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Fairness, Errors and the Power of Competition[1]

Urs Fischbacher,* Christina M. Fong,** and Ernst Fehr*[+]

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Abstract: One of the most basic questions in economics concerns the effects of competition on market prices. We show that the neglect of both fairness concerns and decision errors prevents a satisfactory understanding of how competition affects prices. We conducted experiments which demonstrate that the introduction of even a very small amount of competition to a bilateral exchange situation – by adding just one competitor – induces large behavioral changes among buyers and sellers, causing large changes in market prices. Models that assume that all people are self-interested and fully rational fail to explain these changes satisfactorily. In contrast, a model that combines heterogeneous fairness concerns with decision errors predicts all comparative static effects of changes in competition correctly. Moreover, the combined model enables us to predict the entire distribution of prices in many different competitive situations remarkably well.

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I. Introduction

Economists have long been interested in how changes in competition affect market prices. In this paper, we argue that no satisfactory answer can be given to this basic question if one neglects the presence of fairness motives and decision errors.[1] In particular, the prevailing model, which assumes that individuals are perfectly rational and motivated exclusively by self-interest, prevents a full understanding of how competition affects the behavior of buyers and sellers. As a consequence, the price *level* and basic *comparative static properties* of the price level with regard to changes in competition cannot be fully understood. In contrast, a model that takes heterogeneous fairness preferences and decision errors into account explains well the price level as well as the qualitative and quantitative effects of changes in competition. Therefore, our paper also addresses the question of when and how deviations from full rationality or self-interest economists should take into account. Becker (1962) showed that these deviations may sometimes be of second order importance. However, as our results show, it would be a serious mistake to assume that this is always the case.

Our argument is based on the results of a series of laboratory experiments in combination with recently developed fairness models and quantal response models which capture the impact of decision errors on equilibrium behavior.[2] Our data indicate that both fairness preferences and decision errors are crucial for the understanding of competition. We show, in particular, that the combination of the fairness approach with the quantal response equilibrium approach not only captures the comparative static aspects of buyer and seller behavior very well but also enables us to make precise quantitative predictions of average prices as well as the whole distribution of prices across all our experiments.

The starting point of our examination is a bilateral bargaining experiment, the so-called ultimatum game, in which a buyer and a seller bargain over the price of an indivisible good. The

[1] There is now a large body of evidence indicating that a non-negligible number of people care not only about their own material payoff but also about fairness. It has been shown that fairness motives are behaviorally important even under rather high stake levels and in a wide variety of different contexts. For surveys about the role of fairness concerns in strategic interactions, see Camerer (2003) or Fehr and Schmidt (2003), for example. In addition, there is also a lot of evidence indicating that many individuals deviate from perfect rationality (Camerer 2003).

[2] Recently developed fairness models include Rabin (1993), Levine (1998), Fehr and Schmidt (1999), Dufwenberg and Kirchsteiger (1999), Falk and Fischbacher (1999) and Bolton and Ockenfels (2000). The quantal response equilibrium approach, which captures the idea of noisy best reply behavior, was developed by McKelvey and Palfrey (1995). Goeree and Holt (2000, 2001), Goeree, Holt and Palfrey (2002) and Goeree, Holt and Laury (2002) successfully applied the approach to explain the salient behavioral features of many different games. For a critical discussion of the quantal response approach see Haile, Hortacsu and Kosenock (2003).

buyer's and seller's monetary valuation of the good is common knowledge. The seller can make exactly one price offer to the buyer, which the latter can accept or reject. If the offer is rejected no trade occurs; conversely, the trade occurs at the proposed price if it is accepted. We then conduct market experiments in which we add competing buyers or sellers to the bilateral game in order to examine the impact of competition on prices. The prevailing model predicts that the price setting seller should reap virtually the whole surplus in the bilateral bargaining game, but it is well known that this is generally not the case because the buyers resist unfair offers (Güth, Schmittberger and Schwarze 1982, Güth and Tietz 1990, Roth 1995). The question then is how a little bit of competition – the addition of just one competing buyer or seller – affects market prices and, if so, what the underlying mechanisms are.

We find that the addition of just one competitor has a very large impact on market prices. The introduction of competition between two buyers reduces their average share of the gains from trade from 42 percent to roughly 20 percent. Moreover, if we extend the competition to a total of five competing buyers, their average share further falls to 12 – 14 percent. Thus, competition among buyers has a strong and unambiguous impact on market prices, and there is a sharp discontinuity between no competition and a little bit of competition. The introduction of competition between two sellers further supports this discontinuity. The buyer's average share of the gains from trade increases from 42 percent to roughly 75 percent in this case.

Intuitively, self-interest seems to be an important driving force behind the effects of competition. It is, therefore, ironic, that the prevailing model is unable to capture the powerful effects of buyer competition; according to this model, the price setting sellers already reap the entire gains from trade in the bilateral situation. Thus, the introduction of buyer competition can have no impact on market prices. In contrast, an approach which assumes heterogeneous fairness preferences can explain both why the seller makes greedier offers and why the buyers are willing to accept the seller's lower offers. It predicts, in particular, that fair-minded buyers are less likely to reject low offers if they believe that the competing buyer(s) will accept these offers. The data fully supports this prediction. In fact, the buyers' expectations about their rivals' acceptance behavior is *the* major determinant of changes in buyer behavior across different competitive situations.[3]

[3] Note that a selfish buyer accepts any positive offer regardless of what competing buyers do. Thus, the behavior of a selfish buyer is not affected by the expectation about the other buyers' behavior.

The fairness approach predicts the qualitative comparative static effect of the introduction of seller competition correctly but overestimates the effect quantitatively. Like the prevailing model, the fairness approach predicts that the sellers gain virtually nothing from trade when at least two price setting sellers compete with each other but the empirical results show that the trading seller still receives a non-negligible share. However, the combination of the fairness approach with the quantal response equilibrium (QRE) approach solves this problem. If there is competition among price setting sellers, decision errors are of first order importance because they weaken the sellers' incentives to overbid each other decisively. In the absence of decision errors, Bertrand like competition will force the sellers to overbid until the entire gains from trade go to the buyer. But in an equilibrium based on fairness preferences and decision errors, seller *i* knows that competing seller *j* is likely to bid a price where he retains a sizeable share of the gains from trade. Hence, *i* has no incentive to offer a price giving the buyer the full surplus.

The combination of the fairness approach with the QRE approach also captures the other major qualitative results of our experiments correctly. First, a considerable willingness to reject unfair price offers severely constrains the seller's price-setting power in the bilateral case. Second, as the model predicts, the buyers' willingness to reject a given offer decreases substantially as the number of competitors increases. Third, this reduction in the willingness to reject is due to the impact of competition on buyers' beliefs about their rivals' rejection behavior. The higher the number of competing buyers, the greater is a given buyer's probability belief that one of the other buyers will accept the offer. Fourth, an increase in the number of competing buyers causes a large decrease in the rejection risk the sellers face due to the heterogeneity in fairness preferences and the changes in responder behavior. Ultimately, the sellers take advantage of the lower rejection risk by offering the buyers much less.

In the final part of the paper, we show that the combined approach even enables us to make quantitatively accurate predictions if we apply a fully parameterized version of the model. We use exactly the same distribution of fairness preferences assumed by Fehr and Schmidt (1999). Thus, we completely tie our hands with regard to our assumptions about fairness preferences. Nevertheless, the predicted average, median, and modal prices for all four treatments are quite close to the respective actual average, median, and modal prices.

There are a few other experimental papers which examine the comparative static impact of changes in competition on prices. In a pioneering study Roth, Prasnikar, Okuno-Fujiwara, and

Zamir (1991) compare the results of ultimatum games with those from market games with nine competing sellers and only one buyer who is forced to take the highest offer. Thus, Roth et al. (1991) introduce a very large amount of competition on the sellers' side with nine competing sellers and buyer's obligation to take the highest offer in all cases. Their setting does not permit the study of the impact of a small amount of competition. The focus on seller competition also limits the empirical insights into the comparative statics of buyers' rejection behavior. Güth, Marchand, and Rulliere (1997) and Grosskopf (2003) also conducted experiments where they varied the number of competitors. Grosskopf showed, in particular, that reinforcement learning models are unable to explain important effects of competition. However, none of these papers considers the implications of fairness or QRE models and none of them provides a *unified quantitative* interpretation of the data in terms of fairness and decision errors. To our knowledge, the Goeree and Holt (2000) paper is only one that combines the fairness approach with the QRE approach. Their paper is, however, limited to the study of bilateral bargaining behavior, i.e., they do not examine competition.

The remainder of the paper is structured as follows: In Section II we present the experimental design. In Section III we discuss the predictions of the fairness approach and a QRE approach that assumes selfish preferences. This enables us to see when each of the two approaches, considered individually, fails to predict the empirical regularities. Section IV presents our experimental results and we provide a unified interpretation of the data in terms of a combined QRE-fairness model in Section V. Section VI concludes the paper.

II. The Experimental Design

A. Treatment Conditions

We set up three treatment conditions to test for the effect of competition on market prices. In one treatment, we conducted an ultimatum bargaining game between a buyer and a seller in which competition is completely absent. In the second treatment, we introduced a competing buyer into the bargaining game. In the third treatment, we increased the number of competing buyers by introducing three further buyers, resulting in a total of five competing buyers. In the fourth treatment, we added a competing seller to the ultimatum bargaining game. The comparison between the ultimatum game (henceforth called UG) and the treatments with two competitors – either two competing buyers or two competing sellers – allows us to study how the *introduction* of

competition affects participants' behavior and market prices. The comparison between the treatments with two and five competing buyers gives us information about how an *increase* in buyer competition affects behavior and market prices.

In the UG, a buyer and a seller have to agree on the division of a given bargaining surplus of 100 money units. The rules of the game stipulate that the seller offers the buyer an absolute share $s \in \{0, 1, 2, 3, \ldots, 100\}$ of the gains from trade and the buyer then either accepts or rejects this share. For convenience, we therefore call the seller a "proposer" and the buyer a "responder". If the offer is accepted, the proposer's share of the surplus is $100 - s$ and the responder's share is s[4]. If the offer is rejected, both players earn zero.

In the market games with responder (buyer) competition, we had two or five responders, respectively. In the market game with proposer (seller) competition there were two proposer. In the following, we call the treatment with two responders "responder competition with two responders" (RC2), the treatment with 5 responders "responder competition with 5 responders" (RC5) and the treatment with two proposers "proposer competition with two proposers" (PC2). Since we were interested in the pure effect of one or four additional competitors, respectively, we kept the structure of the games with competition identical to that of the UG. There is just one proposer in RC2 and RC5 who makes a single offer $s \in \{0, 1, 2, 3, \ldots, 100\}$. All responders then simultaneously accept or reject this offer. If all responders reject, no gains from trade occur and all players earn zero. If at least one responder accepts, trade between the proposer and the accepting responder occurs with the proposer earning $100 - s$ and the accepting responder earning s. All other responders earn nothing. If several responders accept the offer, one of them is randomly chosen to be the trader. Each accepting responder has the same probability of winning. The non-trading responders again all earn zero, whereas the proposer and the randomly chosen responder earn $100 - s$ and s, respectively. In PC2, the two proposers simultaneously make an offer $s_i \in \{0, 1, 2, 3, \ldots, 100\}$, $i = 1,2$. Then the responder can accept one of these offers. If the responder rejects both offers, all three players earn zero; if the offer s_i (i = 1,2) is accepted, proposer i earns $100 - s_i$, proposer $j \neq i$ earns zero, and the responder earns s_i.

[4] There is a unique relation between the buyer's share of the gains from trade and the market price p at which the good is sold. Let c denote the cost of the good to the seller while v represents the buyer's monetary valuation of the good. Then the buyer's absolute share s is defined as $s = v - p$ and the sellers' absolute share is p – c. In our experiments we have set c = 0 and v = 100.

B. Procedures

We conducted a total of ten experimental sessions, with two sessions each in UG, in RC2, and in PC2 and four sessions in RC5 we. All sessions took place in January 1999 and January 2000. We recruited 24 subjects for each session.[5] Overall 238 subjects participated in the experiments, with each subject partaking in exactly one session. Subjects were students from the University of Zurich and the Swiss Federal Institute of Technology (ETH) in Zurich. The experiments were implemented with the help of the experimental software z-Tree (Fischbacher 1999).

Subjects were seated at computer terminals, where they received written instructions and entered their decisions without communicating with one another. The computer terminals were located in separate carrels so that subjects could make their decisions in complete confidentiality. Anonymity among the players was guaranteed because at no point during (and after) the experiment did subjects receive information about whom they were interacting with. The subjects earned a show-up fee of 10 Swiss francs (CHF1 ≈ $0.8) plus earnings based on their decisions during the experiment. Their earnings averaged 23.10, 21.30 and 18.20 Swiss Francs for RC5, RC2 and UG, respectively. A session lasted approximately 75 to 90 minutes. In order to maintain a constant stake size per person across the treatments, we varied the exchange rate between experimental money and Swiss Francs. The number of Swiss francs per 100 experimental money units was adjusted so that the gains from trade divided by the number of players was a constant CHF 1.20 across conditions. Thus, the value of 100 experimental money units was CHF 7.20 in RC5, CHF 3.60 in RC2, and PC2, and CHF 2.40 in the UG.

It is well known that behavior in experimental markets sometimes exhibits large changes over time. Therefore, each experimental session lasted 20 periods. Subjects were randomly matched with other proposers and/or responders, respectively, in each period. They knew nothing about the previous behavior of the subjects with whom they were matched in a period. Random matching and the absence of reputation building opportunities ensured that subjects could not condition their current behavior on their current opponents' past behavior. The repetition of the same treatment condition over 20 periods permits the observation whether the subjects' behavior converges to a stable pattern in the different treatments.

Subjects were randomly assigned the role of a proposer or a responder at the beginning of a session. They retained this role throughout the whole session. In each period, proposers entered an

[5] Due to no-show-ups we had only 22 subjects in one of the UG sessions.

offer which was sent to the matched responders. Then the responders simultaneously decided whether to accept or reject the offer. In the RC2 treatment, responders also indicated whether they believed that the other responder would accept or reject the offer. In the RC5 treatment, responders indicated their belief about how many other responders would accept the offer. The computer screens informed subjects at the end of each period about their own actions and payoffs as well as those of their opponents. For instance, each responder was informed about the proposer's offer and payoff and the matched responder's action and payoff in RC2. Subjects received no information about the behavior and the payoff of other players outside of their group.[6]

We used matching groups in each session. A matching group is a subpopulation of players in a session that interacts independently of the other matching groups. In particular, z-Tree randomly matched subjects only with those who belonged to their matching group, and not with players in other matching groups. The advantage of this technique is that it increases the number of independent observations; behavior in each matching group is independent of that in the other matching groups. Without matching groups, an entire session would yield only one independent observation. There were three matching groups per session in the UG, two matching groups per session in RC2 and PC2, and only one matching group per session in RC5. This resulted in 6 independent observations for the UG, and 4 independent observations for each of the other treatments.[7]

III. Predictions

A. Predictions based on Prevailing Economic Theory

The standard prediction assuming rational and self-interested players is straightforward. In any equilibrium of the UG or the market games with responder competition, the responders will always get at most an offer of $s = 1$ and the proposer's offer will always be accepted. The intuition behind these equilibrium outcomes is that selfish responders will accept any positive offer so that a selfish

[6] For example, they were informed about their own action and payoff as well as their opponent's action and payoff in the UG, but not about payoffs and actions in other pairs of players.

[7] We did not tell the subjects that they were in matching groups. The main advantage of using several matching groups per session and not telling subjects about it is that they are likely to have the impression that they are matched with subjects drawn from the entire group of subjects in the laboratory. This is likely to reduce the subjective probability of being rematched with a particular subject and thus foster the one-shot nature of the experiment.

proposer can be sure that all responders will accept an offer of 1.[8] An important point about the prevailing model is that it does *not* predict a difference in the behavior of proposers and trading responders when we move from the UG to responder competition, i. e., responder competition is predicted to have no impact at all on market prices. This contrasts sharply with the prediction for PC2. The addition of just one competing proposer implies that the responder receives at least 98 percent of the surplus in any subgame perfect equilibrium. There is an equilibrium in which both proposers offer s_i = 99 and the responder accepts one of these offers, but there are also other equilibria. Both proposers offering 100, or both offering 98 can also be part of an equilibrium. If both offer 98 their expected payoff is 1 unit and overbidding with s_i = 99 also yields 1 unit of payoff.[9] However, there is always an incentive for overbidding if both proposers offer 97 or less, so that the responder receives at least 98 percent of the surplus in any equilibrium. Therefore, whereas the introduction of responder competition – no matter how strong – is predicted to have no impact on market prices, the introduction of proposer competition – no matter how small – implies a radical change in the market price – from a price that gives the responder almost nothing to a price that gives the responder almost the whole surplus.

B. Predictions of Fairness Models

Several fairness models have been recently developed that capture the idea that a substantial percentage of the subjects is motivated not only by self-interest but also by concerns about equity (Fehr and Schmidt 1999, Bolton and Ockenfels 2000) and reciprocity (Rabin 1993, Levine 1998, Duwfenberg and Kirchsteiger 1999, Falk and Fischbacher 1999). These models are consistent with the fact that responders in the bargaining game frequently reject low, unfair, offers, in turn inducing proposers to make fair offers. In the following, we apply the Fehr and Schmidt (FS) model to generate predictions for our experimental treatments. The main reason for this is that the model specifies a simple, tractable, functional form for subjects' preferences that allows the computation of closed form solutions. Our choice of the FS model does not mean that the other fairness models

[8] There are two subgame perfect equilibria in the UG and two subgame perfect equilibrium outcomes under responder competition. The two equilibria in the UG are 1) the proposer offers one and the responder accepts all positive offers and rejects zero, and 2) the proposer offers zero and the responder accepts all offers. In responder competition, one subgame perfect equilibrium outcome is obtained if the proposer makes the minimum positive offer, i.e., s = 1, which all responders accept. In this equilibrium, all responders have to reject s = 0. The other equilibrium outcome is sustained by an offer of s = 0 which at least one responder accepts.

[9] We assume risk neutrality here which is a reasonable assumption for the prevailing stake levels in our experiment.

are unable to explain our experimental results. Instead, despite differences in the details, the equity and reciprocity models offer a common intuition as to why competition induces players with fairness motives to behave more like selfish players: competition undermines the ability of fair-minded players to enforce equitable outcomes or to punish other players for unfair behavior. For example, when responder competition prevails a fair-minded responder may no longer be able to ensure the punishment of greedy proposers by rejecting low offers because the competing responders may accept these offers. This in turn will induce the selfish proposers to make low offers.

A key idea behind the FS model is that there are both selfish and inequity averse individuals. The inequity averse individuals derive disutility from inequity. In the context of experimental games, inequality is often a good proxy for inequity. Therefore, FS assumed that players with inequity aversion behave according to the following utility function:

$$u_i = \pi_i - \alpha_i \frac{1}{n-1} \sum_{j \neq i} \max\{\pi_j - \pi_i, 0\} - \beta_i \frac{1}{n-1} \sum_{j \neq i} \max\{\pi_i - \pi_j, 0\} \qquad (1)$$

In (1) π_i, i=1,..., n are the monetary payoffs of the n players in the game, α_i is a parameter measuring the disutility of disadvantageous inequality, and β_i is a parameter that captures the disutility arising from advantageous inequality. FS also assume that $\alpha_i \geq \beta_i$ and $0 \leq \beta_i < 1$. The restriction $\beta_i < 1$ is plausible because it implies that subjects are unwilling to burn money in order to reduce advantageous inequality. In the following, we first outline the comparative static predictions for the UG and then for the markets with responder and proposer competition.[10]

In the UG, responders with a sufficiently high aversion to disadvantageous inequity (α_i) will reject low offers. For every given value of α_i there is a unique acceptance threshold *s'*, meaning that offers below *s'* will be rejected whereas offers at or above *s'* will be accepted. Because the rejection of offers above $s = 50$ is expensive, inequity averse responders will never reject such offers because $\beta_i < 1$. Moreover, because responders are assumed to differ in their aversion to disadvantageous inequity, a proposer who does not know the responder's preferences faces a distribution of players with different α_i-values. This means that the probability of rejection declines as the offer increases because more players are willing to accept the higher offer. Proposers who dislike advantageous inequity a lot, i.e., those with $\beta_i > 0.5$, will propose egalitarian offers of $s = 50$. The distribution of

[10] Readers who are interested in the full formal derivation of the predictions should consult the proofs of propositions 1, 2, and 3 in Fehr and Schmidt (1999).

acceptance thresholds does not constrain them because even if they could enforce non-egalitarian offers without any risk of rejection they would not make such offers. This is because the transfer of \$1 to the responder decreases the payoff difference between the proposer and the responder by \$2, which produces a non-pecuniary gain of $2\beta_i$ for the proposer. Thus, if $2\beta_i$ exceeds the \$1 cost of the transfer, the proposer will increase the offer until equality is achieved. Those proposers with $\beta_i < 0.5$ will offer less than s = 50, maximizing their utility against the distribution of acceptance thresholds of the responders. Thus, every force that lowers the responders' willingness to reject low offers will induce the proposers with $\beta_i < 0.5$ to take advantage of the responders' weakness and to make lower offers. This observation leads us directly to the analyses of the impact of responder competition on market outcomes because if responder competition reduces the probability that low offers are rejected the model can explain why competition lowers the offers relative to the bargaining game.

In the context of the FS model, there are two reasons why an increase in responder competition implies that the proposer faces a lower risk of not being able to trade, i.e., that all responders reject a given offer.

1. The first effect is a *statistical effect* that arises (i) from the assumption that there is a distribution of acceptance thresholds, and (ii) from the fact that if there are more responders, more responders must reject the offer to prevent the proposer from trading. The higher the number of responders, the higher is the probability that at least one responder will accept a given offer. For instance, if 50 percent of the responders in the UG, in RC2, and in RC5 have an acceptance threshold of 30 and the other 50 percent exhibit a threshold of 0, the probability that an offer below $s = 30$ is rejected is .5 in the UG, $(.5)^2$ in RC2 and only $(0.5)^5$ in RC5. Thus, the statistical effect decreases the proposers' risk of not trading even if competition has no effect on the distribution of acceptance thresholds.

2. The second effect is a *belief effect*. Increases in competition are likely to affect the responders' behavior because they affect their beliefs about the probability that the competing responders will reject the offer. Whenever an inequity averse responder believes that another responder will accept the offer with certainty, she will accept the offer too. This is because she can no longer ensure equality by rejecting the offer, and given that there will be inequality no matter what she does, she prefers to have a chance of winning the offer; hence, she accepts. The more responders there are, the more likely it is that there is another responder who will accept the

offer so that a rational responder's belief that at least one other responder will accept the offer increases. Therefore, increases in responder competition are likely to lower the responders' acceptance thresholds.[11]

As in the UG, the predictions for proposer behavior under responder competition depend on β_i. If β_i is sufficiently high, the proposer voluntarily refrains from making an offer below s = 50 even if such an offer could be enforced without any risk of rejection. If β_i is not sufficiently high, the proposer maximizes her utility, subject to the distribution of acceptance thresholds. To be precise, the proposer will offer s = 50 if $\beta_i > (n-1)/n$, where n is the number of players in the game.[12] Hence the critical value of β_i equals 1/2 in UG, 2/3 in RC2 and 5/6 in RC5 implying that the fraction of inequity averse proposers who are willing to make low offers increases if the number of responders increases. It is also worthwhile to point out that β values at or above 2/3 are likely to be rather infrequent. If β_i equals 2/3, the proposer in the UG is willing to propose an equal split even if half of the proposer's transfer is lost on the way to the responder.[13] Although one cannot rule out that some players are that generous, it seems doubtful that many are.

Thus, the fairness approach predicts that responders are less willing to reject low offers, that proposers face a lower overall rejection risk, and that proposers are less likely to make the egalitarian offer if the number of responders increases. As a consequence, we expect that accepted offers decline if responder competition is introduced or becomes more intense. However, we can even go beyond these qualitative predictions.

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[11] More precisely, it can be shown (FS 1999, proposition 3) that the highest offer s^h that can be sustained in an equilibrium in the responder competition game depends on the acceptance threshold of the least inequity averse responder. If, for instance, the least inequity averse responder has an acceptance threshold of 20 percent, then it makes little sense for the more inequity averse responders to reject offers above 20 percent because these offers will be accepted. Therefore, as the acceptance threshold of the least inequity averse responder decreases, so will the acceptance threshold of all other responders and so will also s^h. Adding additional responders from a heterogeneous population of subjects increases the likelihood that the least inequity averse responder will have a lower acceptance threshold. This means that an increase in the number of responders lowers the acceptance threshold of all inequity averse responders.

[12] If there are n players altogether, then giving away one money unit to one of the responders reduces inequality vis à vis the receiving responder by 2 units and vis à vis the other n-2 responders by 1 unit. Therefore, the average reduction in inequality relative to all n-1 other players is $(2 + n-2)/(n-1) = n/(n-1)$ Dollars. Thus, if the non-pecuniary gain for the proposer from this reduction in inequality, $\beta[n/(n-1)]$, exceeds the cost of 1, i. e., if $\beta > (n-1)/n$, the proposer prefers to give away money to one of the responders. If, instead, $\beta < (n-1)/n$, the proposer is willing to bear the risk of being rejected by trading off a higher risk of rejection with the higher earnings from an accepted offer.

[13] To be precise, assume that the responder only receives \$$\gamma$ ($\gamma < 1$) for every dollar that the proposer transfers to the responder in the UG. Then the proposer's payoff function can be written as $U_p = 100 - s - \beta[(100 - s) - \gamma s]$. Differentiating with respect to s and assuming that $\beta = 2/3$ yields $-1 + (2/3)(1 + \gamma)$. This expression is non-negative for $\gamma \geq ½$. Thus, in the case where half of the money transferred to the responder is lost ($\gamma = ½$) the proposer is indifferent between keeping a Dollar or transferring a Dollar.

To make quantitative predictions we assume the same distribution of utility parameters as in Fehr and Schmidt 1999 (see Table 1). On the basis of these parameters we predict the offers and the rejection thresholds of the different types of players across the UG, RC2, and RC5. Table 1 shows that – with the exception of the purely selfish types– the acceptance thresholds of the different player types will be highest in the UG and lowest in RC5. Moreover, regardless of the players' types, the offers will be highest in the UG and lowest in RC5.[14] The table also shows that competition homogenizes the behavior of different player types. In RC2, for instance, all types make the same offers while in the UG the selfish players and those with little inequity aversion make different offers. Similar homogenization effects are also predicted for the responders. Thus, the table neatly illustrates the powerful effects of competition on individual behavior that are predicted by the fairness model.

Insert Table 1 about here

In the case of proposer competition, the FS model predicts the same extreme outcome as does the prevailing model with selfish preferences if we rule out the unlikely case of $\beta_i > 2/3$. The reason for this extreme prediction is threefold: (i) as in the UG, the responder will accept offers above ½ because rejecting such high offers is too expensive. (ii) If $\beta_i < 2/3$ the responder always prefers the higher offer. (iii) Every offer s' that gives the responder less than 98 percent of the surplus provides an incentive for the competing proposer to make an offer s'' > s', regardless of how strongly inequity averse they are. Overbidding has three advantages. First, it gives the overbidder a monetary payoff of (1-s''). Second, it reduces the disadvantageous inequality with respect to the proposer. Third, it turns the disadvantageous inequality relative to the responder who made the offer s' into advantageous inequality. It can be shown that, due to these advantages, it is in the interest of the proposers to overbid until almost the whole surplus is reaped by the responder.

C. Quantal Response Equilibrium (QRE) Models with Selfish Preferences

The QRE approach was developed by McKelvey and Palfrey (1995) and it has been successfully applied to many different contexts in recent years, ranging from all-pay auctions (Anderson, Goeree

[14] The computations in Table 1 are based on the assumption that subjects know the distribution of types that is assumed in the table. For the UG this gives us a unique equilibrium prediction. For RC2 and RC5 there are multiple equilibria. In the table we have displayed the equilibrium with the highest sustainable equilibrium offers in RC2 and RC5.

and Holt 1998) and private value auctions (Goeree, Holt and Palfrey 2002) to public goods (Goeree, Holt and Laury 2002), coordination games (Goeree and Holt 2001), and alternating offer bargaining games (Georee and Holt 2000). The key idea behind this approach is that individuals play noisy best replies and expect others to play noisy best replies. Subjects play the best reply to the expected actions of the others with the highest probability for finite decision errors, but they also play the other available actions with positive probability due to decision errors. For example, the best reply for a selfish responder in the UG is to accept any positive offer. Yet, a selfish quantal response player rejects positive offers with positive probability. Moreover, the probability of rejecting positive offers decreases as the cost of rejecting a higher offer increases. Thus, the QRE approach predicts qualitatively similar regularities for the responders in the UG than does the fairness approach. This also means that selfish quantal response proposers have an incentive for making positive offers in the UG. Since the QRE approach leads to similar qualitative predictions in the UG as the fairness approach it is important to know how the introduction and increases in competition affect the behavior of selfish quantal response players.

In a quantal response equilibrium (QRE) each player plays a noisy best reply to the other players' noisy best replies. More formally, let $Pr(i)$ denote the probability of taking action i, let $u^e(i)$ be the expected utility of action i for given beliefs about the strategies of the other players, let μ be the parameter that determines the distribution of decision errors and let N denote the number of available actions. Then, under the assumption that the error is extreme-value distributed (as, e.g., in Goeree, Holt and Palfrey 2001), the quantal (noisy) best replies are given by the conditions

$$\Pr(i) = \frac{\exp(u^e(i)/\mu)}{\sum_{j=1}^{N} \exp(u^e(j)/\mu)}, \qquad i = 1,\ldots,N. \tag{2}$$

If the subjective probabilities of the actions that enter into the calculation of the expected utility of action i are the same as the probabilities $\Pr(i)$ that are determined according to (2) by the expected utility $u^e(i)$, a quantal response equilibrium prevails.

Figure 1 shows the offer distribution for the UG in a QRE for three different assumptions about the error parameter μ. In all three cases we assumed that the players have completely selfish preferences. Thus, the figure illustrates the ability of the QRE approach with selfish preferences to predict positive offers in the UG. Figure 1 also indicates that it is even possible to generate predictions of average offers in the range between 30 and 40. However, such average offers can

only be part of a QRE equilibrium if the error parameter is very high and a large percentage of the offers is above 50.

The comparative static predictions of the QRE approach with selfish responders are illustrated in Figure 2. To construct Figure 2, we assumed that a constant error parameter of $\mu = 4$ across the UG, RC2, and RC5.[15] However, all the qualitative predictions remain the same as long as we assume a finite decision error. In particular, the rejection rate is decreasing in the offer size in all three conditions and it will never exceed 0.5. If responders face an offer of zero, their rejection is costless. Therefore the responders' rejection behavior is completely random, i.e., they reject with probability 0.5. Rejections are costly for positive offers, so that the probability of rejections declines as offers increase. Differences in rejection behavior across treatments are most important for our purposes. Regardless of the (finite and constant) error parameter, QRE predicts that the rejection rate is lowest in the UG and highest in RC5. Thus the QRE approach with selfish preferences predicts the opposite comparative static results compared to the fairness approach.

Figure 1 and Figure 2 about here

The intuition behind the QRE prediction is that an increase in the number of competing responders increases the probability that at least one of the competitors will accept the offer. This means that the expected payoff for accepting the offer (which is identical to the expected cost of rejecting the offer) declines because there are more accepting responders. In other words, if the number of competing responders increases, the expected cost of rejecting the offer becomes smaller and, therefore, the rejection rate increases. The difference between the QRE approach and the fairness approach can also be illustrated in terms of the effect of the responders' beliefs about the other responders' rejection behavior. Recall that a fair responder is *more* likely to reject an offer if she believes that all the other responders will do likewise. In contrast, a selfish quantal response responder is *less* likely to reject the offer if she believes that all other responders will reject the offer because the rejection is more costly than if some of the other responders accept. Since we elicited the responders' beliefs about the other responders' rejection behavior we are in a position to explicitly examine the impact of beliefs on responders' behavior.

[15] Keeping the error parameter constant across conditions is important because by choosing different error parameters for different conditions, we could generate arbitrary comparative static results. The QRE approach would thus no longer generate refutable comparative static predictions. In a recent paper Haile, Hortaçsu and Kosenock (2003) show that any data set can be rationalized as a quantal response equilibrium unless one imposes a priori distributional assumptions on the model.

Although the QRE approach with selfish preferences and the fairness approach make conflicting comparative static predictions with regard to responder behavior, their *qualitative* predictions with regard to proposer behavior are the same. Both approaches predict that the average accepted offer, denoted by ŝ, obeys the order $\hat{s}^{UG} > \hat{s}^{RC2} > \hat{s}^{RC5}$. The reason for this is that the statistical effect, which is also present in the QRE approach, has a dominating effect on the proposers' rejection risk. Thus although each individual responder under responder competition is more likely to reject a low positive offer in, say, RC5 than in the UG, the probability that one of the five competing responders will accept the offer in RC5 is higher than the probability that the only responder will accept in the UG. Due to the lower rejection risk in RC5, the selfish proposers will, therefore, make lower offers on average.

For PC2, the responders' decision errors imply that they will sometimes reject both offers, in particular if they are low, and sometimes they will choose the lower of the two offers. For a given decision error, QRE unambiguously predicts that the proposers make higher offers in PC2 than in UG. This follows simply from the strong overbidding incentive inherent in PC2. Thus, like the fairness approach, QRE predicts $\hat{s}^{PC2} > \hat{s}^{UG}$.

The fairness approach and the QRE approach make, however, different *quantitative* predictions with regard to proposer behavior. This is most transparent for the UG and for PC2. The QRE approach implies that average offers of 30 or 40 are necessarily associated with many offers above 50 in the UG (see Figure 1), whereas the FS model predicts that there will be no offers above 50 because neither the selfish nor the inequity averse proposers will make such offers (see Table 1). The fairness approach predicts that the proposers' offers will be very close to s = 100 in PC2, whereas the cumulative effects of noisy best reply behavior imply that the proposers' offers will be significantly below s = 100, except in the case of extremely low decision errors. There are two reasons behind this QRE prediction. First, the responder will, due to decision errors, not always take the highest offer which weakens the proposers' incentive to overbid. Second, the competing proposer puts positive probability on offers that are substantially below 100 due to decision errors. This creates an incentive for each proposer to make offers that are strictly below 100. Thus, the decision errors generate snowballing effects that drive the behavior away from the equilibrium derived under full rationality.

In the following we will now present our experimental results. This gives us the possibility to address the strengths and the weaknesses of both approaches considered above. In this context,

however, it is important to keep in mind that the fairness approach and the QRE approach are not incompatible. It is possible to compute the players' expected utility of action i, $u^e(i)$, under the assumption that a percentage of the players exhibits inequity averse preferences. It is an open question whether the mutual strengths or the mutual weaknesses of the two approaches reinforce each other in a combined QRE-Fairness model. In principle, it is possible that the potential mispredictions in each of the models add up or that each of the models provides a correction for the other model's misprediction. We defer the answer to this question after the presentation of our experimental results.

IV. Experimental Results

A. The Effect of Competition on Market Prices

In this section, we study the comparative static effects of competition on accepted offers, i.e., on market prices. Recall that if subjects are selfish and rational, the average accepted offer should be less than or equal to one in the UG as well as in RC2 and RC5, whereas the average offers should be at least s = 98 in PC2. In sharp contrast to this prediction, we find the following result:

RESULT 1: *a) The introduction of a small amount of responder competition by moving from the UG to RC2 causes a large reduction in the mean accepted offer. Adding three additional responders by moving from RC2 to RC5 causes a further significant reduction in the mean accepted offer.*

b) The introduction of a small amount of proposer competition by moving from the UG to PC2 causes a large increase in mean accepted offers but proposers still reap a substantial share of the surplus.

The evidence for Result 1 is presented in Figure 3 and Tables 2 and 3. Figure 3 plots the evolution of the average accepted offer for all four treatment conditions and shows that both responder and proposer competition have a strong impact on market prices. The mean accepted offers $\hat{s}$ obey the inequalities $\hat{s}^{PC2} > \hat{s}^{UG} > \hat{s}^{RC2} > \hat{s}^{RC5}$ in every time period. Table 2 presents the means and standard deviations of the accepted offers. The first six rows of columns 1-4 present matching group averages of accepted offers in each treatment over all 20 periods. The first six rows of columns 5-8 show matching group averages of accepted offers in each treatment for the final period. Row 7

shows total averages across matching groups. The average accepted offer, taken over all 20 periods and all matching groups, is 70.3 in PC2 and 42.7 in the UG; it falls to 25.5 in RC5 and to 16.2 in RC5. $\hat{s}$ is substantially higher in every matching group in PC2 than the value of $\hat{s}$ in each of the six matching groups in the UG. Likewise, the mean accepted offer is much higher in each matching group of the UG than in each of the four matching groups in RC2. Moreover, the gap between the UG and the treatments with competition grows even larger over time. Whereas the mean accepted offer in the UG in the final period is similar to the mean in all periods, the offers under proposer competition increase, while declining in the two responder competition treatments (see Figure 2). In the final period, the trading responders earn on the average 77.8 in PC2 and 41.1 in the UG but only 18.8 and 13.8 in RC2 and RC5, respectively.

Figure 3 and Table 2 about here

We conducted non-parametric Mann-Whitney tests with matching group averages as independent units of observation to examine the statistical significance of these treatment differences. These tests show that the UG differs from PC2 and RC2 significantly (p = .005 in both cases). Likewise, the mean accepted offers in RC5 are significantly lower than in RC2 (p = .028). The null hypothesis claiming that there is no trend *across treatments* can, with the use of a non-parametric trend test (nptrend test), be rejected at all conventional significance levels ($p<.001$)[16]. The regressions presented in Table 3 also support these results. This table shows regressions of the mean accepted offer on treatment dummies, the time period, and interactions between the treatments and time period. We pool all four treatments in all 20 periods in the first column of Table 3. The second column takes the data from all four treatments in the final 10 periods. The third and fourth columns pool the RC2 and RC5 treatments in all 20 periods and the final 10 periods, respectively. We compute robust standard errors and allow for correlated errors within matching groups in this and all other regressions reported in this paper. Thus all significance tests associated with the regressions allow for dependent observations within matching groups and treat only observations across matching groups as independent.

In the first two columns of Table 3, the UG is the omitted or baseline category. In columns 3 and 4, RC2 is the omitted category. To simplify interpretations, we number the time periods from –19 to zero in the first and the third regression, and from –9 to zero in the second and fourth

[16] The advantage of the nptrend test is that it takes the order between the treatments into account (see Cuzick 1985). It is, therefore, the appropriate test for examining our comparative static results. The nptrend test is an extension of the Wilcoxon rank sum test.

regression, so that the effects in the final time period are immediately apparent. Thus, the coefficient for the constant in column (1) shows that the mean accepted offer in the final time period of the UG is 42.7. The large and highly significant coefficients for PC2, RC2, and RC5 show that the accepted offer in the competitive treatments differs substantially from that in the UG. The coefficient for RC5 in column 3 indicates that the estimated accepted offers in RC5 are 7.5 units lower than those in RC2. Columns 2 and 4 show that, in the final 10 periods, the treatment differences are of a similar order of magnitude.

In the UG, accepted offers remain rather stable following period 2. This stability is indicated by Figure 3 and regressions 1 and 2, where the estimated coefficient on the variable "time period" is close to zero and insignificant. Figure 3 also reveals that the average offers rise over time in PC2, whereas they fall over time in both RC2 and RC5. However, the average offers remain fairly stable in the final 8 – 10 periods in all three competitive treatments. For example, the mean accepted offer in RC5 is 13.4 in period 10 and 13.8 in period 20. The regressions in Table 3 also confirm this interpretation. The interaction between "time period" and PC2, RC2 and RC5 in regression 1 (which uses the data of all 20 periods) is significant at or below the 5 percent level. In regression 2 (which uses the data of the final 10 periods), the interactions between "time period" and the dummies for the competitive treatments are smaller and no longer significant at the 5 percent level.

Table 3 about here

Result 1 implies that the prevailing model with selfish preferences fails to predict the comparative static results. The model greatly underestimates the impact of responder competition. In addition, regardless of whether we take UG, RC2 or RC5 as the reference treatment, the model overestimates the impact of proposer competition. This contrasts with the FS and the QRE model. Both models correctly predict the qualitative changes in the mean offers across treatments, i.e. they predict $\hat{s}^{PC2} > \hat{s}^{UG} > \hat{s}^{RC2} > \hat{s}^{RC5}$. The FS prediction of the average accepted offer for the UG and RC2 in Table 1 is even remarkably precise in quantitative terms. The predicted values are 43.4 and 17.0, respectively; the actual values in the final period (see Table 2) are 41.1 in the UG and 18.8 in RC2. However, both the FS model and the QRE model also predict some quantitative details of the data incorrectly. In the UG roughly 70 percent of all offers are between 40 and 50 and almost no offers are above 50. However, as Figure 1 indicates, the QRE model is not capable to rationalize this result: It predicts average offers at or above 40 only at the cost of very large decision errors that – counterfactually – imply a large percentage of offers above 50. In contrast, the FS model predicts

this aspect of the data correctly. However, it overpredicts the quantitative impact of proposer competition in PC2.

B. *The Effect of Competition on Proposers' Rejection Risk*

The previous section showed that the introduction of only a small amount of competition has large effects on market prices. Towards the end of the session, the responder's gains from trade in PC2 are almost twice as large as in the UG, while the trading responder in RC2 receives only 50% of the responder's share in the UG. What is the reason for this striking impact of competition? Why does a little bit of competition cause such an unequal distribution of the gains from trade, although many other experiments have demonstrated the existence of a large number of fair minded subjects. According to the fairness and the QRE approach discussed in Section III, responder competition reduces the rejection risk that the proposers face, enabling them to enforce lower accepted offers. In addition, the fairness approach predicts that fewer proposers will be willing to share the gains from trade equally with the trading responder because it requires a stronger fairness motivation to do so when responder competition prevails. Only extremely fair-minded proposers will be willing to share the gains from trade equally under responder competition. Both the fairness and the QRE approach also predict that in PC2 the rejection risk is greater than in the UG which induces the proposers to increase their offers relative to the UG

Our next result shows that the data nicely confirm these predictions regarding the rejection risk.

RESULT 2: a) *The introduction of a small amount of responder competition by moving from the UG to RC2 causes a large reduction in the proposers' rejection risk. Adding three additional responders by moving from RC2 to RC5 causes a further significant reduction of the rejection risk. The money-maximizing offer is, therefore, much lower under responder competition than in the UG.*

b) The introduction of a small amount of proposer competition by moving from the UG to PC2 causes a large increase in the proposers' rejection risk, moving the money maximizing offer far above those in the UG.

Support for Result 2 is presented in Figure 4 and Table 4. Figure 4 plots the proposer's rejection risk against the size of the offer. The proposer's rejection risk for a given offer is defined by the number of such offers that all responders reject divided by the total number of such offers

proposers make. We find that the rejection risk declines dramatically when we move from the UG to RC2. For instance, while the rejection risk for offers below 25 is between 80 and 100 percent in the UG, the risk for the same offer range varies between 5 and 50 percent in RC2. Figure 4 shows a further substantial decline in the rejection risk if five instead of two responders compete with each other. The rejection risk strongly increases in PC2 relative to the UG, although the rejection risk is far below 100 percent for offers above 50. The rejection risk in PC2 obviously does not only depend on the responder's behavior but on that of the competing proposer as well.

Figure 4 and Table 4 about here

Table 4 presents probit estimates of a model predicting whether all responders reject an offer a proposer makes or not.[17] The independent variables are the size of the offer made, the treatment, the time period, and interaction terms for each treatment and the time period. The first regression pools all treatments and all periods, and the second regression pools only the responder competition treatments. The results in Table 4 support Figure 4. The probit coefficients on the offer are negative and significant at the 1% level in both regressions. The associated marginal effects (at the sample means), presented in columns 2 and 4, indicate that an increase in the offer by 10 units decreases the rejection risk by 14 percent in the first regression and by 4 percent in the second regression. The coefficients on PC2, RC2, and RC5 are also highly significant. Controlling for the size of the offer, the time period, the treatment, and interactions between the treatment and time, the predicted probability of an offer being rejected in RC2 is 29.1 percent lower than in the UG. In RC5, the predicted probability is even 38.3 percent lower than in the UG. The first regression also shows that the rejection risk is 79 percent higher in PC2 relative to the UG. The second regression shows that there is also a significant difference between RC5 and RC2. The predicted probability – evaluated at the average offer and time period – of an offer being rejected in RC5 is 9 percent smaller than in RC2.

The large reduction in the proposers' rejection risk is associated with large changes in the expected payoff. In Figure 5 we present the proposers' expected payoff as a function of the offer size across all four treatments. The expected payoff in the UG is maximized at s = 50 but the payoff loss is very small for offers slightly below 50. The peak of the expected payoff is at much lower offer levels in both RC2 and RC5. The expected payoff in RC2 is maximized at s = 5 but the

[17] As in Table 3 all standard errors allow for arbitrary error correlations of observations within matching groups and only observations across matching groups are treated as independent.

payoff is only slightly lower at s = 20. In addition, the very high payoff at s = 5 could well be an artifact of the small number of observations. Offers of s = 5 occurred only in 4 percent of the cases in RC2, whereas 21 percent of all offers are at s = 20. In RC5, however, the peak at s = 5 is surely not an artifact because 33 percent of all offers are at s = 5. In fact, an offer of s = 5 is the mode in RC5. The expected payoff in PC2 is maximized at offers of 65 and 70.[18]

Figure 5 about here

The large differences in the money maximizing offer across treatments provide an explanation for the large differences in proposers' behavior across treatments. In fact, the majority of the proposers' offers are in the vicinity of the money maximizing offer in all four treatments. In the final 10 periods, 69.1 percent of all offers in the UG are in the interval [40, 50]; 61 percent of the offers in PC2 are in the interval [60, 80]; 66.9 percent of the offers in RC2 are in the interval [15, 25] and 79.5 percent of the offers in RC5 are in the range [5, 15]. In section V, we will show that a combination of the FS and the QRE model explains these aspects in the distribution of offers quite well.

There is one interesting quantitative feature in Figure 4 which explains why the pure FS model overpredicts the change in the proposers' behavior if one introduces proposer competition. According to the FS model (and the self-interest model with full rationality), the rejection risk for offers below s = 98 is 100 percent in PC2. In fact, however, the rejection risk is considerably below 100 percent in the interval [50, 97]; for offers above 90 it is even zero. This means that the proposers had an incentive to move away from the predicted equilibrium offers in the range [98, 100].

C. *The Effect of Responder Competition on Responder Behavior*

The fairness approach implies that the reduction in the proposers' rejection risk in RC2 and RC5 is a consequence of heterogeneous fairness preferences among the responders and the behavioral changes which competition induces among the responders. Recall that preference heterogeneity among the responders means that the proposers face a distribution of acceptance thresholds. This, in turn, implies that the probability that *all* responders will reject a given offer declines if the number of responders increases. We have called this the statistical effect because it prevails even if

[18] In PC2 offers at s = 50 are almost as profitable as those of 65 and 70. However, this could also be an artefact of the small number of observations at s = 50.

responders do not change their rejection behavior when additional competitors are added. However, one of the salient predictions of the fairness approach and the QRE approach is that responders will change their rejection behavior across treatments and that the responders' beliefs about the other responders' rejection behavior is the driving force behind these changes. Moreover, the fairness approach and the QRE approach make opposing predictions with regard to the changes in responders' behavior. Therefore, we examine next whether and how the responders changed their rejection behavior in the face of additional competition.

RESULT 3: *The introduction of a small amount of responder competition by moving from the UG to RC2 causes a substantial reduction in individual responders' willingness to reject. A further increase in competition by moving to RC5 causes an additional significant reduction in the willingness to reject. The changes in responders' rejection behavior across treatments can be explained by the belief effect.*

The evidence for Result 3 is presented in Figures 6 and 7 and Tables 5 and 6. In Figure 6, we show the rejection behavior from the responders' perspective. We plot the *responder's rejection rate* against the size of the offer. The rejection rate is measured by the number of responders who rejected an offer divided by the total number of responders who received the corresponding offer. The rejection rate in the UG is 100 percent for any offer below 10, i. e., *all* responders reject such offers. This means that the statistical effect cannot become operative in this offer range unless responder competition reduces some responders' willingness to reject. Therefore, the large reduction in the proposers' rejection risk (in this offer range) observed in Figure 4 is based on the behavioral changes responder competition induces: the responders' rejection rate for offers below 10 is much lower in RC2 and RC5 than in the UG, and varies between 50 and 78 percent (see Figure 6). In all three treatments, the responder's rejection rate decreases in the size of the offer, but this decrease already occurs for offers below 10 in RC2 and RC5. The rejection rate in RC2 for all offer intervals below 40 is at least 20 percent lower than in the UG. Moreover, the rejection rate in RC5 is lower than in RC2 for most offer intervals.

The econometric evidence in column 1 of Table 5 provides further support for Result 3. Table 5 presents coefficients from a probit regression with the responders' rejections as the dependent variable. The independent variables are the offer size, dummies for RC2 and RC5 (UG is the

omitted category), the time period, and interactions between the treatment dummies and the time period. The regression shows that the coefficient on offer size is negative and highly significant and the treatment dummies for RC2 and RC5 are highly significant and negative. The associated marginal effects indicate that at the sample means, the rejection probability is 27 percent lower in RC2 than in the UG. The rejection rate (at sample means) in RC5 is a striking 53 percent lower than in the UG. Thus, the treatment differences observed in Figure 6 are clearly substantial and statistically significant. Moreover, they contradict the QRE approach and are consistent with the predictions of the fairness approach.

Figure 6 and Figure 7 about here

Table 5 and Table 6 about here

Since the fairness approach not only predicts a reduction in the rejection rate under responder competition but also identifies responders' beliefs as the decisive source of this behavioral change, we introduced a belief measure into our regression. Recall that the responders told us in both responder competition treatments how many other responders they expected to accept the going offer. This enables us to add a dummy variable indicating whether the responder believes that all other responders will reject the offer or whether she believes that at least one other responder will accept the offer (see Table 6). The variable "belief that all others reject" in the regressions of Table 6 takes on a value of 1 if a responder believes that all other responders reject. If a responder believes that all others reject, then she considers herself a decisive player in the sense that she can punish the proposer or maintain equity by rejecting the offer, too. Thus, the fairness approach predicts that this variable has a positive effect on rejection rates. We use the same regressors in the first regression in Table 6 as in Table 5, but we also add the "all others reject" dummy. The coefficient on the offer size is again negative and significant. The "all others reject" dummy is positive, highly significant, and implies a high marginal effect. If a responder believes she is decisive, her rejection rate increases by 37.4 percent! Moreover, the treatment dummies for RC2 and RC5 are now insignificant and rather small relative to the regression in Table 5, suggesting that the treatments per se have little or no effect on rejection behavior if we control for the belief effect. This interpretation is further supported by the second regression in Table 6 where we only use the RC2 and the RC5 data. The "all others reject" dummy is again large and significant, indicating an increase in the rejection probability of 41 percent if a responder believes that all others reject, and

the treatment dummy for RC5 is close to zero and insignificant. Thus, again the treatment per se has no effect on the rejection behavior if we control for the responders' beliefs.

Recall that the statistical effect on proposers' rejection risk is based on the presence of heterogeneous responders. To examine responder heterogeneity, we ran probit regressions for each treatment separately in which we included the offer size, time period, and dummies for individual responders. We observed strong evidence for responder heterogeneity in each treatment. Likelihood ratio tests for the joint significance of the individual dummies show that the restricted model (with no individual dummies) is significantly different from the model with individual dummies at all conventional significance levels ($p < .0001$ in each treatment).

The effect of beliefs on rejection behavior is so strong that it can even be detected in the raw data. In Figure 7, we illustrate the responders' rejection probability in RC2 for the case in which the responder believes that the competitor rejects and for the case in which she believes that the competing responder accepts. As one can see, the rejection probability is much higher if the responder believes that the competitor will also reject the offer. Thus, taken together Figures 6 and 7 and the regressions in Tables 5 and 6 provide strong support for the fairness approach because they suggest that the belief effect is the major determinant of the changes in rejection behavior across treatments.

V. Combining the Fairness Approach with the QRE Approach

There is little doubt that our data refutes the prevailing self-interest model with fully rational individuals. The failure to predict the correct level and the comparative static changes in behavior across treatments suggests that this model is unable to capture important behavioral forces that shape the effects of competition. In contrast, both the fairness model and the QRE model with selfish preferences make correct predictions with regard to the qualitative changes in market prices across treatments: The introduction of or an increase in responder competition reduces the mean accepted offers substantially, while the introduction of proposer competition increases the mean accepted offers substantially.

Several quantitative aspects of the data suggest, however, that each of these models alone cannot capture all the important phenomena at work. The fairness model overpredicts the change in market prices if we introduce proposer competition as it overpredicts the proposers' rejection risk.

This suggests that more than the assumption of heterogeneous fairness preferences is needed to explain these facts. For this purpose, one needs a model that explains the relatively low rejection risk for the proposers when they make offers that give them still a sizeable share of the gains from trade. As we explained in Section III, the QRE model provides a natural explanation for this phenomenon.

However, the QRE approach with selfish preferences predicts the wrong comparative static effects of responder competition on responders' behavior. In contrast to the QRE prediction, the introduction of or an increase in responder competition reduces the responders' rejection rate (compare Figure 2 with Figure 6). In addition, the QRE approach underpredicts the rejection rate for low offers in the UG and under responder competition and overpredicts the existence of offers above 50 in the UG. Recall that the rejection rate can never exceed 50 percent according to the QRE approach (see Figure 2), but the rejection rate is between 75 and 100 percent for offers between 0 and 4 in the UG and in RC2 and RC5. The fairness approach provides a natural explanation for these phenomena. In addition, it captures the major driving force behind the responders' reduction in the rejection rate under responder competition: the belief that one of the competing responders will accept the offer.

Our discussion above suggests, therefore, that both heterogeneous fairness preferences and decision errors are needed to explain all important phenomena that shape the effects of competition in our treatments. In principle, the QRE approach can be combined with fairness preferences. There is, however, no guarantee that the combination of the fairness and the QRE approach will not mutually reinforce the weaknesses of each approach. To check the performance of a combined model, we computed the distribution of equilibrium actions of a fully parameterized FS-QRE model. For this purpose, we completely tied our hands with regard to the choice of the parameters for the FS model by using the same preference parameters as in Fehr and Schmidt (1999) which are presented in Table 1. This is very important because otherwise we could rationalize too many different outcomes by choosing the appropriate preference parameters. The only free parameter was, therefore, the error parameter μ from the QRE part of the model.

In Figure 8, we compare the predicted equilibrium distribution of offers across all four treatments with the distribution of the actual offers in the final 10 periods of each treatment. The same preference and error parameters are applied to each treatment in order to generate the

prediction.[19] We take the data from the final 10 periods because we use an equilibrium model to predict behavior. Therefore, it makes sense to take the data from those periods in which a stable behavioral pattern had emerged, i.e., from periods in which there was little or no change in the distribution of offers. A comparison of the predicted and the actual offer distributions indicates that the combined model makes remarkably precise quantitative predictions (see Figure 8). The location of the predicted distribution in each treatment is very close to that of the actual distribution. For instance, the predicted modal interval is given by [5,9] in RC5 which actually is the modal interval. Likewise, the predicted modal interval for RC2 is [15,19] which coincides with the actual modal interval. In addition, the predicted mode for the UG and for PC2 is close to the actual mode. Table 7 provides a further indication of the good match between predicted and actual behavior. The predicted mean and median offers are relatively close to the actual mean and median offers in all treatments.

Figure 8 and Table 7 about here

The QRE model with selfish preferences makes the wrong comparative static predictions with regard to responder behavior under responder competition. It is, therefore, interesting to examine whether the combined QRE-fairness model corrects for this wrong prediction. It turns out that this is indeed the case. For instance, for offers below s = 20 the combined model predicts rejection rates of 76.5, 59.2, and 33.3 percent for the UG, RC2, and RC5, respectively. In fact, the rejection rates in the final 10 periods are given by 100, 50.2 and 31.4 percent in the respective treatments. Thus, the combination of the fairness approach with the QRE-approach explains the qualitative and the quantitative aspects of our data quite well.

VI. Conclusions

The main message of this paper is that basic economic effects of competition cannot be understood without taking fairness concerns and decision errors into account. We supported this provocative claim with a series of experiments and with the development of an alternative to the prevailing

[19] The error parameter is given by CHF 0.216. Since we set the same error parameter across conditions in terms of Swiss francs, we assumed that money illusion does not affect subjects' behaviour in our environment. Note that a constant error parameter in terms of Swiss francs (CHF) implies that the error parameter in terms of experimental money varies because the exchange rate between Swiss francs and experimental money units differs across conditions (in order to keep the gains from trade per player constant across conditions). For example, an error parameter of CHF 0.216 implies that the error parameter in terms of experimental money units is 3 in RC5, 6 in RC2, 9 in the UG, and 6 in PC2. Likewise, a constant error parameter in terms of experimental money units implies that the error parameter in terms of CHF varies across conditions.

model. The prevailing model fails to capture the powerful effects of adding just one additional responder to a bilateral situation. In the case of proposer competition, the model makes the opposite error: it overpredicts the changes in market prices. In contrast, our alternative model, which combines heterogeneous fairness preferences with the quantal response approach, predicts all qualitative changes associated with increased competition correctly and provides a good quantitative characterization of the entire price distribution. In view of these results, we believe that the combined model may generally improve our understanding of the mechanisms behind competitive markets.

References

Anderson, S., Goeree. J. and Holt C. 1998. "The All-Pay Auction: Equilibrium with Bounded Rationality", *Journal of Political Economy* 106(4), 828-853.

Bolton, G. and Ockenfels, G., 2000. "ERC: A Theory of Equity, Reciprocity and Competition." *American Economic Review* 90(1):166-193.

Becker, G. 1962. "Irrational Behavior and Economic Theory", *Journal of Political Economy* 70(1), 1-13.

Camerer, C. 2003. *Behavioral Game Theory – Experiments in Strategic Interaction*, Princeton University Press, Princeton, New Jersey.

Charness, G. and Rabin, M. (2002), "Understanding Social Preferences with Simple Tests." *Quarterly Journal of Economics* 117, 817-869.

Dufwenberg, M. and Kirchsteiger, G. 1999. "A Theory of Sequential Reciprocity." Discussion Paper, CentER, Tilburg University.

Falk, A. and Fischbacher, U., 1999. "A Theory of Reciprocity." Working paper Nr. 6, Institute for Empirical Economic Research, University of Zurich.

Fehr, E. and Schmidt, K. 1999. "A Theory of Fairness, Competition and Cooperation." *Quarterly Journal of Economics* 114:817-868.

Fehr, E., Schmidt, K. 2003. "Theories of Fairness and Reciprocity – Evidence and Economic Applications." in: M. Dewatripont, L. Hansen and St. Turnovsky (Eds.), *Advances in Economics and Econometrics* - 8th World Congress, Econometric Society Monographs.

Fischbacher, U. (1999). "Z-Tree: A Toolbox for Readymade Economic Experiments." IEW Working Paper No. 21, University of Zurich.

Goeree, J. K. and Holt, Ch. A., 2000. "Asymmetric Inequality Aversion and Noisy Behavior in Alternating-Offer Games." *European Economic Review* 44, 1079-1089

Goeree, J. K. and Holt, Ch. A., 2001. "Ten Little Treasures of Game Theory and Ten Intuitive Contradictions." *American Economic Review* 91(5), 1402-1422

Goeree, J. K. and Holt, Ch., and Laury, S. K., 2002. "Private Costs and Public Benefits: Unraveling the Effects of Altruism and Noisy Behavior." *Journal of Public Economics* 83(2), 255-276.

Goeree, J. K., Holt, Ch. A., and Palfrey, T. R, 2002. "Quantal Response Equilibrium and Overbidding in Private-Value Auctions" *Journal of Economic Theory* 104(1), 247-272.

Grosskopf, B., 2002. "Reinforcement and Directional Learning in the Ultimatum Game with Responder Competition", Discussion Paper, Harvard Business School.

Güth, W., Schmittberger R., and Schwarze B., 1982. "An Experimental Analysis of Ultimatum Bargaining," *Journal of Economic Behavior and Organization,* 3, 367–388.

Güth, W., Marchand, N. and Rullière, J.L. 1997. "On the Reliability of Reciprocal Fairness – An Experimental Study." mimeo Humboldt University at Berlin.

Güth, Werner, and Tietz, R., 1990. "Ultimatum Bargaining Behavior – A Survey and Comparison of Experimental Results." *Journal of Economic Psychology* 11, 417-449.

Haile, P. A., Hortacsu A. and Kosenock G., 2003. "On the Empirical Content of Quantal Response Equilibrium", Discussion Paper, University of Chicago.

Levine, D., 1998. "Modeling Altruism and Spitefulness in Experiments." *Review of Economic Dynamics* 1, 593-622.

McKelvey and Palfrey, 1995. "Quantal Response Equilibria for Normal Form Games." *Games and Economic Behavior* 10: 6-38.

Rabin, M., 1993. "Incorporating Fairness into Game Theory." *The American Economic Review.* 83 (5), 1281-1302.

Roth, A., 1995. "Bargaining Experiments." in Kagel, J., and Roth, A. (eds.) *The Handbook of Experimental Economics*. (Princeton: Princeton University Press)

Roth, A., Prasnikar, V., Okuno-Fujiwara, M. and Zamir, S. 1991. "Bargaining and Market Behavior in Jerusalem, Ljubljana, Pittsburgh, and Tokyo: An Experimental Study." *American Economic Review* 81(5), 1068-1095.

Smith, V. L. 1962. "An Experimental Study of Competitive Market Behavior", *Journal of Political Economy* 70, 111-137.

Smith, V. L. 1982. "Microeconomic Systems as an Experimental Science", *American Economic Review* 72(5), 923-955.

TABLE 1

Prediction of offers and acceptance thresholds under responder competition based on the preference parameters of Fehr and Schmidt (1999)

Preference parameters		α=4,β=.6	α=1,β=.6	α=.5,β=.25	α=0,β=0	average accepted offer
Relative frequency		10%	30%	30%	30%	
Offers	UG	50	50	44	33	43.4
	RC2	17	17	17	17	17.0
	RC5	4	4	4	4	4.0
Acceptance thresholds	UG	44	33	25	0	
	RC2	17	17	15	0	
	RC5	4	4	4	0	

TABLE 2

Mean accepted offers

	All periods				Final period			
Matching group	PC2 mean (s.d.)	UG mean (s.d.)	RC2 mean (s.d.)	RC5 mean (s.d.)	PC2 mean (s.d.)	UG mean (s.d.)	RC2 mean (s.d.)	RC5 mean (s.d.)
1	67.7 (10.2)	43.2 (7.8)	26.4 (17.4)	13.6 (8.9)	71.5 (4.4)	45.5 (4.2)	14.3 (15.4)	12.0 (12.4)
2	63.3 (12.0)	44.2 (8.4)	23.5 (8.6)	23.5 (20.0)	76.7 (6.7)	46.5 (4.7)	18.0 (8.5)	21.3 (22.5)
3	72.6 (17.4)	39.7 (4.0)	29.6 (15.7)	17.1 (14.9)	73.0 (2.9)	40.0 (0.0)	25.3 (13.4)	14.0 (10.7)
4	76.1 (13.4)	48.0 (10.7)	22.3 (10.0)	10.9 (8.8)	89.8 (0.5)	37.7 (14.3)	17.8 (3.3)	7.8 (2.1)
5		42.4 (6.2)				42.0 (7.0)		
6		38.1 (8.7)				31.7 (2.9)		
Mean	70.3 (14.4)	42.7 (8.6)	25.5 (13.7)	16.2 (14.5)	77.8 (8.4)	41.1 (7.8)	18.8 (10.8)	13.8 (13.5)

Note: Standard deviations are in parentheses. PC2 denotes the market game with two competing proposers. UG denotes Ultimatum Game, RC2 denotes the market game with two competing responders, RC5 denotes the market game with 5 competing responders.

TABLE 3

Pooled regressions predicting accepted offers

	Dependent variable: accepted offer			
	PC2, UG, RC2, and RC5 Pooled		RC2 and RC5 Pooled	
	all periods	final 10 periods	all periods	final 10 periods
PC2	35.334***	34.301***		
	(5.031)	(4.958)		
PC2*time period	0.817**	0.686*		
	(0.363)	(0.361)		
RC2	-24.167***	-22.366***		
	(2.845)	(2.627)		
RC2*time period	-0.753***	-0.237		
	(0.199)	(0.195)		
RC5	-31.616***	-28.994***	-7.449	-6.628*
	(3.961)	(3.531)	(4.094)	(3.476)
RC5*time period	-0.539***	0.050	0.214	0.287**
	(0.178)	(0.1902)	(0.190)	(0.108)
Time period	0.003	-0.142	-0.750***	-.379***
	(0.137)	(0.178)	(0.150)	(0.083)
Constant	42.737***	42.435***	18.570***	20.069***
	(2.030)	(2.021)	(2.070)	(1.743)
R^2	0.733	0.796	0.163	0.088
N	1234	640	592	305
F-value	62.58	82.65	15.39	8.97
p-value	0.000	0.000	0.002	0.009

Note: Numbers reported are ordinary least squares coefficients. Robust standard errors are in parentheses. Errors are treated as independent across matching groups whereas within matching groups we allow for arbitrarily correlated errors. Time periods are numbered from –19 to 0 in columns 1 and 3 and from –9 to 0 in columns 2 and 4. ***, **, and * denote significance at the 1-, 5-, and 10-percent level, respectively.

TABLE 4

Probit model predicting the proposer's rejection risk

	Dependent variable equals 1 if the proposer's offer is rejected by all responders *Proposers* are the units of observation			
	PC2, UG, RC2, and RC5 pooled		RC2 and RC5 pooled	
	coef. (rob. s.e.)	marginal effects	coef. (rob. s.e.)	marginal effects
Offer	-0.053***	-.014	-0.083***	-0.004
	(0.008)		(0.023)	
PC2	2.778***	0.790		
	(0.265)			
PC2*time period	0.073***	0.020		
	(0.015)			
RC2	-1.861***	-.291		
	(0.307)			
RC2*time period	-0.039**	-.011		
	(0.016)			
RC5	-3.079***	-.383	-1.443***	-0.090
	(0.335)		(0.367)	
RC5*time period	-0.046	-.012	0.000	0.000
	(0.028)		(0.031)	
Time period	-0.021	-.005	-0.072***	-0.004
	(0.265)		(0.020)	
Constant	1.103***		-0.358	
	(0.330)		(0.395)	
N	1700		640	
Wald χ^2	757.60		55.75	
Prob > χ^2	0.000		0.000	

Note: Numbers reported are probit coefficients. Robust standard errors are in parentheses. Errors are treated as independent across matching groups whereas we allow for arbitrarily correlated errors within matching groups. The 20 time periods are numbered from –19 to 0. Marginal effects are calculated at sample means. ***, **, and * denote significance at the 1-, 5-, and 10-percent level, respectively.

TABLE 5

Pooled Probit model predicting the responder's rejection probability

Dependent variable equals 1 if the responder rejects the offer (Responders are the units of observation)		
	UG, RC2, RC5 pooled	
	coef. (rob. s.e.)	marginal effects
Offer	-0.065***	-0.020
	(0.007)	
RC2	-1.076***	-0.268
	(0.263)	
RC2*time period	-0.023	-0.007
	(0.014)	
RC5	-1.666***	-0.532
	(0.292)	
RC5*time period	-0.029***	-0.009
	(0.011)	
Time period	-0.019*	-0.006
	(0.011)	
Constant	1.574***	
	(0.297)	
N	2700	
Wald χ^2	289.42	
P	0.000	

Notes: Numbers reported are probit coefficients. Robust standard errors are in parentheses. Errors are treated as independent across matching groups whereas we allow for arbitrarily correlated errors within matching groups. The 20 time periods are numbered from –19 to 0. Marginal effects are calculated at sample means. ***, **, and * denote significance at the 1-, 5-, and 10-percent level, respectively.

TABLE 6

Pooled Probit models predicting the responder's rejection probability

	Dependent variable: = 1 if the responder rejects the offer Observation unit: each *responder* is an observation			
	UG, RC2, and RC5 pooled		RC2, and RC5 pooled	
	coef. (rob. s.e.)	marginal effects	coef. (rob. s.e.)	marginal effects
Offer	-0.055*** (0.007)	-0.017	-0.049*** (0.006)	-0.016
Belief that all others reject (dummy variable)	1.089*** (0.139)	0.374	1.118*** (0.138)	0.411
RC2	-0.236 (0.278)	-0.072		
RC2*time period	-0.013 (0.018)	-0.004		
RC5	-0.272 (0.296)	-0.088	0.033 (0.186)	0.011
RC5*time period	-0.014 (0.011)	-0.004	-0.000 (0.013)	-0.000
Time period	-0.021** (0.010)	-0.007	-0.031*** (0.014)	-0.010
Constant	0.087 (0.293)		-0.256 (0.166)	
N	2700		2240	
Wald χ^2	199.72		170.43	
P > χ^2	0.000		0.000	

Notes: Numbers reported are probit coefficients. Robust standard errors are in parentheses. Errors are treated as independent across matching groups whereas we allow for arbitrarily correlated errors within matching groups. The 20 time periods are numbered from –19 to 0. Marginal effects are calculated at sample means. ***, **, and * denote significance at the 1-, 5-, and 10-percent level, respectively.

TABLE 7

Actual and predicted offers based on the combined Fairness-QRE approach

	RC5		RC2		UG		PC2	
	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted
Median	9	5	20	24	40	45	68	64
Mean	13.70	5.93	21.16	26.15	41.34	42.93	67.23	64.14

Figure 1: Predicted offer distributions in the UG according to the quantal response approach with selfish preferences

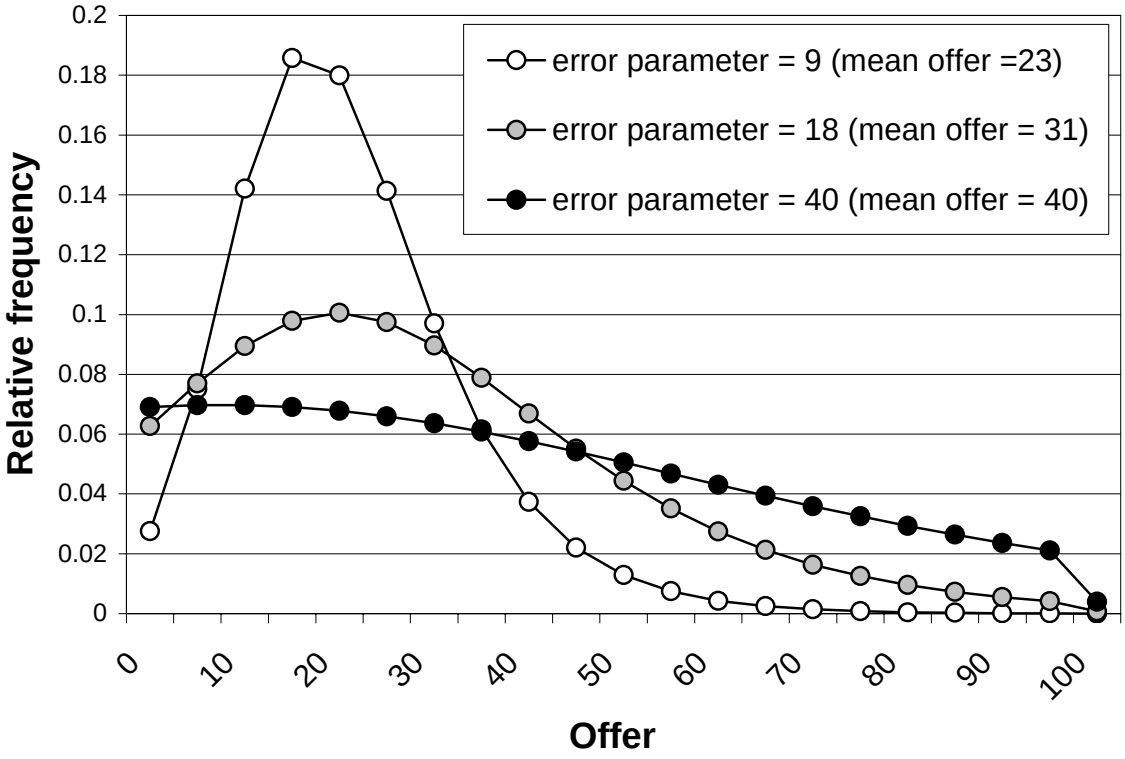

Figure 2: Prediction of responders' rejection rate according to the quantal response equilibrium approach with selfish preferences (μ = 4)

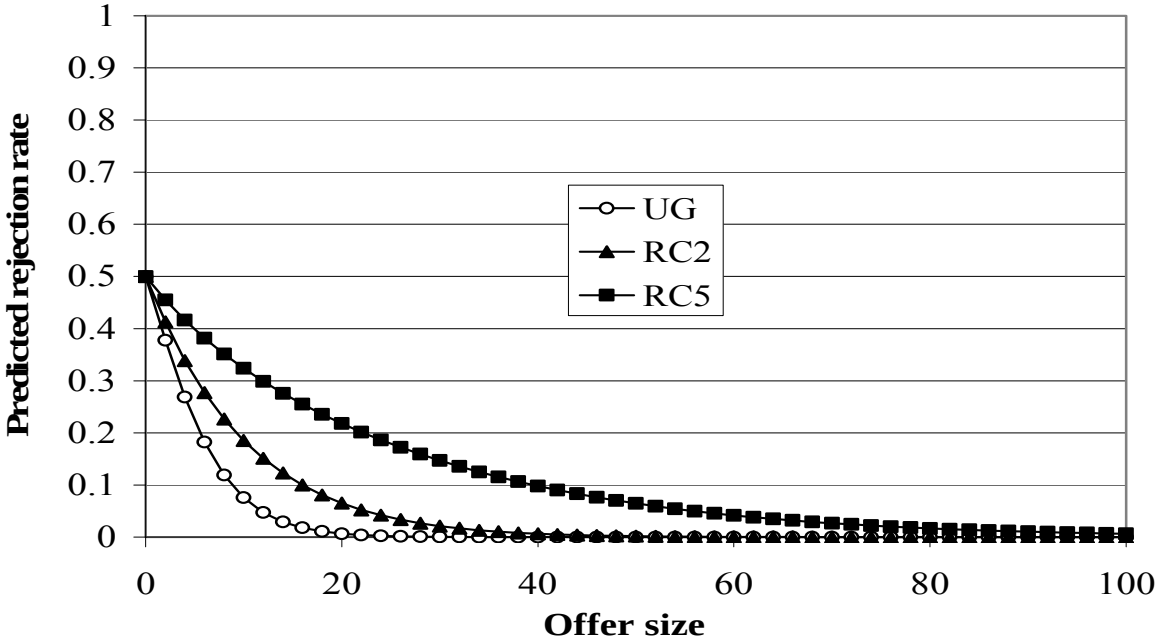

Figure 3: Average accepted offer in bargaining and market experiments

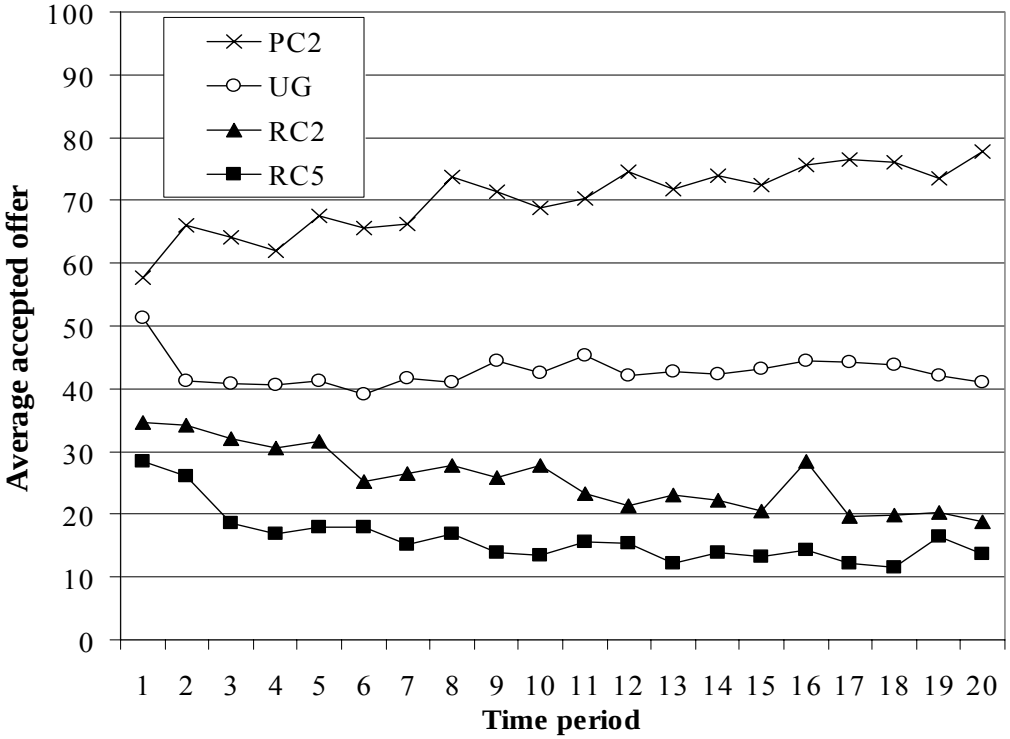

Figure 4: Proposers' rejection risk conditional on offers

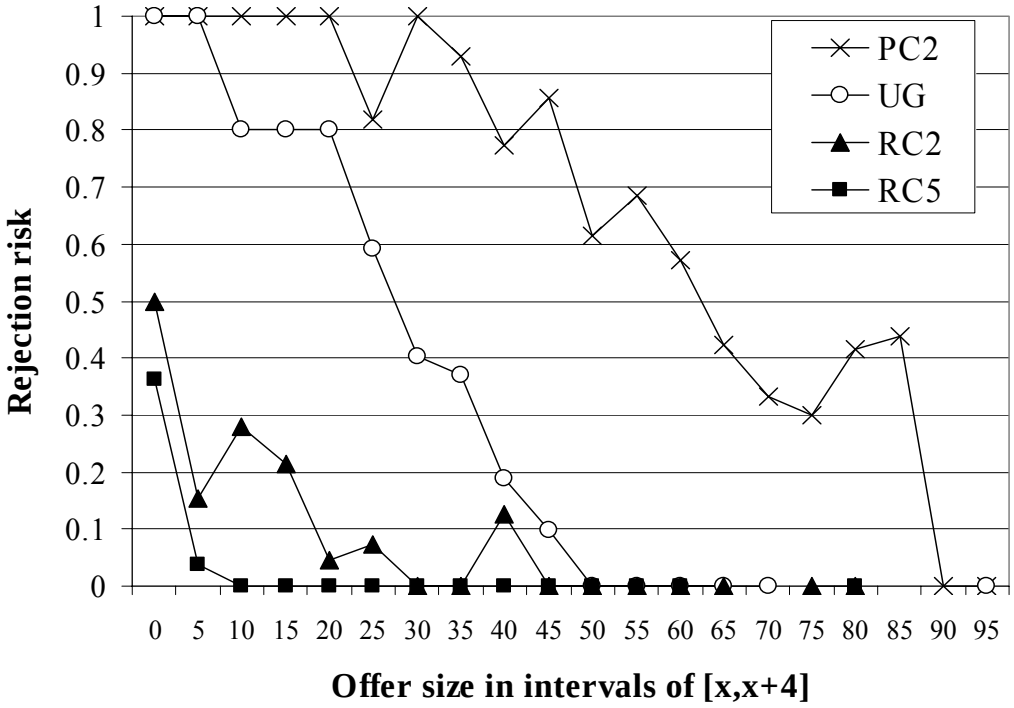

Figure 5: Proposers' expected payoff as a function of offer size

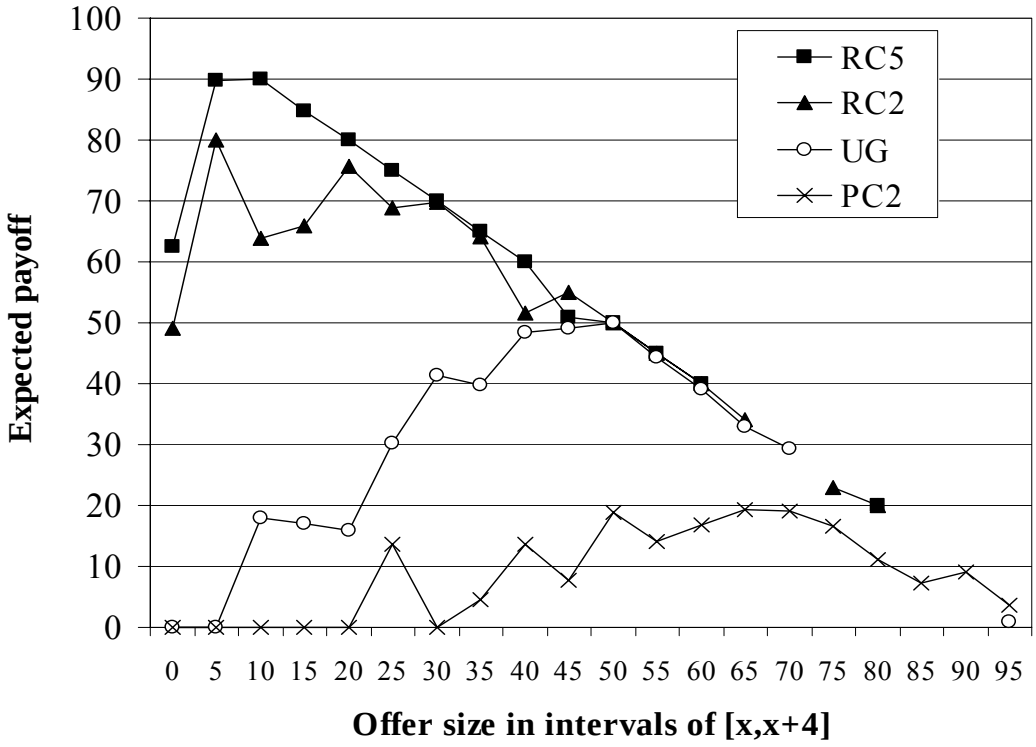

Figure 6: Responders' rejection rate conditional on offer size

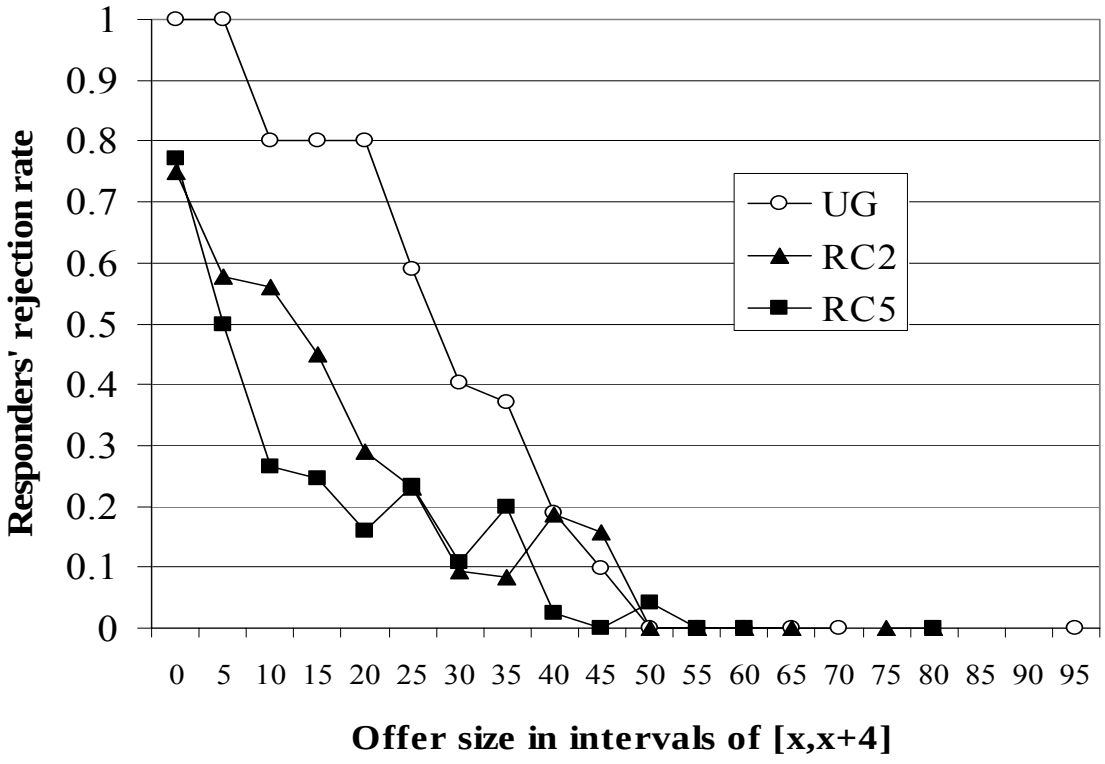

Figure 7: Responders' rejection rate in RC2 conditional on offer size and beliefs about the other responder's behavior

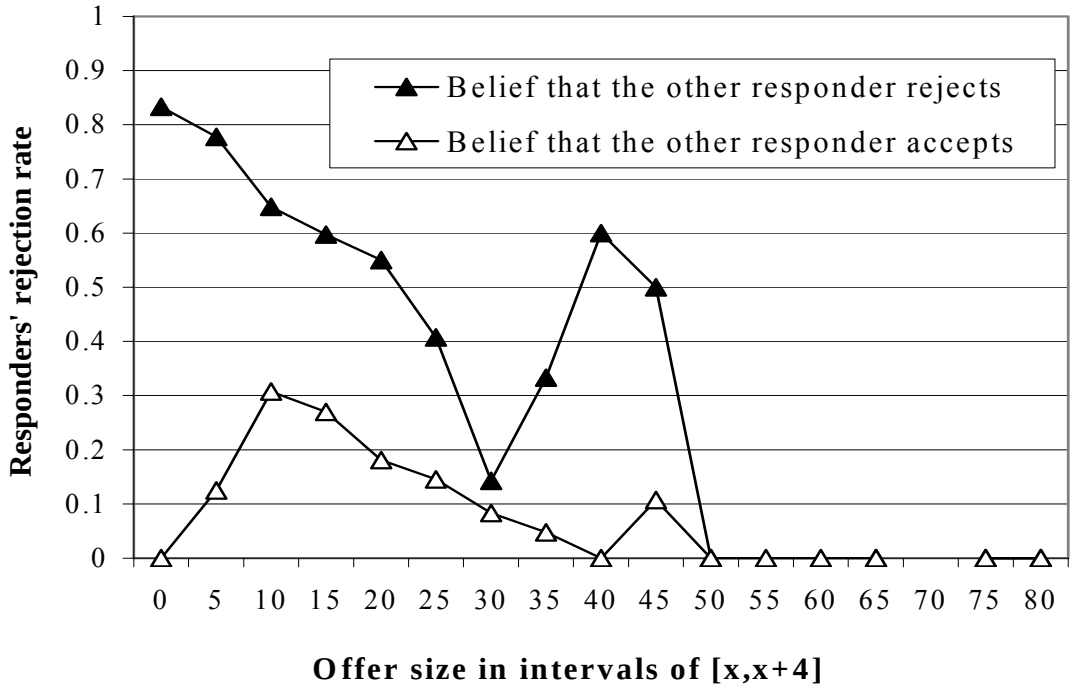
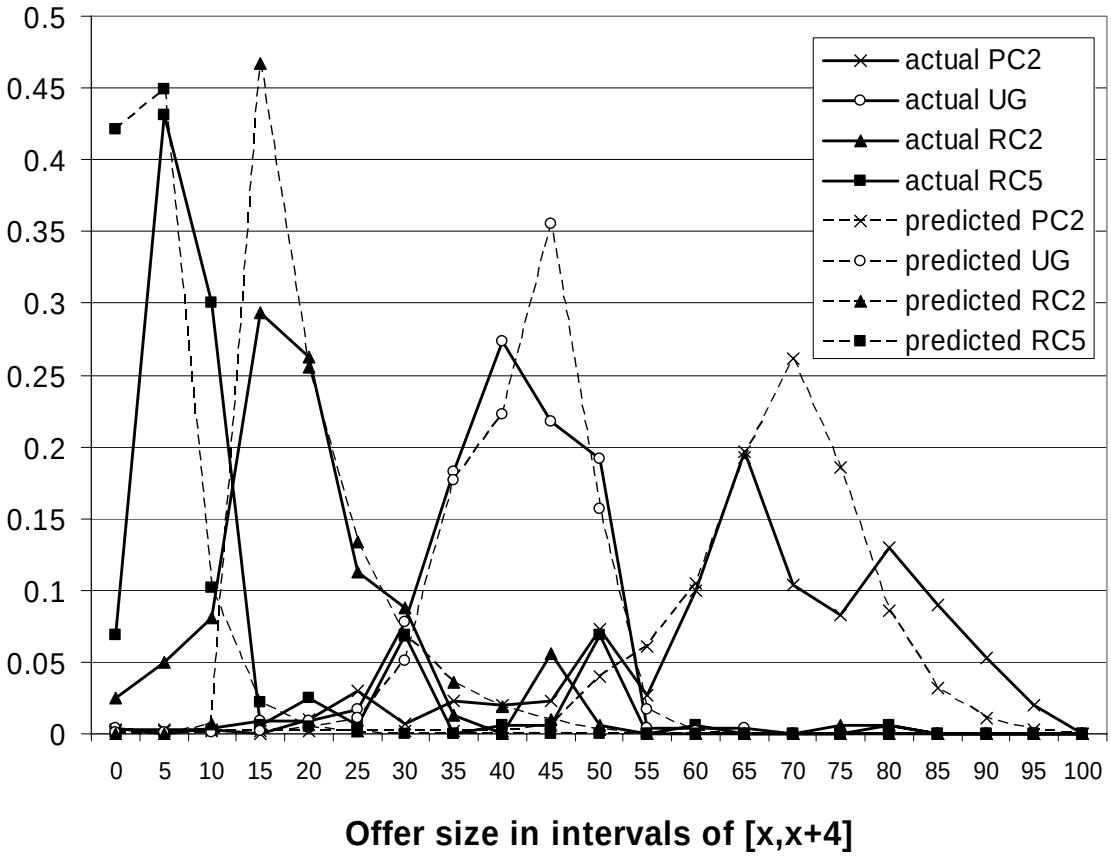
Figure 8: Actual and predicted offer distribution based on the combined Fairness – QRE approach