

Preferences, Intentions, and Subjective Expectations: a Large-Scale Experiment with a Representative Subject Pool *

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Abstract

We specify and estimate a structural model which separately identifies the effects of distributional preferences and perceived intentions on responder behavior 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. We estimate our model combining response decisions and subjective expectations data for a large representative sample from the Dutch population. Distributional preferences and the effects of perceived intentions and subjective expectations are allowed to depend on observed and unobserved characteristics of the participants. We find that the probability to reject an unfair offer falls with the subjective probability a responder attaches to getting such an unfair offer. We also find important differences between distributional preferences and effects of perceived intentions for different socio-economic groups. For example, young and high educated subjects attribute good intentions to very generous offers, while older and less educated subjects attribute negative intentions to the same offers.

1 Introduction

Two distinct approaches to introduce fairness in economics have emerged in the last few years. 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. Intention based models on the other hand (e.g., Rabin, 1993; Dufwenberg and Kirchsteiger, 2004) emphasize the importance of the intentions agents attribute to the actions taken by another player. The empirical relevance of both classes of models can perhaps be best studied using economic experiments. Such experiments have provided mixed support concerning the relevance of intentions attribution in determining behavior.

In this paper, we specify and estimate a structural econometric model which separately identifies the effects of distributional preferences and attribution of intentions on responder behavior in the ultimatum game. Our model exploits the response behavior in two treatments. The first treatment is a normal ultimatum game in which proposers intentionally choose the amounts offered to responders. To the second treatment we refer as random ultimatum game, since responders receive offers randomly drawn from a uniform distribution. In the latter treatment, intentions do not affect responder behavior since there are no proposers who intentionally make offers. The difference in

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response behavior across both treatments thus identifies the impact of intentions. The idea of comparing a normal and random treatment first appeared in Blount (1995). It has since served as one of the main approaches used to study intentions.¹

An important contribution of this paper is that our participants are drawn from a large representative sample from the (Dutch adult) population. In total, we have about 1200 participants of age 16 and over from all socio-economic groups. This is in contrast to most of the existing experiments, which use participants drawn from a homogeneous subject pool, often university students majoring in economics or business. The representativeness of the student subject sample raises concerns about the generalizability of the results to broader populations. There is now growing evidence (e.g., Bellemare and Kröger, 2007, Bellemare, Kröger and van Soest, 2005) indicating that behavior inferred from student subjects may not be representative of the behavior in a broad population. These findings suggest that an empirical analysis of preferences and intentions attribution can greatly benefit from experiments in which subjects represent the population at large. Here, we allow distributional preferences and the attribution of intentions to depend on both observable and unobservable characteristics of our participants.

Another innovation of our paper is that we analyze how the responders' attribution of intentions depends on the responders' subjective expectations concerning proposer behavior.² We directly ask subjective probabilities and incorporate the answers in our structural model. Thus our model allows responders to punish unfair offers more if they expect that such unfair offers are less likely. These expectations can affect responses independently of distributional preferences: two responders with the same preferences may have different expectations of proposer behavior and thus different response behavior. Existing studies on the ultimatum game either do not account for such expectations, or focus on the relationship between social norms and responder behavior (see e.g., Buchan, Croson, and Johnson (2004); the main difference with the expectations analyzed in this paper is that social norms are typically defined as the opinions of players concerning what *should* happen in the experiment).

Our main findings are as follows. Overall, our results imply that attribution of intentions plays a substantial role, although outcome-based preferences have a stronger impact on responder behavior than the attribution of intentions. Young and educated subjects have significantly lower aversion to inequity to both own and others disadvantage than others, and attribute positive intentions to very generous offers. On the other hand, other groups of the population – in particular older and less educated – attribute negative intentions to overly generous offers. Responders with higher subjective probabilities that proposers will make offers closer to the equal split, significantly more often reject offers below the equal split. This effect is significantly weaker for younger than for older subjects.

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 structural model. Section 5 discusses the results of the structural model. Section 6 concludes.

¹See Falk, Fehr, and Fischbacher (2000) for an extended application of the approach.

²See Manski (2004) for a survey of the literature on the measurement of expectations in economics and Manski (2002) who explains how subjective expectations can help to identify models explaining decision behavior in experiments.

2 Experiment

The experiment was conducted in March 2004. Subjects were recruited by CentERdata, the survey research institute affiliated to Tilburg University in the Netherlands. CentERdata carries out panel surveys through an Internet panel: the CentERpanel, consisting of approximately 2000 Dutch households. Every Friday, CentERpanel's household members receive a questionnaire which they are asked to fill in at any time between that Friday and the Tuesday of the following week. In order to make the sample representative of the Dutch population, households without Internet, without a computer, or even without a television set are given the necessary equipment.³

There are many reasons why the CentERpanel is an attractive medium to conduct experiments. First, it gives access to a representative sample, which is one of the key features of our study. Second, the experiment is double blind as participants were told that they will be anonymously matched and that their identities are not revealed to the experimenters. Finally, CentERdata reimburses the weekly telephone costs for answering the questionnaire by crediting the respondents' bank accounts four times a year. This allows us to reimburse the participants in a convenient way which the participants are already familiar with. We follow CentERdata's procedures and present pay-offs in their fictitious currency called CentERpoints (hereafter CP); 1 Euro is equal to 100 CP.

Individuals contacted had to read an opening screen informing them that they were selected to participate in an experiment conducted jointly by a team of university researchers.⁴ A detailed description of the game and the payoff structure followed. Each person was informed that conditional on their participation, they would be randomly assigned to one of the roles and would be randomly matched to another panel member playing the opposite role. We randomly assigned the participants to the roles of proposers and responders to either a normal ultimatum game, or to a treatment which prevents responders to attribute intentions to the offers made by proposers, the "random" ultimatum game. Panel members were informed of their role once they agreed to participate.

In both treatments, two persons, a proposer and a responder,⁵ can share an amount of 1000 CP (10 Euros). In the normal ultimatum game, the proposer suggests an allocation to the responder. We discretized the choice set of the proposer to eight possible allocations (X, Y) : $A \in \{(1000, 0), (850, 150), (700, 300), (550, 450), (450, 550), \dots, (0, 1000)\}$ where the first and second amount denote the payoffs in CP for the proposer and the responder, respectively. Responders made their choices using the strategy method, which means they had to make an accept/reject decision for each of the eight possible offers they could receive. The response which corresponded to the actual offer made by the proposer with whom the responder was matched determined the payoff of both participants. The strategy method was chosen to overcome the difficulty of having CentERpanel members interact in real time. This method has the additional advantage of providing more information, as the responses to all eight possible allocations are elicited, including allocations that are never or hardly ever chosen by the actual proposers.⁶ Asking about every amount separately differs from Blount (1995) and many other studies that only ask for the minimum accept-

³For a description of the recruitment, sampling methods, and past usages of the CentERpanel, see: www.centerdata.nl. Children below 16 years of age as well as immigrants are excluded from the panel, the latter group for the reason that low language proficiency in Dutch makes it difficult to answer the questions on a weekly basis.

⁴Detailed instructions are in appendix ??.

⁵Computer screens of the original experiment (in Dutch) and a translated version are available upon request.

⁶McLeish and Oxoby (2004) found that decisions in the ultimatum game collected using the strategy method were not statistically different from decisions collected in a "hot environment" where responders' only decide about the actual offer.

able amount. The latter assumes “threshold behavior,” every amount exceeding some (respondent specific) threshold will be accepted. Our approach allows to explore the incidence of *plateau behavior*, i.e., the surprising observation that a substantial proportion of responders reject offers which are either relatively disadvantageous or advantageous to them. The incidence of plateau behavior has recently been documented in Henning-Schmidt, Li, and Yang (2006), Bahry and Wilson (2006), and Güth, Schmidt, and Sutter (2003).

After making their decisions, responders in the normal ultimatum game were asked to state their subjective probabilities that each of the eight possible offers will be offered. To simplify this task, probabilities were obtained by asking for natural frequencies. For a given offer of X CP, the following question was asked: “Out of 100 persons who can choose an allocation, how many will offer X CP and keep $1000 - X$ CP?”.⁷ Responders answered this question for all eight possible offers.

After all participants made their decisions, proposers and responders were randomly matched and payoffs were determined based on the decisions of the pair. The final payoffs were computed as usual in the ultimatum game: if the proposer had offered the allocation (X, Y) and the responder had stated he or she would accept this allocation, the responder received X and the proposer received Y CP. If the offer was rejected, the proposer and the responder received both nothing.

In the random ultimatum game, the proposer had no active role in determining the offers. Instead, responders were told that the offer they would receive would be determined by a computer randomly choosing one of the eight offers with equal probability.⁸ Hence, proposers played no active role but would still receive their part of the final payoff. Like in the normal ultimatum game, responders had to make an accept/reject decision for all offers they could receive, and the final payoffs of proposers and responders were determined in the same way.

Two weeks after the experiment, participants received information on the outcome of the game and their final payoff, which was later credited to their CentER bank account.

For this experiment, we contacted 1410 panel members of whom 156 declined to participate and 17 did not respond. Keeping only panel members who completed the experiment and for whom we have a complete set of background characteristics, we have 389 proposers and 311 responders in the normal (random) ultimatum game and 268 “proposers” and 252 responders in the random treatment.⁹

3 Descriptive statistics

Table 1 gives the descriptive statistics of the responders in the two treatments. 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

⁷There is evidence from the psychology literature, see for instance Hoffrage, Lindsey, Hertwig, and Gigerenzer (2000), that people are better at working with natural frequencies than with probabilities. Using natural frequency questions, subjective expectations have been successfully elicited before in economic experiments: Blount (1995) elicited subjective beliefs from responders in an ultimatum bargaining game; Bellemare, Kröger and van Soest (2005) elicited subjective expectations data from proposers in an ultimatum bargaining game; and Bellemare, Bissonnette and Kröger (2006) elicited subjective beliefs from senders and responders in a binary trust game.

⁸The uniform distribution has been used in several studies (see e.g., Offerman (2002), Cox and Deck (2005).)

⁹In order to balance the unequal numbers of players in both roles, 94 responders were randomly assigned twice to a proposer. As all other participants, these responders received payments resulting from only one (the first) matching.

education). We also grouped gross personal income into three groups of about the same size, those with monthly income below 1500 euros, between 1500 and 2500 euros per month, and more than 2500 euros per month. Finally, we include gender and work status dummies.

The dark bars in Figure 1 present the offer distribution in the regular ultimatum game, exhibiting some well-known features (see, e.g., Camerer, 2003): proposers send positive amounts, with the mode around the equal split, and very few offers above this level. Proposers did not have the option to offer exactly the equal split. It seems surprising that the majority of the proposers offer somewhat more than half (550 CP) rather than less than half of the total amount. This may be due to low subjective acceptance probabilities for amounts below the equal split, possibly combined with high risk aversion, or a stronger aversion against inequity at the other player's disadvantage than against inequity at the proposer's own disadvantage.

The light bars in Figure 1 present the average offer distribution expected by responders in the standard ultimatum game. On average, responders placed a slightly higher probability on getting offers below 450 CP compared to what actually materialized. While the mode of the expected offer distribution (550 CP) coincides with the mode of the realized offer distribution, responders appear to place lower subjective probabilities on offers of 450 CP and 550 CP. Correspondingly, average subjective probabilities are higher than actual offer frequencies for offers below 450CP or above 550 CP.

The figure does not show the heterogeneity in some of the subjective probabilities across responders. Particularly for offers 450CP and 550CP, heterogeneity is substantial. One in every four responders attach a probability of at most 15% to an offer of 450CP, and one in every four attach a probability of 40% or more. Similar numbers are found for offers of 550CP (one quarter at most 20%, one quarter at least 40%). We also computed the modes of each responder's subjective probability distribution. About 80% of responders place their highest subjective probability on receiving an offer of either 450 CP or 550 CP. Responders thus typically expect proposers to make fair offers, but a substantial group of responders attach much larger probabilities to unfair offers than actually materialize.

The left hand side of Figure 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% for zero offers to above 90% for proposals around the equal split, before declining to just above 55% 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 (random ultimatum game) than in the treatment where intentions are present (normal ultimatum game). For offers of 0 CP, the difference in aggregate acceptance rates 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 Figure 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. For each treatment, the acceptance rates are always higher than in the overall population. The increases are particularly high for offers above 550 CP, though even for this sub-sample, the acceptance rate falls as the amount offered increases beyond 550 CP.

Table 2 presents the sample distribution of complete response strategies in both treatments. Each line represents a strategy, where the index 1 refers to accepting a given offer and 0 refers to rejecting it. For both treatments separately, the table gives the number and percentage of responders

who chose each strategy. The strategies are split in two groups. The first and most prominent group are *threshold* responders who accept any offer above a certain amount. The second group gathers *plateau* responders who reject both low offers and very generous offers.

The substantial size of the latter group has been discussed in recent studies. Hennig-Schmidt, Li, and Yang (2006) and Bahry and Wilson (2006) report similar levels of plateau behavior in their ultimatum game experiments. Note that plateau behavior cannot be revealed when using the more traditional approach of asking responders for the minimum offer they would accept – this question already assumes threshold behavior. A third group, not reported in the table, accepts and rejects in an inconsistent way. This group is small (3.0%), supporting the conjecture that the large majority of respondents understood the nature of the game. The third group will not be included in our empirical analysis.¹⁰

The likelihood of playing either a threshold or plateau strategy is similar for both treatments. Substantial differences between treatments are only found *within* the group of threshold players. The proportion of individuals accepting any offer from 0 to 1000 CP is 5.2% in the normal ultimatum game versus 19.1% in the random ultimatum game, illustrating that responders in the normal game penalize bad intentions. An opposite difference is found for the strategy of only accepting offers of at least 450 CP – this strategy is used by 27.1% in the normal ultimatum game, but only by 16.3% of responders in the random treatment.

4 An Empirical Structural Model of Preferences and Intentions

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

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

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 pay-off, α_i and β_i are equal to 0.

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

$$u_i(y_{resp}, y_{prop}) = y_{resp} - (\alpha_i + l_i^l) \max\{y_{prop} - y_{resp}, 0\} - (\beta_i + l_i^m) \max\{y_{resp} - y_{prop}, 0\} \quad (2)$$

Depending on the perception of the intentions, the parameters l_i^l and l_i^m 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 l_i^l and l_i^m only play a role in the first regular ultimatum game treatment. We assume the following parametric model of distributional preferences.

$$\begin{aligned} \alpha_i &= x_i' \alpha + \mu_i^\alpha \\ \beta_i &= x_i' \beta + \mu_i^\beta \end{aligned}$$

¹⁰We also estimated the model including these respondents and found results that were very similar to those we present.

where x_i denotes a vector of observable characteristics, and the vector $(\mu_i^\alpha, \mu_i^\beta)$ represents unobserved heterogeneity. We will assume that the vector $(\mu_i^\alpha, \mu_i^\beta)$ is independent of error terms and background variables x_i and follows a bivariate normal distribution with mean zero, variances $(\sigma_\alpha^2, \sigma_\beta^2)$ and correlation coefficient ρ . We expect that ρ is positive since people with a general aversion to inequity probably have large values for both.

We do not *a priori* impose any signs on the intentions parameters t_i^l and t_i^m , thus allowing, in principle, for positive as well as negative attributed intentions to advantageous and disadvantageous offers. Allowing for observed and unobserved heterogeneity, t_i^l and t_i^m are specified as:

$$\begin{aligned} t_i^l &= x_i' t^l + \eta_i^l Q_i(O \leq y_{resp}) + \mu_i^{ll} \\ t_i^m &= x_i' t^m + \eta_i^m Q_i(O \geq y_{resp}) + \mu_i^{mm} \end{aligned}$$

Here (μ_i^{ll}, μ_i^{mm}) represents unobserved components determining the effect of perceived intentions, assumed to follow a bivariate normal distribution with mean zero, variances $(\sigma_{ll}^2, \sigma_{mm}^2)$, and correlation coefficient ρ_l . The variable $Q_i(O \leq y_{resp})$ represents the subjective probability that responder i places on receiving offers of y_{resp} or less, introduced to capture the effects of subjective expectations on responder behavior. Keeping y_{resp} constant, a smaller value of $Q_i(O \leq y_{resp})$ indicates that the responder considers an offer as low as y_{resp} or worse more unlikely. We expect that this will lead to a larger tendency to "punish" the sender if such a low offer would materialize, and will thus increase t_i^l . Thus we expect a negative value for η^l . Similarly, $Q_i(O \geq y_{resp})$ is the subjective probability that offers are at least as high as the received offer y_{resp} . We expect a negative value of η^m , implying that responders who place a higher probability on getting the offer under consideration or an even larger offer have a lower tendency to punish the proposer for an unreasonably high offer (if $t_i^m > 0$), or a higher tendency to reward the proposer for the very generous offer (if $t_i^m < 0$). We allow the response to expectations to vary with characteristics x_i by specifying:

$$\begin{aligned} \eta_i^l &= x_i' \eta^l \\ \eta_i^m &= x_i' \eta^m \end{aligned}$$

Under the assumptions above, a responder i who gets an offer $y_{resp}(j) = 1000 - y_{prop}(j)$ with $(y_{prop}(j) = \{0, 150, 300, \dots, 1000\})$ 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

$$u_{ij}^A = y_{resp}(j) - (\alpha_i + t_i^l) \max\{1000 - 2y_{resp}(j), 0\} - (\beta_i + t_i^m) \max\{2y_{resp}(j) - 1000, 0\}. \quad (3)$$

A perfect pay-off maximizing responder would thus choose to accept the offer if and only if $u_{ij}^A > u_{ij}^R (= 0)$. To allow for suboptimal behavior, we add GEV(I) errors that are independent of everything else to 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:

$$P(\text{Responder } i \text{ accepts offer } j | u_{ij}^A, \text{ with intentions}) = \frac{1}{1 + e^{-u_{ij}^A / \lambda_N}} \quad (4)$$

$$P(\text{Responder } i \text{ accepts offer } j | u_{ij}^A, \text{ without intentions}) = \frac{1}{1 + e^{-u_{ij}^A / \lambda_R}} \quad (5)$$

One possible drawback of the model outlined above is that reported subjective probabilities $Q_i(O \leq y_{resp})$ and $Q_i(O \geq y_{resp})$ are taken at face value. Therefore, we also estimated a more general model

where the unsystematic part of reported probabilities can be correlated with unobserved heterogeneity terms driving preferences. Model estimates of the extended model were very close to the one of the structural model presented here. Details of this generalized model, estimation methods, and tables of results can be found in the appendix.

5 Econometric results

Model fit

The observed and predicted acceptance frequencies in both treatments are given in Figure 3. Overall, the fit of our structural model is reasonably 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. Thus it appears that our model is able to capture the differences in responses between both treatments.

Preference estimates

Table 3 presents the average predicted values of $(\alpha_i, \beta_i, \iota_i^l, \iota_i^m)$ based on our model estimates. The top of the table reports the averages and standard deviations of the parameter predictions for all sample participants. The bottom of the table reports the average predictions for young and high educated individuals. By comparing these groups, we will get an indication of the difference between a representative sample and the results based upon recruiting from student populations.¹¹

The parameters α and β capture distributional concerns, net of intentions and the effect of uncertainty. They can be interpreted as the α and β parameters of the Fehr and Schmidt (1999) model. The average predicted population value of α is 1.892 with a relatively small standard deviation of 0.640 indicating that most responders in the population have some aversion to inequity to their own disadvantage. The average predicted population value of β is 0.801 with a high standard deviation of 0.921, indicating that a substantial portion of subjects have a high predicted aversion to other's disadvantage. These predicted averages are higher than previous estimates (Goeree and Holt, 2000, Bellemare, Kröger and van Soest, 2005) and calibrations (Fehr and Schmidt, 1999, Huck, Müller, and Normann, 2001) of those distributional parameters.

Positive (negative) values of ι^l indicate that the offers below an equal split signal bad (good) intentions, resulting in higher (lower) rejection rates. The average predicted value of ι^l is 0.382, indicating that, on average, responders attribute bad intentions to offers placing them in a disadvantageous position. Negative (positive) values of ι^m on the other hand indicate that the offers above the equal split signal good (bad) intentions, and lead to lower (higher) rejection rates. The average predicted value of ι^m is -0.164 , indicating that, on average, responders attribute good intentions to generous offers. The substantial dispersion in the predicted values of ι^m suggests however that a considerable amount of subjects have positive values for this parameter, and thus attribute negative intentions to overly generous offers.

Table 3 also reveals that, averaging over the entire population, distributional preferences have a stronger effect on utility than perceived intentions. Keeping expectations fixed, our estimates

¹¹The predicted (α, β) are averaged over responders from both treatments, while the predicted averages of (ι^l, ι^m) are averaged only over responders in the normal ultimatum game

indicate a one CP increase in inequity to own disadvantage is associated with a loss of 2.274 utils, where 83.2% (1.892 CP) of the loss results from inequity aversion, and 16.8% (0.382 CP) results from penalizing perceived bad intentions. Similarly, a one CP increase in inequity to other's disadvantage is associated with a loss of 0.637 utils, composed of a dominating loss of 0.801 utils due to inequity aversion, a minor gain of 0.164 utils resulting from rewarding perceived good intentions.

The average predicted values of α and β of the young and educated subjects are both lower than the corresponding predictions for the population average, indicating that young and high educated individuals have lower concerns for inequitable outcomes. Moreover, young and educated subjects attribute substantially higher positive intentions to offers above the equal split ($\iota^m = -1.167$) than the overall population average.

Table 4 shows in detail how the parameters α , β , ι^l and ι^m vary with all observed characteristics. We find that men have a significantly higher disutility from own disadvantage α . Responders with the highest level of education have significantly lower aversion to own disadvantage. Older responders have higher aversion to own disadvantage, although this effect is only significant at the 10% level. There is not much observed heterogeneity in the effect of intentions for offers to the responder's own disadvantage (ι^l).

Observed characteristics also play a role for inequity at the other player's disadvantage and particularly the importance of intentions. Looking at the distributional preferences (β), the oldest age group shows larger inequity aversion at the other participant's disadvantage. Moreover, both older age groups have a significantly larger tendency to reject high offers in the treatment where intentions are present. This might be an effect of pride, with older respondents unwilling to accept "gifts" from the proposers. Even though regarded in the psychology literature as positive emotion, pride may depress take-up of social benefits or might lead to "irrational" 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. Furthermore, we find that high educated responders have a significantly lower aversion to other's disadvantage. They do not however react significantly different to other education groups when intentions are present. Finally, high income responders tend to perceive the intentions behind high offers more positively than others, reflected in a significantly lower ι^m .

The effects of subjective expectations on responder behavior appears to be more important for disadvantageous offers than very favorable offers. We find that the intercept in η^l is significant and negative, indicating that responders who expect a higher offer will punish more unfair offers significantly more. This effect is found to be significantly weaker for older subjects. Relative to younger subjects, middle aged and older subjects punish unfair offers significantly less when these offers are expected to occur with low probability. When offers are very favorable to responders, we find little evidence that responders reject very favorable offers because these offers are considered quite unlikely. We find a small gender effect, with women rejecting unexpected favorable offers more than men. This is, however, only significant at the 10% level.

The estimated scale parameters, covariance matrix parameters, and η^l , η^m are given on the right hand side of Table 4. The estimated values of λ_N and λ_R suggest that the amount of idiosyncratic noise is similar for the two treatments. 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_m^2). Moreover, as expected, the unobserved heterogeneity

components in l_i and m_i are positively correlated, with a significant correlation coefficient of $\rho = 0.675$. Unobserved heterogeneity plays only a minor role in determining the effects of perceived intentions for high offers (σ_{im}^2), while no evidence of unobserved heterogeneity is found for the extra inequity aversion at one's own disadvantage (σ_i^2).

Responses and expectations

In this subsection, we investigate the quantitative implications of subjective expectations on responder behavior. We do so by predicting the acceptance probabilities in the normal ultimatum game under three different scenarios. The first "benchmark" scenario allows for heterogeneous expectations, using our model estimates and the subjective probabilities for each responder. The second scenario assumes that responders do not react to intentions and respond as if the offer was drawn randomly by the computer, as in the no intentions treatment. The final scenario assumes that intentions play a role, but that responders expect that proposers will always make an offer that is disadvantageous to the responder: an offer of 0 CP occurs with 40% probability, and offers of 150 CP, 300 CP, and 450 CP each occur with 20% probability. In other respects, all scenarios copy the benchmark model. We perform the simulations first for the entire sample of responders, and then only for young responders with university education, our proxy for the typical sample of subjects used in laboratory experiments.

Figure 4 presents the predicted distributions in the three scenarios for both groups. Consistent with our parameter estimates, the effects of expectations on high offers are of the expected signs but relatively small in all scenarios. Differences are much larger for the offers to the responder's disadvantage. As expected, the subjective expectations scenario gives lower acceptance rates than the no intentions scenario, illustrating that disadvantageous offers induce attribution of negative intentions which are penalized by higher rejection rates. For these two treatments, the model predicted acceptance rates correspond well to the acceptance rates in the subsamples.

The 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 offered on average, and acceptance rates are high - even exceeding the acceptance rates in the no intentions treatment. What are "bad intentions" under the reported subjective expectations thus become "(relatively) good intentions" under the alternative with "expected disadvantageous offers." It illustrates the important role of expectations in how intentions drive responders' acceptance decisions.

For the group of young responders with high education level, the differences between the three scenarios are similar, and in general, acceptance rates are higher than for the total population, particularly for the "expected disadvantageous offers" scenario. Even offers of zero are quite often accepted by this group.

6 Conclusion

This paper exploited a well established experimental design to separately identify distributional preferences and the effects of perceived intentions on responder behavior in the ultimatum game. We extended existing studies in two important directions. First, we specified and estimated a structural econometric model of responder behavior relating outcome-based preferences and the effects

of perceived intentions to both observable and unobservable characteristics of a large representative sample of subjects drawn from the Dutch population. Second, we allowed the effects of the intentions perceived to depend on the subjective probability distributions of relevant responders.

Our analysis has revealed 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 these each of these factors is likely to vary across sub-groups of a broad population. We found that limiting ourselves to young and educated subjects provided estimates of more self-oriented preferences, and more positive perception of the intentions behind very generous offers. We showed that other groups of the population not only have substantially higher levels of inequity aversion to both own and other's disadvantage inequity, but also appear to perceive negatively the intentions of overly generous offers. Plateau behavior in particular appears to be more important amongst older and less educated subjects who not only have stronger inequity aversion for high offers, but attribute bad intentions to these offers. These results suggest that using convenience samples (e.g. students) may provide a distorted picture of both the distributional preferences and the perceived intentions in the population.

While we found evidence of heterogeneity in subjective expectations, there appears to be a consensus amongst responders that the most likely offers will be fair. We found that these expectations were consistent with observed offers, although responders generally overestimated the probability of getting offers below and above the equal split.

The literature on social norms has established that expectations of what should be offered are important determinants of response behavior. In this paper, we showed that expectations of what will happen are also important : controlling for preferences, responders significantly punish offers violating their subjective expectations. These expectations clearly reinforce the norm of offering fair offers. An interesting exercise for future research would consist in comparing expectations of what will happen with expectations of what responders think should happen. A high correlation between both sets of expectations would suggest that responders expect proposers to behave as they think they should.

Variables	Mean	Description
Gender	0.527	1 if male, 0 otherwise
Low education	0.294	1 if primary education or vocational training, 0 otherwise
Middle education	0.352	1 if general secondary education or vocational training, 0 otherwise
High education	0.353	1 if university education or high vocational training, 0 otherwise
Young	0.241	1 if below 35 years of age, 0 otherwise
Middle age	0.454	1 if between 35 and 54 years of age, 0 otherwise
Old	0.305	1 if above 54 years of age, 0 otherwise
Low income	0.362	1 if monthly gross personal income is below 1500 Euros, 0 otherwise
Middle income	0.331	1 if monthly gross personal income is between 1500 and 2500 Euros, 0 otherwise
High income	0.306	1 if monthly gross personal income is above 2500 Euros, 0 otherwise
Work	0.582	1 if involved in paid work, 0 otherwise
Number of observations	577	

Table 1: Definitions and sample means of the explanatory variables for all responders in our normal and random ultimatum game treatments.

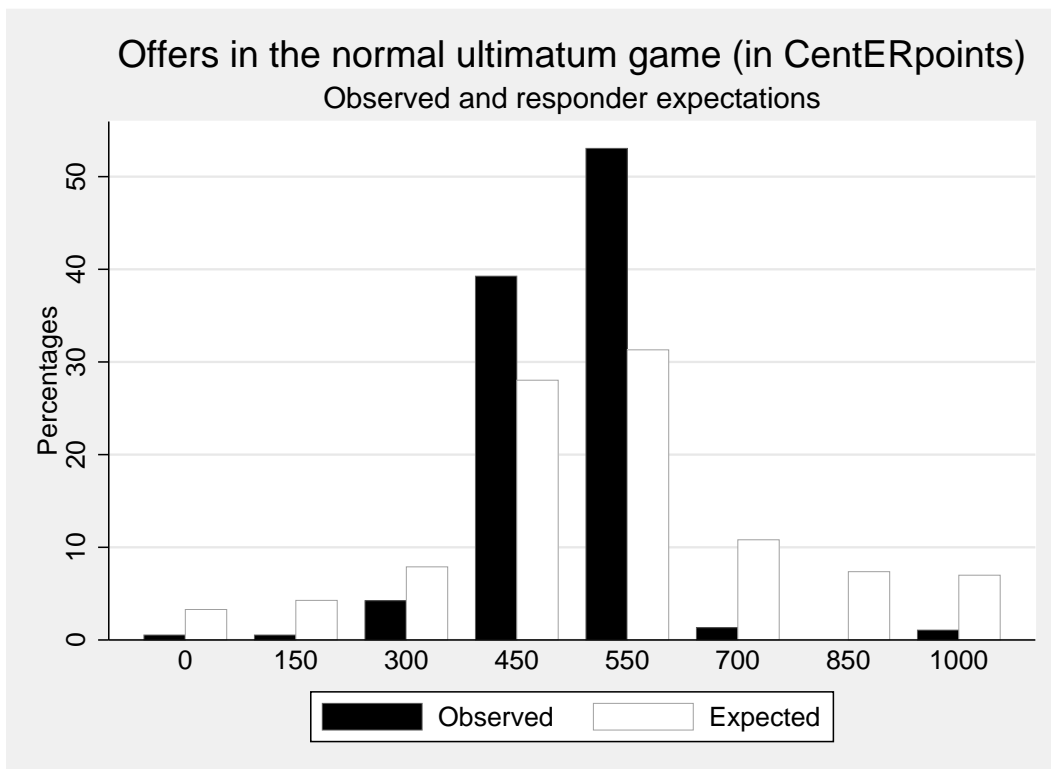


Figure 1: Distribution of offers made by proposers and average expected offer distribution of responders in the normal ultimatum game.

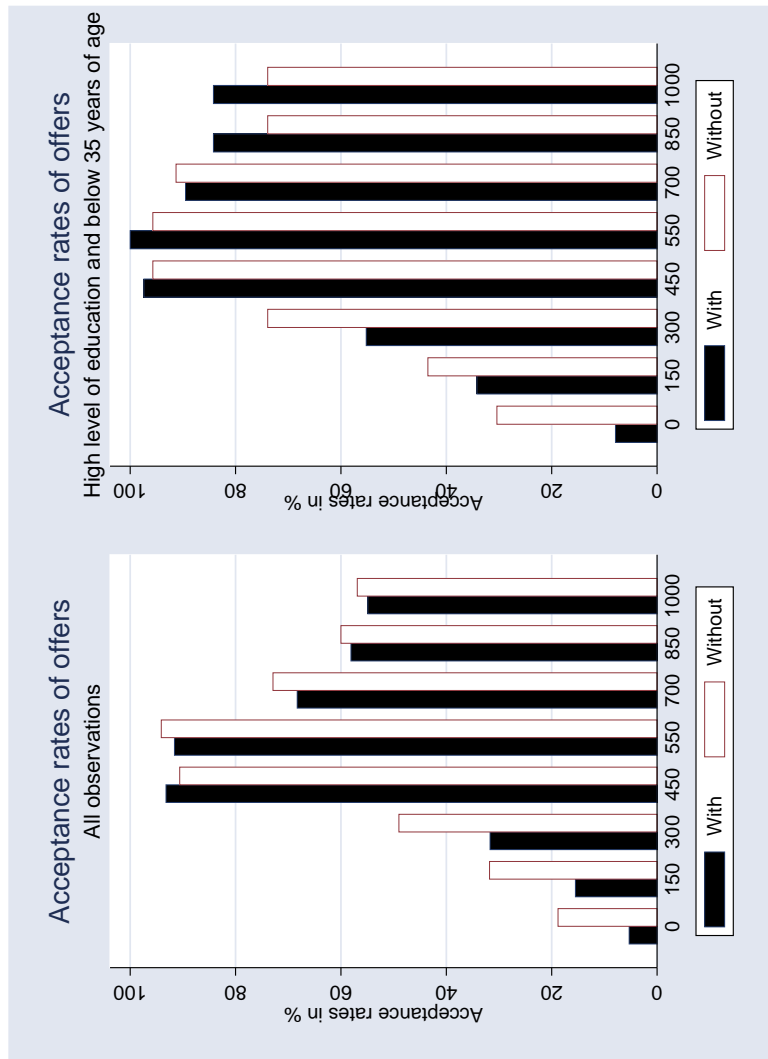


Figure 2: Acceptance rates in the normal and random ultimatum games for all observations and for individuals with high level of education and who are below 35 years of age.

	0	150	300	450	550	700	850	1000	Normal		Random	
									N	%	N	%
<i>Threshold behavior</i>												
	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 <i>Threshold</i>									169	54.34	141	56.34
<i>Plateau behavior</i>												
	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 <i>Plateau</i>									142	45.65	105	46.66
Total									311	100	252	100
<i>Aggregate acceptance rates</i>												
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				

Table 2: Observed choice sequences for responders. Columns: amounts that can be offered (strategy method). 1: accept offer; 0: reject offer; N: number of observations.

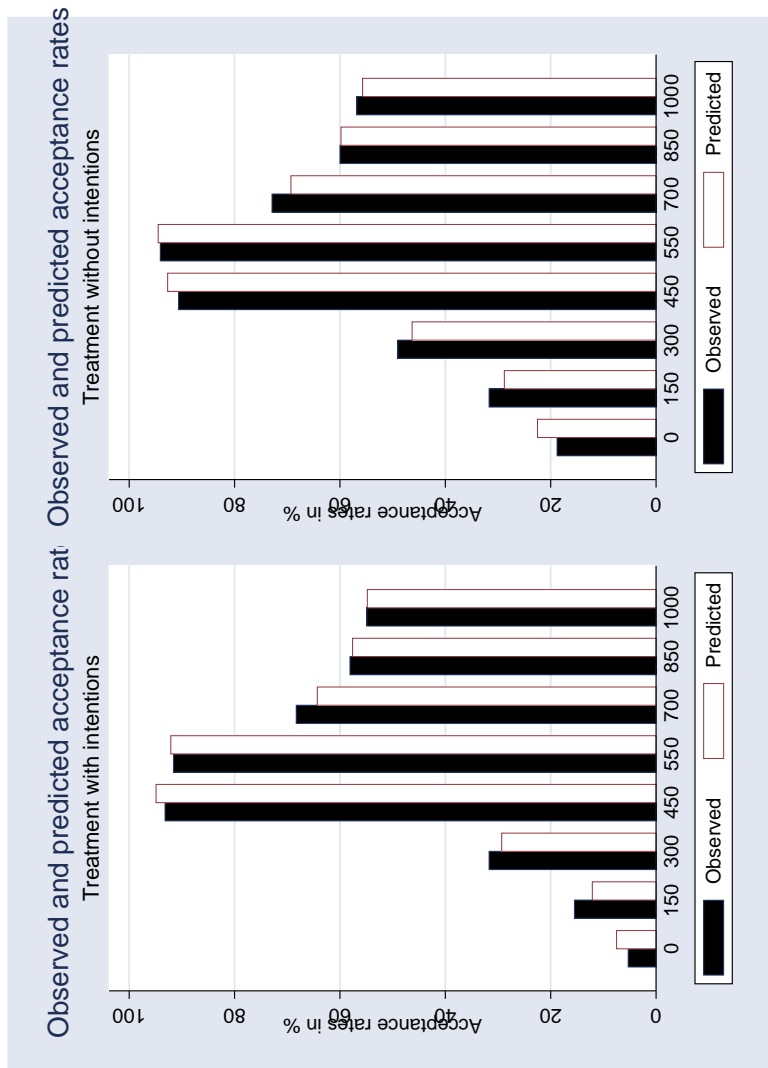


Figure 3: Observed and predicted response distributions in the normal and random ultimatum games.

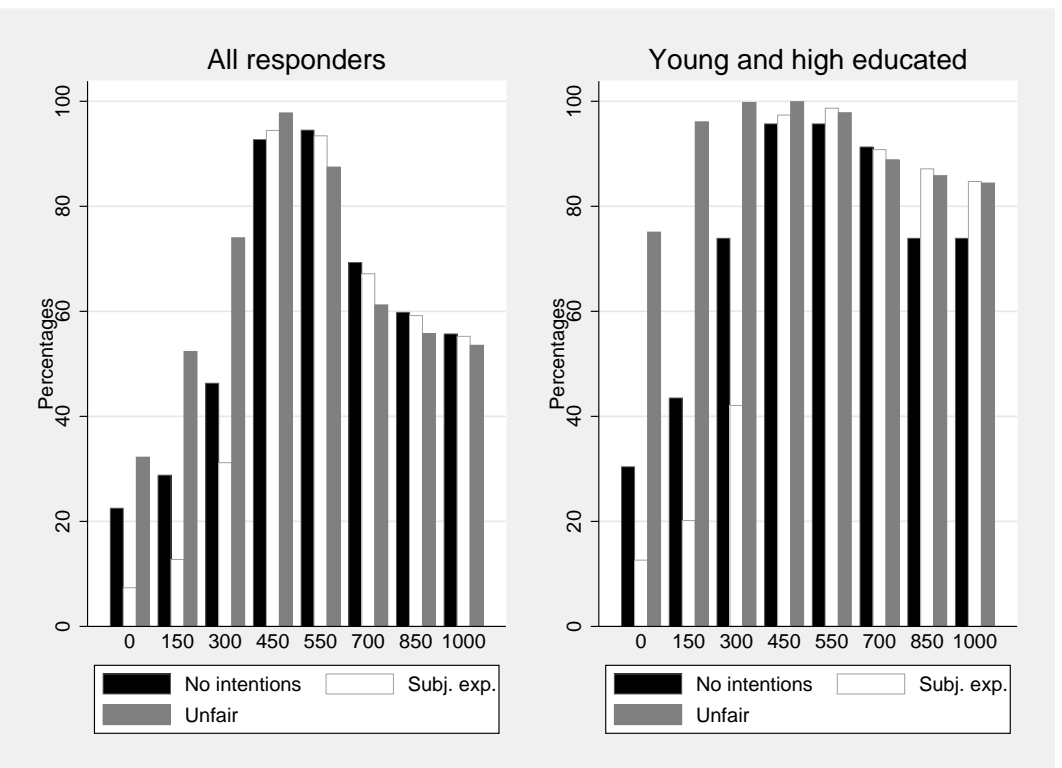


Figure 4: Predicted acceptance probabilities for all responders (left graph) and only for young and high educated responders (right graph) as a function of the amount offered. The light bars represent the predicted acceptance rates in the normal ultimatum game with subjective expectations. The black bars represent the predicted acceptance rates computed under the assumption that responders have uniform expectations : each offer is equally likely. The grey bars represent the predicted acceptance rates computed under the assumption that responders expect disadvantageous offers (EDO) : they expect an offer of 0 CP occurs with 40% probability, and offers of 150 CP, 300 CP, and 450 CP each occur with 20% probability.

	α	β	ι^l	ι^m
<i>All observations</i>				
Average	1.892	0.801	0.382	-0.164
Std. deviation	0.640	0.921	0.459	1.128
<i>High education level and below 35 years of age</i>				
Average	1.018	-0.271	0.227	-1.167
Std. deviation	0.325	0.503	0.397	0.773

Table 3: Predicted average preference parameters.

	α	ι^l	β	ι^m	η^l	η^m	Remaining parameters	
Constant	1.072*** (0.250)	0.894* (0.471)	-0.162 (0.433)	-0.811 (0.880)	-6.159*** (2.054)	-0.517 (2.595)	λ_R	126.305*** (6.187)
Male	0.375* (0.201)	-0.022 (0.364)	-0.451 (0.320)	0.265 (0.621)	-1.769 (1.610)	3.716* (1.913)	λ_N	111.631*** (7.319)
Educ2	-0.188 (0.211)	0.097 (0.373)	0.093 (0.344)	-0.662 (0.645)	1.478 (1.250)	-1.571 (1.777)	σ_α^2	1.296*** (0.136)
Educ3	-0.693*** (0.230)	0.363 (0.384)	-1.317*** (0.399)	0.605 (0.711)	0.721 (1.400)	-1.952 (1.957)	σ_β^2	4.770*** (0.527)
Age2	0.013 (0.218)	-0.100 (0.379)	0.521 (0.350)	2.595*** (0.790)	3.920** (1.646)	-2.978 (2.160)	ρ	0.770*** (0.024)
Age3	0.427* (0.250)	-0.045 (0.439)	1.867*** (0.437)	2.594*** (0.948)	3.628* (2.018)	-3.419 (2.668)	$\sigma_{\iota^l}^2$	0.010 (0.201)
Work	-0.279 (0.210)	0.527 (0.371)	0.458 (0.410)	-0.641 (0.713)	-1.056 (1.241)	1.018 (1.822)	$\sigma_{\iota^m}^2$	5.656*** (0.703)
Income2	-0.099 (0.237)	-0.417 (0.448)	0.035 (0.442)	0.183 (0.792)	1.032 (1.713)	-2.677 (2.285)	ρ_{ι}	0.122 (0.130)
Income3	0.005 (0.283)	-0.662 (0.540)	0.833 (0.532)	-2.284** (0.944)	2.351 (2.121)	-0.919 (2.196)		

Table 4: Structural model estimates. *, **, ***: significant on 10, 5, and 1 percent level. Standard errors in parenthesis.

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A The extended model

Let Q_{ij} denote the subjective probability that responder i in the normal ultimatum game places on getting an offer j , where $j = 0, 150, \dots, 1000$. Let the observation rule be given by

$$\begin{aligned} Q_{ij}^* &= \mathbf{x}_i' \boldsymbol{\delta}_j + \epsilon_{ij} \\ Q_{ij} &= 0 \quad \text{if } Q_{ij}^* < 0 \\ &= Q_{ij}^* \quad \text{if } 0 < Q_{ij}^* < 1 \\ &= 1 \quad \text{if } Q_{ij}^* > 1 \end{aligned}$$

where ϵ_{ij} denotes the unobserved component of the subjective probability individual i places on the occurrence of offer j , and $\boldsymbol{\delta}_j$ are unknown parameters also specific to an offer of j . We assume that the vector $(\epsilon_{i0}, \epsilon_{i150}, \dots, \epsilon_{i1000})$ is jointly normally distributed, with vector mean 0, variances $(\sigma_0^2, \sigma_{150}^2, \dots, \sigma_{1000}^2)$, and an arbitrary correlation structure.

The expected value of Q_{ij} conditional on \mathbf{x}_i , denoted \bar{Q}_{ij} is given by

$$\bar{Q}_{ij} = \Phi(\mathbf{x}_i' \boldsymbol{\delta}_j / \sigma_j) (\mathbf{x}_i' \boldsymbol{\delta}_j + \sigma_j \phi(\mathbf{x}_i' \boldsymbol{\delta}_j / \sigma_j))$$

where $\Phi(\cdot)$ and $\phi(\cdot)$ respectively denote the standard normal cumulative and density functions. When evaluating the utilities of responders in the normal ultimatum game, the predicted rather than the true stated probabilities are used to construct the subjective measures

$$Q_i(O \leq y_{resp}) = \sum_{j|j \leq y_{resp}} \bar{Q}_{ij} \quad (6)$$

$$Q_i(O \geq y_{resp}) = \sum_{j|j \geq y_{resp}} \bar{Q}_{ij} \quad (7)$$

In practice, it is important to ensure that the predicted subjective probabilities sum to 1 over j . We do so by modelling subjective probabilities placed over all offers except offers of 550 CP. The predicted subjective probability of receiving an offer of 550 CP is obtained as the remainder $1 - \sum_{j|j \neq 550} \bar{Q}_{ij}$. We chose probabilities of offers of 550 CP because this residual probability has substantial mass in the data. This should make it easier to predict values of the remainder probability between 0 and 1.¹²

Likelihood function of the extended model

Let \mathbf{Q}_{ci}^* be a $\tilde{J} \leq 7$ dimensional vector of latent variables associated with stated probabilities censored from below at zero, and \mathbf{Q}_{ui}^* denote the $7 - \tilde{J}$ dimension vector of latent variables associated with stated probabilities greater than zero. Moreover, let and \mathbf{Q}_{ci} and \mathbf{Q}_{ui} as the corresponding vectors of observed probabilities. Denote the choice vector $\mathbf{R}_i = [R_{i0}, R_{i150}, \dots, R_{i1000}]'$, where $R_{ij} = 1$ if offer j is accepted. The likelihood of the choice vector in the normal ultimatum game, conditional on $(\mu_i^\alpha, \mu_i^\beta, \mu_i^l, \mu_i^{lm})$, is given by

$$\begin{aligned} &\mathcal{C}(\mathbf{R}_i | \mu_i^\alpha, \mu_i^\beta, \mu_i^l, \mu_i^{lm}) \\ &= \prod_{j=0}^{1000} \left[R_{ij} \Pr(R_{ij} = 1 | \mu_i^\alpha, \mu_i^\beta, \mu_i^l, \mu_i^{lm}) + (1 - R_{ij}) \Pr(R_{ij} = 0 | \mu_i^\alpha, \mu_i^\beta, \mu_i^l, \mu_i^{lm}) \right] \end{aligned}$$

¹²Ex-post calculations revealed that the predicted expected probability of offers of 550 CP were well within the [0,1] interval for all responders in the normal ultimatum game.

Given our distributional assumptions,

$$\Pr \left(R_{ij} = 1 | \mu_i^\alpha, \mu_i^\beta, \mu_i^l, \mu_i^m \right) = \frac{1}{1 + e^{(-u_{ij}^A / \lambda_i)}}$$

The choice likelihood $\mathcal{C}(\mathbf{R}_i)$ is obtained by integrating over the domain of the unobservable characteristics

$$\mathcal{C}(\mathbf{R}_i) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \left[\mathcal{C} \left(\mathbf{R}_i | \mu_i^\alpha, \mu_i^\beta, \mu_i^l, \mu_i^m \right) d\mu_i^\alpha d\mu_i^\beta d\mu_i^l d\mu_i^m \right] \quad (8)$$

The likelihood of the subjective probability data is given by

$$\mathcal{P}(\mathbf{Q}_{ci}, \mathbf{Q}_{ui}) = \int_{\mathbb{D}} \phi_7(\mathbf{Q}_{ci}^*, \mathbf{Q}_{ui}^*) d\mathbf{Q}_{ci}^* \quad (9)$$

where $\phi_7(\cdot)$ denotes the seven dimension multivariate normal density function and where \mathbb{D} denotes the domain of integration over the latent variables of censored probabilities.

The complete likelihood for a responder i in the normal ultimatum game $\mathcal{L}(\mathbf{R}_i, \mathbf{Q}_{ci}, \mathbf{Q}_{ui})$ is simply the product of the likelihood of choices $\mathcal{C}(\mathbf{R}_i)$ with the likelihood of the subjective probability data $\mathcal{P}(\mathbf{Q}_{ci}, \mathbf{Q}_{ui})$.

For efficiency reasons, the choice and subjective probability likelihoods are maximized jointly due to the presence of the the predicted expectations entering the choice likelihood through the disutility parameters l_i and m_i . Maximization of the complete likelihood requires approximating the integrals in (8) and those in (9). We approximate the first set of integrals by simulation using a sequence of draws

$\left\{ \left(\mu_r^\alpha, \mu_r^\beta, \mu_r^l, \mu_r^m \right) : r = 1, 2, \dots, R \right\}$ taken from the joint distribution of $\left(\mu_i^\alpha, \mu_i^\beta, \mu_i^l, \mu_i^m \right)$ and computing

$$\begin{aligned} & \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \left[\mathcal{C} \left(\mathbf{R}_i | \mu_i^\alpha, \mu_i^\beta, \mu_i^l, \mu_i^m \right) d\mu_i^\alpha d\mu_i^\beta d\mu_i^l d\mu_i^m \right] \\ & \approx \frac{1}{R} \sum_{r=1}^R \left[\mathcal{C} \left(\mathbf{R}_i | \mu_r^\alpha, \mu_r^\beta, \mu_r^l, \mu_r^m \right) \right] \end{aligned}$$

The likelihood of the subjective expectations data $\mathcal{P}(\mathbf{Q}_{ci}, \mathbf{Q}_{ui})$ is approximated using the GHK simulator (see Train (2003))

$$\begin{aligned} & \mathcal{P}(\mathbf{Q}_{ci}, \mathbf{Q}_{ui}) \\ & = \int_{\mathbb{D}} \phi_7(\mathbf{Q}_{ci}^*, \mathbf{Q}_{ui}^*) d\mathbf{Q}_{ci}^* \\ & \approx \frac{1}{S} \sum_{s=1}^S \Psi_s^{GHK} \left(\mathbf{x}'_i \delta_0, \dots, \mathbf{x}'_i \delta_{\bar{j}}, \mathbf{Q}_{2i}^* \right) \end{aligned}$$

where $\Psi_s^{GHK} \left(\mathbf{x}'_i \delta_0, \dots, \mathbf{x}'_i \delta_{\bar{j}}, \mathbf{Q}_{2i}^* \right)$ is a simulator of $\int_{\mathbb{D}} \phi_7(\mathbf{Q}_{ci}^*, \mathbf{Q}_{ui}^*) d\mathbf{Q}_{ci}^*$. We set $R = S = 100$ and all draws are generated using Halton sequences (see Train (2003)).

For responders in the random ultimatum game, the probabilities Q_i are assumed known to all responders and can be treated as exogenous. Accordingly, the likelihood for a responder in the random ultimatum game corresponds simply to the choice likelihood in the above model.

	α	ι^l	β	ι^m	Remaining parameters	
Constant	1.055*** (0.244)	0.961* (0.548)	-0.132 (0.430)	-0.243 (0.810)	η^l	-3.089** (1.032)
Male	0.364* (0.197)	0.012 (0.440)	-0.448 (0.319)	0.661 (0.593)	η^m	-1.471* (0.790)
Educ2	-0.184 (0.205)	0.285 (0.407)	0.089 (0.341)	-1.475** (0.651)	λ_R	121.729*** (7.562)
Educ3	-0.678*** (0.226)	0.598 (0.439)	-1.292*** (0.398)	0.643 (0.643)	λ_N	126.419*** (6.165)
Age2	0.011 (0.212)	0.412 (0.442)	0.510 (0.347)	1.377** (0.651)	σ_α^2	1.229*** (0.256)
Age3	0.409* (0.243)	0.745 (0.494)	1.827*** (0.438)	1.753** (0.782)	σ_β^2	4.593*** (1.133)
Work	-0.277 (0.204)	0.301 (0.385)	0.443 (0.406)	-0.155 (0.628)	ρ	0.771*** (0.032)
Income2	-0.087 (0.230)	-0.551 (0.482)	0.040 (0.437)	0.182 (0.749)	$\sigma_{\iota^l}^2$	0.073 (0.088)
Income3	0.019 (0.275)	-0.425 (0.614)	0.831 (0.527)	-1.962** (0.863)	$\sigma_{\iota^m}^2$	2.824** (0.847)
					ρ_{ι}	0.073 (0.114)

Table 5: Model estimates for extended structural model with endogenous subjective probabilities. *, **, ***: significant on 10, 5, and 1 percent level. Standard errors in parenthesis.

	0	150	300	450	700	850	1000
Extended model							
Constant	-0.054 (0.059)	0.014 (0.023)	0.061*** (0.018)	0.197*** (0.048)	0.114*** (0.031)	0.117*** (0.041)	0.107* (0.061)
Male	0.006 (0.058)	-0.017 (0.019)	-0.013 (0.015)	0.005 (0.034)	0.007 (0.029)	0.012 (0.031)	0.009 (0.054)
Educ2	0.014 (0.044)	0.006 (0.016)	-0.012 (0.014)	0.025 (0.033)	-0.006 (0.023)	-0.017 (0.028)	-0.033 (0.055)
Educ3	-0.018 (0.051)	0.004 (0.018)	-0.003 (0.016)	0.045 (0.037)	-0.011 (0.026)	-0.020 (0.030)	-0.069 (0.059)
Age2	0.010 (0.057)	0.005 (0.017)	0.008 (0.014)	0.054 (0.034)	-0.035 (0.024)	-0.051* (0.029)	-0.080 (0.057)
Age3	-0.015 (0.069)	0.015 (0.023)	0.015 (0.018)	0.079* (0.044)	-0.028 (0.030)	-0.086** (0.035)	-0.119* (0.070)
Work	-0.021 (0.047)	0.008 (0.019)	0.019 (0.014)	0.009 (0.037)	0.018 (0.022)	-0.016 (0.029)	-0.008 (0.062)
Income2	-0.018 (0.068)	0.003 (0.022)	0.006 (0.017)	0.008 (0.045)	-0.006 (0.032)	0.012 (0.036)	-0.016 (0.061)
Income3	0.016 (0.071)	0.012 (0.026)	0.009 (0.020)	-0.019 (0.048)	0.016 (0.035)	0.007 (0.041)	-0.008 (0.083)
Expectations data only							
Constant	-0.060 (0.057)	0.010 (0.021)	0.059*** (0.017)	0.196*** (0.047)	0.115*** (0.030)	0.118*** (0.038)	0.108* (0.057)
Male	0.007 (0.055)	-0.015 (0.018)	-0.014 (0.015)	0.002 (0.034)	0.008 (0.028)	0.013 (0.030)	0.010 (0.048)
Educ2	0.011 (0.042)	0.004 (0.015)	-0.014 (0.013)	0.031 (0.033)	-0.008 (0.022)	-0.019 (0.027)	-0.035 (0.053)
Educ3	-0.022 (0.050)	0.003 (0.018)	-0.004 (0.016)	0.051 (0.035)	-0.012 (0.025)	-0.021 (0.029)	-0.072 (0.055)
Age2	0.019 (0.053)	0.011 (0.017)	0.011 (0.014)	0.054 (0.034)	-0.036 (0.024)	-0.052* (0.027)	-0.082 (0.056)
Age3	-0.012 (0.063)	0.017 (0.021)	0.017 (0.017)	0.084** (0.042)	-0.030 (0.028)	-0.088*** (0.032)	-0.123* (0.064)
Work	-0.021 (0.044)	0.008 (0.017)	0.019 (0.013)	0.011 (0.034)	0.018 (0.021)	-0.016 (0.026)	-0.010 (0.059)
Income2	-0.018 (0.061)	0.002 (0.021)	0.006 (0.016)	0.008 (0.043)	-0.005 (0.030)	0.012 (0.033)	-0.014 (0.053)
Income3	0.015 (0.066)	0.010 (0.025)	0.008 (0.020)	-0.022 (0.046)	0.017 (0.034)	0.008 (0.039)	-0.004 (0.073)

Table 6: Multivariate Tobit estimates of the subjective probabilities. Extended model: estimation performed using both the choice and the subjective probability data. Bottom panel: Estimation performed using only the subjective probability data. *, **, ***: significant on 10, 5, and 1 percent level. Standard errors in parenthesis.

<i>Corr</i> (ϵ_a, ϵ_b)	ϵ_0	ϵ_{150}	ϵ_{300}	ϵ_{450}	ϵ_{700}	ϵ_{850}	ϵ_{1000}
Extended model							
ϵ_0	1						
ϵ_{150}	0.671	1					
ϵ_{300}	0.307	0.559	1				
ϵ_{450}	-0.268	-0.239	0.053	1			
ϵ_{700}	-0.193	-0.046	0.091	-0.483	1		
ϵ_{850}	-0.099	0.012	-0.117	-0.593	0.467	1	
ϵ_{1000}	0.094	-0.008	-0.251	-0.588	0.102	0.403	1
Expectations data only							
ϵ_0	1						
ϵ_{150}	0.667	1					
ϵ_{300}	0.300	0.553	1				
ϵ_{450}	-0.265	-0.237	0.056	1			
ϵ_{700}	-0.195	-0.046	0.092	-0.484	1		
ϵ_{850}	-0.101	0.012	-0.117	-0.594	0.467	1	
ϵ_{1000}	0.094	-0.006	-0.251	-0.589	0.102	0.404	1

Table 7: Estimated covariance matrix of $\{\epsilon_j : j = 0, 150, 300, 450, 700, 850, 1000\}$ for the structural model. Top panel: Estimation performed using both the choice and the subjective probability data. Bottom panel: Estimation performed using only the subjective probability data.