). Engelmann and Strobel (2010) focus on the predictive power of inequality aversion for behavior in the moonlighting game and do not find any significant correlations in situations where inequality aversion and reciprocity make different predictions.[4] Yamagishi et al. (2012) find that rejection of offers in the UG is not correlated with behavior in other games, including a standard DG. See also Kümmerli et al. (2010), Burton-Chellew and West (2013) and Capraro and Rand (2018) for similar claims.

Several papers find mixed evidence for the predictive power of social preferences for behavior in experimental games. Teyssier (2012) studies the role of inequity aversion and risk preferences for cooperative behavior in two versions of a PGG. She employs the same method to elicit inequity aversion as Blanco et al. (2011) and finds that inequity aversion explains contributions in a sequential PGG, but not in a simultaneous PGG. Dannenberg et al. (2007) classify subjects into Fehr-Schmidt and non-Fehr-Schmidt types based on their choices in a DG and an UG. On the one hand, they find that the composition of groups based on these social preferences significantly influences contribution behavior in a PGG in the sense that inequality averse subjects contribute more. On the other hand, it turns out that information about the players in the own group is required to raise contributions, such that "fair" groups contribute more to the common good. Harbaugh and Krause (2000) find mixed evidence for the correlation of behavior in a DG and a repeated PGG with children. In particular, there is a correlation between DG behavior and behavior in the first round of the PGG in the expected direction, but no strong correlation to behavior in the last round of the PGG. Finally, Dreber, Fudenberg, and Rand (2014) examine whether giving in a standard DG explains cooperation in a repeated PD. They find

[4] In the moonlighting game by Abbink, Irlenbusch, and Renner (2000) the first mover can give money to or take money from the second mover, who can then either reward or punish the first mover.

evidence for a correlation when no equilibrium involving cooperation exists, but not when cooperation is an equilibrium.

Several studies have found evidence that distributional preferences predict behavior in games. Most closely related to our work is Bruhin, Fehr, and Schunk (2019) who estimate a mixture model of social preference types. Their model includes distributional as well as reciprocal concerns. They find three preference types in a student sample: strong altruists, moderate altruists and a "behindness averse" type. In addition to classifying subjects into types based on the posterior probabilities from the mixture model, the authors show that the structural parameters from the mixture model predict behavior in a TG and a 'reward and punishment game'. Kamas and Preston (2012) elicit behavior in a DG, an UG and a TG and conclude that their data offers "strong support" for social preferences to matter across games. Yang, Onderstal, and Schram (2016) elicit the two parameters of the Fehr-Schmidt model at the individual-level and find that these parameters matter in explaining choices in a 'production game'. Peysakhovich, Nowak, and Rand (2014) find evidence for a correlation of pro-social behavior across five different games conducted 124 days apart, including a DG. They conclude that there is a general and temporally stable component to pro-social behavior, which they dub the "cooperative phenotype".

Offerman, Sonnemans, and Schram (1996) and Murphy and Ackermann (2017) show that subjects' social value orientation predicts cooperativeness in a PGG, see also Yamagishi et al. (2013). Hernandez-Lagos, Minor, and Sisak (2017) find that social preferences predict effort provision and coordination in a lab experiment. Gächter, Nosenzo, and Sefton (2013) show that Fehr-Schmidt preferences are better able to explain peer effects in a three-person UG than social norms. Holm and Danielson (2005) find that behavior in the DG is significantly related to behavior in the TG in Tanzania and in Sweden.

We shed new light on these mixed findings and make several contributions to the literature. First, we use individual-level measures of distributional preferences to make point predictions of behavior in other games which allows for a sharper test. This seemingly subtle issue is, we believe, important and distinguishes the current paper from the rest of the literature (again, one exception is Blanco et al. (2011) who also use individual-level measures of distributional preferences to make predictions; however, since they do not elicit beliefs, they cannot make point predictions for the PGG): If one does not measure distributional preferences, there is no way of telling whether they matter or not. Also, the evidence presented in this paper shows that the preference elicitation needs to distinguish between benevolence in the domain of advantageous and benevolence in the domain of disadvantageous inequality. This is so, because (i) those inclinations are empirically uncorrelated and (ii) it is otherwise mathematically impossible to calculate point predictions across games. Thus, empirical elicitation procedures that do not distinguish these domains – like the Ring Test and the Circle Test developed by Griesinger and Livingston (1973) and Liebrand (1984) and the basic version of the Social-Value-Orientation Slider introduced by Murphy, Ackermann, and Handgraaf (2011) – are not suited to study the question that the current paper tackles. Second, our results demonstrate that there is a component to distributional preferences that is stable over longer periods of time because one game was implemented one year prior to the other games. Third, we demonstrate the predictive power of social preferences in a representative sample instead of a convenience sample of students.

Our findings therefore suggest that distributional preferences can predict behavior not only among possibly more highly educated student samples recruited for controlled laboratory experiments but also in an online survey involving a random sample from the general population. Fourth, we demonstrate that distributional preferences are the most important predictor of behavior relative to a large set of potentially relevant covariates. This demonstration is particular powerful in a heterogeneous sample which exhibits larger variation than convenience samples. Fifth, we find that while the EET predicts well, the standard DG does not. Thus, this finding suggests that the EET is a more appropriate measure of distributional preferences.

3 Experiments in the iLEE and the EET

This section first provides a short introduction to the Equality-Equivalence Test (EET) proposed by Kerschbamer (2015) and then informs about the online experiments conducted in the internet Laboratory for Experimental Economics (iLEE) that we exploit to gather our data.

3.1 The Equality-Equivalence Test

The EET is a price-list technique that aims at identifying the benevolence, neutrality or malevolence of the decision maker towards an anonymous other subject (the recipient) in two domains of inequality – the domain of advantageous inequality where the decision maker is ahead of the other person, and the domain of disadvantageous inequality where the decision maker is behind. Depending on the revealed benevolence, neutrality or malevolence of the decision maker in the two domains, the decision maker is classified into one of nine social preference types – for instance, as altruistic if the decision maker reveals benevolence towards the recipient in both domains, as inequality averse if the decision maker reveals benevolence in the domain of advantageous and malevolence in the domain of disadvantageous inequality and as selfish if the decision maker reveals neutrality in both domains. See Figure 1 for details.[5]

More specifically, the EET exposes subjects to a number of binary choices between two income distributions (m, o), where m (for "my") stands for the own material payoff of the decision maker while o (for "other") stands for the material payoff of the other person. In each choice problem one of the two alternatives consists of a symmetric reference allocation in which both subjects receive the same material payoffs. In the version of the test we use (this version is displayed in Table 1 and graphically illustrated in Figure 2), the symmetric reference allocation was set to 50 Danish Kroner (Dkr; approximately 7 euros) for each person. The second allocation is always asymmetric. In half of the binary choices (the advantageous inequality block – the *Y-list*) the decision maker gets more than the recipient, in the other half (the disadvantageous inequality block – the *X-list*) the decision maker always gets less. Within each of the two blocks the material payoff of the recipient in the asymmetric allocation is held constant, while the material payoff of the decision maker increases monotonically from one choice to the next.[6] This design feature (together with the fact that the symmetric allocation

[5] A positively (negatively) sloped indifference curve in a given domain corresponds to malevolence (benevolence) in that domain, while a vertical segment corresponds to neutrality.

[6] We varied the incremental change in m in the asymmetric allocation (the "step size", which is constant in the basic version of the test) so that it is small (2 DKr) close to the reference point but grows larger (up to 10 DKr) when moving

remains the same in all choices) guarantees that a rational decision maker switches at most once from the symmetric to the asymmetric allocation (and never in the other direction) within each block.[7] As Kerschbamer (2015) shows, the two switching points of a subject can be used to construct a two-dimensional index – the (x, y)-score – representing both archetype and intensity of distributional concerns. A positive score corresponds to benevolence and a negative score to malevolence. The y-score thereby refers to preferences in the domain of advantageous inequality and the x-score to preferences in the domain of disadvantageous inequality. Moreover, a higher score means more benevolence. For instance, a subject that switches from the symmetric to the asymmetric allocation in row 2 of the X-list shown in Table 1 reveals more benevolence in the domain of disadvantageous inequality than a subject who switches in row 3. This is so because the former subject reveals that it is willing to give up at least 20 Dkr to increase the income of the recipient by 25 Dkr, while the latter subject reveals that it is not willing to give up 20 Dkr to increase the income of the recipient by 25 Dkr, but would be willing to give up 8 Dkr to do so. To account for the difference in benevolence, the EET assigns an x-score of 3.5 to the former subject and an x-score of 2.5 to the latter. Suppose now a subject switches from the symmetric to the asymmetric allocation in row 5 (row 6, respectively). This subject reveals that it is not willing to give up 2 Dkr to increase (decrease) the material payoff of the recipient by 25 Dkr, but is willing to do so if the change in the income of the recipient does not involve a cost in own-money terms. The EET assigns to such a subject an x-score of 0.5 (-0.5, respectively), as the subject reveals to be weakly benevolent (weakly malevolent, respectively). In the EET, the scores +0.5 and -0.5 are interpreted as selfishness in the respective domains, as the subject has revealed that it is not willing to give up 2 Dkr to change the income of the recipient by 25 Dkr.[8]

The EET provides several advantages over alternative approaches to elicit distributional preferences. First, it is derived from a small set of axioms on preferences. Thus, the conditions under which the test holds are well-defined. Second, the same set of assumptions result in a *well-delineated, mutually-exclusive* and *comprehensive* set of distributional types. Thus, the set of distributional types tested for is not ad hoc but rather derived from assumptions about preferences. Third, the test is non-parametric and hence does not rely on any functional form assumption. Fourth, the preferences are elicited in an environment uncontaminated by intentions and beliefs – which is in contrast to large parts of previous literature.

Given the direct relation of the current paper to the work by Blanco et al. (2011), it is instructive to compare their elicitation procedures to the EET. To estimate the parameter of aversion against advantageous inequality Blanco et al. use a technique that bears similarities to the EET. In terms of Figure 2, Blanco et al.'s 20 binary decisions correspond to 20 points on the 45° line through the positive orthant each compared to a single point that has exactly the same m as the rightmost point on the 45° line but an o of zero. Thus, by observing the choices of a subject in the 20 binary decision problems one can deduce the shape of the indifference curve through this latter point. While this is an

away from the reference point. This modification in comparison to the basic version of the test was made to increase the power to discriminate between selfish and non-selfish (that is, benevolent or malevolent) behavior without increasing the test size or decreasing the discriminatory power at the borders.

[7]The rationality requirements underlying the EET are low. In terms of axioms on preferences the assumptions are ordering (completeness and transitivity) and strict own-money monotonicity – see Kerschbamer (2015) for details.

[8]In the EET, selfishness 'has a sign': A subject with a score of +0.5 reveals benevolence (and one with -0.5 reveals malevolence) only in those decisions in which no own money is at stake.

elegant procedure it has some disadvantages in comparison to the EET employed here, namely (i) that the shape of the indifference curve can only be assessed for the domain of advantageous inequality; and (ii) that positively sloped indifference curves in that domain cannot be identified correctly. To estimate a subject's parameter of aversion against disadvantageous inequality Blanco et al. (2011) use data from second-mover behavior in the ultimatum game. A potential disadvantage of this approach is that the second mover is likely to read first-mover intentions into observed first-mover choices.[9]

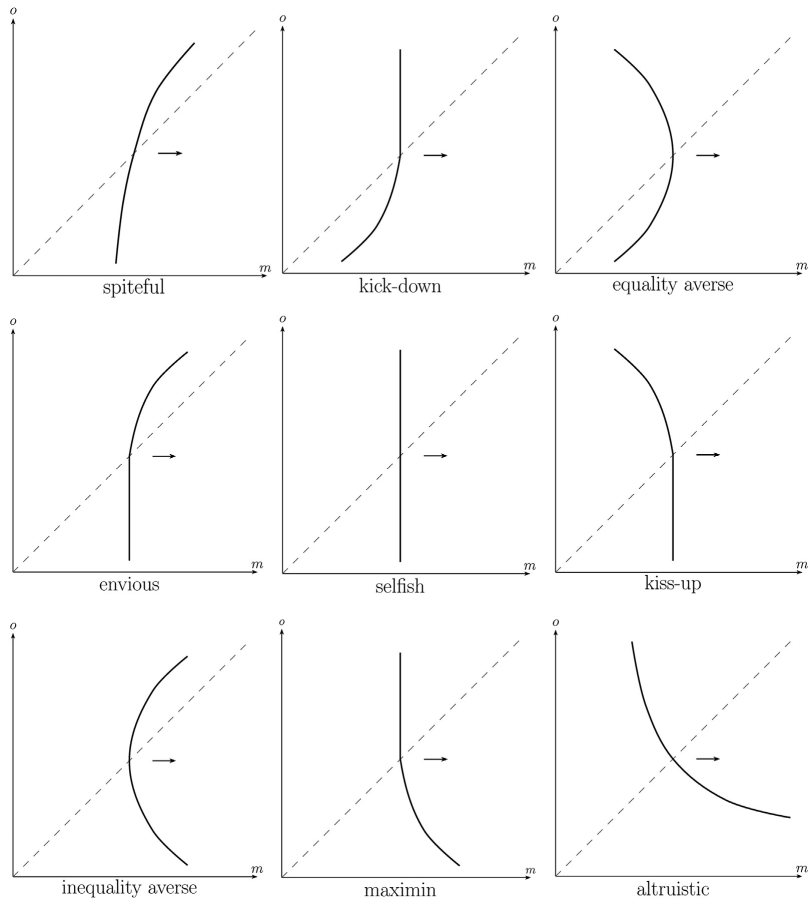

Figure 1: Indifference curves for the nine archetypes of distributional preferences.

The EET was part of wave 3 of the internet Laboratory for Experimental Economics (iLEE). The procedures of the test were as follows. Participants were first explained the rules of the experiment. See Section A.6 in the appendix for experimental instructions and A.7 for screenshots. Choices were made one at the time on separate screens where decision makers choose between Left and Right before moving on to the next choice. Once they have made all 14 choices, subjects saw a confirmation screen. This screen provided an overview of the choices made by the subject in the EET with a horizontal line separating the X- and the Y-list. The chosen distributions were color highlighted and decision makers could go back and change their decisions as many times as they wished. Once they confirmed their decisions, they moved on to the next experiment in the wave.

[9]This should not be read as a critique of Blanco et al.'s (2011) approach. After all, the Fehr and Schmidt model has been designed to explain behavior in strategic games and the 'calibration' of parameters with ultimatum game data has been suggested by the authors of the original paper. A possible advantage of Blanco et al.'s approach (in terms of explaining behavior in strategic games) is that it captures not only distributional preferences but also other forms of other-regarding preferences (such as reciprocity motives, for instance).

The X-list				The Y-list			
Left		Right		Left		Right	
m	o	m	o	m	o	m	o
20	75	50	50	42	25	50	50
30	75	50	50	48	25	50	50
42	75	50	50	50	25	50	50
48	75	50	50	52	25	50	50
50	75	50	50	58	25	50	50
52	75	50	50	70	25	50	50
58	75	50	50	80	25	50	50

Table 1: The X- and the Y-list implemented in the iLEE. All numbers in Danish kroner.

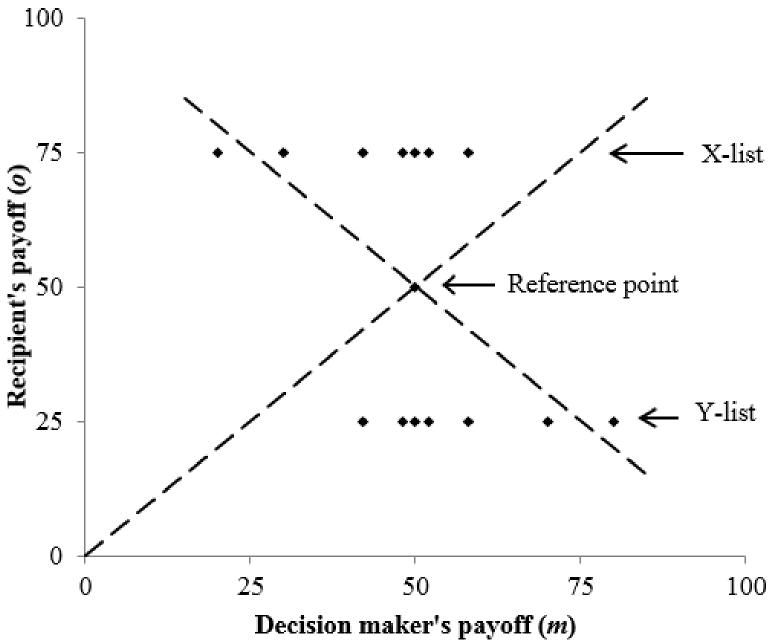

Figure 2: Graphical illustration of the allocations.

We employed two conditions that relate to the roles and possible interaction of decision makers and recipients. In the *FixedRoles* condition half of the participants were decision makers, the other half were recipients. Roles were randomly assigned and revealed after participants read the instructions but before any decisions were made. Decision makers then made their choices in the EET while recipients made no decisions. At the very end of the experiment, each decision maker was randomly assigned to a recipient and one randomly selected choice was then actually paid out in each pair. In the *RandomRoles* condition all participants made choices as if they were decision makers. A random draw determined ex-post which role each participant was paid for. Again, half of the subjects received the decision maker role and half the recipient role, each subject in the decision maker role was randomly assigned to one in the recipient role and one randomly selected choice was then actually paid out. Instructions were kept as similar as possible across conditions and treatment allocation was random with one-third of participants in the *FixedRoles* condition and two-thirds in the *RandomRoles* condition. We implemented these two conditions to explore whether the role assignment has an impact on the elicited distributional type – which could potentially explain the conflicting evidence reported in Section 2. Our ex-ante hypothesis in this regard was that the role assignment is of secondary importance.

3.2 The Internet Laboratory for Experimental Economics

The experiment uses a "virtual lab" approach and is conducted using the platform of the internet Laboratory for Experimental Economics (iLEE) at the University of Copenhagen, Denmark – see Thöni, Tyran, and Wengström (2012). Subjects for the platform are recruited with the assistance of the official statistics agency (Statistics Denmark) who selects a random sample from the general population. The iLEE consists of four different waves, issued between May 2008 and June 2011.[10]

In the binary trust game (TG), which was part of wave three of iLEE in July 2010, each subject makes two decisions, one in the role of the first mover and one in the role of the second mover. Subjects were informed in the instructions that only one of the two decisions would actually be paid out. For half of the subjects the first-mover decision was selected to be payoff relevant, for the other half the second-mover decision was payoff relevant. The matching of subjects was random and one-to-one. The first mover had to decide between *in* and *out*. *Out* implies payoffs of 50 Dkr and 20 Dkr for the first and the second mover. *In* implies that the decision is passed on to the second mover. The second mover then decides between *betrayal* and *honor*, which implements the payoff pair (20,90) or (80,40), respectively. Here, we only consider the decisions of the second mover, as they are clearly distributive in nature.

The linear public good game (PGG) was part of the first wave of the iLEE. In this experiment, subjects are matched into groups of four. Each subject is endowed with Dkr 50 and decides how much to contribute to a pool of common resources (the public good) and how much to keep for herself (the private good). The total amount contributed by the group to the common pool is doubled and shared equally among the group members (the marginal per capita return, MPCR, is hence equal to 0.5). The PGG is played as a one-shot game. In this game, half of the participants were randomized into a "give" frame and the other half into a "take" frame.[11] While it is socially optimal that all group members contribute the full endowment, individual income is maximized by contributing zero. After the contribution decision, we elicit beliefs about the average contribution of the three other group members incentivized using a quadratic scoring rule.

When analyzing the data, we include three different sets of control variables in our regressions, all taken from the iLEE survey: First, the socio-demographic set consists of age; age squared; a gender dummy; education (coded in four different categories); dummies for employed, retired, student and self-employed status; income (coded in quartiles); and the number of hours worked per week. Second, the personality and cognitive controls comprise the IQ score; the score from the cognitive reflection

[10] More detailed information about the iLEE is presented in Section A.5 in the appendix. See also the web page http://www.econ.ku.dk/cee/ilee/description/ for further information. On this web page one can also find comparisons of the characteristics of the sample with those of the general Danish population.

[11] The average contributions are in fact not influenced by this frame, but we nevertheless control for the frame in all regressions. More details can be found in Fosgaard, Hansen, and Wengström (2019).

test; and the Big-5 character traits. Third, the set of attitude controls consists of three different variables indicating political preferences and trust. All these variables are explained in more detail in Section A.5.

4 The Distribution of Social Preferences in Denmark

In total, 1067 participants took part in the experiment – with average earnings of 51.8 Dkr. From these 1067 subjects, 885 played the role of a decision maker in the EET, while the rest was only in the role of a recipient (in the *FixedRole* condition). The assumptions of ordering and strict m-monotonicity imply that decision makers switch at most once from Right to Left (and never from Left to Right) in each list of the EET. Of the $n = 885$ decision makers, 650 fulfill this rationality criterion while 235 (27%) make choices that are not consistent with it.[12] In the main analysis we focus on the consistent decision makers. Later on, in the robustness section, we also estimate mixture models and use posterior probabilities to classify inconsistent participants into one of the four main types. Regarding the two payment protocols, we find very little evidence that these two payment protocols cause differences in behavior. In particular, we do not find evidence that the number of consistent subjects or the frequency of distributional types is affected. Appendix A.3 reports more details. In the following, we therefore merge the data without using dummies for the protocols. The results with the dummies are very similar and available upon request.

Table 2 displays the distribution of social preferences types in Denmark. The first column of the table shows that, among the classified subjects, the empirically most frequent preference type is (with roughly a third of the population) altruism. Subjects are classified as altruistic if they reveal benevolence both when they are ahead and when they are behind. Around a quarter of subjects (23 percent) act in a way that is consistent with inequality aversion – they reveal benevolence when ahead and malevolence when behind; a fifth (20 percent) behaves is a selfish manner – their behavior seems to be unaffected by the material consequences for others, independently of whether they are ahead or behind; and 14 percent are classified as having maximin preferences – they reveal benevolence when ahead and neutrality when behind.[13] In total, these four most prevalent types make up almost 90 percent of the sample. Of the remaining, less than six percent act in a way that is consistent with envy and less than three percent are spiteful, while kiss-up, equality averse and kick-down each account for only about one percent of the sample. Thus, while the EET provides a comprehensive framework which allows for the distinction between nine social preference types, only five of these

[12] This share is relatively large – compared to the 5% share reported by Kerschbamer (2015) for a standard lab experiment based on a student subject pool, for instance. A possible reason for the large share of inconsistent subjects is the heterogeneity and representativeness of the sample on which our study is based. Evidence in support of this conjecture comes from an earlier wave of the iLEE: Andersson, Holm, Tyran, and Wengström (2016) report that 35% of the sample had multiple switching points in a variation of the Holt and Laury (2002) risk attitudes elicitation procedure – which is similar to the EET with regards to complexity.

[13] For a two-player decision problem, the label "maximin" for a player who is benevolent towards a player with lower payoff and neutral towards a player with higher payoff seems fine. However, we are later analyzing a game with four players. In such a game benevolence towards players with lower payoffs and neutrality towards players with higher payoffs is only consistent with maximin preferences if all players with lower payoffs have exactly the same low payoff. Hence, a different term – 'charitable', for instance – seems more appropriate. To avoid the introduction of new names for preference types, we stick to the term maximin throughout the paper.

types attract more than 5% of our subjects.[14] Figure 3 plots the distribution of social preference types in our population in the (x, y) space. In this space, the x-score, measuring the benevolence of the decision maker in the domain of disadvantageous inequality, is represented on the x-axis and the y-score, measuring benevolence in the domain of advantageous inequality, is represented on the y-axis (in both cases negative values mean malevolence, see Subsection 3.1 for details). The figure clearly shows that there are pronounced mass points in the top-left corner (inequality-aversion) and in the center (selfishness), and that there is a densely populated area of somewhat smaller mass points in the positive orthant (with maximin covering the left-hand side of the area and altruism covering the rest).

Types	Distribution
Altruist	32.2
Inequality averse	23.2
Selfish	20.0
Maximin	13.7
Envious	5.5
Spiteful	2.6
Kiss-up	1.2
Equality averse	1.1
Kick-down	0.5
N	650

Table 2: Distribution of social preference types in percent.

5 Trust Game

We now turn to the assessment of the predictive power of distributional preferences across different games. We first investigate how distributional preferences explain behavior in the binary TG. Section 6 then considers the linear PGG.

[14]The share of inequality-averse subjects might seem rather high in comparison to the findings in Kritikos and Bolle (2001), Charness and Rabin (2002) and Engelmann and Strobel (2004). A possible explanation is that the EET is biased in the direction of detecting more inequality averse people – for instance, because the EET uses a symmetric reference allocation that might act as an anchor. We are not convinced by this explanation for several reasons: First, when the EET is employed in student samples, the fraction of inequality averse subjects is typically rather low – see Kerschbamer (2015), Balafoutas et al. (2017) or Kerschbamer at al. (2019). Second, there are several recent papers that do not make use of the EET and still find relatively large shares of inequality averse subjects – see Bruhin et al. (2019). Third, the study by Krawczyk and Le Lec (2021) implements a variant of the EET with asymmetric reference points and detects a similar fraction of inequality averse subjects as Kerschbamer (2015). Given all this evidence we consider it as more plausible that differences in subject pools are responsible at least to large parts for the differences in results. See Fehr et al. (2006) for experimental evidence indicating that students (especially students of economics) are less egalitarian and more efficiency oriented than the rest of the population. See also the response by Engelmann and Strobel (2006) in the same issue.

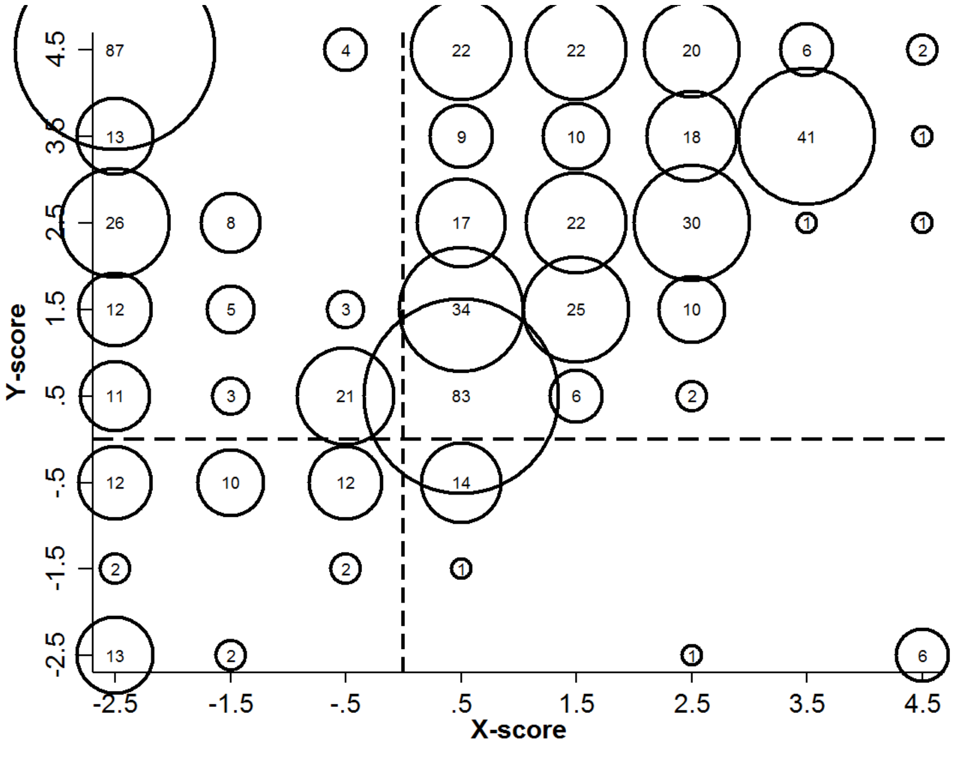

Figure 3: Scatterplot of (x, y) scores.

5.1 Prediction for the TG

We first analyze the predictive power of distributional preferences for second-mover behavior in the binary TG contained in wave 3 of the iLEE. A screenshot of the TG is shown in Figure 6 in the appendix.

In order to make an individual-level prediction for our binary TG, we use the piecewise-linear social utility function proposed by Fehr and Schmidt (1999), but lift their parameter restrictions. For the two-agents case, the Fehr-Schmidt function reads:

$$U(m,o) = \begin{cases} (1-\sigma)m + \sigma o & \text{if } m \leq o \\ (1-\rho)m + \rho o & \text{if } m > o, \end{cases} \tag{1}$$

where m (for *my*) denotes again the income of the decision maker and o (for *other's*) the income of the second person and where σ and ρ are two parameters that determine the weight the decision maker puts on the income of the other person when she is behind ($m \leq o$) or ahead ($m > o$), respectively.[15]

To simplify the exposition, we assume in the main text that $\sigma \leq \rho < 1$. The former inequality means that the decision maker is more benevolent (less malevolent) in the domain of advantageous than in the domain of disadvantageous inequality and it guarantees that indifference curves in the (m, o)-space are convex.[16] The latter inequality makes sure that the preferences of the decision maker are monotone in the own material payoff.

[15] Note that we use the parameters σ and ρ here (and not the conventional α and β) in order to make clear that we do not make the usual assumptions about the values of the parameters, i.e. $0 \leq \beta \leq \alpha$.

[16] The convexity assumption excludes three types of preferences (equality-averse, kiss-up and kick-down) and we will discuss the prediction for these types in footnotes.

A second mover in the TG faces the decision between *betrayal* and *honor*, implying the allocations $(20, 90)$ and $(80, 40)$, respectively.[17] Inserting these payoffs into (1), we see that the second mover prefers $(80, 40)$ over $(20, 90)$ iff

$$(1 - \sigma)40 + \sigma 80 \geq (1 - \rho)90 + \rho 20, \tag{2}$$

which yields the prediction:

Prediction for the TG: *Consider a binary TG, in which the second mover has the choice between the payoff allocations* $(20, 90)$ *and* $(80, 40)$. *Suppose the second mover's preferences are of the Fehr-Schmidt form, but with parameters only restricted by* $\sigma \leq \rho < 1$. *Then*

- *if* $4\sigma + 7\rho > 5$ *the second mover's uniquely optimal move is to pick honor;*
- *if* $4\sigma + 7\rho = 5$ *the second mover is indifferent between betrayal and honor; and*
- *if* $4\sigma + 7\rho < 5$ *the second mover's uniquely optimal move is to pick betrayal.*

In our main analysis we test the above prediction in two ways: First, we use a dummy that indicates a higher utility from the *honor* allocation (*Prediction-honor* dummy) and second we use the actual utility difference between *honor* and *betrayal* (Δ-*honor*) as predictor. For these tests we need the preference parameters σ and ρ at the individual level. These are calculated from the choices in the x- and the y-list for each individual. Doing so is possible because there is a one-to-one relationship between the scores and these preference parameters. Tables 9 and 10 in the Appendix summarize these relationships. It is important to note that according to the above prediction, since $\sigma < 1$, a necessary, but not sufficient, condition for a decision maker to pick *honor* is $\rho > 0$. A strictly positive ρ means benevolence in the domain of advantageous inequality – or, put in terms of the EET, a positive y-score. Based on this observation, we regress in a complementary analysis a dummy indicating whether the subject picked *honor* on the x- and the y-score (and covariates). The prediction is that the y score – but not necessarily the x score – is a significant predictor of actual behavior in the TG. In terms of distributional types, altruistic, maximin and inequality averse subjects are benevolent when ahead – while all other distributional types exhibit either neutrality or malevolence in this domain. Based on this observation we also regress the *honor* dummy on distributional types. Here the prediction is that altruistic, maximin and inequality averse subjects are more likely to pick *honor* than the other types.[18]

5.2 Results: Trust Game

Our main results are presented in Table 3 in which we regress the *honor* choice, first, on the dummy that indicates a higher utility from the *honor* allocation (*Prediction-honor* dummy) and, second, on

[17] In those vectors, the first (second) entry is the first- (second-) mover payoff in the respective allocation.

[18] It is interesting to note that – according to the prediction for the TG – an inequality averse participant would only pick *honor* if her inequality aversion is of a very specific form – namely strong aversion against advantageous inequality (large positive ρ) combined with very weak aversion against disadvantageous inequality (small negative σ). Specifically, a necessary condition for an inequality averse subject to choose *honor* is that her ρ is larger than $\frac{5}{7}$ and that her σ is negative and smaller than $\frac{1}{2}$ in absolute terms – a parameter constellation that explicitly violates the restrictions of the Fehr and Schmidt model.

the actual utility difference between *honor* and *betrayal* (Δ-*honor*), with and without controls. We divide our controls into three distinct sets as: Socio-demographic, personality, cognitive and attitude controls.[19] The results show that both *Prediction-honor* and Δ-*honor* are robust predictors in the expected direction of actual choices of second movers. This statement holds independently of whether we include control variables or not.[20] In addition, Table 4 shows that, as predicted, the y-score – indicating benevolence when ahead – is also a robust predictor of trustworthiness, confirming our earlier conclusions. Again, this holds when we include different sets of controls.

In Table 14 in the appendix we also regress the *honor* dummy on distributional types. We find that types that are benevolent when ahead (altruists, maximin and inequality averse subjects) are indeed all more likely to pick honor. This holds true independently of whether we include dummies for each of these types or a merged dummy for all three types together and independently of whether we include our standard set of controls or not.

Table 5 shows the results of a dominance analysis, which allows assessing the relative importance of predictors in a multiple regression framework. A dominance analysis attributes the overall R^2 of the model to its individual components not only considering the direct individual contributions of each regressor, but also the interactions with other variables. To do so, it estimates the R^2 of all subsets of models with a given regressor and compares it to the R^2 of all models without this regressor. Thus, in the case of p regressors, a dominance analysis measures the average difference in fit between all p! subsets of models that include a regressor x_i and those that do not (Azen and Budescu, 2003). The table shows the standardized dominance statistic which compares the relative contribution of each predictor to the overall predictive power of the model. We find that the variable *prediction* contributes between 55% and 73% to the overall model fit compared to the three sets of covariates, see columns (1) - (3). When pitched against all 21 covariates, this variable remains important and contributes with around 36% to a large degree to the total model fit. It is also noteworthy that *prediction* is never dominated by any other of the 21 control variables as predictor of behavior. This exercise corroborates the finding that distributional preferences are the single most important predictor of behavior within an extensive set of covariates. In fact, *prediction* is more important than any of the three *sets of*

[19]Specifically, the socio-demographic set includes the variables: age, age squared, gender, education, employed-dummy, retired-dummy, student-dummy, self-employed-dummy, income quartiles and hours worked. The personality and cognitive controls include IQ score, score in the cognitive reflection test and the Big-5 (one variable for each of the five traits). The attitude controls are political left-right assessment, responsibility of the individual versus the government, attitudes toward competition (all three variables coded between one and ten) and the generalized trust question (a binary indicator). Moreover, we always control for the role treatment in the EET and also, whenever possible, for the framing of the PGG.

[20]We show OLS regressions throughout the paper. Logit models (in case of the TG) and two-limit Tobit models (in case of the PGG) deliver very similar results (available upon request). Note that the lower number of observations in some columns stems from missing observations for some covariates.

covariates.[21]

Result TG: *Distributional preferences are a significant determinant of second mover behavior in a TG. Subjects who are benevolent when ahead (altruistic, maximin and inequality averse subjects) are more likely to pick honor than all other subjects.*

[21]Note that our finding of significant predictive power of social preferences for behavior in the TG corroborates the earlier finding of Blanco et al. (2011) who have shown such an effect to prevail in the sequential prisoners' dilemma which is structurally similar to the TG studied here. Also note that the fact that the individual-level point predictions correlate with actual choices does not mean that most point predictions are actually correct. Checking for exact matches we find that 474 out of 650 second movers in the TG behave exactly as predicted. This amounts to 73% of the observations. Due to the much larger number of available options the corresponding figure is much lower for the PGG: In that game for only 140 out of 650 observations (22%) the point prediction is fully correct.

Subject picked *honor*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Prediction-honor	0.233***	0.198***	0.221***	0.222***	0.195**					
	(0.06)	(0.08)	(0.06)	(0.06)	(0.08)					
Δ-honor						0.359***	0.331***	0.354***	0.334***	0.315***
						(0.08)	(0.10)	(0.08)	(0.08)	(0.10)
Socio-demographics	No	Yes	No	No	Yes	No	Yes	No	No	Yes
Cognition & Personality	No	No	Yes	No	Yes	No	No	Yes	No	Yes
Attitudes	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Observations	650	443	650	603	412	650	443	650	603	412
R^2	0.027	0.043	0.042	0.037	0.066	0.036	0.052	0.051	0.042	0.071

Table 3: Dependent variable is a dummy that indicates whether subject picked *honor* in trust game. *Prediction-honor* is a dummy that is equal to one for subjects who are predicted to pick honor on the basis of the elicited Fehr-Schmidt parameters. Δ-*honor* is the actual utility difference between the two allocations. OLS regression, robust standard errors in brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. A constant is included in all cases but not displayed here.

Subject picked *honor*	(1)	(2)	(3)	(4)	(5)
y-score	0.042***	0.042***	0.039***	0.038***	0.039***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
x-score	0.016*	0.009	0.018*	0.017*	0.008
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Socio-demographics	No	Yes	No	No	Yes
Cognition & Personality	No	No	Yes	No	Yes
Attitudes	No	No	No	Yes	Yes
Observations	650	443	650	603	412
R^2	0.040	0.057	0.054	0.045	0.075

Table 4: Dependent variable is a dummy that indicates whether subject picked *honor* in the trust game. The *y-score* measures benevolence in the domain of advantageous inequality. The *x-score* measures benevolence in the domain of disadvantageous inequality. OLS, robust standard errors in brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. A constant is included in all cases but not displayed here.

	Socio-demographics	Personality	Attitudes	All Controls
Prediction	0.55	0.67	0.73	0.36
Socio-demographics	0.45	-	-	0.27
Cognition & Personality	-	0.33	-	0.15
Attitudes	-	-	0.27	0.22

Table 5: Table displays standardized dominance statistics (in %). Dependent variable is a dummy indicating whether subject picked *honor* in the TG in an OLS regression model.

6 Public Good Game

6.1 Prediction for the PGG

To derive predictions for behavior in the PGG, we again use the Fehr and Schmidt (1999) utility function given in equation (1). To apply this function to the four player game under consideration, we assume that each subject compares her payoff to the average payoff of the other members of his reference group – as in Bolton and Ockenfels (2000). Technically, we simply add the payoffs of the three other players and divide the resulting sum by three. Furthermore, we interpret the elicited belief of the subject about the average contribution of the three other group members as a point belief, and we denote this belief by b and the own contribution by c. The approach we use here implicitly makes two assumptions: First, it assumes that the decision maker compares her payoff to the average payoff of the other three group members and not to the payoff of each other participant separately. Second, it assumes that in forming their expectations, participants put 100% probability on a single number. While it would have been possible to work without those simplifying assumptions, the more general approach would have forced us to elicit from each participant a belief about the contribution of each other member in his group (and not only a belief about the average contribution of the others) and to allow this belief to be a probability distribution over different contribution levels (and not only a belief that puts 100% on a single contribution). We decided to stick to the simpler approach to avoid exposing subjects to a complex belief elicitation procedure and to get simpler predictions.

Using the b, c notation and taking the budget restriction and the technology of the linear PGG into account, the variables m and o in equation (1) can be written as:

$$m = (E - c) + (c + 3b)\frac{2}{4} = 50 - 0.5c + \frac{3}{2}b \tag{3}$$

$$o = (E - b) + (c + 3b)\frac{2}{4} = 50 + 0.5c + 0.5b. \tag{4}$$

Substituting into equation (1) and taking into account that $m \leq o \Longleftrightarrow c \geq b$ we get utilities of

$$50 - \frac{1}{2}c + \frac{3}{2}b + \sigma(c - b) \tag{5}$$

if $c \geq b$ and

$$50 - \frac{1}{2}c + \frac{3}{2}b + \rho(c - b) \tag{6}$$

if $c < b$.

Given the piecewise linearity of the preferences with a kink at $c = b$ and the linearity of the constraint, each subject has either a unique optimal contribution level at one of the points in $\{0, b, E\}$, or the subject is indifferent among several contribution levels. Specifically, we get the following prediction for the PGG:[22]

Prediction for the PGG: *Consider the linear PGG with marginal per capita return of one-half. Suppose the decision maker's preferences are of the Fehr-Schmidt form, but with parameters only restricted by $\rho \geq \sigma$. Further assume that the decision maker believes that all other group members contribute b. Then*

- *if $\rho \geq \sigma > 0.5$ then the unique optimal contribution level is at $c = E$;*
- *if $\rho > \sigma = 0.5$ then any contribution level in $[b, E]$ is optimal;*
- *if $\rho > 0.5 > \sigma$ then the unique optimal contribution level is at $c = b$;*
- *if $\rho = \sigma = 0.5$ then any contribution level in $[0, E]$ is optimal;*
- *if $\rho = 0.5 > \sigma$ then any contribution level in $[0, b]$ is optimal;*
- *if $0.5 > \rho \geq \sigma$ then the unique optimal contribution level is at $c = 0$.*

[22]The prediction in the main part focuses on the standard case of convex preferences as it simplifies the exposition. Subjects with concave distributional preferences ($\rho < \sigma$) have either a strict preference for $c = E$ (if $\sigma > 0.5 + (\sigma - \rho)b/50$), or a strict preference for $c = 0$ (if $\sigma < 0.5 + (\sigma - \rho)b/50$), or they are indifferent between the points $c = 0$ and $c = E$ (if the restriction holds as an equality). There are only 47 subjects with strictly concave distributional preferences. For all but one of those subjects the prediction is $c = 0$. For the remaining subject, the prediction is $c = 50$.

In the empirical analysis below, we first regress the actual contribution of a subject in the PGG on the predicted value based on the estimated preference parameters. It is important to note that according to the above prediction, a necessary condition for a subject with convex distributional preferences to contribute to the PGG is $\rho \geq 0.5$. A strictly positive ρ means benevolence in the domain of advantageous inequality. Or, put in terms of the EET, a positive y-score. We will thus in what follows additionally also use both, the x- and the y-score, as right-hand side variables in a regression in which the actual contributions are the independent variables. Again, the prediction is that the y-score, but not necessarily the x-score, is a significant predictor of actual behavior.

6.2 Results: Public Good Game

Figure 4 displays the distribution of actual contributions. There are spikes in contributions at zero, around 50% of the endowment and, most pronounced, at full contribution of 50 Dkr. Except for the relatively high level of full contributions observed in this Danish sample, this pattern is quite standard in PGGs.

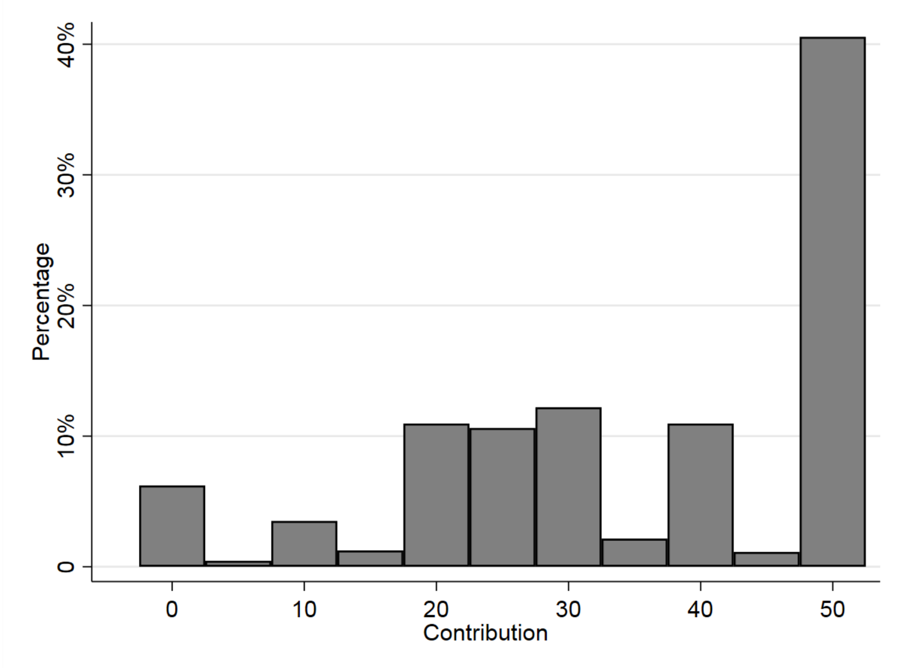

Figure 4: PGG contributions.

Our main results are presented in Table 6 in which we regress the actual individual contributions in the PGG on the predicted contributions, with and without controls.[23] We find that the calculated predictor is highly significant in those regressions, independently of whether we include control variables or not.[24]

[23] There are 49 subjects (7.5%) who we predict to be indifferent over all possible contribution levels. Another 14.8% are predicted to be indifferent either between all contributions in $[0, b]$ or between all contributions in $[b, 50]$. Hence, in total, 22.3% of our participants are affected by a theoretical indifference based purely on distributional preferences. We treat this issue in the following way: In the main text, we assign to each indifferent subject as the prediction the highest contribution level that is optimal for this subject. The appendix presents results where we assign the lowest optimal value. Table 19 in the appendix shows that our conclusions remain unaffected.

[24] All results reported in this section again use OLS regressions and heteroscedasticity robust standard errors and also

While the results in Table 6 are in line with the hypothesis that distributional preferences shape decisions in the PGG, there are at least two alternative explanations for the positive coefficient on the variable *prediction*: First, the theoretical prediction combines social preferences and beliefs. Hence, if the prediction correlates with the contribution (and this is what Table 6 shows), we learn that social preferences, or beliefs, or both are related to contributions. But we cannot conclude for sure which one it is. Second, if beliefs matter, we cannot be sure which way the causality runs, because, due to the false consensus effect, contributions may affect beliefs. The false consensus effect here refers to the possibility that subjects hold beliefs about other subjects' contributions that are too close to their own behavior relative to reality.[25]

To receive information on whether social preferences matter for contributions to the PGG even when we control for beliefs, we next regress (in Table 7) actual contributions simultaneously on beliefs and the estimated x and y scores (and a set of control variables). Remember that a necessary condition for a positive contribution in the PGG is benevolence in the domain of advantageous inequality – that is, a positive y-score. As Table 7 shows both the x score and the y score have explanatory power when not controlling for beliefs. However, controlling for beliefs, the x score is not significant anymore, while the y score remains significant. Hence not controlling for beliefs, one might falsely get the impression that benevolence in the domain of disadvantageous inequality is also relevant for contributions. But controlling for beliefs, one sees that this is not the case, apparently because the x-score correlates with beliefs. Table 7 also reveals a strong correlation between beliefs and contributions (conditioning on social preferences). This correlation could be due to the false consensus effect discussed in the previous paragraph, but it could also just be best response to beliefs. We simply cannot discriminate between these two explanations for the correlation.

A related question is whether the distributional types that display benevolence when ahead (inequality averse, maximin and altruistic subjects) contribute more to the public good. In the raw data, it turns out that altruists contribute on average 38.5 tokens, inequality-averse subjects 35.2 and maximin subjects 35.5 tokens – compared to 31.7 tokens by all other subjects (selfish subjects contribute 31.6 tokens and spiteful ones contribute 25.9 tokens, on average). Table 15 in the appendix displays results from regressions in which the distributional types serve as right-hand side variables. The results show that inequality-averse, maximin and altruistic subjects indeed contribute more to the public good. However, once we control for beliefs, this statement only holds when we merge those three types into a single summary category.

Table 8 shows the results of the dominance analysis for the PGG. It displays the standardized dominance statistics for the prediction variable in each model. We find that the variable *prediction* predicts between almost half – in column (1) – and two-thirds – in column (3) – of the total explained variation across the three subsets of covariates. Finally, the last column of the same table shows that *prediction* still explains almost one-third (27%) of the total explained variation in behavior when pitched against *all three* subsets of covariates together. Similar to the TG, *prediction* is never

use the same set of controls as in the previous section. The choice of the empirical model is again inconsequential for the conclusions.

[25]For early evidence on the relevance of the (false) consensus effect for behavior in a public good game, see Offerman, Sonnemans, and Schram (1996). For recent evidence on a strong consensus effect in a sequential prisoner's dilemma and its relevance for the explanation of observed behavior, see Blanco, Engelmann, Koch, and Normann (2014).

dominated by any other of the 21 control variables as predictor of actual behavior and always has the highest dominance statistic, i.e., *prediction* predicts better than any other variable across all subsets of models.

Result PGG: *Distributional preferences do correlate with cooperation in the PGG. Subjects who are benevolent when ahead (altruistic, maximin and inequality averse subjects) contribute more than selfish ones.*

Contribution	(1)	(2)	(3)	(4)	(5)
Prediction	0.208***	0.165***	0.186***	0.176***	0.150***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
Socio-demographics	No	Yes	No	No	Yes
Cognition & Personality	No	No	Yes	No	Yes
Attitudes	No	No	No	Yes	Yes
Observations	650	443	650	603	412
R^2	0.064	0.091	0.105	0.074	0.136

Table 6: Dependent variable is the individual contribution in the PGG. *Prediction* is the predicted contribution of the piecewise linear model. OLS, robust standard errors in brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. A constant is included in all cases but not displayed here.

Contribution	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
y-score	1.438***	1.335***	1.237***	1.075***	1.234***	0.700***	0.822***	0.602***	0.465**	0.671**
	(0.33)	(0.39)	(0.34)	(0.35)	(0.42)	(0.22)	(0.27)	(0.22)	(0.23)	(0.28)
x-score	0.764***	0.778**	0.751**	0.804***	0.964**	0.153	0.345	0.149	0.160	0.352
	(0.29)	(0.36)	(0.30)	(0.30)	(0.38)	(0.19)	(0.22)	(0.19)	(0.20)	(0.23)
Beliefs	–	–	–	–	–	0.911***	0.886***	0.899***	0.911***	0.887***
						(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
Socio-demographics	No	Yes	No	No	Yes	No	Yes	No	No	Yes
Cognition & Personality	No	No	Yes	No	Yes	No	No	Yes	No	Yes
Attitudes	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Observations	650	443	650	603	412	650	443	650	603	412
R^2	0.042	0.088	0.088	0.058	0.139	0.598	0.614	0.610	0.608	0.635

Table 7: Dependent variable is the individual contribution in the PGG. The *y-score* measures benevolence in the domain of advantageous inequality. The *x-score* measures benevolence in the domain of disadvantageous inequality. OLS, robust standard errors in brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. A constant is included in all cases but not displayed here.

	Socio-demographics	Cognition & Personality	Attitudes	All Controls
Prediction	0.47	0.53	0.66	0.27
Socio-demographics	0.53	-	-	0.35
Cognition & Personality	-	0.47	-	0.35
Attitudes	-	-	0.34	0.04

Table 8: Table displays standardized dominance statistics (in %). Dependent variable is the individual contribution in the PGG in an OLS regression model.

7 Concluding Remarks

Evidence for the predictive power of distributional preferences for behavior in strategic decisions is surprisingly sparse and the available evidence is inconclusive. The present paper contributes to this literature by showing that social preferences are significantly correlated to behavior in two other experimental games, one of which was played more than a year earlier. We infer from this predictive success that social preferences exhibit a stable component. This finding is noteworthy on two accounts. First, the predictive success is remarkably strong because it is greater than the success of alternative predictive measures like socio-demographics, measures of cognitive ability, personality, and attitudes. Second, it sheds new light on the debate about whether social preferences are context dependent (Levitt and List, 2007). There is indeed evidence that behavior in the dictator game is motivated by a desire to signal that one is not entirely selfish or by a desire to follow a social norm that is choice-set dependent, see List (2007) and Bardsley (2008). This finding has been replicated by Cappelen et al. (2013) using the same subject pool and the same "virtual lab" approach as in the current study. Consistent with these results, we find that behavior in the standard dictator game has no predictive power for the two experimental games under consideration here. The predictive power rather comes from Kerschbamer's (2015) Equality-Equivalence Test which elicits distributional preferences in a systematic and comprehensive way. Hence, our findings caution against the use of the standard dictator game to elicit social preferences.

Another interesting finding arising from this study, is the characterization of the distribution of social preferences in a large and heterogeneous sample. We find that almost 90% of consistent subjects are classified into one of just four preference types: altruism, inequality aversion, maximin and selfishness. This finding is in line with Bruhin, Fehr, and Schunk (2019) as well as Kerschbamer and Müller (2020). Both studies present evidence indicating that four preference types are sufficient to classify the vast majority of people. However, there are also nuances in the findings. In particular, we find that altruistic concerns are a more important driver of behavior than inequality aversion which contrasts with the results in Kerschbamer and Müller (2020) who use representative German data.

In all, our findings suggest a reconsideration of the relevance of distributional preferences for behavior in strategic interactions and highlight the importance of using a theory-driven approach to measure distributional preferences.

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A Appendix

A.1 The Relation between Scores, WTP and Fehr-Schmidt Parameters

X-list: subject chooses LEFT for the first time in row	X-score	Parameter range of σ	WTP_d
1	+ 4.5	$0.545 \leq \sigma$	$1.2 \leq WTP_d$
2	+ 3.5	$0.444 \leq \sigma < 0.545$	$0.8 \leq WTP_d < 1.2$
3	+ 2.5	$0.242 \leq \sigma < 0.444$	$0.32 \leq WTP_d < 0.8$
4	+ 1.5	$0.074 \leq \sigma < 0.242$	$0.08 \leq WTP_d < 0.32$
5	+ 0.5	$0 \leq \sigma < 0.074$	$0 \leq WTP_d < 0.08$
6	- 0.5	$-0.087 \leq \sigma < 0$	$-0.08 \leq WTP_d < 0$
7	- 1.5	$-0.471 \leq \sigma < -0.087$	$-0.32 \leq WTP_d < -0.08$
Never	- 2.5	$\sigma < -0.471$	$WTP_d < -0.32$

Table 9: WTP_d: amount of own material payoff the decision maker is willing to pay in the domain of **disadvantageous** inequality in order to increase the other's material payoff by one unit. The parameter σ is the weight on the other's income in the piecewise linear model. Note that the parameter α in the Fehr-Schmidt model corresponds to $-\sigma$ here.

Y-list: subject chooses LEFT for the first time in row	Y-score	Parameter range of ρ	WTP_a
1	- 2.5	$\rho \leq -0.471$	$WTP_a \leq -0.32$
2	- 1.5	$-0.471 < \rho \leq -0.087$	$-0.32 < WTP_a \leq -0.08$
3	- 0.5	$-0.087 < \rho \leq 0$	$-0.08 < WTP_a \leq 0$
4	+ 0.5	$0 < \rho \leq 0.074$	$0 < WTP_a \leq 0.08$
5	+ 1.5	$0.074 < \rho \leq 0.242$	$0.08 < WTP_a \leq 0.32$
6	+ 2.5	$0.242 < \rho \leq 0.444$	$0.32 < WTP_a \leq 0.8$
7	+ 3.5	$0.444 < \rho \leq 0.545$	$0.8 < WTP_a \leq 1.2$
Never	+4.5	$0.545 < \rho$	$1.2 < WTP_a$

Table 10: WTP_a: amount of own material payoff the decision maker is willing to pay in the domain of **advantageous** inequality in order to increase the other's material payoff by one unit. The parameter ρ is the weight on the other's income in the piecewise linear model. Note that the parameter β in the Fehr-Schmidt model corresponds to ρ here.

A.2 Dictator Game

In this section, we present evidence for the lack of correlation of behavior in the standard dictator game (DG) with behavior in other games. The DG was part of wave 2 in the iLEE. In this game, the dictator is endowed with 150 Dkr and decides on passing any amount of money from her endowment to the recipient. We use the amount kept by the dictator as dependent variable in the regressions below. In particular, in Table 11 we regress the y-score in columns (1) and (2), and the x-score in columns (3) and (4) on the amount kept by the dictator. In Table 12 we use the contribution in the

PGG as dependent variable, while in Table 13 a dummy, equal to one if the participant picked the right allocation as the second mover in the TG, serves as the dependent variable. In all cases, we present results with and without the usual set of controls.

As it turns out, in no case is this measure a significant predictor of behavior across games. In fact, it is not even related to behavior in the EET, which is a modified dictator game. This finding adds to the growing evidence suggesting that behavior in the standard dictator game is not reliable, see for example List (2007) and Bardsley (2008).

Equality-	Y-score		X-score	
Equivalence Test	(1)	(2)	(3)	(4)
Amount kept by Dictator	-0.004	-0.006	0.002	-0.002
	(0.00)	(0.00)	(0.00)	(0.01)
Controls	No	Yes	No	Yes
Constant	2.541***	8.000***	-0.101	3.794
	(0.42)	(3.04)	(0.45)	(3.55)
Observations	207	146	208	146
R^2	0.004	0.231	0.001	0.237

Table 11: Dependent variable is the y-score in columns (1) an (2) and the x-score in columns (3) and (4). OLS, robust standard errors in brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. A constant is included in all cases but not displayed here.

Contribution	(1)	(2)
Amount kept by Dictator	-0.047	-0.048
	(0.03)	(0.03)
Controls	No	Yes
Constant	40.646***	2.285
	(2.92)	(21.07)
Observations	314	213
R^2	0.009	0.167

Table 12: Dependent variable is the individual contribution in the PGG. OLS, robust standard errors in brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. A constant is included in all cases but not displayed here.

Subject picked *honor*	(1)	(2)
Amount kept by Dictator	-0.000	0.000
	(0.00)	(0.00)
Controls	No	Yes
Constant	0.268***	0.034
	(0.08)	(0.49)
Observations	314	213
R^2	0.000	0.104

Table 13: Dependent variable is a dummy that indicates whether subject picked *honor* in trust game. OLS, robust standard errors in brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. A constant is included in all cases but not displayed here.

A.3 Payments in the EET

The EET was carried out using two different payment protocols that vary whether there is uncertainty about the final role (decision maker or recipient) a subjects takes on in the EET. In the *FixedRoles* condition, roles are determined ex-ante and participants chosen to be decision makers know that their choices will affect the own material payoff and the payoff of a recipient for sure – while recipients make no choices and cannot affect outcomes. In the *RandomRoles* condition, all participants take decisions as if they are decision makers and actual roles are randomly determined ex-post. We find that the two conditions do not affect the distribution of social preference types. We find however subtle evidence suggesting that the degree of benevolence in one domain might be affected.

Using Fisher exact tests, we do not find any evidence that the two payment protocols *FixedRoles* and *RandomRoles* influence the number of inconsistent decision makers ($p = 0.64$). Next, we test whether the payment protocol influences the distribution of types. Here, too, we are unable to find any evidence that supports the hypothesis that the payment protocol influences the decisions of subjects in the EET. The corresponding p-value of the likelihood ratio test is 0.49.[26] Looking at the intensity of social preferences – by considering the two scores, the x-score representing the benevolence of the decision maker in the domain of disadvantageous inequality and the y-score measuring the benevolence in the domain of advantageous inequality – we find some evidence suggesting that people exhibit a higher y-score (but not x-score) in the *RandomRoles* than in the *FixedRoles* condition. A Fisher exact test yields a p-value of 0.02 (0.96) for the y-score (the x-score, respectively). In particular, the average y-score (x-score) is 1.88 (0.24) in the *FixedRole* condition and 2.28 (0.19) in the *RandomRole* condition, indicating that benevolence in the advantageous domain might be somewhat higher in the *RandomRoles* protocol. Nevertheless, all of this is of course inconsequential for the main results of the paper.

[26]The Fisher exact test delivers basically same result ($p = 0.55$). The finding that the payment protocol does not influence the distribution of social preference types is also backed up by nine different Fisher exact tests with the null hypothesis that a specific type is as frequent in the *FixedRoles* as in the *RandomRoles* condition.

A.4 Robustness Section

We follow several different approaches to evaluate the robustness of our findings. First, we present results from regressions in which the distributional types serve as right-hand side variable, see section A.4.1. Second, we estimate a finite-mixture model of the four most prevalent distributional types – altruists, inequality averse, selfish and maximin – and use the posterior probability to classify inconsistent people into one of those four types. Section A.4.2 presents the results. This robustness check confirms that the predictive power of distributional preferences does not depend on inconsistent subjects. Third, Section A.4.3 presents results assigning the lowest prediction to those who are indifferent over some interval.

A.4.1 Distributional Types

In this section, we present additional results in which the distributional types – and not the scores – serve as the independent variables. Table 14 shows the results from the TG; Table 15 from the PGG. The results overwhelmingly confirm previous conclusions: the types that display benevolence when ahead are more likely to pick *honor* and contribute more to the public good. This statement holds both when we control for the types individually and when we include a dummy that is equal to one for either of these three types and zero otherwise. It also holds for different sets of controls and when additionally controlling for beliefs in the public good regression. There is one exception: In the PGG, once we control for beliefs, this statement only holds when we merge those three types into a single summary category (see columns (5) and (12) of Table 15). This finding might be partially driven by the low number of observations since the corresponding column in Table 18 below shows that the coefficient on altruists is significant when additional observations are included via the mixture model.

Subject picked *honor*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IA-Alt-Maximin	0.139***	0.124***	0.129***	0.126***	0.103**					
	(0.03)	(0.04)	(0.03)	(0.04)	(0.05)					
Altruist						0.182***	0.170***	0.178***	0.167***	0.139**
						(0.05)	(0.06)	(0.05)	(0.05)	(0.06)
Inequality averse						0.146***	0.149**	0.125**	0.130**	0.128*
						(0.05)	(0.06)	(0.05)	(0.05)	(0.07)
Maximin						0.106*	0.031	0.111*	0.119**	0.044
						(0.06)	(0.07)	(0.06)	(0.06)	(0.08)
Envious						-0.041	-0.038	-0.029	-0.010	-0.008
						(0.06)	(0.08)	(0.06)	(0.07)	(0.09)
Infrequent						0.132	0.125	0.130	0.111	0.100
						(0.08)	(0.10)	(0.08)	(0.08)	(0.10)
Socio-demographics	No	Yes	No	No	Yes	No	Yes	No	No	Yes
Cognition & Personality	No	No	Yes	No	Yes	No	No	Yes	No	Yes
Attitudes	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Observations	650	443	650	603	412	650	443	650	603	412
R^2	0.022	0.041	0.037	0.029	0.058	0.029	0.054	0.044	0.033	0.065

Table 14: Dependent variable is a dummy that indicates whether subject picked *honor* in trust game. *IA-Alt-Maximin* is a dummy indicating that the subject is either inequality averse, maximin or altruistic. *Infrequent* is a dummy indicating that the subject is either spiteful, kick-down, equality-averse or kiss-up. OLS, robust standard errors in brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. A constant is included in all cases but not displayed here.

Contribution	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IA-Alt-Maximin	2.815***	2.593**	2.505***	2.016**	4.343**	2.003*						
	(0.89)	(1.05)	(0.91)	(0.95)	(1.76)	(1.13)						
Altruist							3.459***	2.394*	3.276***	2.867**	5.280**	2.149
							(1.17)	(1.31)	(1.16)	(1.27)	(2.26)	(1.46)
Inequality averse							3.379***	1.489	3.014**	2.380*	1.437	0.795
							(1.22)	(1.37)	(1.25)	(1.30)	(2.23)	(1.48)
Maximin							3.064**	1.429	2.782**	2.452*	4.042	0.766
							(1.41)	(1.87)	(1.39)	(1.40)	(2.71)	(1.73)
Envious							1.359	-2.125	1.918	1.610	-1.426	-2.111
							(2.05)	(2.55)	(2.12)	(2.11)	(3.94)	(2.67)
Infrequent							1.698	-1.888	1.458	1.883	-2.746	-1.562
							(2.19)	(2.75)	(2.14)	(2.27)	(4.42)	(2.78)
Beliefs	0.917***	0.892***	0.904***	0.915***	-	0.895***	0.917***	0.891***	0.904***	0.914***	-	0.893***
	(0.03)	(0.04)	(0.03)	(0.03)		(0.04)	(0.03)	(0.04)	(0.03)	(0.03)		(0.04)
Socio-demographics	No	Yes	No	No	Yes	Yes	No	Yes	No	No	Yes	Yes
Cognition & Personality	No	No	Yes	No	Yes	Yes	No	No	Yes	No	Yes	Yes
Attitudes	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Observations	650	443	650	603	412	412	650	443	650	603	412	412
R^2	0.597	0.608	0.610	0.608	0.119	0.631	0.598	0.610	0.610	0.609	0.128	0.633

Table 15: Dependent variable is the individual contribution in the PGG. *IA-Alt-Maximin* is a dummy indicating that the subject is either inequality averse, maximin or altruistic. *Infrequent* is a dummy indicating that the subject is either spiteful, kick-down, equality-averse or kiss-up. *Belief* is the belief about the average contribution of other participants. OLS, robust standard errors in brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. A constant is included in all cases but not displayed here.

A.4.2 Mixture Model

In this section, we present robustness checks of our results using a finite-mixture of types model. Finite-mixture models have recently become increasingly popular in experimental economics (less so in the literature on social preferences, though), as they allow for several data-generating processes at the same time and are consequently a way to account for individual heterogeneity (Moffatt, 2015). We use this model to classify inconsistent subjects into distributional types based on posterior probabilities. We then include these subjects in our previous analysis. It is however important to note one main methodological difference to most other studies: The EET allows us to *perfectly* account for individual heterogeneity. Hence, we use the mixture model purely as a robustness check. Most other papers, like e.g. Bruhin, Fehr, and Schunk (2019), need to rely on these models for the main part of their analysis because their design does not allow to classify subjects into types at the individual-level.

In particular, we estimate a mixture of the four most prevalent distributional types – altruists, inequality averse, selfish and maximin subjects – in a random utility framework. Together these four types describe the behavior of almost 90% of the (consistent) subjects. Random utility models are based on the assumption that the utilities of all options are perturbed by a random error term. The decision maker then picks the option in which this perturbed utility is highest. That is, the decision maker has the highest *probability* of picking the option with the highest utility. The parametric structure that we impose on utility is again that of the piecewise linear utility function of Fehr and Schmidt (1999) introduced earlier in equation (1).

The Fechner error version of the random utility model then assumes that the decision maker picks allocation (m^A, o^A) over (m^B, o^B) iff $U(m^A, o^A) + \varepsilon^A > U(m^B, o^B) + \varepsilon^B$. Denote the utility difference between allocation A and B by $\Delta = U(m^A, o^A) - U(m^B, o^B)$. Given the normally distributed Fechner error ε, the index Δ is transformed into a cumulative probability via the normal linking function $\Phi(\Delta)$. The log-likelihood for any given values of ρ and σ is then given by

$$lnL\left(\rho, \sigma | d\right) = \sum_{i=1}^{N} \left[d_i ln\left(\Phi(\Delta)\right) + (1 - d_i) ln\left(\Phi(-\Delta)\right)\right] \tag{7}$$

where d_i is a dummy that is equal to 1 if the DM picked allocation A.

The four main distributional types in our sample emerge from the Fehr-Schmidt via the following restrictions: $\rho > 0$ and $\sigma > 0$ (altruist), $\rho > 0$ and $\sigma < 0$ (inequality averse), $\rho = 0$ and $\sigma = 0$ (selfish) and finally $\rho > 0$ and $\sigma = 0$ (maximin). Let l_i^a, l_i^{ia}, l_i^s and l_i^m denote the individual likelihood contribution of observation i for the altruistic, inequality averse, selfish and maximin model, respectively. Then the grand log-likelihood of the mixture model is given by:

$$lnL\left(\sigma^a, \sigma^{ia}, \rho^a, \rho^{ia}, \rho^m, p^a, p^{ia}, p^s, \lambda | d\right) = \sum_{i=1}^{N} ln\left[p^a l_i^a + p^{ia} l_i^{ia} + p^s l_i^s + (1 - p^a - p^{ia} - p^s) l_i^m\right] \tag{8}$$

where p^t denotes the mixing proportion (that is, the relative frequency in the sample) of type $t \in \{a, ia, s, m\}$. The mixing proportion of maximin types is given by $p^m = 1 - p^a - p^{ia} - p^s$, without loss of generality. Finally, $\lambda > 0$ denotes the variance parameter. We restrict the variance to be equal across types, that is, we assume a homoscedastic error which eases the computational burden considerably relative to the heteroscedastic case.

Given parameter estimates and d, the posterior probability of subject j being of type t can be calculated using Bayes rule:

$$post_j^t = \frac{p^t L_j^t}{p^a L_j^a + p^{ia} L_j^{ia} + p^s L_j^s + (1 - p^a - p^{ia} - p^s) L_j^m} \tag{9}$$

where $L_j^t = \prod_{i=1}^{14} l_{j,i}^t$ and $t \in \{a, ia, s, m\}$. A subject that is inconsistent in the EET, is classified into one of the four types according to the highest posterior probability of her choices. The consistent participants are directly classified into types based on their choices in the EET.

	Coefficient	Standard Error	Z-statistic	p-value
σ^a	0.413	.0155	26.57	0.000
ρ^a	0.125	.0153	8.18	0.000
σ^{ia}	-0.999	0.0001	-9219	0.000
ρ^{ia}	0.125	.017	7.49	0.000
ρ^m	0.554	.011	49.03	0.000
p^{ia}	0.205	.0193	11.02	0.000
p^s	0.112	.038	2.92	0.004
p^a	0.210	.023	9.12	0.000
λ	0.879	.004	198.21	0.000

Table 16: Parameters of the 4-type mixture model. Standard errors clustered at the individual-level are calculated using the delta method. $N = 12,390$.

Table 16 reports the parameter estimates. Tables 17 and 18 replicate the previous analysis.[27] As these tables show, this robustness check strongly confirms our previous conclusions.

[27]The other results where the individual-level prediction serves as a regressor can of course not be replicated because the mixture model only allows for the classification into types.

Subject picked **honor**	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IA-Alt-Maximin	0.065**	0.084**	0.071**	0.057*	0.076**					
	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)					
Altruist						0.151***	0.127**	0.158***	0.128***	0.107**
						(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
Inequality averse						0.135***	0.150***	0.123***	0.123***	0.134**
						(0.04)	(0.05)	(0.04)	(0.05)	(0.06)
Maximin						0.096**	0.039	0.094**	0.094**	0.041
						(0.04)	(0.05)	(0.04)	(0.05)	(0.05)
Envious						-0.072	-0.055	-0.076	-0.044	-0.042
						(0.06)	(0.08)	(0.06)	(0.07)	(0.09)
Infrequent						0.103	0.111	0.098	0.086	0.087
						(0.08)	(0.10)	(0.08)	(0.08)	(0.10)
Socio-demographics	No	Yes	No	No	Yes	No	Yes	No	No	Yes
Cognition & Personality	No	No	Yes	No	Yes	No	No	Yes	No	Yes
Attitudes	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Observations	885	588	885	820	549	885	588	885	820	549
R^2	0.007	0.029	0.016	0.013	0.045	0.023	0.042	0.031	0.024	0.053

Table 17: Robustness Check **Mixture Model**. Dependent variable is a dummy that indicates whether subject picked *honor* in **trust game**. *IA-Alt-Maximin* is a dummy indicating that the subject is either inequality averse, maximin or altruistic. *Infrequent* is a dummy indicating that the subject is either spiteful, kick-down, equality-averse or kiss-up. OLS, robust standard errors in brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. A constant is included in all cases but not displayed here.

Contribution	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IA-Alt-Maximin	2.258***	2.154***	1.961***	1.886***	3.532***	1.907**						
	(0.67)	(0.80)	(0.68)	(0.69)	(1.31)	(0.83)						
Altruist							3.177***	2.505**	2.986***	2.703***	4.095**	2.152*
							(0.98)	(1.14)	(0.98)	(1.05)	(1.93)	(1.23)
Inequality averse							2.881***	1.496	2.551**	2.475**	0.525	1.092
							(1.02)	(1.19)	(1.04)	(1.07)	(1.92)	(1.27)
Maximin							2.120**	0.846	1.897*	1.748	3.131	0.354
							(1.05)	(1.35)	(1.05)	(1.07)	(2.02)	(1.33)
Envious							1.199	-2.023	1.782	1.624	-1.075	-1.458
							(1.96)	(2.46)	(2.00)	(1.98)	(3.79)	(2.54)
Infrequent							1.413	-1.717	1.281	1.731	-2.790	-1.281
							(2.12)	(2.68)	(2.07)	(2.19)	(4.32)	(2.73)
Belief	0.909***	0.888***	0.898***	0.911***	-	0.893***	0.910***	0.889***	0.898***	0.912***	-	0.895***
	(0.03)	(0.03)	(0.03)	(0.03)		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)		(0.03)
Socio-demographics	No	Yes	No	No	Yes	Yes	No	Yes	No	No	Yes	Yes
Cognition & Personality	No	No	Yes	No	Yes	Yes	No	No	Yes	No	Yes	Yes
Attitudes	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Observations	885	588	885	820	549	549	885	588	885	820	549	549
R^2	0.590	0.596	0.599	0.602	0.098	0.618	0.591	0.597	0.601	0.603	0.101	0.619

Table 18: Robustness Check **Mixture Model**. Dependent variable is the individual contribution in the **PGG**. *IA-Alt-Maximin* is a dummy indicating that the subject is either inequality averse, maximin or altruistic. *Infrequent* is a dummy indicating that the subject is either spiteful, kick-down, equality-averse or kiss-up. *Belief* is the belief about the average contribution of other participants. OLS, robust standard errors in brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. A constant is included in all cases but not displayed here.

A.4.3 Robustness: Prediction in PGG

Contribution	(1)	(2)	(3)	(4)	(5)
Prediction-low	0.224***	0.202***	0.205***	0.196***	0.199***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Socio-demographics	No	Yes	No	No	Yes
Cognition & Personality	No	No	Yes	No	Yes
Attitudes	No	No	No	Yes	Yes
Observations	650	443	650	603	412
R^2	0.049	0.088	0.096	0.067	0.140

Table 19: Dependent variable is the individual contribution in the PGG. OLS, robust standard errors in brackets. *Prediction-low* is the predicted contribution of the piecewise linear model using the **lowest value** for indifferent subjects. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. A constant is included in all cases but not displayed here.

A.5 General iLEE Procedures

The experiment is conducted using the platform of the internet laboratory for experimental economics (iLEE) at the University of Copenhagen, Denmark. Subjects for the platform are recruited with the assistance of the official statistics agency (Statistics Denmark) who select a random sample from the general population. Statistics Denmark sends the selected individuals physical letters, inviting them to participate in an online scientific experiment that is jointly organized by the University of Copenhagen and Statistics Denmark. Participants log in to the experiment using a personal identification code provided by Statistics Denmark. Payments are executed by electronic bank transfer and participants remain anonymous to the researchers at the University throughout the experiment. The EET is part of the third wave of experiments conducted on the iLEE platform. All three waves were run using the same set of participants, thus creating a panel data set useful for cross game analysis. For the third wave, we invited the 2291 people who completed the first wave. In total, 1067 participants completed the third wave between July and September, 2010. Participants could log on at any point during this period and are free to log out and continue later at their convenience. The third wave consisted of a total of six different parts. The first part of the third wave consisted of a trust game, followed by four other, smaller parts: a real effort task, a voting game, measures of risk and loss aversion and our application of the EET. The order of these four parts was random. The final part is a questionnaire which included questions on age, gender and education. In total, the median person spent 63 minutes completing the entire wave and earns 279 DKr (37 euros). Cooperation with Statistics Denmark was necessary to obtain the names and addresses of participants needed to send out invitations but our cooperation also yields additional advantages. First, it allowed us to target a representative sample of the population. Combined with the high penetration of internet access in Denmark, this means that we have participants from all walks of life, which enables us to investigate how experimental behavior is correlated with self-reported socio-economic variables such as age, education and employment. Second, our procedures entailed double blindness in the sense that participants are anonymous not only to other participants but also to us, the experimenters. Anonymity is important to minimize potential experimenter-demand effects. Levitt and List (2007) survey evidence that shows how the lack of anonymity between experimenters and participants increases the level of pro-social behavior when measuring distributional preferences. Double-blindness should decrease such effects. Participants also answered questions regarding their basic socio-economic background, including their age, gender and level of education. In the analysis below, we group education in four categories: primary (no more than 10 years, 6 percent), secondary (vocational and high school, 22 percent), short tertiary (50 percent) and long tertiary (22 percent). In addition, we asked participants to answer five attitude questions from the World Values Survey. Participants had the option of not answering the questions. About 8 percent choose to not answer at least one of the following five questions:

LeftRight: "In political matters, people talk of 'the left' and 'the right'. How would you place your views on this scale if 1 means the left and 10 means the right?" Possible answers are integers ranging from 1: "left" to 10: "right".

Responsibility: "We would like your opinion on important political issues. How would you place your views on a scale from 1 to 10?" Possible answers are integers ranging from 1: "People should take more responsibility to provide for themselves" to 10: "The government should take more responsibility to ensure that everyone is provided for".

Competition: How would you place your views on a scale from 1 to 10?" Possible answers are integers ranging from 1: "Competition is good. It stimulates people to work hard and develop new ideas" to 10: "Competition is harmful. It brings out the worst in people".

Trust: "Generally speaking, would you say that most people can be trusted or that you cannot be too careful in dealing with people?" Possible answers are 0: "Cannot be too careful" and 1: "Most people can be trusted".

Fairness: "Do you think most people would try to take advantage of you if they got a chance, or would they try to be fair?" Possible answers are integers ranging from 1: "Would take advantage of you" to 10: "Would try to be fair".

Psychological measures:

We are also able to include psychological measures in the survey that participants answer. These measures consist of a cognitive reflection test (CRT), an IQ test and a personality test. The CRT is due to Frederick (2005) and consists of three short questions that all have incorrect but "intuitive" answers. Hence, the CRT is aimed at capturing participants ability to reflect upon a question and resist the temptation of giving the first (wrong) answer that comes to mind. Frederick finds that the CRT is predictive of behavior in a number of decision making environments. The three questions are: 1: "A bat and a ball cost 110 Dkr in total. The bat costs 100 Dkr more than the ball. How much does the ball cost?" Answer is given in Dkr. 2: "If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?" Answer is given in number of minutes. 3: "In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?" Answer is given in number of days.

The intuitive answers to the questions are (10, 100 and 24) while the correct answers are (5, 5 and 47). The variable CRT score is calculated as the number of correct answers, i.e. 0, 1, 2 or 3. Our measure of IQ is based on the I-S-T 2000R intelligence structure test (which we use by permission of Dansk Psykologisk Forlag who administers it in Denmark). The test is based on Raven's Progressive Matrices and participants have 10 minutes to solve 20 puzzles. As our IQ score variable, we use the number of correct answers, from 0 to 20.

Our measure of personality is based on the Five Factor Model (McCrae and Costa Jr, 2004) which describes human personality according to the "Big Five" dimensions or traits: Openness (to experience), Conscientiousness, Extraversion, Agreeableness and Neuroticism. Openness is related to creativity, to being curios and original and to the person's ability to contemplate new ideas. Conscientiousness is related to having a will to achieve, to being conscientious, hard-working and well-organized and to being ambitious. Extraversion is related to being social, passionate, talkative and dominating in groups. Agreeableness is related to kindness and altruism and to being good-natured and trusting. Neuroticism is related to being emotional, worried, self-conscious and temperamental. We use the short version of the NEO PI-R test with 60 questions. The test yields scores for each of the five dimensions on a scale from 1 to 48. A higher score means that a personality is correlated with a higher degree of the particular trait. For example, a person who scores 40 on Neuroticism is likely to be more emotional than a person who scores 5.

A.6 Instructions

The first part of the instructions are identical for both the FixedRoles and RandomRoles conditions.

In this part of the experiment, there are two roles: decision makers and recipients. A decision maker makes 14 choices on behalf of the person him-/herself and a randomly selected second participant (the recipient). Every choice is between two alternatives: LEFT and RIGHT. The alternative chosen by the decision maker will determine the payment for both the decision maker and the recipient.

Here is an example:

If the decision maker chooses LEFT, he/she gets 70 Dkr and the recipient gets 25 kr. If the decision maker chooses RIGHT, he/she gets 50 Dkr and the recipient gets 50 Dkr.

The continued instructions differ depending on the condition:

FixedRole condition:

Only decision makers are asked to make the 14 choices. Recipients make no decisions. Half the participants will be decision makers and the other half will be recipients. What role you get is determined randomly before the decisions are made. It is as likely that you will be decision maker as it is that you will be recipient. Once the roles are determined, each decision maker is randomly matched with a recipient. Only one of the decision maker's 14 choices will be selected for payment. All choices have the same probability of being selected.

On the next screen you will be told whether you have been chosen to be a decision maker or a recipient. Remember that if you are selected to be a decision maker, your choices will determine both your own and a recipient's earnings from this part of the experiment. The recipient will only get a payment from your decisions and no further payment. If you are selected to be a recipient, your earnings will be solely determined by another participant's choices. In this case, you will not yourself make any choices in this part of the experiment.

RandomRoles condition:

All participants are asked to make the 14 choices as if they are decision makers. Half the participants will actually be decision makers whose choices will count whereas the other half will be recipients whose choices will not count. What role you get is determined randomly after the experiment has ended. It is as likely that you will be decision maker as it is that you will be recipient. Once the roles are determined, each decision maker is randomly matched with a recipient. Only one of the decision maker's 14 choices will be selected for payment. All choices have the same probability of being selected. On the next screens you will make the 14 choices between LEFT and RIGHT. Remember that if you are selected to be a decision maker, your choices will determine both your own and a recipient's earnings from this part of the experiment. The recipient will only get a payment from your decisions and no further payment. If you are selected to be a recipient, your earnings will be solely determined by another participant's choices. In this case, your choices in this part of the experiment will have no effect on anyone's payment (neither on your own payment nor on anybody else's payment).

Subjects in the FixedRoles condition see an additional screen informing them of the outcome of the random draw that determines their role:

Fixed Roles – Subjects chosen to be decision makers:

You have been randomly selected to be a decision maker. On the next screens you will make the 14 choices between LEFT and RIGHT. Remember that your choices will determine both your own and a recipient's earnings from this part of the experiment. The recipient will only get a payment from your decisions and no further payment.

Fixed Roles – Subjects chosen to be recipients:

You have been randomly selected to be a recipient. Your earnings will be solely determined by another participant's choices. You will not make choices in this part of the experiment yourself.

A.7 Screenshots Experiment

Translation Figure 5:

Confirm your choices. You now have the option to examine your choices and possibly to revise them. Your selections are pointed out by colors in the table below. If you wish to revise a decision, click Revise (Revider). You will then again see the decision screen for this decision. Afterwards, you will return here and your revised choice will be apparent below.

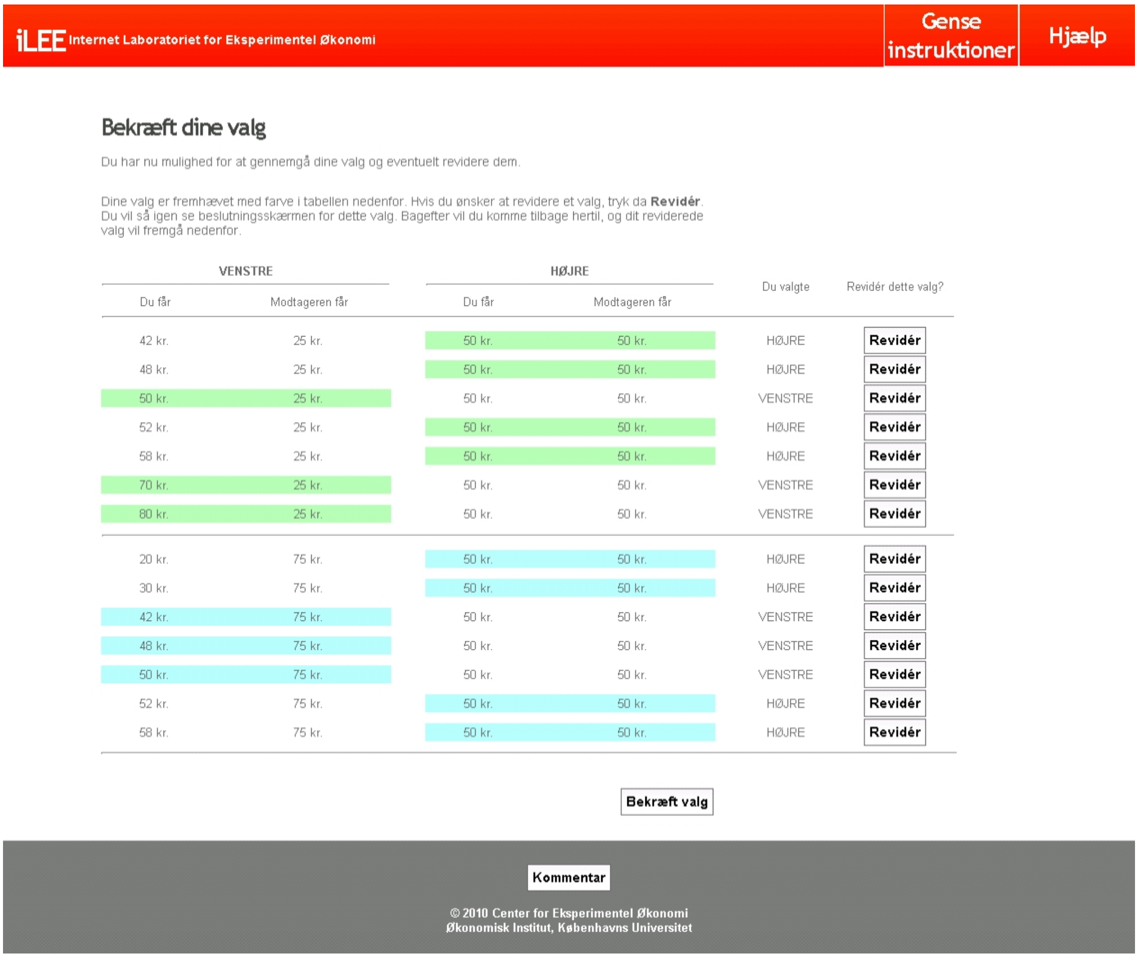
VENSTRE = LEFT, HØJRE = RIGHT

Du får = you get, modtageren får = the recipient gets.

Du valgte = You chose.

Revider dette valg? = Revise this decision.

Bekræft valg = Confirm decisions



iLEE Internet Laboratoriet for Eksperimentel Økonomi

Gense instruktioner | Hjælp

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Dine valg er fremhævet med farve i tabellen nedenfor. Hvis du ønsker at revidere et valg, tryk da **Revidér**. Du vil så igen se beslutningsskærmen for dette valg. Bagefter vil du komme tilbage hertil, og dit reviderede valg vil fremgå nedenfor.

VENSTRE		HØJRE			
Du får	Modtageren får	Du får	Modtageren får	Du valgte	Revidér dette valg?
42 kr.	25 kr.	50 kr.	50 kr.	HØJRE	Revidér
48 kr.	25 kr.	50 kr.	50 kr.	HØJRE	Revidér
50 kr.	25 kr.	50 kr.	50 kr.	VENSTRE	Revidér
52 kr.	25 kr.	50 kr.	50 kr.	HØJRE	Revidér
58 kr.	25 kr.	50 kr.	50 kr.	HØJRE	Revidér
70 kr.	25 kr.	50 kr.	50 kr.	VENSTRE	Revidér
80 kr.	25 kr.	50 kr.	50 kr.	VENSTRE	Revidér
20 kr.	75 kr.	50 kr.	50 kr.	HØJRE	Revidér
30 kr.	75 kr.	50 kr.	50 kr.	HØJRE	Revidér
42 kr.	75 kr.	50 kr.	50 kr.	VENSTRE	Revidér
48 kr.	75 kr.	50 kr.	50 kr.	VENSTRE	Revidér
50 kr.	75 kr.	50 kr.	50 kr.	VENSTRE	Revidér
52 kr.	75 kr.	50 kr.	50 kr.	HØJRE	Revidér
58 kr.	75 kr.	50 kr.	50 kr.	HØJRE	Revidér

Bekræft valg

Kommentar

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Økonomisk Institut, Københavns Universitet

Figure 5: Screenshot EET.

Top bar: Gense instruktioner = Repeat instructions.

Hjælp = Help.

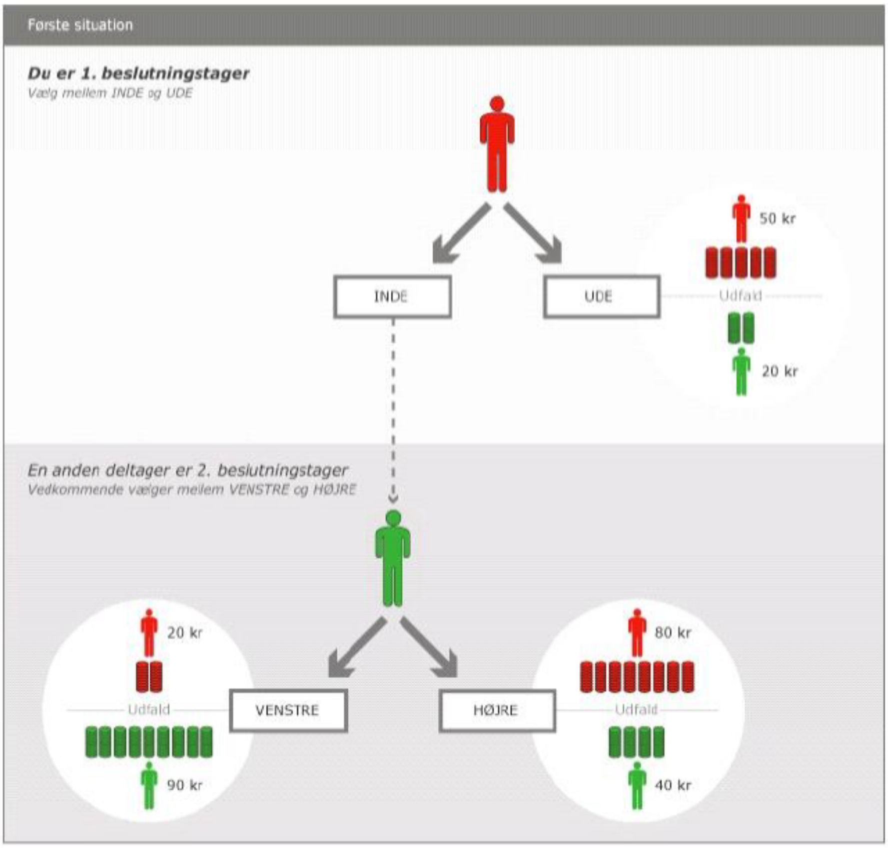

Figure 6: Screenshot Trust Game.

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Morten Hedegaard, Rudolf Kerschbamer, Daniel Müller, Jean-Robert Tyran

Distributional Preferences Explain Individual Behavior Across Games and Time

Abstract
We use a large and heterogeneous sample of the Danish population to investigate the importance of distributional preferences for behavior in a trust game and a public good game. We find robust evidence for the significant explanatory power of distributional preferences. In fact, compared to twenty-one covariates, distributional preferences turn out to be the single most important predictor of behavior. Specifically, subjects who reveal benevolence in the domain of advantageous inequality are more likely to pick the trustworthy action in the trust game and contribute more to the public good than other subjects. Since the experiments were spread out more than one year, our results suggest that there is a component of distributional preferences that is stable across games and over time.

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