A Social Utility Explanation of Results in Experimental Ultimatum Bargaining Games

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Abstract

We explain the main features of the results of the ultimatum bargaining experiments of Roth et al. (1991) by a model in the style of Harsanyi (1973), in which players are uncertain about the utilities of their opponents. We investigate a model that introduces social considerations into the model with utility uncertainty. As a simple measure of social utility (Edgeworth (1881)) we add (subtract) a portion of the opponent's earnings to each player's monetary income, i. e. each player's modified utility is a linear combination of the player's own and her opponent's monetary earnings. We find that, on the aggregate, players have negative regard for their opponents' monetary earnings in these experiments. Finally, we provide evidence that both responders and proposers have negative regard for each others' monetary earnings which suggests that proposers are neither sophisticated maximizers of their *own* monetary income given the rejection rates of responders nor altruists that have positive regard for the monetary earnings of their opponents.

JEL Classification Numbers: A13, C19, C44, C72, C92, D63, D64

1 Introduction

The ultimatum bargaining game is a frequently studied game in experimental economics. In this game there are two players: a proposer and a responder. The proposer proposes how to divide a sum of money with a second bargainer. The responder has the choice of either accepting or rejecting the proposed division of the sum of money (the pie). If the responder accepts the proposed division, then the division is as proposed by the proposer. If the responder rejects the proposed division, each player earns nothing and the game ends.

The above version of the ultimatum bargaining game has a continuum of Nash equilibria but a unique subgame perfect equilibrium. All the Nash equilibria that are not subgame perfect involve threats by the responder that she would not want to carry out if she were called upon to move. In the unique subgame perfect equilibrium the proposer receives the whole pie and the responder receives nothing. To see this, notice that subgame perfection implies that the responder will accept *any* strictly positive offer. But under subgame perfection, offering a strictly positive amount to the responder cannot be part of a Nash equilibrium since the proposer can increase her payoff by undercutting her own offer. A best response of the responder to the proposer's offer of nothing is to accept, since she is indifferent between accepting and rejecting. Therefore we have a unique subgame perfect equilibrium with the first bargainer getting all of the pie for herself.

If the pie is not perfectly divisible, the story is similar. Suppose offers can only be made in units no smaller than a token. We now have two subgame perfect equilibria. One subgame perfect equilibrium is characterized in the previous paragraph. In the other subgame perfect equilibrium, the proposer offers a token to the responder (and keeps the rest for herself) and the responder accepts (again subgame perfection), but would reject a lower offer. As the smallest unit that offers can be made in goes to zero, these two subgame perfect equilibria become identical. Again (almost) all the pie goes to the proposer.

The subgame perfect equilibrium prediction gives all the bargaining power to the proposer. This bargaining power comes from the deletion of weakly dominated strategies of the responder. Let us suppose that the responder has some beliefs about the part of the pie that will be offered to her. She can best respond to these beliefs by only accepting an offer that gives her at least that part of the pie. But this strategy is weakly dominated by any strategy where she accepts a smaller part of the pie. Therefore, she would be no worse off by using a strategy where she accepts anything that is offered to her.

The large body of experimental evidence on ultimatum games shows a very different picture. For excellent surveys of this literature see Binmore et al. (1985), Thaler (1988), Camerer and Thaler (1995), Guth and Tietz (1990), and Roth (1995). Proposers tend to offer positive amounts of money almost always averaging more than 40% of the total which is very far away from the prediction of offers of negligible amounts. Also, responders tend to reject offers less times as the percentage of the pie offered goes up, instead of never rejecting strictly positive offers. Rejecting positive offers is "irrational" when players prefer more money to less, and so the observed frequency of rejections is evidence against the joint hypothesis that players are rational and that they only care about their own payoffs. Given the experimental evidence on rationality (e.g. Crawford (1997)) in related settings, it seems unlikely that these deviations from the subgame perfect equilibrium are due mainly to subjects' failure to understand the game or the incentives the experiment creates. It seems that responders assign payoffs to outcomes that do not simply correspond to their own monetary payoffs. Moreover, proposers seem to know this given that they offer positive amounts of money with very few exceptions.

Changes of the basic design (for example, labeling proposers and responders as sellers and buyers, or having players go through a contest prior to the play of the game to determine proposers and responders) still produce experimental data that do not resemble the subgame perfect equilibrium prediction. In these experiments the distribution of offers and the conditional distribution of acceptances tend to first order stochastically dominate the corresponding distributions from the basic design. Moreover, the value of the pie appears to influence the conditional distribution of rejections in terms of the percentage of the pie only to a very small extent (Hoffman, McCabe, and Smith (1996)).

There are several explanations in the literature for these phenomena. Earlier studies emphasize the special nature of these experiments. For example, in an early study of the ultimatum game, Guth et al. ((1982), p. 384) attributed these phenomena to the fact that "subjects often rely on what they consider a fair or justified result. Furthermore, the ultimatum aspect cannot completely be exploited since subjects do not hesitate to punish if their opponent asks for 'too much'."

Recent studies of the ultimatum games and attempts to reconcile the data from the ultimatum game experiments with standard game theory are numerous. Roth et al. (1991) ran the ultimatum games in four different countries with similar results as those characterized above but they also find that behavior in the ultimatum game is to some extent substantially different in different countries. Bolton (1991) makes the utility functions of bargainers explicitly dependent on a relative comparison of monetary payoffs, i. e. the ratio of monetary payoffs, which has the effect of forcing a more even split of the pie. Rabin (1993) proposes a game-theoretic solution concept, called "fairness equilibrium" by deriving a psychological game (Geanakoplos et al. (1989)) from the game at hand. It incorporates explicitly the notion that players want to sacrifice their own payoff to punish unfair behavior. Rabin (1993) provides a theoretical framework for incorporating fairness into games. Roth and Erev (1995) use simulations of reinforcement learning models to track intermediate term behavior in the ultimatum game experiments starting from random and estimated initial conditions. The simulations show that intermediate term behavior stays away from the subgame perfect equilibrium and is very sensitive to initial conditions. Gale, Binmore, and Samuelson (1995) analyze ultimatum games using replicator dynamics. Their simulations show that if the noise introduced in the replicator dynamics is larger for responders than for proposers then only a small amount of noise is sufficient to lead the dynamics to non-subgame perfect equilibria. The resulting behavior is similar to the behavior observed in the ultimatum game experiments. Levine (1996) examines an altruism model. Using the ultimatum game and centipede game experiments he obtains a distribution of altruism and tries to explain behavior in the earlier rounds of the centipede game and public good experiments. Fudenberg and Levine (1997) compute losses of players from not maximizing the payoffs specified by the experimental design for different experimental games and find that these losses are larger for the ultimatum game experiments than other experimental games like the centipede games and the best shot games. McKelvey and Palfrey (1996) refine equilibria in simplified versions of the ultimatum game using the concept of quantal response equilibrium.

Most of these studies do not provide a detailed statistical analysis of the data or a maximum likelihood estimation of the proposed model. Some of them rely for the most part on simulations with specific parameter values

(Roth and Erev (1995), Gale, Binmore and Samuelson (1995)) or on descriptive statistics (Roth et al. (1991)).

We propose the following payoff uncertainty model based on the one used in the context of the centipede games by Zauner (1996). Each player has a payoff function which represents her Von Neumann-Morgenstern utility for each of the possible outcomes in the game. However, players do not have precise knowledge of the other players' payoff functions. Although players observe their opponents' monetary payoffs, they do not observe the corresponding Von Neumann-Morgenstern utilities. The same is true about the experimenter's knowledge of the utility functions of players. Although in most experiments there is no uncertainty regarding monetary payoffs (which are common knowledge among subjects and experimenter), each player only has exact knowledge of her own utility function but is uncertain about her opponents' utility functions.[1] A possible interpretation is that players face strategic uncertainty about their opponents in the form of, for example, uncertainty about the rationality of players, about strategy choices of opponents, etc. We follow Harsanyi (1973) p. 1 – 2: "Classical game theory assumes that in any game Γ every player has precise knowledge of the payoff function of every other player (as well as of his own). But it is more realistic to assume that — even if each player does have exact knowledge of his own payoff function — he can have at best only somewhat inexact information about the other player's payoff functions ... The payoff function of every player is subject to random disturbances ..., due to small stochastic fluctuations in his subjective and objective conditions (e.g. in his mood, taste, resources, social situation, etc.)."

These random disturbances are modeled as a random perturbation that is added to each player's monetary earnings. After discretizing the ultimatum bargaining game, each player's monetary payoffs are independently perturbed across nodes with normal noise; each player is told her own payoffs in the game, but not the payoffs of the other player. When players play the game, they know their own payoffs but they may be uncertain about the preferences of the other player. We then examine the equilibrium of the perturbed game assuming that either the statistical law governing the responder's perturbations is common knowledge or that the proposer has correct beliefs regarding

[1] Henceforth we will use the terms utility and payoff as having the same meaning, and we will refer to dollar amounts as monetary payoffs or monetary earnings.

the behavior of the responder.

This approach is similar to the one used in Zauner (1996) in the context of the centipede game experiments, with one important difference. The structure of the ultimatum game is different from the structure of the centipede game. In the ultimatum game, each player is called upon to move only once. In the centipede game it is possible for a player to move twice along some paths of play. Therefore the question arises whether the actions of a player at different information sets are coordinated or not. There are therefore different ways to analyze the centipede game. One way is to analyze the game in the usual way where each player is able to coordinate her actions and therefore is able to commit to a whole strategy profile upfront. Given the experimental design (players did not commit to complete strategy profiles), Zauner (1996) applies an "agent" analysis for the centipede games. In an "agent" approach players are not able to coordinate their own behavior at later decision nodes. To implement an "agent" approach, each information set is manned by a different agent. Each agent has the same perturbed payoffs as the player to which this agent belongs. In other words, agents only observe the disturbances corresponding to their current behavior strategy payoffs and not all the disturbances of all payoffs of the player to which this agent belongs. In effect, players are unable to predict their own behavior at later decision nodes. In the ultimatum game this difference between an "agent" approach and the usual approach is immaterial since each player moves only once in the game and therefore both approaches coincide. This means that at the beginning of the game the proposer (responder) observes all the disturbances corresponding to her own payoffs, but not the disturbances corresponding to the responder's (proposer's) payoff.

The noise structure is unbiased in the sense that is has zero mean, thus systematic deviations from the subgame perfect equilibrium are explained by a non-systematic change of the payoffs of the underlying ultimatum game. This is in contrast to the usual incomplete information games (for example Kreps et al. (1982), McKelvey and Palfrey (1992)) where non-Nash behavior is explained by a systematic change in payoffs. For other models that use an unbiased noise structure see McKelvey and Palfrey (1995a), (1995b), (1996).

Using data from the ultimatum experiments in the US by Roth, Prasnikar, Okuno-Fujiwara, and Zamir (1991) we estimate the variance of the payoff uncertainty of players that fits the data best by maximum likelihood techniques. We find that the estimation results are qualitatively similar to

Roth et al.'s results. The estimated probabilities of rejected offers are inversely related to the size of the offer. The estimation results also imply that offers below $2 are very rare, even though in the subgame perfect equilibrium only offers of $0 or $1 would be made.

As noted above, the data from the ultimatum bargaining experiments are in direct conflict with the joint hypothesis that players are rational and only care about their own monetary payoffs. Players frequently choose $0 over strictly positive dollar amounts. In some cases such choices are made 80% of the time. Such rejection rates cannot be explained by a *non-systematic* change in the payoffs since even large noise (with zero mean) can only give random behavior (i. e. rejection rates of at most 50 %).

A model with social considerations provides a better description of the features of the data. We use a social utility model where players' payoffs are a *linear* combination of the player's own and her opponents' monetary earnings augmented by payoff uncertainty. Models where players' payoffs are a *convex* combination of the player's own and her opponents' monetary earnings are usually called altruism models. Such simple models with altruism and/or social utility have appeared in the literature, first in Edgeworth (1881) and more recently in Ledyard (1995), Levine (1996), Anderson et al. (1996), and Camerer (1997). The difference between our model and those used in the bargaining literature is that social utility is added to a random utility model.[2] As in Bolton (1991) and Rabin (1993), the social utility part of our model introduces social considerations in the utility functions. Our concept of social utility is very simple, and easier to implement than the fairness concept proposed by Rabin (1993). Rabin's model uses player's beliefs to derive a psychological equilibrium. Given the experimental design of the ultimatum bargaining experiments, the experimenter does not know the beliefs of players and/or has difficulties to elicit these beliefs. Compared to Bolton (1991), where a more even split increases the utility of players, our model leaves it open a priori whether a more even split of the pie increases or decreases the utility of players. Compared to Levine (1996), our model allows a full maximum likelihood estimation. This is one advantage of introducing full support noise (random utility) into the model.

We use three nested models, estimate the social utility parameter and/or

[2]Anderson et al. (1996) analyze public good games using a model with altruism and a logit error structure.

the variance of the payoff uncertainty for these models, test hypotheses, and show that the estimated probabilities display the characteristics of Roth et al.'s results. We find that both responders and proposers have negative regard for their opponents' monetary earnings, which is in contrast to the usual claim that proposers maximize their expected monetary payoff given responders' behavior or that proposers are altruists since they offer positive amounts of money to the proposers. The level of payoff uncertainty is substantially smaller in the social ultility model than in the payoff uncertainty model.

In the rest of the paper, we start by describing the experiment of Roth et al. (1991), as well as its results. In section 3, we describe the models and show the computation of an equilibrium and the likelihood function. In section 4, we provide the estimation results, and we conclude in section 5.

2 Experimental Data of Roth et al. (1991)

Since the ultimatum game has been tested experimentally several times there exists a reasonable number of data sets that one could use. We decided to use the data of the bargaining experiments of Roth et al. (1991) because of the careful experimental design and also because of the large number of observations contained in the data set. Other data sets of ultimatum bargaining experiments display very similar characteristics than the data set of Roth et al.

In this experiment players were first assigned a role: proposers or responders. Then they played the game in their respective roles for 10 rounds, each time with a different, anonymous, and randomly selected opponent. Subjects were paid according to their monetary payoffs in one randomly selected round. Although different runs were conducted in different countries (Israel, Japan, U.S. and Yugoslavia), we only use the data of the U.S. runs since, as the results of Roth et al. (1991) show, cultural factors play an important role in these experimental data. The experiments run in the U.S. used two different treatments, one with a pie of \$10, and the other with a pie of \$30. We restrict our attention to the treatment with a \$10 pie. The experiment consisted of three sessions (one with 8 players in each role, one with 9, and another one with 10) with this treatment, which produced 270 observations. Since the possible offers by the proposer had to be multiples of 5 cents we have two subgame perfect Nash equilibria which were described in the previous section. Although the experimental setting provided room to observe 201 different offers (corresponding to multiples of 5 cents), most of them were concentrated on integer dollar values (i.e., \$1, \$2, etc.). Of the 270 observations, only 75 were *not* integer dollar values. This characteristic of the data led us to group the observed offers in 11 categories corresponding to integer dollar amounts, a procedure also used by Roth and Erev (1995).[3] Therefore we discretize the ultimatum game and assume in our analysis that offers cannot be made in units smaller than \$1. To be exact, we grouped all the offers between $\$X - \$0.49$ and $\$X + \$0.50$, where $X = 0, 1, \ldots, 10$ and considered them to be offers of $\$X$ (with the obvious change for the largest and smallest possible offer), which leads to the game tree in Figure 1. Table I, Table II and Table III summarize the data of this experiment.[4] Table I gives the observed distribution of offers of the proposer to the responder. Table II gives the observed conditional frequencies (of the responder) of accepting particular offers. Table III displays the frequencies of the endnodes of the discretized version of the game.

In the data there are several things worth mentioning. First, offers are mainly concentrated around \$4 and \$5 which means that the pie is shared approximately equally. As we can see in Table I, we observe offers implied by the subgame perfect equilibrium of the (discretized) game (i. e. offers of \$0 or \$1) in only 0.7% and 1.9% of cases.

Second, Table II shows that the frequency of rejected offers is inversely related to the size of the offer, i. e. low offers are rejected more frequently than high offers, contrary to the prediction of subgame perfection where any strictly positive offer should not be rejected.

Third, Table III shows that the endnodes with the highest frequency are the nodes (Offer \$5, Accept) in 37.41% and (Offer \$4, Accept) in 28.52% of cases. One can observe behavior consistent with subgame perfect equilibrium outcomes of the discretized game (Offer \$0, Accept), (Offer \$1, Accept) in only 0.37% of cases.

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[3] Roth and Erev (1995) only use 9 categories, since they exclude from their analysis offers of \$0 and \$10.

[4] We pooled the data of all 10 rounds.

Table I: Distribution of Offers

Offers	Observations	Frequency (%)
$ 0	2	0.7
$ 1	5	1.9
$ 2	12	4.4
$ 3	24	8.9
$ 4	109	40.4
$ 5	110	40.7
$ 6	5	1.9
$ 7	2	0.7
$ 8	0	0.0
$ 9	0	0.0
$ 10	1	0.4

Table II: Implied (Conditional) "Acceptance" Frequencies

Offers	Acceptances	Rejections	Freq. of Acceptance (%)
$ 0	0	2	0.0
$ 1	1	4	20.0
$ 2	3	9	25.0
$ 3	6	18	25.0
$ 4	77	32	70.6
$ 5	101	9	91.8
$ 6	3	2	60.0
$ 7	2	0	100.0
$ 8	–	–	—
$ 9	–	–	—
$ 10	1	0	100.0

Table III: Frequencies of Endnodes

Offer	Acc./Rej.	Frequency	Rel. Frequency (%)
$ 0	Accept	0	0.0
$ 0	Reject	2	0.74
$ 1	Accept	1	0.37
$ 1	Reject	4	1.48
$ 2	Accept	3	1.11
$ 2	Reject	9	3.33
$ 3	Accept	6	2.22
$ 3	Reject	18	6.67
$ 4	Accept	77	28.52
$ 4	Reject	32	11.85
$ 5	Accept	101	37.41
$ 5	Reject	9	3.33
$ 6	Accept	3	1.11
$ 6	Reject	2	0.74
$ 7	Accept	2	0.74
$ 7	Reject	0	0.00
$ 8	Accept	0	0.00
$ 8	Reject	0	0.00
$ 9	Accept	0	0.00
$ 9	Reject	0	0.00
$ 10	Accept	1	0.37
$ 10	Reject	0	0.00

3 Utility Uncertainty

In this section we look at utility uncertainty alone. Later, we will add social considerations into the utility function and use several nested models to test hypotheses regarding the results of the ultimatum bargaining experiments. First, we discretize the original ultimatum game. Offers can only be made in whole dollars. The strategies for the proposer are therefore to offer $\$X$, $X = 0, 1, 2, \ldots, 10$, to the responder and demand $\$10 - X$ for herself. The responder can accept or reject the offer. If the responder accepts the offer, the proposer receives $\$10 - X$ and the responder $\$X$. If the responder rejects the offer both earn $0.

As outlined above, we now introduce utility uncertainty in the discretized ultimatum game. This approach was already used successfully in Zauner (1996) to analyze the centipede game experiments. To this end, each player i's, $i = p, r$,[5] monetary payoffs are independently perturbed across endnodes k, $k = 1, 2, \ldots, 22$, with additive noise $\epsilon_{(i,k)}$[6]; each player is told her own utilities in the game, but not the utilities of the other player. Then we examine the equilibrium consequent upon assuming that either the statistical law governing the perturbations is common knowledge or that the beliefs of the proposer about the behavior of the responder are correct. When the players play the game, they know their own utilities but they may be uncertain about the preferences of the other player.

We sketch the computation of an equilibrium for the discretized and perturbed game. We assume throughout the paper that the random variables $\epsilon_{(i,k)}$ are distributed according to normal distributions with mean zero and variance σ^2 and that they are independent across nodes and across players. The game tree of the perturbed game is given in Figure 2. Zauner (1993) proves the existence of equilibrium in such incomplete information games in extensive form.

First, we compute the acceptance and rejection probabilities for the responder. If the proposer offers $0 to the responder, we can compute the acceptance probability, which is the probability that the perturbed utility for accepting the offer is greater than the perturbed utility for rejecting the offer, as $Pr\{0 + \epsilon_{(r,1)} > 0 + \epsilon_{(r,2)}\} = 1/2$. Similarly, if the proposer

[5]The letters p, r stand for proposer and for responder, respectively.

[6]We count endnodes from top to bottom in Figure 1

offers \$1 to the responder, we can compute the acceptance probability as $Pr\{1+\epsilon_{(r,3)} > 0+\epsilon_{(r,4)}\}$. Similar computations apply to all the other acceptance probabilities of the responder.

After the computation of the acceptance probabilities, q_X, i. e. accepting an offer of $\$X$, $(X = 0, 1, \ldots, 10)$, we can compute the probabilities of offering $\$X$. Offering $\$X$ to the responder[7] leads to a (random) utility for the proposer that has a normal distribution with mean $(10 - X)q_X$ and variance $[q_X^2 + (1-q_X)^2]\sigma^2$. We denote the normally distributed random variable corresponding to an offer of $\$X$ to the responder by $N_{(10-X)}$, the corresponding distribution function by $F_{(10-X)}$, and the corresponding density function by $f_{(10-X)}$. Therefore, the probability of offering, for example, \$0, p_{10}, is given by

$$Pr\{N_{10} > \max\{N_9, N_8, \ldots, N_0\}\} = \int_{-\infty}^{\infty} F_9(x)F_8(x)\cdots F_0(x)f_{10}(x)dx. \quad (1)$$

Similar expressions can be derived for the other offers. This approach gives an equilibrium in the perturbed game.

From the acceptance probabilities and the probabilities of offers it is possible to compute the probability

$$s(\sigma^2) = (s_1(\sigma^2), \ldots, s_{22}(\sigma^2))$$

of observing each of the possible outcomes, (offer \$0, accept), (offer \$0, reject), (offer \$1, accept), (offer \$1, reject), ... The entries in the vector

$$s(\sigma^2) = (s_1(\sigma^2), \ldots, s_{22}(\sigma^2))$$

are the expected frequencies of the different endnodes. Therefore, $s_1(\sigma^2) = p_{10}(\sigma^2)q_0(\sigma^2)$, $s_2(\sigma^2) = p_{10}(\sigma^2)(1-q_0(\sigma^2))$, etc. is the likelihood of observing a particular vector $n = (n_1, \ldots, n_{22})$ of outcomes given (σ^2). The likelihood function is thus given by

$$\mathcal{L}(\sigma^2) = \prod_{k=1}^{22}(s_k(\sigma^2))^{n_k}, \quad (2)$$

[7]The probability of offering $\$X$ is denoted by $p_{(10-X)}$.

Table IV: Payoff Uncertainty: Estimated Distribution of Offers

Offer	Prob. of Offer	Data	Model
$ 0	p10	0.007	0.0986
$ 1	p9	0.019	0.1474
$ 2	p8	0.044	0.1801
$ 3	p7	0.089	0.1801
$ 4	p6	0.404	0.1609
$ 5	p5	0.407	0.1086
$ 6	p4	0.019	0.0681
$ 7	p3	0.007	0.0374
$ 8	p2	0.000	0.0181
$ 9	p1	0.000	0.0077
$ 10	p0	0.004	0.0029

and the log-likelihood function by

$$L(\sigma^2) = \sum_{k=1}^{22} n_k \ln s_k(\sigma^2). \tag{3}$$

Standard maximum likelihood methods can now be used to estimate the the variance (σ^2) of the model that fits the data best.

The estimation gives the following results. The log-likelihood is maximized at $\hat{\sigma}^2 = 7.12036$ with a maximized value of the log-likelihood of -710.0250. Table IV shows the estimated distribution of offers. The offers are mostly concentrated between $0 and $5. The offers drop off sharply for offers over $6. The offers with the highest estimated frequency are offers of $2, $3, and $4 dollars. The offers implied by the subgame perfect equilibrium(a) receive relatively small mass. These estimation results roughly resemble the data of the experiments. Figure 3 shows the estimated distribution of offers and the empirical frequency of offers.

Table V displays the estimated conditional probabilities of acceptance. The estimated acceptance rates increase with the size of offers. In other words, estimated rejection rates are inversely related to the size of the offer. The estimated acceptance rates show that low offers are more frequently

Table V: Payoff Uncertainty: Estimated Conditional "Acceptance" Probabilities

Offer	Prob. of Acceptance	Data	Model
\$ 0	q0	0.000	0.5000
\$ 1	q1	0.200	0.6045
\$ 2	q2	0.250	0.7019
\$ 3	q3	0.250	0.7867
\$ 4	q4	0.706	0.8554
\$ 5	q5	0.918	0.9074
\$ 6	q6	0.600	0.9441
\$ 7	q7	1.000	0.9682
\$ 8	q8	—	0.9830
\$ 9	q9	—	0.9915
\$ 10	q10	1.000	0.9960

rejected than high offers. Subgame perfection on the other hand implies that any positive offer should be accepted. The estimated probabilities again have the qualitative features of the data. However, the estimated acceptance rates start off much higher than the corresponding acceptance rates of the data. This is no surprise. If the proposer offers \$0, then the responder is indifferent between accepting and rejecting and since the perturbations for accepting and rejecting are the same this implies a fifty-fifty split between accepting and rejecting. For higher offers (i. e. offers of \$1, \$2, ...) the acceptance rate has to be higher than 50% given that we use symmetric distributions concentrated around the unperturbed payoffs of each endnode of the ultimatum game. Figure 4 shows the estimated probabilities of acceptance and the empirical frequencies of acceptance.

Table VI displays the estimated frequencies of the endnodes of the ultimatum game. The estimated probabilities roughly display the features of the data. The estimated probabilities of endnodes that correspond to accepted offers increase (offers of \$0 to \$3) and then fall (offers of \$4 to \$10). The estimated probabilities of endnodes that correspond to rejected offers display a similar behavior. The outcomes that correspond to the subgame perfect equilibria receive only little mass [0.0493 vs. 0.000 (data) for (offer

\$0, accept) and 0.0891 vs. 0.0037 (data) for (offer \$1, accept)].

This random utility model which explains the deviations from the subgame perfect equilibria by a *non-systematic* change of the payoff of players does reasonably well since it reproduces the patterns found in the data. Figure 5 (Figure 6) displays the estimated probabilities of endnodes corresponding to acceptances (rejections) and the empirical frequencies of endnodes.

A major reason why the fit of this model is not better is the underestimation of the rejection probabilites of the responder. The responder that rejects an offer of, for example, \$1 values a monetary payoff of \$0 more than \$1. In our model this translates to the player putting a higher value on ($\$0 + \epsilon$) than on ($\$1 + \epsilon$). Since we add the same unbiased noise (i.e. the noise has expected value zero) to the payoffs corresponding to acceptance and rejection of an offer, no offer can have a higher rejection rate than 50%. Note that the rejection rates (implied by the data) for low offers are 100%, 80%, and 75%. In the next section we will change players' utility function by adding social considerations to the utility.

4 Social Utility

We now introduce social utility into the previous model. We use a model where a player's utility is a linear combination of the player's own and her opponent's monetary earnings augmented by utility uncertainty. We call the fraction of the opponent's monetary payoff that is added or subtracted to a player's monetary payoff, the social utility parameter (cf. Camerer (1997)).

In order to incorporate social utility into the model above, we assume that the (modified) utility of each bargainer is a linear combination of the monetary payoff of the proposer u_p and the monetary payoff of the responder u_r. The (modified) payoff v_i of player i is therefore

$$v_i = u_i + au_j \ , \tag{4}$$

where $a \in \Re$ and $i \neq j$. The social utility parameter a can be interpreted as follows: $a = 0$ corresponds to a selfish player, $a > 0$ corresponds to an altruistic player and $a < 0$ corresponds to a player who has negative regard for her opponent's monetary payoff.[8]

[8]This specification of the utility function is similar to the specification in Levine (1996).

Table VI: Payoff Uncertainty: Estimated Frequencies of Endnodes

Offer	Acc./Rej.	Data	Model
$ 0	Accept	0.0000	0.0493
$ 0	Reject	0.0074	0.0493
$ 1	Accept	0.0037	0.0891
$ 1	Reject	0.0148	0.0583
$ 2	Accept	0.0111	0.1265
$ 2	Reject	0.0333	0.0537
$ 3	Accept	0.0222	0.1417
$ 3	Reject	0.0667	0.0384
$ 4	Accept	0.2852	0.1291
$ 4	Reject	0.1185	0.0218
$ 5	Accept	0.3741	0.0985
$ 5	Reject	0.0333	0.0101
$ 6	Accept	0.0111	0.0642
$ 6	Reject	0.0074	0.0038
$ 7	Accept	0.0074	0.0362
$ 7	Reject	0.0000	0.0012
$ 8	Accept	0.0000	0.0178
$ 8	Reject	0.0000	0.0003
$ 9	Accept	0.0000	0.0077
$ 9	Reject	0.0000	0.0001
$ 10	Accept	0.0037	0.0029
$ 10	Reject	0.0000	0.0000

First, we assume that there is a common parameter value a for all members in the subject pool. This assumption is reasonable if we believe that the social utility parameter does not vary within the population and that it does not depend on the role a player (proposer or responder) plays. We estimate its value for the population from the data of the experiment. Second, we investigate whether the value of the social utility parameter depends on the role players are assigned to. We denote the social utility parameter of the proposer (responder) by a_p (a_r).

We take the discretized ultimatum bargaining game with the modified payoffs according to equation (4) and perturb each player's modified payoff with independent normal noise across endnodes and across players. The modified and perturbed payoff of player i at endnode k is given by

$$v_{(i,k)} = u_{(i,k)} + au_{(j,k)} + \epsilon_{(i,k)} \ , \tag{5}$$

where $\epsilon_{(i,k)}$ are independent normal random variables with mean 0 and variance σ^2.

If we perturb all payoffs of the discretized ultimatum game by adding independent normal noise to each player's monetary earnings at each endnode and then take a linear combination of the player's own and her opponent's *perturbed* payoffs at that endnode as in equation (4), the resulting perturbed and modified utility of player i at endnode k is

$$v_{(i,k)} = u_{(i,k)} + \epsilon_{(i,k)} + a\big(u_{(j,k)} + \epsilon_{(j,k)}\big) \ , \tag{6}$$

where $\epsilon_{(\cdot,k)}$ are independent normal random variables with mean 0 and variance σ_1^2. This expression can be rewritten as

$$v_{(i,k)} = u_{(i,k)} + au_{(j,k)} + \eta_{(i,k)} \ , \tag{7}$$

where $\eta_{(i,k)}$ are independent normal random variables with mean 0 and variance $\sigma_1^2(1 + a^2)$. The specifications in equations (5) and (7) are equivalent since we can derive σ_1^2 in equation (7) from σ^2 in equation (5), and vice versa. Thus, if we perturb the modified payoffs or perturb the monetary payoffs and then modify the perturbed payoffs, we will obtain the same model, as long as the utility perturbations enter in an additive way.

The computation of the equilibrium for this model and the derivation of the likelihood functions is similar to the outline above (with extra parameters

a or a_p and a_r). We assume that either there is common knowledge about the responder's social utility and variance parameter as well as the statistical law governing the responder's utility perturbations or that the proposer has correct beliefs about the behavior of the responder. We estimate the variance σ^2 and the value of the social utility parameter a for the first model and then the variance σ^2 and the social utility parameters a_p and a_r for the second model.[9]

Table VII, Table VIII, Table IX, and Table X give the estimation results for the model of the last section, the social utility models, and the restricted model. Table VII displays the estimated parameter values and the maximized log-likelihood values of the payoff uncertainty model (column 2), the model with a common social utility parameter (column 3), the model where the social utility parameter value is allowed to differ between proposers and responders (column 4), and the restricted model (column 5).

The estimated value of the social utility parameter a is -0.542 (column 3 of Table VII). We can now test wether the social utility parameter is significantly different from zero. We can reject the null hypothesis that a is equal to 0 (i.e. that subjects are selfish), since twice the difference of the maximized values of the log-likelihood functions between the common social utility (column 3 of Table VII) and the payoff uncertainty model (column 2 of Table VII) which is distributed according to a chi-square with 1 degree of freedom, is 375.014, giving a p-value of less than 1.5×10^{-83}. Subjects have therefore negative regard for their opponents' monetary earnings. The estimated value of σ^2 is 1.58256 and is lower than in the payoff uncertainty model. Figure 7 shows the estimated and empirical distribution of offers of the common social utility model. Figure 8 displays the estimated and empirical distribution of acceptances and Figure 9 (Figure 10) shows the estimated and empirical distribution of endnodes that correspond to acceptances (rejections).

By comparing the estimated distribution of offers to the empirical distribution (Table VIII or Figure 7) we can see that the common social utility model fits the data well. The empirical frequency of the offers increases from an offer of \$0 to an offer of \$5 and then falls sharply. Similarly, the estimated

[9]We do not provide the estimation results for the model where, in addition, the variance varies between proposers, σ_p, and responders, σ_r, since, as will be evident from the estimation results below, the results are mainly driven by the social utility parameter.

Table VII: Payoff Uncertainty and Social Utility Models: Estimation Results

Model	Uncertainty	Common SU	Differing SU	Restricted
Log-Likeli. (L)	-710.0250	-522.5181	-516.6061	-557.9424
Var. $\hat{\sigma}^2$	7.12036	1.58256	1.72397	2.5664
SU—Prop. ($\hat{a}_p$)	—	-0.542	-0.441	0.0
SU—Resp. ($\hat{a}_r$)	—	-0.542	-0.538	-0.336

Table VIII: Social Utility Models: Estimated Distribution of Offers

Offer	Prob. of Offer	Data	Common SU	Differing SU	Restricted
\$ 0	p10	0.007	0.0156	0.0109	0.0011
\$ 1	p9	0.019	0.0183	0.0131	0.0035
\$ 2	p8	0.044	0.0353	0.0271	0.0237
\$ 3	p7	0.089	0.1504	0.1233	0.1516
\$ 4	p6	0.404	0.4529	0.4187	0.3195
\$ 5	p5	0.407	0.2735	0.3150	0.2794
\$ 6	p4	0.019	0.0507	0.0824	0.1473
\$ 7	p3	0.007	0.0032	0.0090	0.0548
\$ 8	p2	0.000	0.0001	0.0004	0.0153
\$ 9	p1	0.000	0.0000	0.0000	0.0032
\$ 10	p0	0.004	0.0000	0.0000	0.0005

probabilities of offers increase up to an offer of \$4 and then decline. The common social utility model underestimates offers of \$5 and overestimates offers of \$4. But the estimated probabilities mirror the sharp drop-off of offers of over \$6. Overall, the social utility model gets the main characteristics of the empirical distribution of the offers right, although underestimating offers of \$5.

A comparison between the empirical acceptance rates and the estimated acceptance rates (Table IX or Figure 8) reveals that the common social utility model exhibits the qualitative features of the data. The estimated probabilities of acceptance increase up to offers of \$8 as do the data.[10] Offers over \$6 are (essentially) accepted. The acceptance rates for smaller offers are underestimated. The social utility model fits the empirical distribution over endnodes well, as Table X, Figure 9, and Figure 10 show.

Most of the literature appears to agree that while the behavior of responders provides evidence against standard (rational) decision theory, proposers seem to be maximizing their expected monetary payoffs given the behavior of responders (see Roth et al. (1991) and Camerer and Thaler (1995)).[11] We will provide some evidence that even the behavior of proposers cannot be reduced to maximization of the proposers' own monetary income given the rejection rates of responders.

Since our estimates suggest that on the aggregate proposers and responders have negative regard for their opponents' monetary earnings we estimate the value of the social utility parameter separately for proposers (a_p) and responders (a_r). The estimation results of this model, the differing social utility model, are given in Table VII, column 4. We can reject the null hypothesis that a_p is equal to a_r, i. e. that proposers and responders have the same value of the social utility parameter, since twice the difference of the maximized values of the log-likelihood functions between the differing social utility (column 4 of Table VII) and the common social utility model (column 3 of Table VII), which is distributed according to a chi-square with 1 degree of freedom, is 11.824 and the corresponding p-value is less than 6×10^{-4}. Proposers appear to have less negative regard for their opponents' monetary earnings than responders.

We can test whether proposers make their decision based on the objective of maximizing their expected monetary payoffs or not. We impose the restriction that the proposers are selfish ($a_p = 0$) on this model and re-estimate it. The estimation result is shown in Table VII, last column (Restricted). We can reject the null hypothesis that $a_p = 0$, i. e. that proposers are selfish, since twice the difference of the maximized log-likelihood values (distributed

[10]Offers of \$6 are the exception.

[11]Roth et al. (1991) note that the modal offer in the last round seems to equal the value that would maximize proposers' expected monetary payoffs, where this is estimated from the empirical conditional distribution of rejections of all 10 rounds, thereby assuming stationarity in responders' behavior. This does not provide a full description of all offers of proposers in the last round, nor of all offers made during the 10 rounds.

Table IX: Social Utility Models: Estimated Conditional "Acceptance" Probabilities

Offer	Prob. of Accept.	Data	Common SU	Differing SU	Restricted
$ 0	q0	0.000	0.0012	0.0019	0.0690
$ 1	ql	0.200	0.0146	0.0193	0.1858
$ 2	q2	0.250	0.0946	0.1073	0.3807
$ 3	q3	0.250	0.3277	0.3340	0.6126
$ 4	q4	0.706	0.6629	0.6612	0.8094
$ 5	q5	0.918	0.9010	0.8933	0.9286
$ 6	q6	0.600	0.9844	0.9809	0.9800
$ 7	q7	1.000	0.9987	0.9981	0.9959
$ 8	q8	—	0.9999	0.9999	0.9994
$ 9	q9	—	1.0000	1.0000	1.0000
$ 10	q10	1.000	1.0000	1.0000	1.0000

as a chi-square with 1 degree of freedom) is 82.673, which has a corresponding p-value of less than 10^{-19}.

The differing social utility model reproduces the characteristics of the data as does the common social utility model. In addition, it predicts that the endnode (Offer $5, Accept) has the highest frequency. We summarize the estimation results of the model with differing social utility for proposers and responders in several figures. Figures 11 - 14 display the estimated and empirical distributions of offers, acceptances, endnodes corresponding to acceptances, and endnodes corresponding to rejections, respectively.

5 Conclusions

We use three nested models to test hypotheses regarding the results of the ultimatum bargaining experiment of Roth et al. (1991). The simplest model is a model à la Harsanyi (1973), in which players are uncertain about the utilities of their opponents. In this model the payoffs of each player are perturbed randomly in a *non-systematic* fashion. The estimation results show

Table X: Social Utility: Estimated Frequencies of Endnodes

Offer	Acc./Rej.	Data	Common SU	Differing SU	Restricted
$ 0	Accept	0.0000	0.0000	0.0000	0.0001
$ 0	Reject	0.0074	0.0156	0.0109	0.0010
$ 1	Accept	0.0037	0.0003	0.0003	0.0007
$ 1	Reject	0.0148	0.0180	0.0129	0.0029
$ 2	Accept	0.0111	0.0033	0.0029	0.0090
$ 2	Reject	0.0333	0.0320	0.0242	0.0147
$ 3	Accept	0.0222	0.0493	0.0419	0.0928
$ 3	Reject	0.0667	0.1011	0.0814	0.0587
$ 4	Accept	0.2852	0.3003	0.2769	0.2586
$ 4	Reject	0.1185	0.1527	0.1419	0.0609
$ 5	Accept	0.3741	0.2464	0.2814	0.2595
$ 5	Reject	0.0333	0.0271	0.0336	0.0200
$ 6	Accept	0.0111	0.0499	0.0808	0.1444
$ 6	Reject	0.0074	0.0008	0.0016	0.0029
$ 7	Accept	0.0074	0.0032	0.0090	0.0546
$ 7	Reject	0.0000	0.0000	0.0000	0.0002
$ 8	Accept	0.0000	0.0001	0.0004	0.0153
$ 8	Reject	0.0000	0.0000	0.0000	0.0000
$ 9	Accept	0.0000	0.0000	0.0000	0.0000
$ 9	Reject	0.0000	0.0000	0.0000	0.0000
$ 10	Accept	0.0037	0.0000	0.0000	0.0000
$ 10	Reject	0.0000	0.0000	0.0000	0.0000

that this model can explain the qualitative features of the data of the ultimatum bargaining experiment but it is unable to predict the high rejection rates (of up to 80%) of the data. Rejections are equivalent to subjects choosing $0 over strictly positive dollar amounts. Even extremely high (unbiased) uncertainty about opponent's preferences can only lead to rejection rates of at most 50 %. We therefore amend the model with social considerations and introduce a measure of social utility into each player's utility function (Edgeworth (1881)). We look at a model where the opponent's monetary payoff enters each player's utility. We find, on the aggregate, a significant amount of "negative social utility" or negative regard for the opponent's payoff in these experiments. Finally, we provide evidence that both responders and proposers have negative regard for their opponents' monetary earnings. This is therefore evidence against the view that proposers are either altruists, since they offer considerable amounts of money, or selfish, which they would be if they made offers that maximized their expected monetary earnings given the rejection rates of responders.

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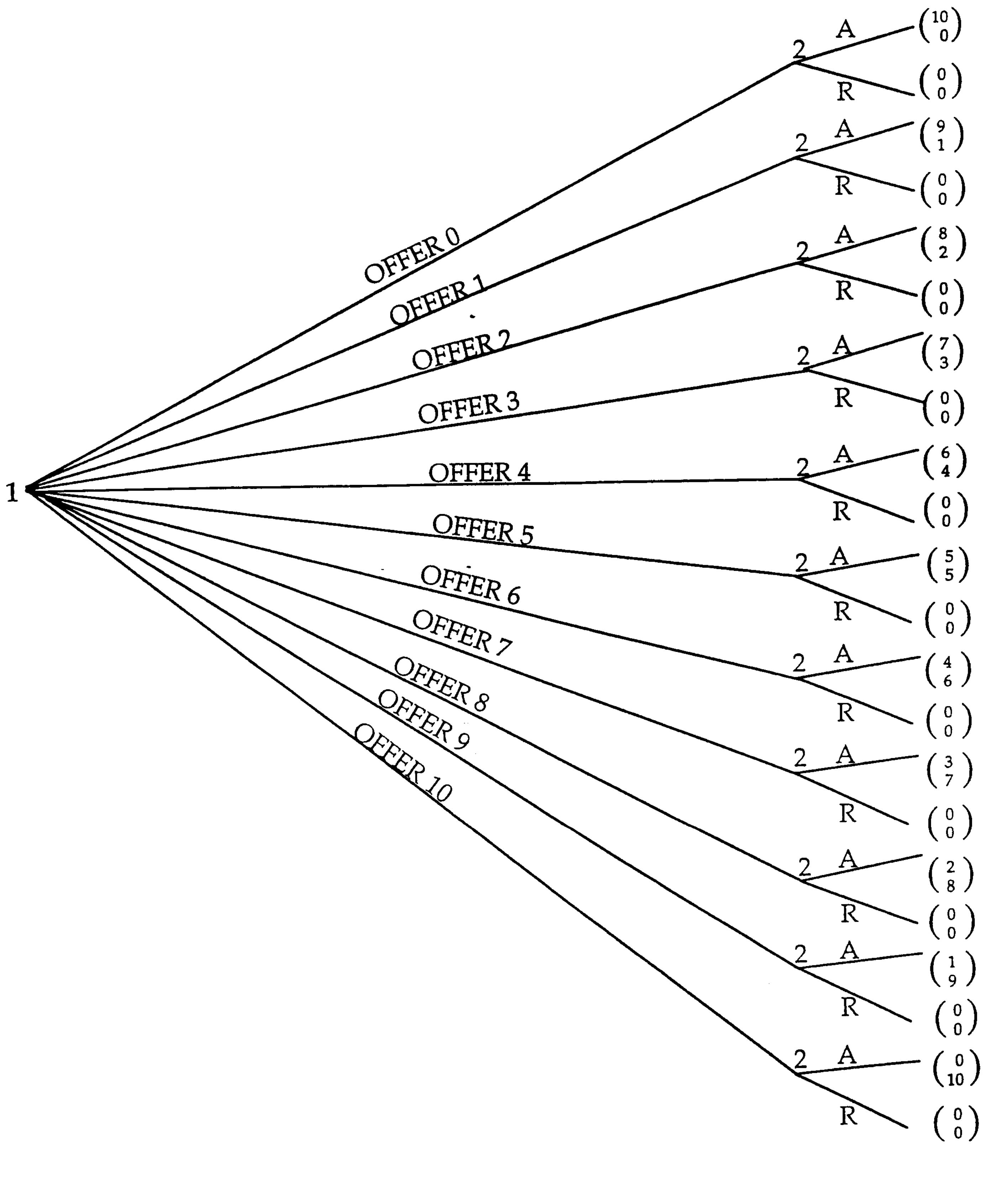

Figure 1: Game Tree of the Discretized Ultimatum Game

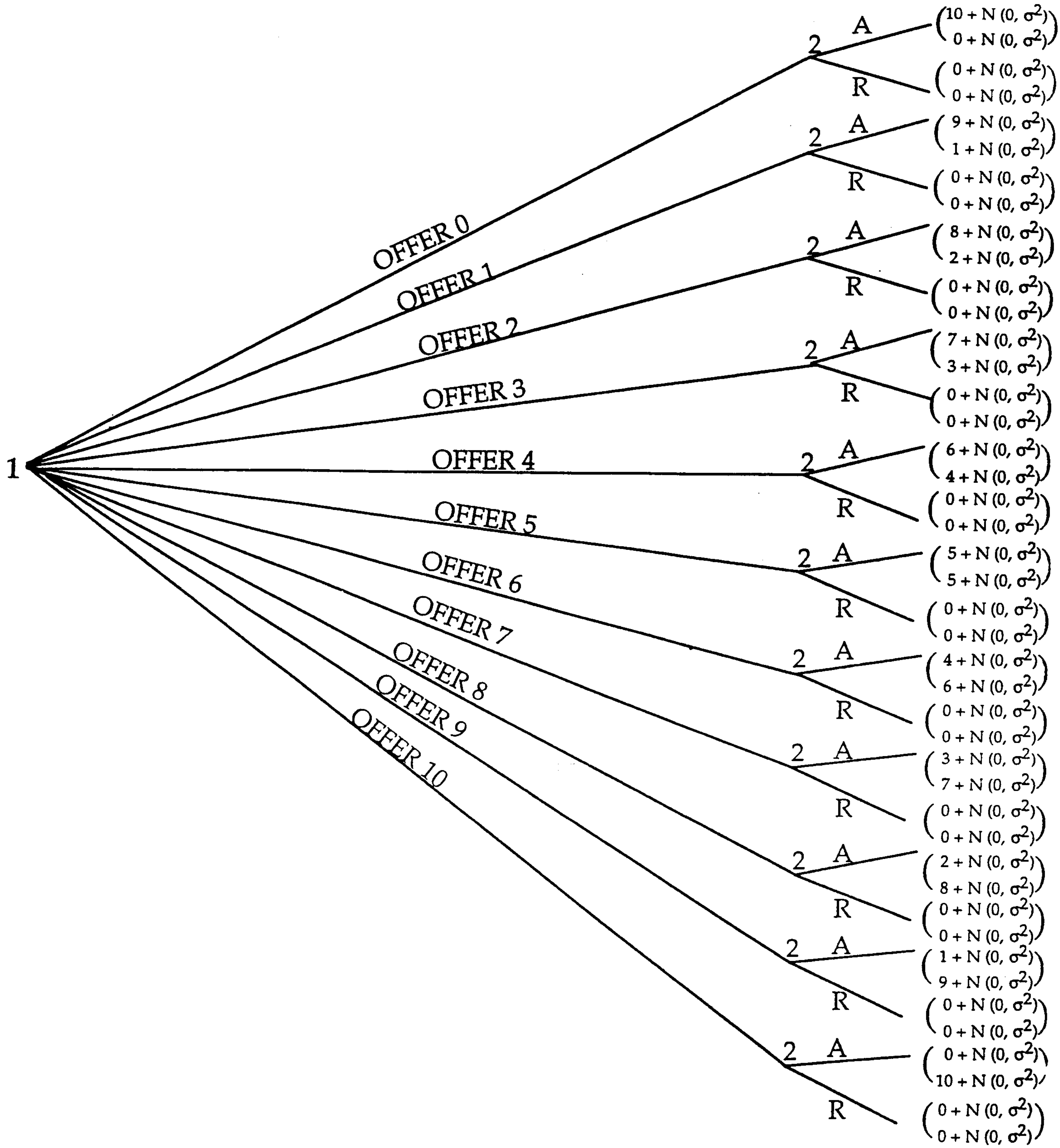

Figure 2: Game Tree of the Perturbed Ultimatum Game

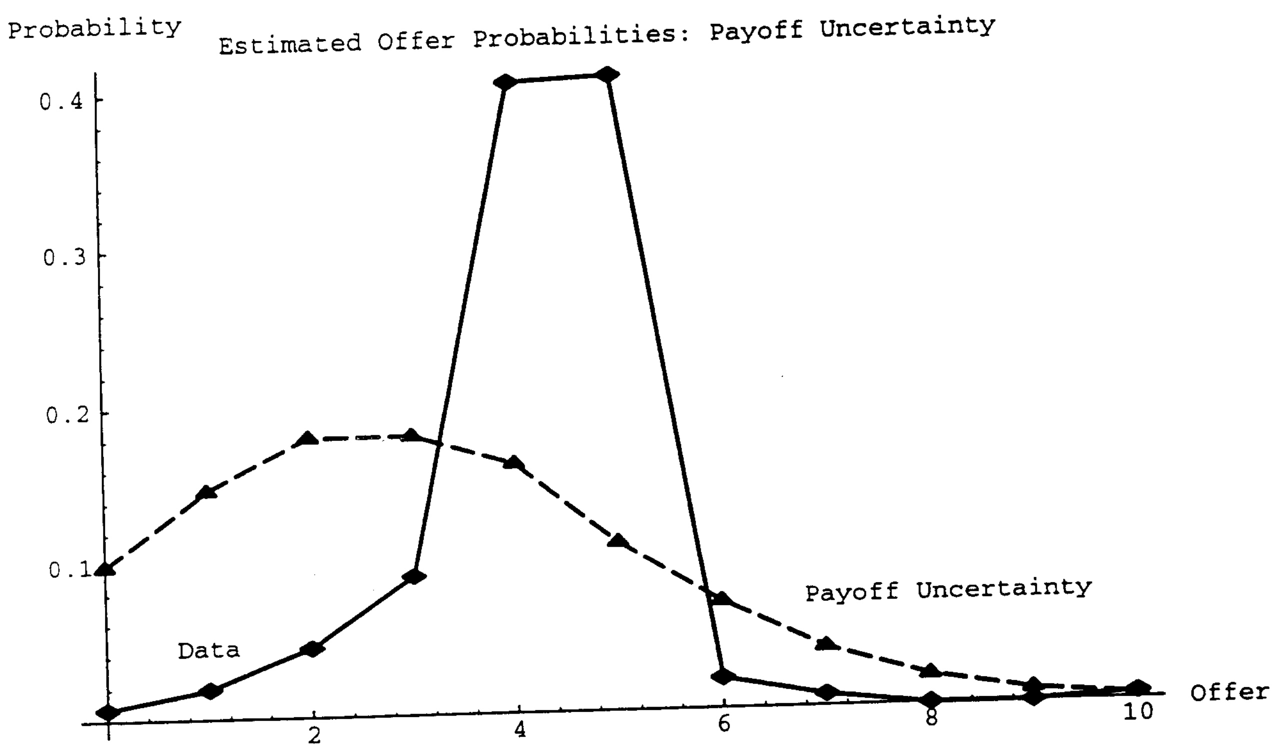

Figure 3: Estimated Probabilities and Empirical Frequencies of Offers:
Payoff Uncertainty

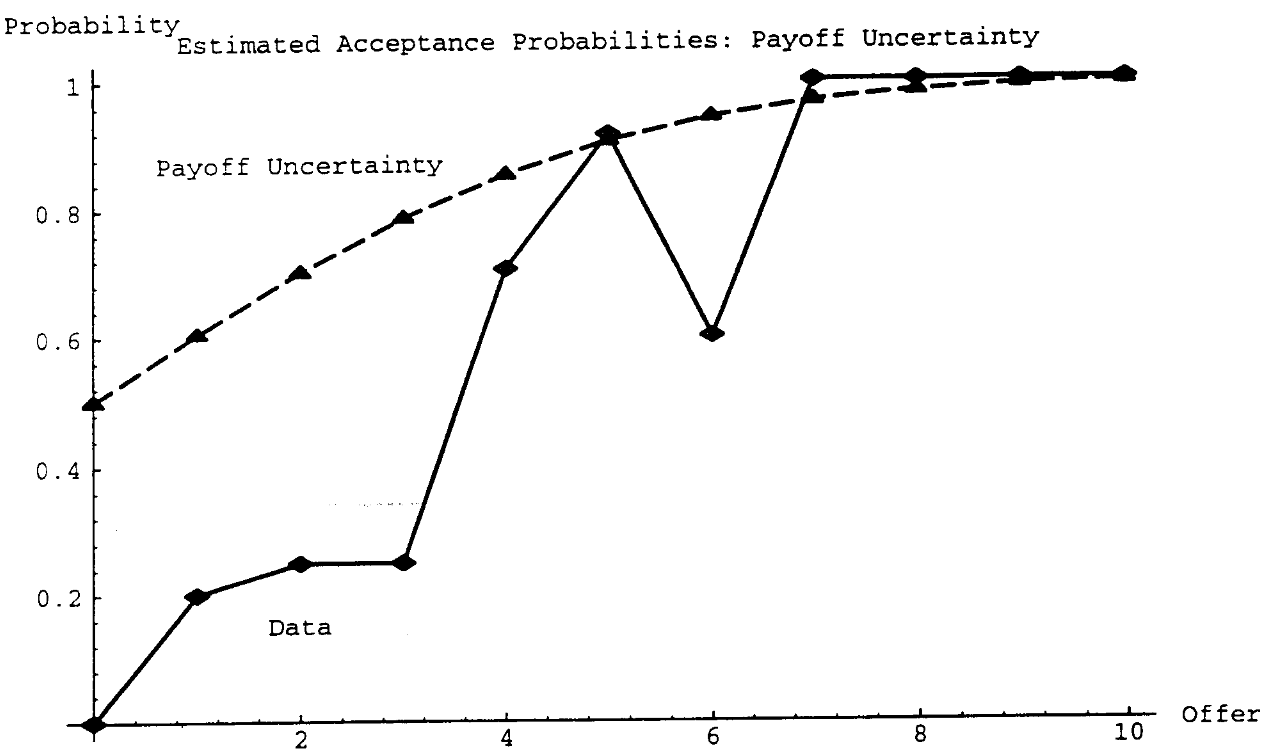

Figure 4: Estimated Probabilities and Empirical Frequencies of Acceptance: Payoff Uncertainty

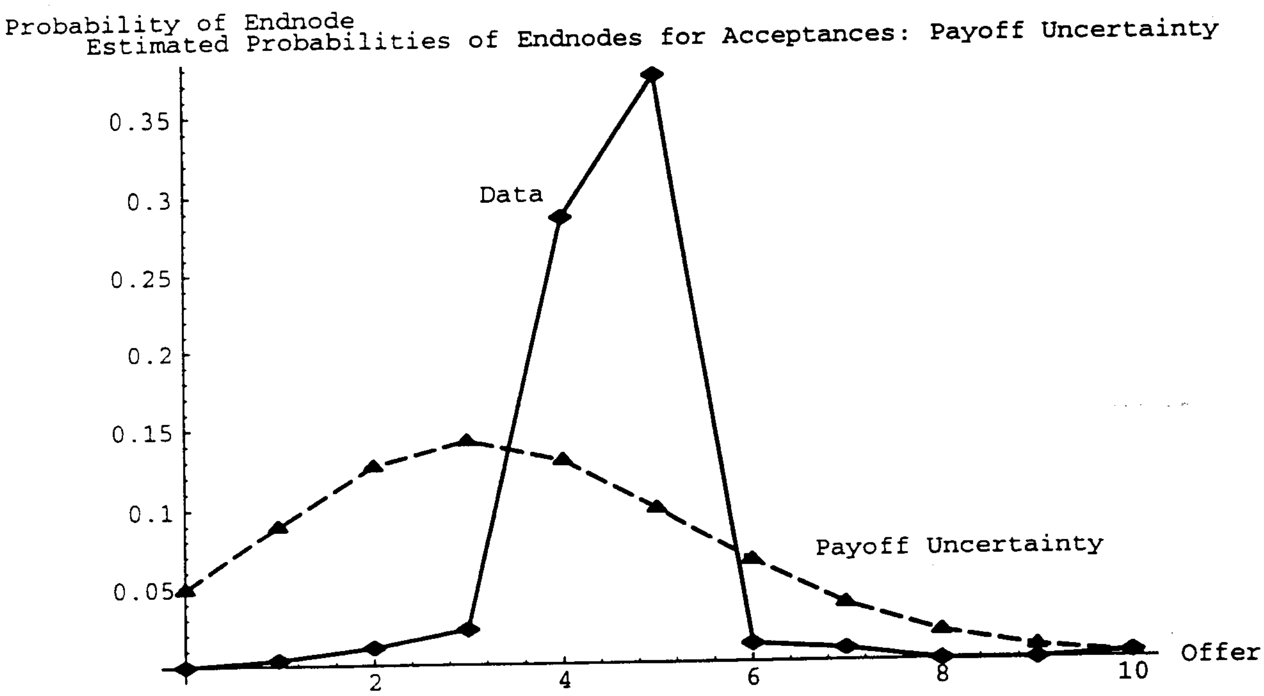

Figure 5: Estimated Probabilities and Empirical Frequencies of Endnodes (Acceptance): Payoff Uncertainty

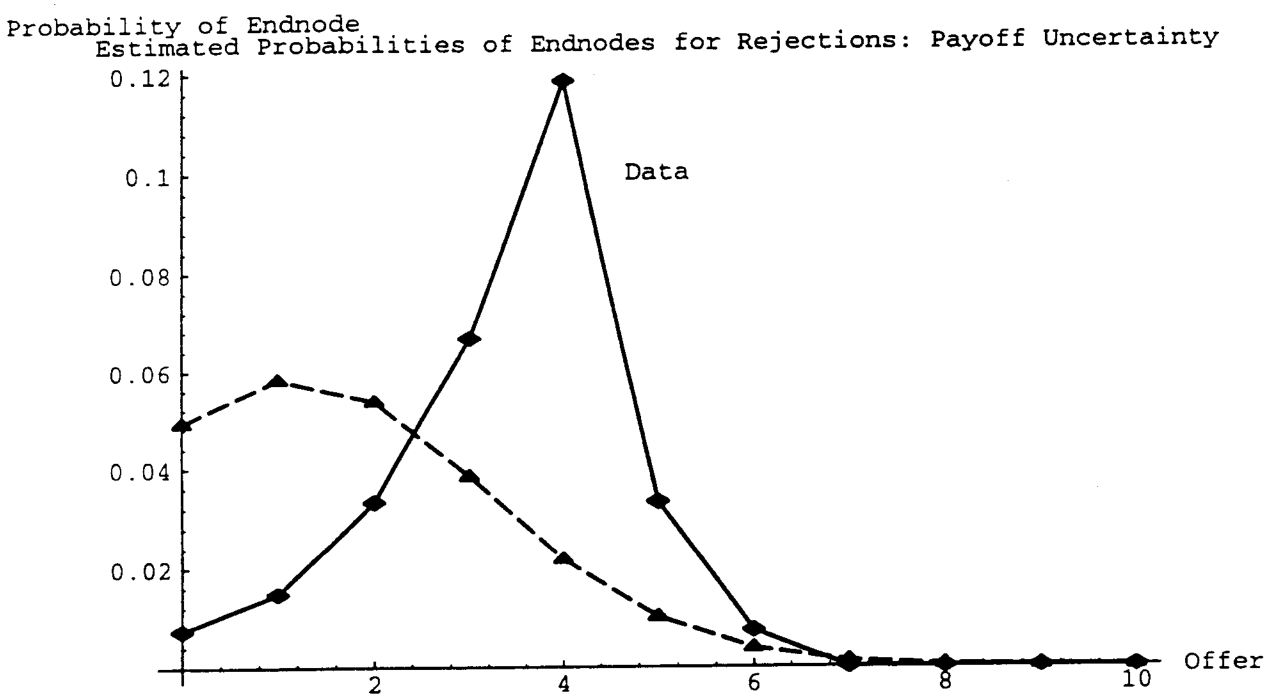

Figure 6: Estimated Probabilities and Empirical Frequencies of Endnodes (Rejections): Payoff Uncertainty

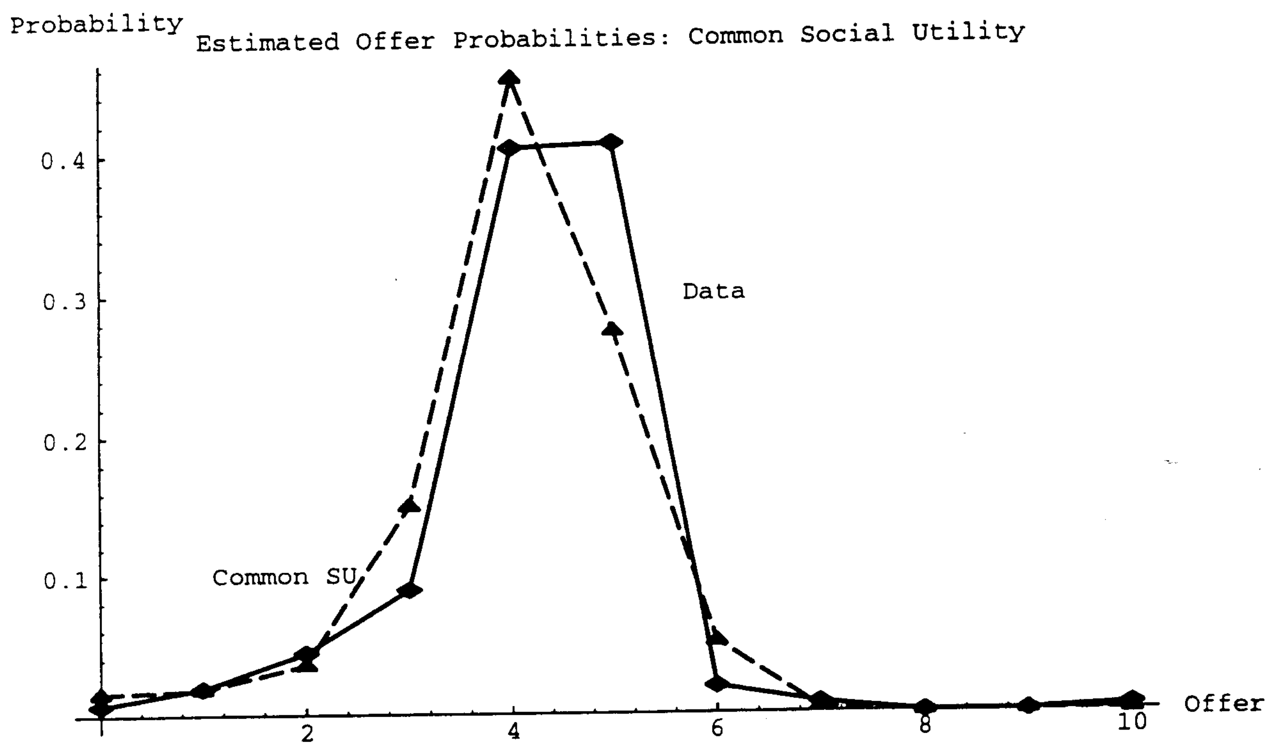

Figure 7: Estimated Probabilities and Empirical Frequencies of Offers: Common Social Utility

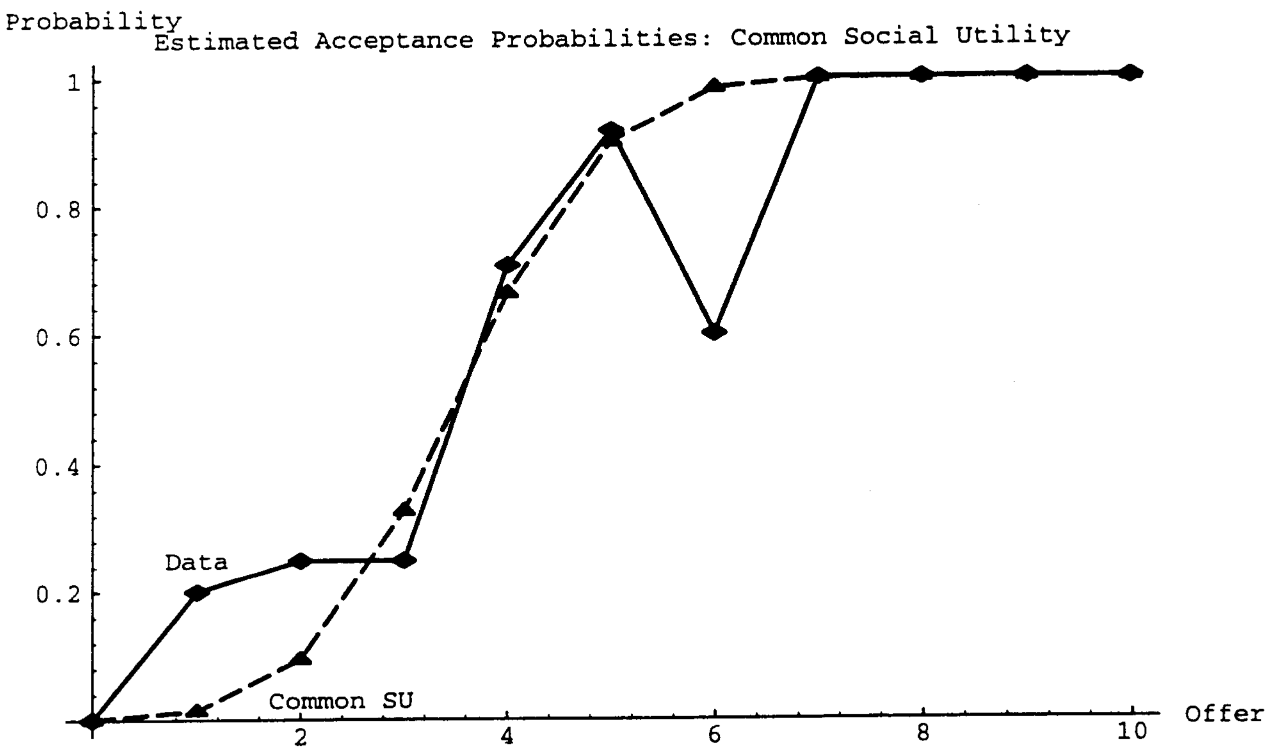

Figure 8: Estimated Probabilities and Empirical Frequencies of Acceptance:
Common Social Utility

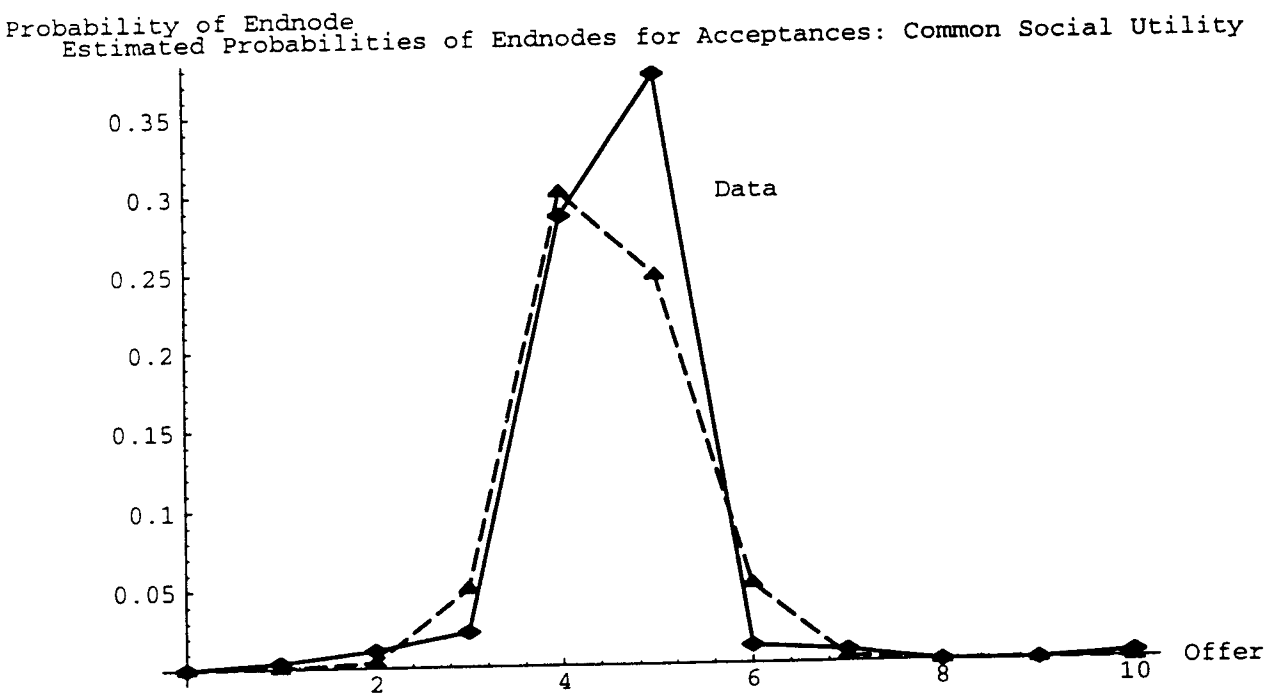

Figure 9: Estimated Probabilities and Empirical Frequencies of Endnodes (Acceptance): Common Social Utility

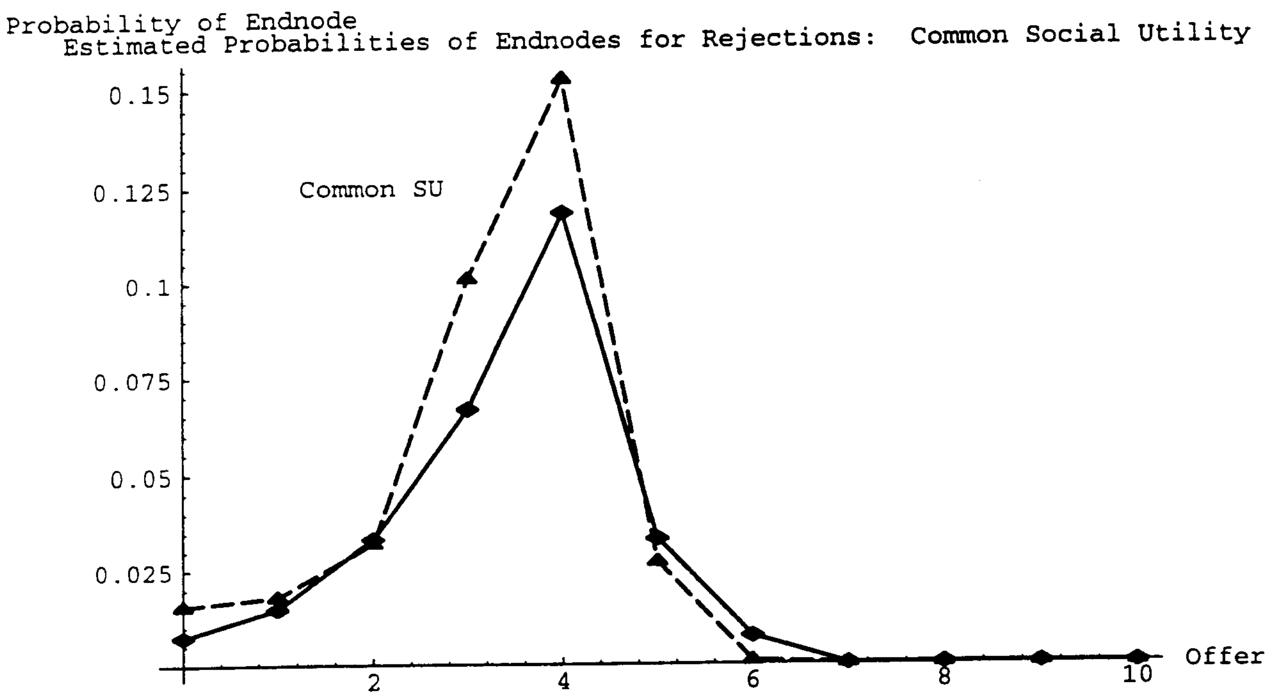

Figure 10: Estimated Probabilities and Empirical Frequencies of Endnodes (Rejections): Common Social Utility

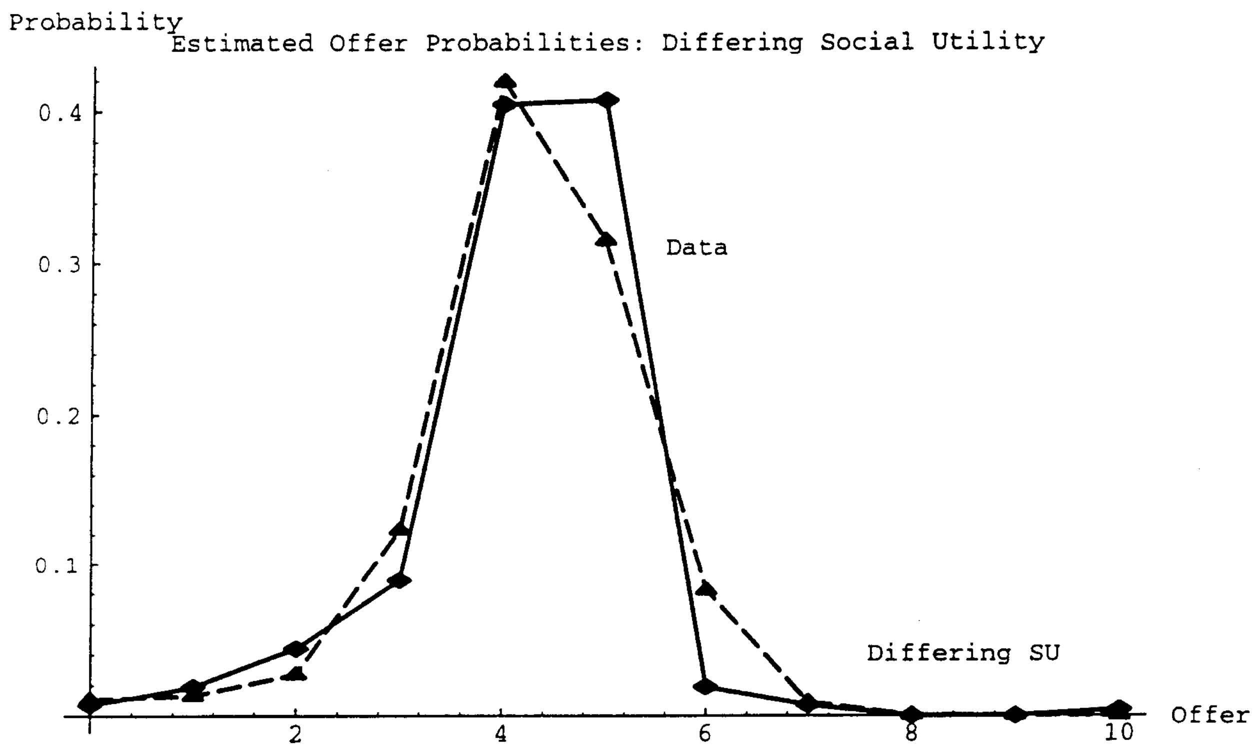

Figure 11: Estimated Probabilities and Empirical Frequencies of Offers: Differing Social Utility

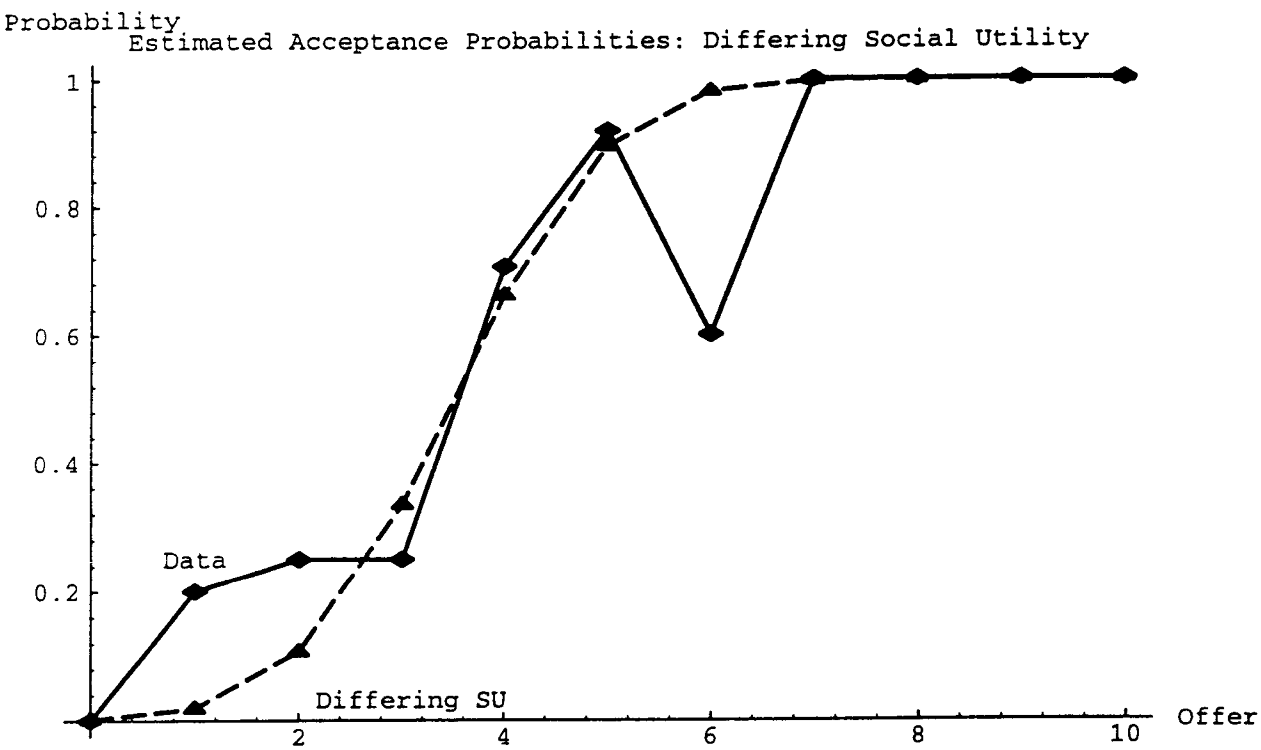

Figure 12: Estimated Probabilities and Empirical Frequencies of Acceptance: Differing Social Utility

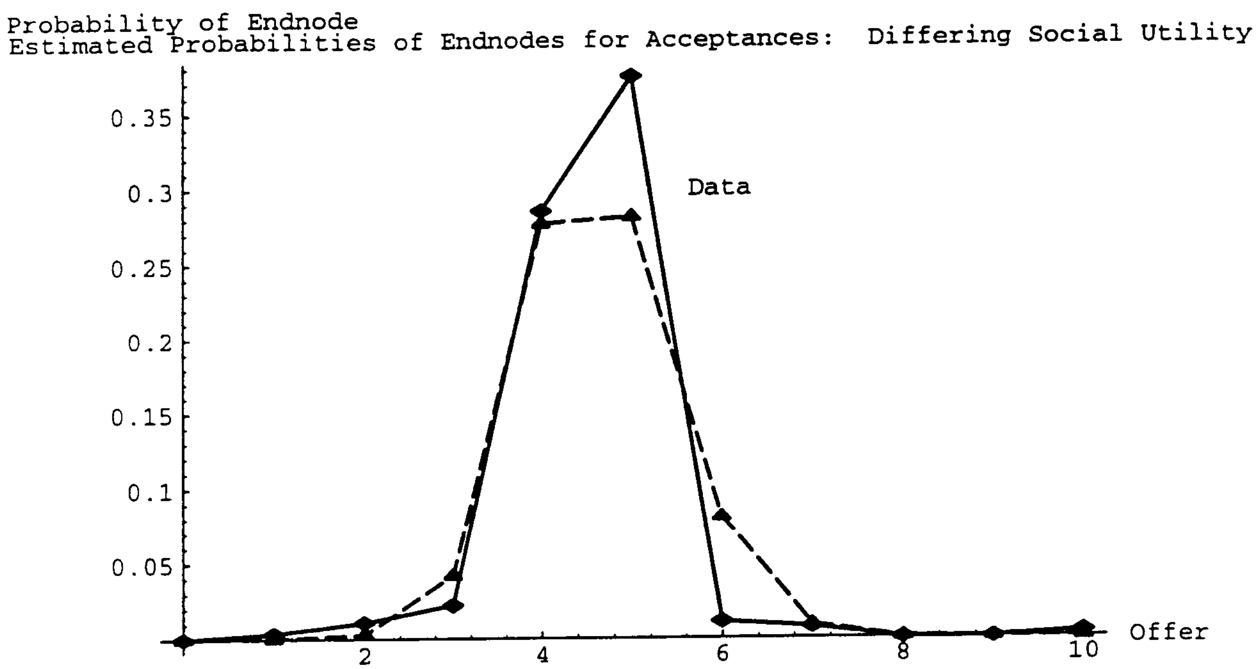

Figure 13: Estimated Probabilities and Empirical Frequencies of Endnodes (Acceptance): Differing Social Utility

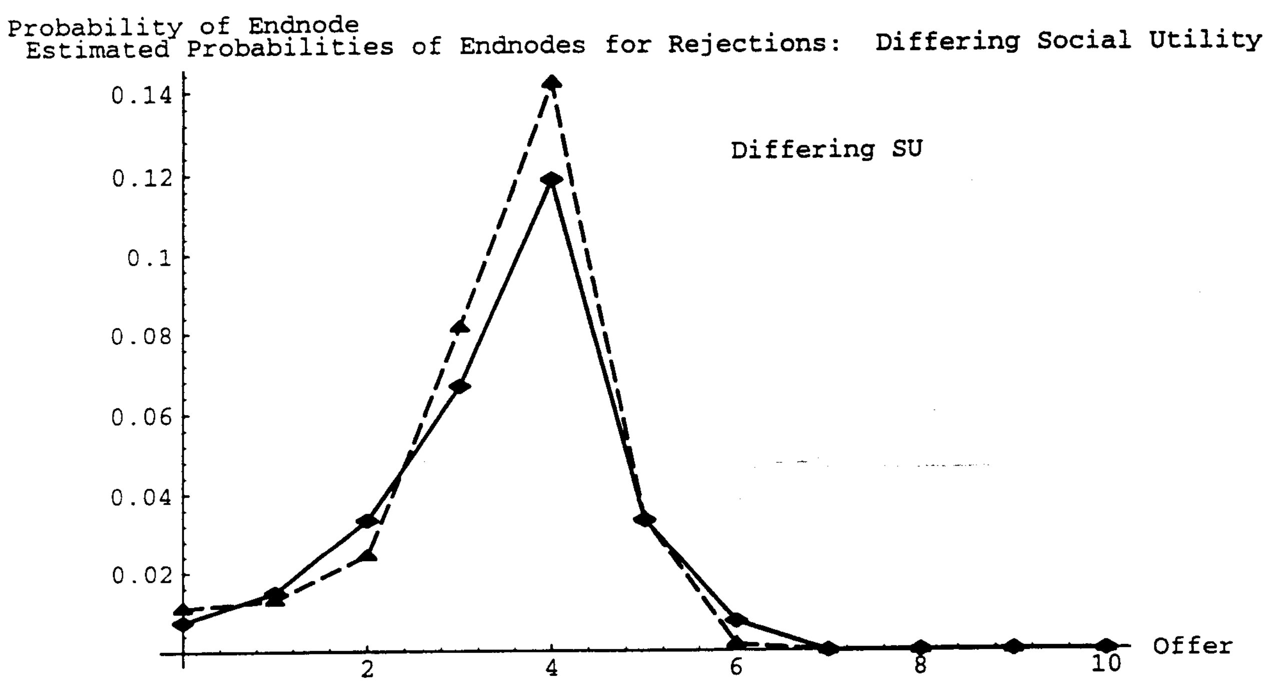

Figure 14: Estimated Probabilities and Empirical Frequencies of Endnodes (Rejections): Differing Social Utility

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