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Preferences, intentions, and expectation violations: A large-scale experiment with a representative subject pool☆

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ABSTRACT

We specify and estimate an econometric model which separately identifies the effects of distributional preferences and penalizing unfair proposer behavior ("perceived intentions") on responder decisions in the ultimatum game. We allow the effects of perceived intentions to depend, among other things, on the subjective probabilities responders attach to the possible offers. The latter allows expectation violations to be a driving force for responder behavior. We estimate the model on a large representative sample from the Dutch population. We find that the relative importance of distributional preferences and perceived intentions depends significantly on the socio-economic characteristics of responders. Strong inequity aversion to the other player's disadvantage is found for lower educated and older respondents. Responders tend to punish more unequal offers made by proposers if they expect that unequal proposals are made less often.

1. Introduction

Two distinct approaches to introduce fairness in economics have emerged over the last decade. On the one hand, outcome based models (e.g., Fehr and Schmidt, 1999; Bolton and Ockenfels, 2000) interpret fairness as the concern for equitable material payoffs. Intentions based models (e.g., Rabin, 1993; Dufwenberg and Kirchsteiger, 2004) on the other hand emphasize the importance of the intentions agents attribute to the actions of another player. The empirical relevance of both classes of models has mostly been analyzed using laboratory experiments (see, e.g., Blount, 1995; Cox and Deck, 2005; Charness and Levine, 2007). Results of these experiments have provided convincing support for both approaches, suggesting that it is important to model both distributional concerns and the reactions to perceived intentions.

In this paper, we specify and estimate an econometric model which separately identifies the effects of distributional preferences and perceived intentions on responder behavior in the ultimatum game, exploiting information on response

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behavior in two different treatments. The first treatment is a normal ultimatum game where proposers intentionally choose the amounts they offer to the responders and the responder's decision can be driven both by preferences for the distribution of the payoffs and by a tendency to penalize the proposer for an unfair proposal or reward him for a fair proposal ("perceived intentions"). The second treatment is a random alternative to the ultimatum game where responders receive offers randomly drawn from a uniform distribution. In this treatment, perceived intentions cannot affect responder behavior as proposers do not intentionally make offers (and responders know this). The differences in response behavior between the two treatments thus identify the impact of intentions attribution. This idea of comparing a normal and a random treatment first appeared in Blount (1995) and has since served as one of the main approaches to measure the role of intentions (see, e.g., Falk et al., 2008).

Direct structural estimation of an existing intention based model would typically require measuring second order beliefs of responders (e.g., Dufwenberg and Kirchsteiger, 2004; Falk and Fischbacher, 2006). Because such beliefs involve expectations of responders over the expectations proposers have concerning responder behavior, they are difficult to elicit.[1] By modeling the effect of the presence of intentions on responses, we can quantify the empirical relevance of perceived intentions relative to distributional preferences, without measuring second order beliefs and without making reference to a specific intention based model.

The difference between the two treatments identifies how much perceived intentions matter *on average* without requiring elicitation of either first or second order beliefs. A second contribution of this paper is that we investigate how reactions to the presence of intentions change with expectations about proposer behavior, using elicited first order beliefs of responders concerning the distribution of proposer behavior. Here we build on the recent literature on measuring expectations; see Manski (2004) for a survey and Manski (2002) for a discussion of possible applications in economic experiments. Existing studies on the ultimatum game typically either do not account for such expectations, or focus on the relationship between responder behavior and social norms, defined as the opinions of players concerning what constitutes a fair offer (see, e.g., Buchan et al., 2004). The elicited first order beliefs allow us to test the validity of the *expectancy violation theory* proposed by social psychologists, which predicts that individuals who make more favorable decisions than expected are evaluated more positively, while individuals whose decisions are less favorable than expected are evaluated more negatively (see, e.g., Jussim et al., 1987). Furthermore, several studies in that literature have found that unexpected negative and positive outcomes can affect the causes an individual attributes to explain the actions of other individuals (see, e.g., Jackson et al., 1993; Bettencourt et al., 1997). For economic experiments, these results suggest that responders' actions not only depend on the proposer's decision itself, but also on how the proposer's decision deviates from the responder's expectations. In the ultimatum game, it implies that an unfair offer may be penalized by a responder who thinks such unfair offers are very uncommon, but not by a responder who believes that many proposers make such unfair offers. In other words, how much a responder penalizes or rewards perceived proposer intentions depends on how common the responder believes such intentions to be. Accordingly, we investigate whether the effect of intention attribution, measured as the difference between responder's reactions in the two treatments, varies with the likelihood the responder attaches to such an offer.

A potential problem with analyzing the effects of subjective beliefs is that estimates may be biased due to the possible correlation between stated beliefs and preferences, because subjects may tend to believe that others have similar inequity aversion or a similar tendency to penalize bad intentions as they themselves have.[2] We present an extension of our benchmark model which takes this into account by allowing for correlation between subjective beliefs and the preference parameters, but our estimates do not show any evidence of such a correlation.

A final contribution of this paper is that our participants are a large representative sample from the Dutch population of ages 16 and over. We analyze the behavior of in total 557 responders in (the two different versions of) the ultimatum game, from different socio-economic groups. This is in contrast to most of the existing experiments, which typically use participants drawn from a homogeneous subject pool, often university students majoring in economics or business. The representativeness of homogeneous (student) subject pools raises concerns about the generalizability of the results to broader populations.[3] There is now growing evidence indicating that behavior inferred from student subjects is not representative of the behavior in a broad population (e.g., Bellemare and Kröger, 2007; Bellemare et al., 2008).[4] This suggests that an analysis of preferences and intentions attribution can greatly benefit from experiments in which subjects represent the population at large. We account for the heterogeneous nature of the pool of respondents by allowing both distributional preferences and the effects of perceived intentions to depend on observed as well as unobserved characteristics of the participants.

A similar econometric approach was pursued by Bellemare et al. (2008), who focused on estimating distributional preferences using decisions and first order beliefs of proposers along with decisions of responders in a normal ultimatum game. They did not separate the effects of perceived intentions from distributional preferences—the main goal of the present paper. In this paper, we combine the responder data from the normal ultimatum game in Bellemare et al. (2008) with new data

[1] A notable exception is Dhaene and Bouckaert (2010).

[2] This is one interpretation of biases which may originate from so-called false consensus effects. See Ross et al. (1977) for a discussion.

[3] Henrich et al. (2004) offer a different form of generalization by conducting experiments in specific small scale societies. Such findings cannot be extrapolated to broader populations or societies, however.

[4] Other studies have found similar discrepancies between student behavior and behavior of specific non-random subgroups of the population; see Ball and Cech (1996) for a survey, and Carpenter et al. (2005) for a more recent example.

on responders in a random ultimatum game. Moreover, we use first order beliefs of responders instead of proposers. The econometric models we use are somewhat similar in spirit to the models of Bellemare et al. (2008) in modeling unobserved heterogeneity in preferences, but differs because we separately model preferences, the effects of perceived intentions, and the effects of expectations violations (see Section 4).

Our results can be summarized as follows. We find that distributional preferences and perceived intentions are both important determinants of responder behavior in the ultimatum game. The relative importance of each of these factors is found to vary significantly across sub-groups of the broad population and on whether offers are favorable or unfavorable to responders. Averaging across the entire population, distributional concerns tend to dominate the effects of perceived intentions, especially for low offers. However, intentions are estimated to play a more important role for young and educated subjects, in particular for advantageous offers.

We also find that rejection of low offers significantly increases when such offers are perceived as less likely, suggesting that negative expectation violations can affect how responders penalize or reward intentionally made offers. This suggests that expectation violations play an important role in determining responder behavior when intentions are present. The effect is significantly stronger for younger than for older subjects.

Finally, we find that young and educated subjects have significantly more self-oriented preferences, and accept more often very generous offers than other groups of the population. In contrast, other groups of the population have substantially higher levels of inequity aversion to both own and other's disadvantage, and reject more often very generous offers. Plateau behavior in particular, i.e., rejecting unequal offers both to own and other's disadvantage, is more important amongst older and less educated subjects as they have stronger inequity aversion for high offers.

The remainder of the paper is organized as follows. Section 2 presents the experimental design. Section 3 gives an overview of the data. Section 4 presents our model. Section 5 discusses the estimation results of our structural model. Section 6 concludes.

2. Experiment

The experiment was conducted with the CentERpanel, an Internet survey consisting of approximately 2000 persons representative for the Dutch adult population.[5] The large size and representative nature of the sample is one of the key features of our study. The experiment took place in March 2004. More details on the survey design and the general set up of the experiment are given in Bellemare et al. (2008).

Panel members were randomly assigned to either the "normal" or the "random" ultimatum game.[6] In the normal ultimatum game, a randomly assigned proposer was asked to choose how much of a total amount of €10 to offer to a randomly assigned responder, who can accept or reject the offer. In fact, the survey questions talk about CentERpoints rather than euros, where €1 is 100 CentERpoints. The reason is that the participants in this ongoing panel are used to get their compensations and rewards for participating in terms of CentERpoints (CP hereafter).

Proposers could choose one out of eight possible allocations: $A \in \{(1000, 0), (850, 150), (700, 300), (550, 450), (450, 550), \ldots, (0, 1000)\}$, where the first and second amounts denote the payoffs for the proposer and responder in CP, respectively. We collected decisions of responders using the strategy method: responders were asked to decide whether they would accept or reject each of the eight possible offers before they were informed about the actual choice of the proposer, implying that we observe several decisions for each responder. This differs from Blount (1995) and other studies who ask responders to report their minimum acceptable offer. The latter assumes *threshold behavior*, i.e., every amount exceeding some (respondent specific) threshold will be accepted. Our approach allows to explore the incidence of *plateau behavior*, i.e., the observation that a substantial proportion of responders reject offers which are either relatively disadvantageous or advantageous to them.

All players were informed that only the response that corresponded to the allocation chosen by the proposer would determine the payoff of both players. The accepted allocations were paid out to both players. Both players received nothing if the relevant allocation was rejected by the responder.

After responders had made their decisions, we elicited their beliefs concerning proposer behavior with a series of subjective probability questions.[7] These belief questions were not incentivized. Responders were asked to state their subjective probabilities that each of the eight possible allocations would be offered, where the eight responses had to add up to 100.[8]

The random ultimatum game differed from the normal ultimatum game in one respect: proposers could not offer an allocation. Instead, the offer was determined by a computer which randomly chose one of the eight allocations, with equal probabilities for all of them.[9] We chose the uniform distribution primarily for its simplicity and ease of understanding.[10]

[5] Survey participants without Internet access are provided with the necessary tools so that the sample not only covers the population with Internet access.

[6] The normal ultimatum game data were also used in Bellemare et al. (2008); see that paper for more details and motivation of this part of the experiment.

[7] Bellemare et al. (2008) do not use beliefs of responders; they only use beliefs of proposers concerning behavior of responders elicited in a similar way.

[8] Following Hoffrage et al. (2000) the questions were asked using numbers of natural frequencies rather than percentages: for each amount X, the question was: "*Out of 100 persons who can choose an allocation, how many will offer X and keep* $1000 - X$?"

[9] Other studies using the uniform distribution to generate offers are Offerman (2002) and Cox and Deck (2005).

[10] An alternative design would provide responders in the random ultimatum game with a distribution of possible offers calibrated to actual offers observed in the normal ultimatum game. We decided against this alternative as we wanted to avoid effects from indirect reciprocity (see Dufwenberg et al., 2001).

Table 1
Definitions and sample means of the explanatory variables, separately for those who decided to participate, for non-participants, and for persons with missing values in their background characteristics.

Responder				
Variables	Data	Non participants	Missing values	Description
Gender	0.528	0.550	0.500	1 if male, 0 otherwise
Young	0.243	0.057	0.272	1 if below 35 years of age, 0 otherwise
Middle age	0.451	0.261	0.500	1 if between 35 and 54 years of age, 0 otherwise
Old	0.306	0.681	0.227	1 if above 54 years of age, 0 otherwise
Low education	0.289	0.492	0.333	1 if primary education or vocational training, 0 otherwise
Middle education	0.355	0.275	0.303	1 if general secondary education or vocational training, 0 otherwise
High education	0.355	0.231	0.363	1 if university education or high vocational training, 0 otherwise
Low income	0.362	0.420	0.272	1 if monthly gross personal income is below €1500, 0 otherwise
Middle income	0.326	0.289	0.242	1 if monthly gross personal income is between €1500 and €2500, 0 otherwise
High income	0.311	0.289	0.484	1 if monthly gross personal income is above €2500, 0 otherwise
Work	0.579	0.347	0.575	1 if involved in paid work, 0 otherwise
Number of obs.	557	69	66	

In total, 1443 panel members were invited to participate and 139 of them declined. Of the 1304 who participated, 678 were assigned the role of proposer (389 in the normal ultimatum game and 289 in the random ultimatum game), and 626 were assigned the role of responder (355 in the normal ultimatum game and 271 in the random ultimatum game). The week after the experiment, proposers and responders were randomly matched and their payoffs were computed. Payoffs corresponded to the allocation chosen by the proposer (in the normal ultimatum game) or the computer (in the random ultimatum game) for responders who had indicated they would accept this allocation. Both participants received nothing in case the responder had rejected the offer. All participants received information on their payoffs two weeks after the experiment. These amounts were later credited to their bank accounts.

3. Descriptive statistics

Our empirical analysis focuses on behavior of the responders in both treatments. For our analysis we dropped observations with incomplete or inconsistent information on background characteristics or choices (see caption of Table 2). We are left with 311 responders in the normal ultimatum game and 246 in the random ultimatum game. The column "Data" in Table 1 presents the descriptive statistics of the sample of responders in the two treatments used for the estimation. We group age into three categories, participants younger than 35, between 35 and 54 years, and 55 years and older. Similarly, three education categories are used, low (primary and vocational training), middle (general secondary or standard vocational training), and high (high vocational training and university education). We also use three income groups of about the same size: monthly gross personal income below €1500, between €1500 and €2500, and more than €2500. Finally, we include gender and work status dummies. Discretizing our background characteristics in this way will allow us to capture flexible non-linear relationships between the background characteristics of the responders and the key parameters of the model presented in Section 4.[11]

Table 1 also presents statistics of two groups of panel members not used in our analysis. The second group (under the heading *Non-participants*) consists of panel members which have been approached but chose not to participate in the experiment. The third group (*Missing values*) are dropped from the sample because of incomplete or inconsistent information on background characteristics or choices. We tested whether proportions for each variable in Table 1 are significantly different between the three groups. We find that non-participants are significantly older and less educated than respondents used in our analysis.[12] Hence, our sample somewhat over-represents young and high educated respondents, but the proportions of each variable in Table 1 do not differ significantly between respondents used in our analysis and those dropped because of insufficient information.

Fig. 1 compares the actual distribution of offers in the normal ultimatum game with the distribution of offers according to the average beliefs of the responders. The dark bars present the distribution of actual offers (the same as in Fig. 1 of Bellemare et al., 2008). Proposers typically offer an allocation close to the equal split. Most proposers offer slightly more than half of the total amount of €10 to the other player (€5.5 = 550 CentERpoints (CP)), either because they fear that offers below the equal split will be rejected, or because of strong aversion against inequity at the other player's disadvantage.

The light bars in Fig. 1 present the average offer distribution expected by responders in the normal ultimatum game. While the mode of the expected offer distribution (550 CP) coincides with the mode of the realized offer distribution, responders'

The latter would occur if responders react in a reciprocal way because offers were the result of decisions taken by other individuals.

11 We also estimated a model incorporating linear and quadratic terms in age and income. This model gave similar results to those reported in Section 5.

12 The proportions of "Young" and "Middle age" are significantly lower for non-participants (both p-values are less than 0.01)), while the proportion "Old" is significantly larger for non-participants (p-value = 0.000). The proportion with "Low education" is significantly larger (p-value = 0.000) while the proportion with "High education" is significantly smaller (p-value = 0.02) for non-participants than for the respondents used in our analysis.

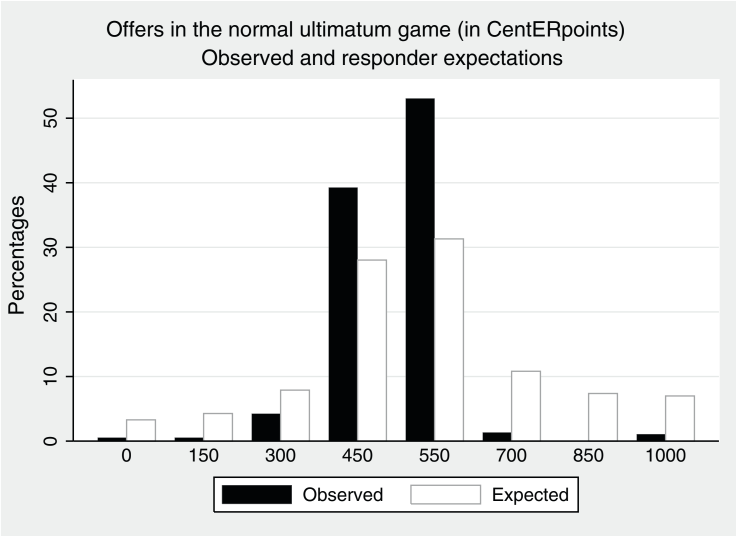

Fig. 1. Distribution of actual offers made by proposers and average distribution expected by responders in the normal ultimatum game.

subjective probabilities of offers of 450 CP and 550 CP appear to be lower than the actual frequencies. Correspondingly, average subjective probabilities are higher than actual offer frequencies for offers below 450 CP and above 550 CP.

The figure does not show the heterogeneity in the subjective probabilities across responders. Heterogeneity is substantial, particularly for offers of 450 CP and 550 CP. One in every four responders attaches a probability of at most 15 percent to an offer of 450 CP, and one in every four attaches a probability of 40 percent or more to the same offer. Similar numbers are found for offers of 550 CP: one quarter of responders give this a probability of at most 20 percent, and one quarter at least 40 percent). About 80 percent of responders place their highest subjective probability on an offer of either 450 CP or 550 CP. Responders thus typically expect proposers to make offers close to the equal split, but a substantial group of responders also attach much larger probabilities to unequal offers than actually materialize.

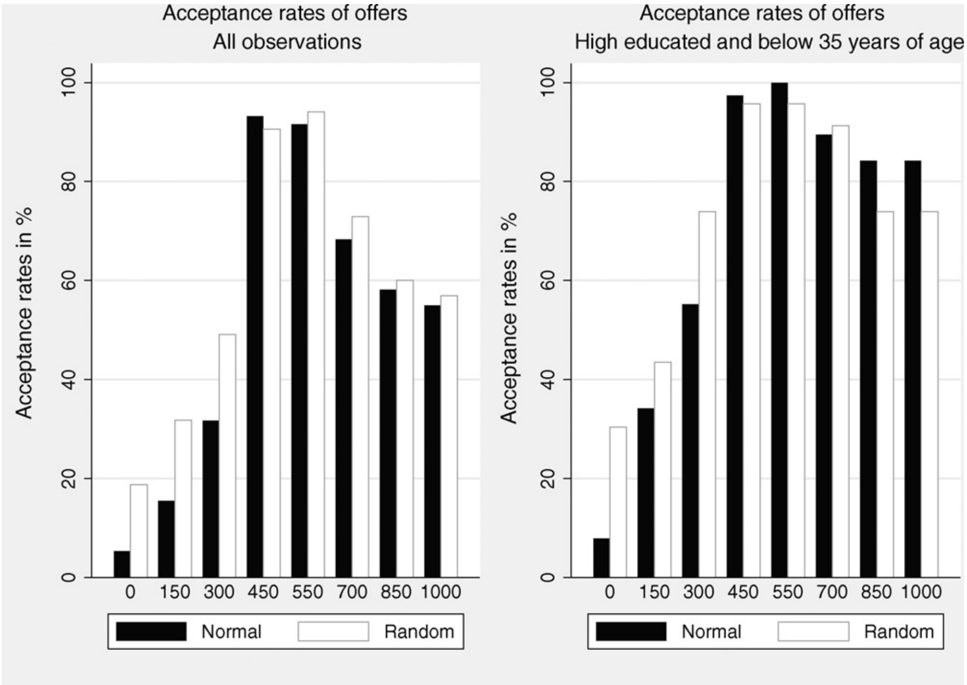

Fig. 2. Acceptance rates in the normal and random ultimatum games for all subjects and for subjects with high education and younger than 35.

Table 2
Response Patterns. The table columns present the acceptance decision (coded as 1 if accepted) for all possible 8 offers. *N* denotes the number of observations.

	0	150	300	450	550	700	850	1000	Normal		Random	
									N	%	*N*	%
	Threshold behavior											
	1	1	1	1	1	1	1	1	16	5.14	48	19.05
	0	1	1	1	1	1	1	1	27	8.68	20	7.94
	0	0	1	1	1	1	1	1	28	9.00	21	8.33
	0	0	0	1	1	1	1	1	86	27.65	41	16.27
	0	0	0	0	1	1	1	1	11	3.53	9	3.57
	0	0	0	0	0	0	0	1	1	0.32	2	0.79
	Subtotal threshold								169	54.34	141	56.34
	Plateau behavior											
	0	0	0	1	1	1	0	0	20	6.43	7	2.78
	0	0	0	1	0	0	0	0	20	6.43	6	2.38
	0	0	0	1	1	0	0	0	60	19.29	48	19.04
	0	0	0	1	1	1	1	0	6	1.93	2	0.79
	0	0	1	1	1	0	0	0	8	2.57	4	1.58
	0	0	0	0	1	0	0	0	7	2.25	4	1.58
	0	0	1	1	0	0	0	0	2	0.64	0	0
	0	1	1	1	1	1	1	0	4	1.29	7	2.78
	0	0	1	1	1	1	0	0	11	3.53	18	7.14
	0	0	0	0	1	1	0	0	1	0.32	1	0.39
	0	0	0	0	0	1	0	0	1	0.32	1	0.39
	0	1	1	1	0	0	0	0	1	0.32	0	0
	0	0	1	1	1	1	1	0	1	0.32	0	0
	0	0	1	1	1	1	1	0	0	0	2	0.79
	0	1	1	1	1	0	0	0	0	0	1	0.39
	0	1	1	1	1	1	0	0	0	0	2	0.79
	0	0	0	0	1	1	1	0	0	0	2	0.79
	Subtotal plateau								142	45.65	105	46.66
	Total								311	100	246	100
Aggregate acceptance rates												
Normal	0.053	0.155	0.317	0.932	0.916	0.683	0.581	0.549				
Random	0.188	0.318	0.490	0.906	0.941	0.729	0.600	0.569				

The left hand side of Fig. 2 presents the sample acceptance rates in both treatments, where dark bars denote the normal ultimatum game and light bars the random ultimatum game. In both treatments, the acceptance rates rise from numbers below 20 percent for zero offers to above 90 percent for proposals around the equal split, before declining to just above 55 percent when proposers offer the whole amount to the responder. The acceptance rates of offers below 450 CP are much higher in the intentions free treatment (the random ultimatum game) than in the treatment where offers are made intentionally (the normal ultimatum game).[13] For offers of 0 CP, the difference in the acceptance rate between random and normal ultimatum game treatments is 13.5 percentage points; the difference in the likelihood of accepting all eight offers is 13.9 percentage points.

The right hand side of Fig. 2 presents acceptance rates for individuals younger than 35 with a high level of education, our proxy for the student subject pool commonly used in laboratory experiments.[14] For each treatment, the acceptance rates in this sub-sample are significantly higher than in the complete representative sample.[15] The differences are particularly high for offers above 550 CP, though even for this sub-sample, acceptance rates fall as the amount offered increases beyond 550 CP.

Table 2 presents the sample distribution of complete responder strategies in both treatments.[16] Each line is one strategy, with 0 denoting that an offer is rejected and 1 that it is accepted. The table gives the frequency distribution of strategies played by responders for both treatments separately. Strategies are split in two groups: *threshold* responders who accept all offers above a certain amount, and *plateau* responders who reject not only very low but also very generous offers. The substantial size of the latter group among responders in the normal ultimatum game was already discussed in Bellemare et al. (2008); here we see this behavior is equally common among responders in the random ultimatum game where rejecting overly generous offers cannot be due to penalizing actual proposers for unfair offers. A third group (not in the table) consists of responders who accept and reject offers in a way which cannot be predicted by existing theoretical models of behavior.

[13] A *t*-test rejects the null hypothesis of no differences in the acceptance behavior between both treatments for offers below 450 CP in favor of the alternative of higher acceptance rates in the random treatment; p-value = 0.026.

[14] The data do not provide direct information on whether a respondent is a student or not; moreover, the numbers of responders below age cut offs like 25 or 30 years of age are too low to get accurate results.

[15] The *t*-tests for the treatments without and with intentions give p-values 0.006 and 0.005, respectively.

[16] For the normal ultimatum game treatment, this is the same as in Bellemare et al. (2008).

For example, some responders in this group accept offers of 0 CP, 300 CP, 550 CP, 850 CP but not offers of 150 CP, 450 CP, 700 CP and 1000 CP. This only contains 3.0 percent of all responders, who probably did not understand the nature of the game. They will not be included in our empirical analysis.[17]

Substantial differences between treatments are found *within* the group of threshold players. The proportion of individuals accepting any offer from 0 CP to 1000 CP is 5.2 percent in the normal ultimatum game versus 19.1 percent in the random ultimatum game, illustrating that responders in the normal game penalize perceived bad intentions. The opposite difference is found for the strategy of only accepting offers of at least 450 CP—it is used by 27.1 percent of responders in the normal ultimatum game, compared to only 16.3 percent in the random treatment.

4. An empirical structural model of preferences, intentions, and beliefs

We now specify a structural econometric model, starting with the model of responder behavior without intentions, which is the relevant model for responders in the random treatment. Here we use a standard Fehr and Schmidt (1999) utility function, with utility of responder i from payoffs y_{resp} to him- or herself and y_{prop} to the other participant (the "inactive proposer" in this treatment) given by:

$$u_i(y_{resp}, y_{prop}) = y_{resp} - \alpha_i \max\{y_{prop} - y_{resp}, 0\} - \beta_i \max\{y_{resp} - y_{prop}, 0\} \tag{1}$$

where α_i and β_i capture inequity aversion from having less and more than the other participant, respectively. For respondents who only care about their own payoff, α_i and β_i are equal to 0.[18] Furthermore, the Fehr and Schmidt specification allows indifference curves to be kinked around the equal split, thus offering the flexibility to explain plateau behavior in the random ultimatum game.[19] In particular, such response patterns can be predicted for responders with $\beta > 1$. Fehr and Schmidt (1999) argued that such values of β were unlikely as responders with $\beta > 1$ are willing to throw away some of their money to reduce their advantage relative to the other player. However, allowing for $\beta > 1$ in our empirical model is necessary in order to predict systematic rejections of offers above the equal split observed in our data.

For the normal ultimatum game, we extend this model to account for rewarding or penalizing proposer intentions. In particular, we assume that the utility to responder i from payoffs y_{resp} to him- or herself and y_{prop} to the proposer is given by

$$u_i(y_{resp}, y_{prop}) = y_{resp} - (\alpha_i + \iota_i) \max\{y_{prop} - y_{resp}, 0\} - (\beta_i + \kappa_i) \max\{y_{resp} - y_{prop}, 0\} \tag{2}$$

Depending on the perception of the intentions, the parameters ι_i and κ_i can increase or decrease the disutility from receiving a disadvantageous or very advantageous offer. The outcome-based preference parameters (α_i, β_i) affect utility over offers of responders in both treatments, while the intentions based preference parameters ι_i and κ_i only play a role in the normal ultimatum game. This is the main idea behind the current paper, following Blount (1995), as discussed in the introduction: if perceived intentions of proposers matter for responder decisions, they only play a role in the normal ultimatum game treatment and not in the random treatment, while distributional preferences play the same role in both treatments. In other words, positive values of ι_i and κ_i would imply that responders penalize unfair offers made intentionally by proposers; if ι_i and κ_i are zero, responders can still reject offers, but then only because of inequity averse preferences. Note that none of this requires data on the beliefs of responders yet: the difference between distributional preferences and penalizing unfair proposer behavior is identified without information on these beliefs.

We will consider two specifications. The first ("baseline") model is the model described so far which does not use the beliefs data. The second ("general") model identifies the responders' reaction to expectation violations by making the extent to which intentionally made unfair offers are penalized by a given responder dependent on how uncommon this responder believes such offers are. This implies we allow parameters ι_i and κ_i to vary across offers y_{resp} with the responder's subjective probabilities (Q_i) of an at least as small offer ($Q_i(O \leq y_{resp})$) for offers below the equal split and an at least as large offer ($Q_i(O \geq y_{resp})$) for offers above the equal split, respectively.

Our econometric model specifies how the four parameters α_i, β_i, ι_i and κ_i vary with unobserved and observed characteristics of the responders and, in the general model, how ι_i and κ_i vary with the responder beliefs $Q_i(O \leq y_{resp})$ and $Q_i(O \geq y_{resp})$.

We make the following assumption on the distribution of α_i:

$$\alpha_i = \mathbf{x}_i' \boldsymbol{\alpha} + \mu_i^{\alpha}$$

where $\mathbf{x}_i$ denotes a vector of observable characteristics, and μ_i^{α} represents unobserved heterogeneity. Assumptions on the distribution of μ_i^{α} will be given below.

[17] The model estimates including these respondents were very similar to those we present.

[18] Bellemare et al. (2008) show that adding quadratic terms in the payoff differences significantly improves the fit. As this does not change the substantive conclusions, however, we decided to work with the original Fehr and Schmidt specification.

[19] Other models of fairness do not allow for similar flexibility around the equal split (see, e.g., Cox et al., 2007).

We do not *a priori* impose any signs on the intention parameters ι_i or κ_i, allowing, in principle, for positive as well as negative attributed intentions to advantageous or disadvantageous offers. Allowing for observed and unobserved heterogeneity, ι_i in the general model is specified as:

$$\iota_i = \mathbf{x}_i'\boldsymbol{\iota} + \eta_i Q_i(O \le y_{resp}) + \mu_i^{\iota}$$

where μ_i^{ι} represents unobserved components determining the effect of perceived intentions. Assumptions on its distribution will be given below.

The general model for β_i and κ_i is specified analogously:

$$\beta_i = \mathbf{x}_i'\boldsymbol{\beta} + \mu_i^{\beta}$$
$$\kappa_i = \mathbf{x}_i'\boldsymbol{\kappa} + \zeta_i Q_i(O \ge y_{resp}) + \mu_i^{\kappa}$$

with unobserved heterogeneity terms μ_i^{β} and μ_i^{κ}. The baseline model is the special case with $\eta_i = \zeta_i = 0$ for all responders *i*.

We will assume that $(\mu_i^{\alpha}, \mu_i^{\beta})$ is independent of error terms and background variables $\mathbf{x}_i$ and follows a bivariate normal distribution with means zero, variances $(\sigma_{\alpha}^2, \sigma_{\beta}^2)$ and correlation coefficient $\rho_{\alpha\beta}$. We expect that $\rho_{\alpha\beta}$ is positive as people with a general aversion to inequity probably have large values for both parameters. Similarly, we assume that $(\mu_i^{\iota}, \mu_i^{\kappa})$, the unobserved components determining the effects of perceived intentions, are independent of error terms, background variables $\mathbf{x}_i$, and $(\mu_i^{\alpha}, \mu_i^{\beta})$, and are bivariate normal with means zero, variances $(\sigma_{\iota}^2, \sigma_{\kappa}^2)$, and correlation coefficient $\rho_{\iota\kappa}$.

In the baseline model with $\eta_i = \zeta_i = 0$ for all *i*, the model is relatively straightforward, because righthand side variables are all exogenous. This is still a reasonably flexible model as the effect of intentions is allowed to depend upon observed and unobserved characteristics of the responder. Our general model is more ambitious, in the sense that it also considers the effect of beliefs concerning proposer behavior on the probability to penalize bad intentions: keeping y_{resp} (<500) constant, a smaller value of $Q_i(O \le y_{resp})$ indicates that the responder considers an offer as low as y_{resp} or worse more unlikely, which is expected to lead to a larger tendency to "punish" the proposer if such a low offer would materialize, and will thus increase ι_i. Hence, we expect negative values for η_i. On the other hand, the expected sign of ζ_i is unclear a priori—it depends on whether very high offers are seen as good or bad by the responder. We allow the response to expectations to vary with characteristics $\mathbf{x}_i$ by specifying:

$$\eta_i = \mathbf{x}_i'\boldsymbol{\eta}$$
$$\zeta_i = \mathbf{x}_i'\boldsymbol{\zeta}$$

An important issue in the general model is whether the subjective probabilities $Q_i(O \le y_{resp})$ (and $Q_i(O \ge y_{resp})$) can be treated as exogenous. Two arguments for endogeneity can be given. First, strongly inequity averse subjects may think that all proposers are equally inequity averse and may therefore avoid very low (and very high) offers. This would imply a negative correlation between the unobserved heterogeneity component μ_i^{α} of α_i and the subjective probabilities. Second, subjects with a large tendency to penalize low offers themselves may think it is common that low offers are penalized and may therefore also think proposers will avoid being penalized by not making (very) low offers. This leads to a negative correlation between the unobserved heterogeneity component μ_i^{ι} of ι_i and the subjective probabilities. Both arguments imply that the subjective probabilities can be correlated with unobservables in the model for responder behavior, leading to a potential endogeneity bias in estimates treating the subjective probabilities as exogenous.

To account for this potential endogeneity problem, the subjective probabilities can be modeled jointly with the parameters of interest, explicitly incorporating the potential correlations referred to above. In this extended model, the parameters of main interest in η and ζ are still identified without exclusion restrictions on the background characteristics, because endogeneity only enters through correlation with the unobserved heterogeneity terms that do not vary across choice problems for a given subject. This is a similar argument as the identification argument in fixed effects panel data models where endogeneity only enters through individual effects, not through correlated error terms. Specification details and estimation results of the extended model can be found in Appendix A. The results show that the null hypothesis of exogeneity cannot be rejected and that the estimates allowing for endogeneity are very similar to those imposing exogeneity. We therefore focus on the model specification and the results imposing exogenous beliefs in the main text.

Under the assumptions above, a responder *i* who gets an offer $y_{resp}(j) = 1000 - y_{prop}(j)$ with $y_{prop}(j) \in \{550, 700, 850, 1000\}$ has to trade off the utility of rejecting, u_{ij}^R, and the utility of accepting the offer u_{ij}^A. According to (2), these values are $u_{ij}^R = 0$ and

$$u_{ij}^A = y_{resp}(j) - (\alpha_i + \iota_i)(1000 - 2y_{resp}(j)). \tag{3}$$

Similar expressions can be given for offers above the equal split (involving β_i and κ_i). A perfectly payoff maximizing responder would thus choose to accept the offer if and only if $u_{ij}^A \ge 0$. To allow for suboptimal behavior, we add logistic errors to the utility of accepting that are independent of everything else in the model, multiplied by a noise-to-signal ratio parameter λ_N in the normal ultimatum game, and λ_R in the random ultimatum game. We assume that the responder maximizes over the contaminated values rather than the exact values, giving the binary logit probabilities:

$$
\begin{aligned}
&P(\text{Responder } i \text{ accepts offer } j|u_{ij}^{A},\ \text{with intentions}) = \frac{1}{1+e^{-u_{ij}^{A}/\lambda_N}}\\
&P(\text{Responder } i \text{ accepts offer } j|u_{ij}^{A},\ \text{without intentions}) = \frac{1}{1+e^{-u_{ij}^{A}/\lambda_R}}
\end{aligned}
\tag{4}
$$

4.1. Estimation

The models are estimated using maximum simulated likelihood. Conditional on the unobserved heterogeneity terms, the likelihood contribution of a given subject is the product of eight logit probabilities (as in (4)). The actual likelihood contribution is the expectation of this over the unobserved heterogeneity terms. This multi-dimensional integral is replaced by a simulated mean based upon R draws of the unobserved heterogeneity terms. If R tends to infinity faster than the square root of the number of subjects, then the resulting estimator is asymptotically equivalent to exact Maximum Likelihood. We used $R = 100$ and Halton draws (see, e.g., Train, 2003).

5. Econometric results

5.1. Model selection

We estimated several specifications to investigate the importance of intentions and subjective beliefs. A first model does not allow for any differences between the two treatments (estimating parameters related to (α, β) and setting $\iota_i = \kappa_i = 0$) and (accordingly) does not use stated beliefs. This model has 23 parameters and a log likelihood of −1842.80. The second model allows for differences between the two treatments that depend on observed and unobserved characteristics, but does not incorporate the subjective beliefs. This is the "baseline model" in the previous section, with $\boldsymbol{\eta} = \boldsymbol{\zeta} = 0$. It has 44 parameters and a log-likelihood of −1433.02. A likelihood ratio test shows that the second model significantly outperforms the first (p-value: 0.000). Thus we can conclude that intentions matter even without considering the subjective beliefs which capture reactions to expectancy violations as the baseline model which accounts for differences between both treatments fits the data significantly better, suggesting significant differences in responder behavior between both treatments.

The third model is the model that incorporates subjective beliefs and treats them as exogenous, the "general" model in the previous section. This model has 62 parameters and a log-likelihood of −1392.38, significantly outperforming the "baseline" model (p-value: 0.000). Finally, we also estimated the joint model for responder choices and subjective beliefs referred to in the previous section and described in detail in Appendix A, allowing for endogeneity of subjective beliefs. In this model, exogeneity of beliefs is equivalent to two zero restrictions on the parameters driving the covariances between unobservables in the beliefs equations and unobservables in preferences. This hypothesis of exogeneity is not rejected at conventional significance levels (p-value = 0.211) and the estimates of the parameters of interest in this extended model are very similar to those in the "general" model (see Appendix A). All this makes the third ("general") model our preferred model, and we will focus on this model in the remainder. In addition, to illustrate what we can say about the role of intentions without using reported beliefs, we will also present some results of the second ("baseline") model without beliefs.

5.2. Model fit

The observed acceptance frequencies and the frequencies predicted by the general model in both treatments are given in Fig. 3. Overall, the fit of the model is rather good. For both treatments, the model captures both the increase in acceptance frequencies between 0 CP and 450 CP and the decrease in acceptance frequencies for offers exceeding 550 CP. It also captures the differences in responses between both treatments.

5.3. Preferences

Tables 3 and 4 present the estimation results for the baseline and general model, respectively. First we discuss how inequity aversion parameters α_i and β_i vary with observed characteristics; results are similar here in the two models and we focus on the general model (Table 4). We find that men have higher disutility from own disadvantage (α_i) than women, though the difference is only marginally significant. Responders with the highest level of education have significantly lower aversion to own disadvantage than the lower educated. The estimates of $\boldsymbol{\beta}$ show that observed characteristics also play a role for inequity at the other player's disadvantage: those with low or intermediate education and the oldest age group have significantly higher aversion towards inequity at the other player's disadvantage than high educated and young respondents. Similar effects were also found in Bellemare et al. (2008) and together can explain why among the young and high educated (a proxy for a sample of students) acceptance rates of large offers in the no intentions treatment are higher than in the complete sample (cf. Fig. 2).

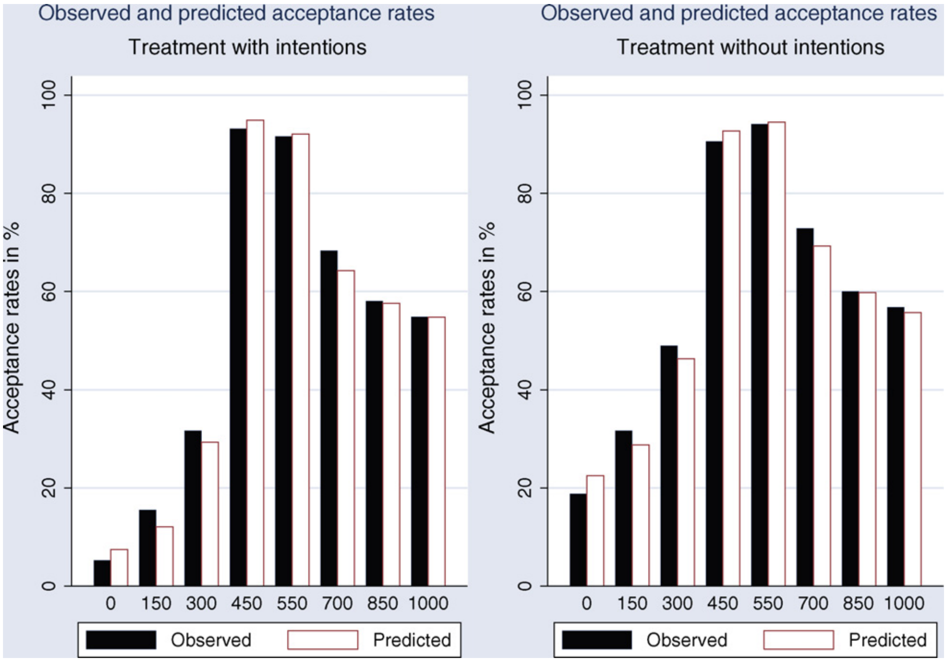

Fig. 3. Observed and predicted response distributions in the normal and random ultimatum games.

In the case of the baseline model, the parameter estimates for ι and κ in Table 3 show how the extent to which responders penalize intentionally made low (ι) or high (κ) offers varies with responder characteristics. Expectation violations are not taken into account here, so that the coefficients in this model can therefore be loosely interpreted as the coefficients for someone with average beliefs. There is no significant variation with responder characteristics in penalizing intentionally made low offers (and this is confirmed by a joint Wald test on all slope coefficients in ι). On the other hand, the lower κ_i for high income responders and responders with an intermediate education level indicate that these groups have a relatively low tendency to penalize overly generous high offers, while the two older age groups both have a significantly larger tendency to penalize intentionally made high offers than the young. The latter effect is significant at the 1 percent level and might be an effect of pride, with older respondents unwilling to accept "gifts" from the (anonymous) proposers. Even though regarded in the psychology literature as positive emotion, pride may reduce take-up of social benefits or lead to "irrationally" hard negotiation positions (Lea and Webley, 1997). It might also reflect a general suspicion of older respondents towards generosity from an anonymous party—in spite of the stated rules of the game, they may use their experience with companies advertising free deals and think that in the end, nothing comes for free.

Table 3
Estimation results of the baseline model (N = 557). Standard errors in parentheses.

	α	ι	β	κ	Remaining parameters	
Constant	0.887 ***	0.269	0.063	−0.091	λ_R	99.379 ***
	(0.183)	(0.284)	(0.388)	(0.602)		(5.785)
Male	0.285 *	−0.134	−0.545	0.732	λ_N	108.530 ***
	(0.150)	(0.219)	(0.337)	(0.451)		(5.724)
Educ2	−0.017	−0.012	0.071	−1.064 **	σ^2_α	0.762 ***
	(0.159)	(0.243)	(0.320)	(0.467)		(0.083)
Educ3	−0.572 ***	0.373	−1.291 ***	0.415	σ^2_β	3.437 ***
	(0.164)	(0.258)	(0.372)	(0.502)		(0.378)
Age2	0.045	0.155	0.573 *	1.241 **	$\rho_{\alpha\beta}$	0.721 ***
	(0.166)	(0.243)	(0.348)	(0.486)		(0.028)
Age3	0.208	0.304	1.437 ***	1.529 ***	σ^2_ι	0.054
	(0.185)	(0.280)	(0.393)	(0.593)		(0.036)
Work	−0.267 *	0.334	0.168	−0.463	σ^2_κ	2.234 ***
	(0.152)	(0.225)	(0.356)	(0.506)		(0.361)
Income2	−0.100	−0.069	−0.049	0.279	$\rho_{\iota\kappa}$	0.100
	(0.177)	(0.264)	(0.405)	(0.551)		(0.111)
Income3	0.017	−0.121	0.825 *	−1.594 **		
	(0.205)	(0.314)	(0.485)	(0.640)		

* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

Table 4
Estimation results of the general model ($N = 557$). Standard errors in parentheses.

	α	ι	β	κ	η	ζ	Remaining parameters	
Constant	0.997 ***	0.947 **	−0.165	−0.920	−6.133 ***	−0.760	λ_R	111.364 ***
	(0.219)	(0.464)	(0.494)	(0.941)	(2.068)	(2.619)		(7.330)
Male	0.402 **	−0.034	−0.434	0.377	−1.755	3.478 *	λ_N	105.975 ***
	(0.198)	(0.361)	(0.380)	(0.683)	(1.683)	(1.914)		(5.822)
Educ2	−0.161	0.073	−0.170	−0.426	1.481	−1.563	σ^2_α	1.277 ***
	(0.201)	(0.365)	(0.356)	(0.663)	(1.250)	(1.851)		(0.136)
Educ3	−0.707 ***	0.386	−1.607 ***	0.899	0.770	−1.910	σ^2_β	5.209 ***
	(0.212)	(0.372)	(0.466)	(0.774)	(1.408)	(2.026)		(0.568)
Age2	−0.094	0.002	0.221	2.957 ***	3.862 **	−2.862	$\rho_{\alpha\beta}$	0.737 ***
	(0.210)	(0.373)	(0.430)	(0.888)	(1.643)	(2.179)		(0.029)
Age3	0.323	0.061	1.854 ***	2.738 ***	3.604 *	−3.222	σ^2_ι	0.011
	(0.240)	(0.431)	(0.510)	(1.028)	(2.011)	(2.627)		(0.025)
Work	−0.121	0.377	0.695	−0.878	−1.030	1.256	σ^2_κ	6.036 ***
	(0.198)	(0.364)	(0.452)	(0.771)	(1.242)	(1.865)		(0.732)
Income2	−0.246	−0.281	−0.263	0.423	1.050	−2.706	$\rho_{\iota\kappa}$	0.120
	(0.219)	(0.435)	(0.500)	(0.885)	(1.722)	(2.355)		(0.133)
Income3	−0.023	−0.655	0.732	−2.359 **	2.330	−0.859		
	(0.278)	(0.533)	(0.600)	(1.005)	(2.167)	(2.228)		

* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

In the general model, each observable characteristic affects the intention parameters ι_i (and κ_i) in two ways (cf. Eq. (3)). The first is the effect of intentions if $Q_i = 0$ as measured by the parameter vectors $\boldsymbol{\iota}$ and $\boldsymbol{\kappa}$. The interpretation of equations for ι and κ is therefore somewhat different in Table 4 from that in Table 3: they now show how penalizing intentionally made unfair offers varies with responder characteristics for responders who consider such offers very unlikely ($Q_i = 0$). Still, the results are qualitatively similar to those in Table 3, with no significant variation with responder characteristics in ι,[20] and significantly larger values of κ among older age groups and lower and medium income groups. The most notable difference is that education no longer has a significant effect, suggesting that education affects κ_i for responders who expect that those offers materialize with positive probability ($Q_i > 0$).

The second way in which responder characteristics affect penalizing intentionally made unfair offers is through the effect of expectation violations, measured by the parameter vectors $\boldsymbol{\eta}$ and $\boldsymbol{\zeta}$. Expectations appear to be more important for disadvantageous offers than for favorable offers. The intercept in $\boldsymbol{\eta}$ measures the effect for disadvantageous offers for the benchmark group of young non-working women with low education and income levels. The estimated average η_i for this group are negative and significant, indicating that the subjects in this group punish low offers significantly more if they consider such offers more unlikely. This effect is found to be significantly stronger for the youngest age group than for the middle aged and older respondents. On the other hand, we find no evidence that responders reject very favorable offers because these offers are considered unlikely. There is a small gender effect, suggesting a negative expectation violations effect for women only, but the gender difference is only significant at the 10 percent level.

The estimated scale parameters and covariance matrix parameters are given in the right hand side column of Tables 3 and 4. The estimated values of λ_N and λ_R are both positive and significant. Moreover, a chi-square test ($\chi^2_1 = 1.715$, p-value = 0.190 in the general model) fails to reject the null hypothesis that λ_N and λ_R are equal. The estimates of the covariance parameters show that there is significant unobserved heterogeneity in inequity aversion, particularly in inequity aversion at the other participant's disadvantage (σ^2_β). Moreover, as expected, the unobserved heterogeneity components in α_i and β_i are positively correlated, with a significant correlation coefficient of $\rho_{\alpha\beta} = 0.74$ (general model) or 0.72 (baseline model). Unobserved heterogeneity plays a significant role in determining the effects of perceived intentions for high offers (σ^2_κ), but not for offers at one's own disadvantage (σ^2_ι is small and insignificant; as a consequence, $\rho_{\iota\kappa}$ is poorly identified).

Table 5 presents the average predicted values of (α_i, β_i, ι_i, κ_i) based on the estimates of the general model in Table 4. The top panel reports the averages and standard deviations of the parameter predictions for all participants. The bottom panel reports the average predictions for young and high educated individuals. Comparing these panels gives an indication of the difference between a representative sample and the results based upon young and highly educated populations like students.[21]

The parameters α_i and β_i capture distributional concerns, net of intentions–like the α and β parameters of the Fehr and Schmidt (1999) model. The average predicted population value of α is 0.796 with a relatively small standard deviation of 0.422 indicating that most responders in the population have some aversion to inequity to their own disadvantage. The

[20] A chi-square test does not reject the null hypothesis that all eight slope parameters in $\boldsymbol{\iota}$ are equal to zero ($\chi^2_8 = 3.867$, p-value = 0.869).
[21] The predicted α_i and β_i are averaged over responders from both treatments, while the predicted κ_i and ι_i are averaged only over responders in the normal ultimatum game.

Table 5
Predicted average preference parameters. The predicted values of α and β are averaged over responders from both treatments. The predicted values of ι and κ are averaged only over responders in the normal ultimatum game.

	α_i	ι_i	β_i	κ_i
All individuals				
Average	0.796	0.554	0.183	−0.246
Standard deviation	0.422	0.441	1.029	1.594
High education and below 35 years				
Average	0.248	0.474	−1.267	−1.668
Standard deviation	0.241	0.791	0.552	1.183

average predicted population value of β is 0.183 with a high standard deviation of 1.029, reflecting substantial heterogeneity in the predicted aversion to other's disadvantage. These predicted averages are similar to previous point estimates (Goeree and Holt, 2000) and calibrations (Blount, 1995; Huck et al., 2001) measured without controlling for the role played by intentions.

Positive values of ι_i indicate that intentionally made offers below the equal split provoke negative reactions, which can be interpreted as penalizing perceived unfair proposer intentions by rejecting their offers. The estimated average ι_i of 0.554 indicates that, on average, responders indeed attribute bad intentions to offers below the equal split. But the dispersion in ι_i is substantial – the standard deviation is almost as large as the mean – and implies that many responders do not penalize proposers for their intentionally made unfair offers.

Negative values of κ_i indicate that offers above the equal split signal good intentions, and lead to lower rejection rates. The estimated average κ_i of −0.246 indicates that the average responder indeed attributes good intentions to generous offers. The large dispersion in the predicted values of κ_i, however, suggests that many subjects attribute negative intentions to overly generous offers, emphasizing the population heterogeneity in the perception of intentions and the tendency to penalize intentionally made overly generous offers.

The average predicted values of α_i and β_i of young and well educated subjects are lower than the corresponding predictions for the population average, indicating that young and high educated individuals have lower than average inequity aversion. In particular, the average predicted value of β_i in this subgroup is −1.267, indicating competitive preferences: young and well educated subjects value having more than others. Moreover, young and educated subjects react significantly better to intentionally made generous offers than the average responder (their predicted average κ_i is much more negative than the overall population average). Taken together the results in Table 5 indicate that inequity aversion tends to be more important than perceived intentions in the population as a whole, especially for low offers. However, the effects of perceived intentions weigh more heavily for young and educated subjects, in particular for advantageous offers.

5.4. Responses and expectation violations

In this subsection, we illustrate the relationship between expectation violations and responder behavior by predicting the acceptance probabilities in the normal ultimatum game under three different scenarios, using the estimates of the general model (Table 4). The first "benchmark" scenario allows for heterogeneous expectations, using each responder's reported subjective probabilities. In the second scenario, we predict the behavior of responders who expect that all offers occur with the same probability (uniform expectations). In the third scenario, we predict the behavior of responders who expect disadvantageous offers (EDO): an offer of 0 CP has probability 40 percent, and offers of 150 CP, 300 CP, and 450 CP each have probability 20 percent. In other respects, all scenarios predict behavior as implied by the estimates in Table 4. We perform the simulations for the entire sample (left graph), and for young responders with university education, our proxy for the typical sample of student subjects used in most laboratory experiments (right graph).

Fig. 4 presents the predicted distributions in the three scenarios for both groups. The effects of expectation violations on high offers are of the expected signs (in line with our parameter estimates) but relatively small. Differences are much larger for the offers to the responder's disadvantage. Compared to the benchmark, the uniform expectations scenario places more probability mass on low offers. The benchmark scenario using reported subjective expectations gives lower acceptance rates than the uniform expectations scenario, illustrating that responders penalize intentionally made disadvantageous offers more the more unexpected the responders think these offers are, which we also found in our estimates.

The most interesting case is the third one, where responders were given the (quite unrealistic) expectations that proposers often make very disadvantageous offers. In this perspective, most offers still seem relatively generous compared to what is expected to be offered on average, and acceptance rates are much higher - even exceeding the acceptance rates in the no intentions treatment. Intentionally made offers perceived as unusually unfair under the benchmark scenario become quite common under the alternative EDO scenario. Thus, our model predicts that low offers have a very high probability of being accepted if responders expect that such offers will occur. This illustrates the important role of expectation violations in responders' acceptance decisions of intentionally made unfair offers.

For the group of young responders with high education level, the differences between the three scenarios are particularly large. Moreover, acceptance rates are generally higher than for the total population, particularly under the EDO scenario.

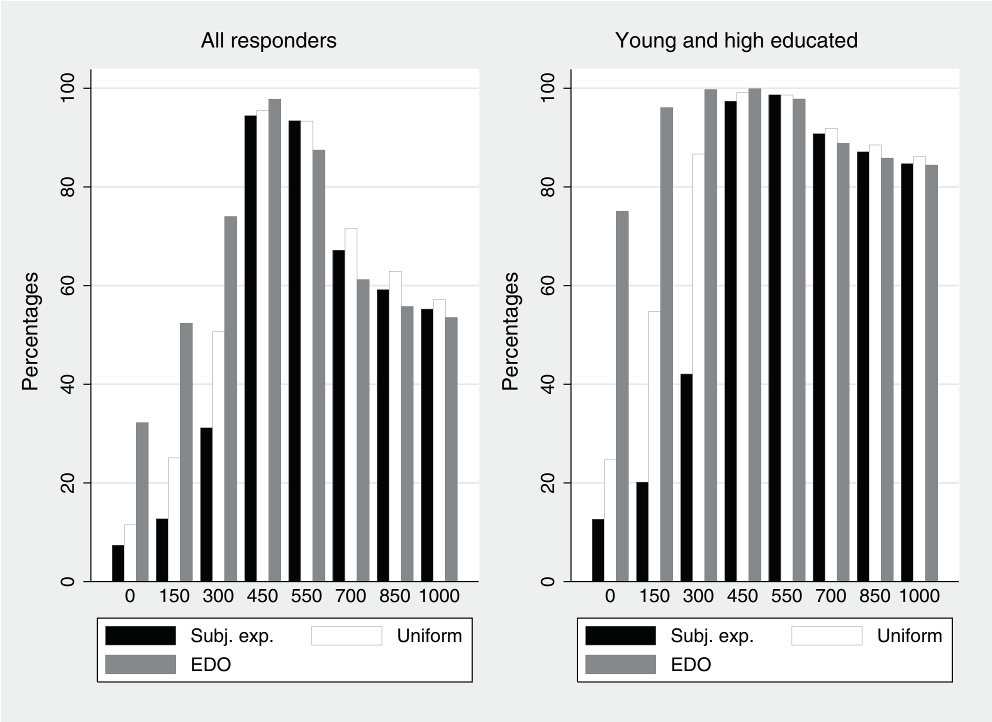

Fig. 4. Predicted acceptance probabilities in the normal ultimatum game for all responders (left graph) and for young high educated responders (right graph) as a function of the amount offered, for different expectations. Black: reported subjective expectations; white: uniform expectations (probability 0.125 for each amount); grey: responders expect disadvantageous offers (EDO): an offer of 0 CP occurs with 40 percent probability, and offers of 150 CP, 300 CP, and 450 CP each occur with 20 percent probability.

Even offers of zero are often accepted by this group. The main reason is that this group has lower inequity aversion than the rest of the population.

6. Conclusion

This paper exploited experimental data consisting of two different treatments to separately identify distributional preferences and the effects of perceived proposer intentions on responder behavior in the ultimatum game. In one treatment, the normal ultimatum game, responder decisions are based upon both distributional preferences and penalizing perceived unfair proposer intentions. In the second treatment, the random ultimatum game, only distributional preferences affect responder decisions. There, responders have no reason to penalize the players they were matched with as the offer was made by a random generator. Compared to existing studies, our paper has three main innovations. First, we specify and estimate a structural econometric model of responder behavior relating distributional preferences and the effects of perceived intentions to both observed and unobserved characteristics. Second, we allow the effects of perceived intentions to depend on the responders' expectation violations. Thereby, we focused on a model in which the reported subjective probabilities are treated as exogenous variables, but also investigated their potential endogeneity. And third, our sample is representative of a broad population with rich variation in background characteristics.

Our structural model reveals that distributional preferences and perceived intentions are both important determinants of responder behavior in the ultimatum game. A key insight of this paper is that the relative importance of each of these factors varies across sub-groups of the broad population, and on whether offers are favorable or unfavorable to responders. Averaging across the entire population, inequity aversion dominates the effects of perceived intentions. However, perceived intentions were found to weigh more heavily for young and educated subjects, in particular for advantageous offers.

We also found that young and educated subjects have more self-oriented distributional preferences than others (i.e., lower inequity aversion to both own and other's disadvantage), as well as a lower tendency to penalize intentionally made very generous offers. Both findings imply that young and highly educated responders accept more often than other population groups. These results suggest that using convenience samples comprising subgroups of the population (e.g., students) may provide a distorted picture of both distributional preferences and the effects of perceived intentions in the population.

Finally, we found significant evidence that expectation violations are important determinants of the measured impact of intentions attribution. We found that the rejection rate of intentionally made low offers significantly increases when such offers are perceived as less likely, suggesting that negative expectation violations can affect the intentions attributed to proposers and the tendency to penalize them for low offers. In other words, our model predicts that low offers have a very high probability of being accepted if responders expect that such offers will occur. While this effect was found for all sub-groups of the population, the estimated effect was significantly stronger for younger subjects. Hence, expectation violations provide additional incentives for proposers to make fair offers when such offers are expected.

Appendix A. The extended model

In this appendix, we extend the model in the paper with an equation explaining the subjective probability distribution of offers reported by the responders in the normal ultimatum game, to account for potential endogeneity of these beliefs. We present the beliefs model for offers below the equal split; the model for offers above the equal split is similar. We have estimated these models separately, for computational convenience. The only thing we lose because of this is that we do not estimate the correlation coefficients $\rho_{\alpha\beta}$ and $\rho_{\iota\kappa}$. Moreover, we have different scale parameters λ_R and λ_N for errors in acceptance decisions concerning offers below and above the equal split (denoted by λ_l^R, λ_l^N, λ_m^R and λ_m^N, where l stands for "less" and m for "more" than the equal split).

Let Q_{ij} denote the subjective probability that responder i in the normal ultimatum game places on getting an offer j, where $j=0$, 150, 300, 450. As many responders report zero probabilities for one or more of the low offers, we will use a censored regression framework. We model the Q_{ij} as follows:[22]

$$\begin{aligned} Q_{ij}^* &= \mathbf{x}_i'\boldsymbol{\delta}_j + \tau_\alpha^j \mu_i^\alpha + \tau_\iota^j \mu_i^\iota + \epsilon_{ij} \\ Q_{ij} &= 0 \qquad \text{if} \quad Q_{ij}^* < 0 \\ &= Q_{ij}^* \quad \text{if} \quad Q_{ij}^* > 0 \end{aligned}$$

where $\tau_\alpha^j \mu_i^\alpha + \tau_\iota^j \mu_i^\iota + \epsilon_{ij}$ denotes the unobserved component of Q_{ij}, τ_α^j, τ_ι^j and $\boldsymbol{\delta}_j$ are unknown parameters, specific to offer j. As explained in the main text, the parameters τ_α^j and τ_ι^j are expected to be negative. If both τ_α^j and τ_ι^j are zero for all j, subjective probabilities are exogenous. We assume that the vector of ϵ_{ij} (with $j=0, \ldots, 450$ CP), is independent of background characteristics and unobserved heterogeneity terms, and normally distributed with mean zero and arbitrary covariance matrix to be estimated.

A.1. Identification

Identification of the model with $\tau_\alpha^j = \tau_\iota^j = 0$ is straightforward, because this assumption makes the beliefs exogenous to the choices so that the choice model has no endogenous right hand side variables. Identification of the general model is less straightforward. The parameters of main interest are the parameters in $\boldsymbol{\eta}$ (and $\boldsymbol{\zeta}$). These will be identified, even without exclusion restrictions on the background characteristics, because endogeneity only enters through correlation with the unobserved heterogeneity terms that do not vary with j (and not through, for example, correlation between the logistic errors in the choice part and the errors ϵ_{ij} in the subjective probability part of the model). This is the same identification argument as in panel data models where endogeneity only enters through fixed individual effects that are correlated with the regressors, not through correlated error terms.

In contrast to $\boldsymbol{\eta}$ (and $\boldsymbol{\zeta}$), the auxiliary parameters τ_α^j and τ_ι^j are not (separately) identified. The reason is that we only observe the subjective probabilities for the responders who play the real ultimatum game, not for those who got the random treatment. (We did not ask the latter because we felt they would get confused if we had to explain both versions of the game to them.) This implies that we can estimate the covariance of the unobservable in the equation of subjective probability j with the sum of the two unobserved heterogeneity terms $\mu_i^\alpha + \mu_i^\iota$ but not with each of them separately.

To make this more precise, we can write:

$$\tau_\alpha^j \mu_i^\alpha + \tau_\iota^j \mu_i^\iota = \gamma_j(\mu_i^\alpha + \mu_i^\iota) + \psi_j \left(\frac{\mu_i^\alpha}{\sigma_\alpha^2} - \frac{\mu_i^\iota}{\sigma_\iota^2} \right), \tag{5}$$

where

$$\gamma_j = \frac{\tau_\alpha^j \sigma_\alpha^2 + \tau_\iota^j \sigma_\iota^2}{\sigma_\alpha^2 + \sigma_\iota^2}$$

and

$$\psi_j = \frac{\tau_\alpha^j - \tau_\iota^j}{\sigma_\alpha^{-2} + \sigma_\iota^{-2}}$$

[22] In principle there is also censoring at 100 percent but as probabilities are always well below 100 percent this can be ignored.

Table 6
Estimation results of the extended model–choice part ($N = 557$).

	α	ι	η	β	κ	ζ	Remaining parameters			
Constant	1.109***	0.635	−6.219**	0.152	−1.111	−2.996	λ_l^R	117.425***	γ_0	0.002
	(0.275)	(0.534)	(2.557)	(0.463)	(1.254)	(4.578)		(12.440)		(0.018)
Male	0.406**	0.070	−1.413	−0.395	−0.470	4.802*	λ_l^N	100.580***	γ_{150}	−0.005
	(0.200)	(0.465)	(2.179)	(0.359)	(0.956)	(2.535)		(10.661)		(0.008)
Educ2	−0.165	0.142	1.333	0.066	−1.549*	−2.319	λ_m^R	136.319***	γ_{300}	−0.005
	(0.215)	(0.475)	(1.710)	(0.355)	(0.872)	(2.802)		(10.496)		(0.007)
Educ3	−0.549**	0.431	1.016	−0.863**	−0.074	−2.646	λ_m^N	130.490***	γ_{450}	0.020
	(0.244)	(0.446)	(1.795)	(0.423)	(0.928)	(2.519)		(27.820)		(0.012)
Age2	−0.017	0.277	3.355*	0.556	3.061**	−2.170	σ_α^2	1.289***	γ_{550}	−0.002
	(0.236)	(0.412)	(1.761)	(0.408)	(1.286)	(4.045)		(0.235)		(0.004)
Age3	0.266	0.508	3.012	1.205**	3.942***	−1.987	σ_β^2	3.600**	γ_{700}	−0.002
	(0.263)	(0.422)	(2.156)	(0.484)	(1.462)	(4.414)		(0.878)		(0.003)
Work	−0.300	0.704	−1.165	0.067	−0.550	1.662	σ_ι^2	0.443	γ_{850}	0.000
	(0.218)	(0.435)	(1.562)	(0.408)	(0.932)	(2.391)		(0.364)		(0.003)
Income2	−0.112	−0.798	1.779	0.101	0.548	−4.197	σ_κ^2	9.582**	γ_{1000}	−0.001
	(0.247)	(0.520)	(2.285)	(0.451)	(1.138)	(3.107)		(4.024)		(0.007)
Income3	−0.048	−0.905	2.219	0.755	−0.963	−2.417				
	(0.284)	(0.680)	(2.820)	(0.540)	(1.272)	(2.952)				

*Significant at the 10 percent level.
**Significant at the 5 percent level.
***Significant at the 1 percent level.

The first term in decomposition (5) is identified by the covariance between choices and subjective probabilities in the ultimatum game treatment; the second term, however, can be subsumed in the errors ϵ_{ij} as this term is independent of the unobserved heterogeneity term $\mu_\alpha^i + \mu_\iota^i$ in the choice part. Thus the γ_j are identified but ψ_j is not, so that only a specific linear combination of τ_α^j and τ_ι^j is identified. The conclusion from this is that we cannot precisely unravel the correlation structure of all unobservables, but we can estimate γ_j and, more importantly, we can estimate $\boldsymbol{\eta}$ (and, in an analogous way using the subjective probabilities of offers above the equal split, $\boldsymbol{\zeta}$).

A.2. Estimation

The extended model is estimated using maximum simulated likelihood, in a similar way as the general model presented in the main text. Conditional on the unobserved heterogeneity terms, the likelihood contribution of a given subject is the product of eight logit probabilities for the choices (as in Eq. (4) in Section 4) and a multivariate Tobit part for the reported subjective probabilities. The latter is the product of a multivariate normal density (for the reported probabilities that are larger than zero) and a multivariate normal cumulative probability (for the reported zero probabilities). The cumulative probability is approximated using the GHK simulator if its dimension is larger than two (cf., e.g., Train, 2003). The actual

Table 7
Estimation results for the extended model–beliefs equations ($N = 557$).

Offer	0 CP	150 CP	300 CP	450 CP	550 CP	700 CP	850 CP	1000 CP
Constant	−0.053	0.010	0.060***	0.194***	0.283***	0.112***	0.118***	0.095*
	(0.064)	(0.022)	(0.016)	(0.043)	(0.039)	(0.026)	(0.036)	(0.056)
Male	0.011	−0.016	−0.013	0.003	−0.022	0.009	0.015	0.013
	(0.056)	(0.017)	(0.012)	(0.029)	(0.031)	(0.025)	(0.027)	(0.045)
Educ2	−0.001	0.003	−0.014	0.031	0.027	−0.008	−0.021	−0.039
	(0.047)	(0.015)	(0.013)	(0.030)	(0.029)	(0.020)	(0.025)	(0.052)
Educ3	−0.028	0.001	−0.003	0.054*	0.065*	−0.012	−0.023	−0.070
	(0.051)	(0.017)	(0.014)	(0.031)	(0.035)	(0.023)	(0.028)	(0.056)
Age2	0.013	0.011	0.010	0.056*	0.002	−0.035*	−0.054**	−0.082
	(0.054)	(0.017)	(0.013)	(0.033)	(0.028)	(0.021)	(0.024)	(0.057)
Age3	−0.031	0.015	0.016	0.084**	0.042	−0.030	−0.096***	−0.145**
	(0.062)	(0.020)	(0.015)	(0.039)	(0.033)	(0.027)	(0.030)	(0.059)
Work	−0.027	0.007	0.018	0.011	0.006	0.019	−0.016	−0.008
	(0.044)	(0.016)	(0.012)	(0.029)	(0.026)	(0.019)	(0.023)	(0.052)
Income2	−0.027	0.002	0.006	0.005	−0.014	−0.004	0.013	−0.010
	(0.062)	(0.020)	(0.014)	(0.035)	(0.034)	(0.027)	(0.030)	(0.053)
Income3	0.012	0.011	0.007	−0.026	−0.013	0.017	0.013	0.015
	(0.067)	(0.023)	(0.017)	(0.039)	(0.045)	(0.031)	(0.037)	(0.072)

*Significant at the 10 percent level.
**Significant at the 5 percent level.
***Significant at the 1 percent level.

Table 8
Correlations between unobservables ϵ_{ij} in the beliefs equations.

	ϵ_0	ϵ_{150}	ϵ_{300}	ϵ_{450}
ϵ_0	1			
ϵ_{150}	0.702	1		
ϵ_{300}	0.330	0.556	1	
ϵ_{450}	−0.381	−0.253	0.031	1

	ϵ_{550}	ϵ_{700}	ϵ_{850}	ϵ_{1000}
ϵ_{550}	1			
ϵ_{700}	−0.154	1		
ϵ_{850}	−0.408	0.476	1	
ϵ_{1000}	−0.575	0.118	0.426	1

likelihood contribution is the expectation of this over the unobserved heterogeneity terms, which is approximated in the same way as for the benchmark model.

A.3. Results

Complete results are presented in Tables 6 (choice part), 7 (subjective probability equations), and 8 (error structure in subjective probabilities). In Table 6, the estimates of γ_j are all small and insignificant. A likelihood ratio test also shows that they are jointly insignificant (p-value = 0.211). As a consequence, the estimates of the preference parameters $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\iota}$ and $\boldsymbol{\kappa}$ are generally very similar to those of the benchmark model discussed in the main text. Standard errors are somewhat larger in most cases, but the same variables remain significant and the qualitative conclusions remain unchanged.

Table 7 shows that the reported subjective probabilities hardly vary with observed subject characteristics. Only age plays a role—with older subjects giving significantly lower probabilities to overly generous offers. The signs of the correlations in Table 8 suggest that, for offers below the equal split, subjects either have a tendency to attach a high probability to the offer near the equal split (450 CP), or to all lower offers (0, 150, 300 CP). A similar conclusion applies to offers above the equal split.[23]

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[23] Separate estimation of a multivariate tobit model for all subjective probabilities shows that subjects who attach high probabilities to very low offers, also attach particularly low probabilities to offers just above the equal split, but not to very high offers.

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