Online Appendix to "What Makes a Price Fair? An Experimental Study of Transaction Experience and Endogenous Fairness Views"

Holger Herz and Dmitry Taubinsky

December 29, 2016

A   Results for Market Games

In this appendix we consider predictions for the PC and RC market games. Proposers' preferences (β_P, r_P) are drawn from some distribution F_P and responders' preferences (β_R, r_R) are drawn from some distribution F_R. The solution concept we consider is a pure strategy Perfect Bayesian Equilibrium.

Proposition 1. *There is a unique PBE in the PC market game: both proposers offer 100 chips, and the responder randomly chooses one of the offers.*

Proof. [sketch] Let $\underline{a}$ be Proposer 1's offer, and suppose that $\underline{a} < 100$. Clearly, it is never strictly optimal for Proposer 2 to offer anything less than $\underline{a}$. It is also not optimal to offer $\underline{a}$. By choosing $\underline{a} + \epsilon$ instead of $\underline{a}$, the proposer increases his chance of winning from 1/2 to 1. The net impact on utility is $(100 - \underline{a} - \epsilon) - (100 - \underline{a})/2 > 0$ for ϵ sufficiently small. Thus, it is not possible to have $\underline{a} < 1$ in equilibrium.

□

Proposition 2. *The following is a PBE of the RC market game: the proposer offers 0 chips and the responders accept with probability 1.*

Proof. [sketch] First, we show that the Proposer offering 0 and the responders accepting all offers is an equilibrium. Since $\alpha < 1$, it is always optimal for a proposer to offer nothing if that offer will be accepted with probability 1. Next consider a responder's best response function in this proposed equilibrium. Note that by deviating and choosing to reject the offer, the responder cannot decrease the size of the pie. Since the other responder will accept, the final outcome after the deviation will still be the proposer getting 100 chips and the responders getting nothing. Thus there is no incentive to deviate.

□

B Appendix to Section 4

B.1 Reference dependence over monetary payoffs

Here we consider a model in which preferences are reference-dependent with respect to monetary payoffs, but the fairness preferences are fixed. Let a responders' preferences be given by $u(\pi_R, \pi_P | r) = \pi_R + \mu(\pi_R - r) + f(\pi_R, \pi_P)$ where r is the reference point, μ is the gain-loss utility, and f is the fairness utility. Let μ and f be continuous and assume that $u(\pi_R, 300 - 3\pi_R | r)$ is strictly increasing in π_R for each r. This guarantees that for each value of r, there is a minimally acceptable offer $MAO(r)$. Finally, we make the standard assumption that μ is concave.[1]

Proposition 1. $MAO(r)$ is decreasing in r.

The intuition for the Proposition is simple: the higher the reference point r, the more painful it is to get a payoff of 0, and thus the lower the MAO. Formally, $\mu(\pi_R - r) - \mu(0 - r)$ is decreasing in r because of the concavity of μ.

Now the natural assumption to make about how experience shapes the reference point is that experiencing higher offers or payoffs should lead to a higher reference point r. This is the case in theories of backwards-looking reference points, as in Bowman et al. (1999). Alternatively, if r is shaped by expectations which are based on the types of offers observed, then r should again be increasing in history of offers. Thus in experiment 1, r should be higher for responders in the PC market than for responders in the RC market. The Proposition thus implies that PC responders should actually have lower MAOs than RC responders - the opposite of our experimental results. This implies that unless fairness preferences are themselves shaped by past experience, there is no natural model of reference-dependence over monetary payoffs that is consistent with our experimental results.

B.2 Belief-based reciprocity models

We now argue that belief-based reciprocity models do not offer a natural explanation of our results. First, consider Dufwenberg and Kirchsteiger's (2004) extension of Rabin's (1993) intention based reciprocity model. For the proposer, $[0, 100]$ is the efficient set of offers a, and thus the "equitable" benchmark is given by $a^{e_p} = 50$. If the proposer believes that a responder accepts his offer of a with probability θ, then his kindness toward this responder is thus $\theta a - 50$.

For the responder, the set of efficient strategies conditional on an offer a is simply to accept; thus the "equitable" payoff to the proposer conditional on an offer a is simply a. Therefore, if a responder rejects a proposer's offer, his kindness toward the proposer is $-a$. Letting ϕ denote the strength of the reciprocity motive, the responder's payoff from choosing an MAO is given by

$$\int_x [a - \phi a(50 - a\tilde{\theta}] \mathbf{1}_{x \geq M} d\tilde{F}(x) \tag{B.1}$$

---

[1]Note that our assumptions on μ are more general than those of Kőszegi and Rabin (2006).

where $\tilde{F}$ are the responder's beliefs about the strategy of the proposer, and $\tilde{\theta}$ is the probability that the proposer thinks his offer will be accepted (from the responder's perspective; i.e., it is the responder's second order belief). Thus the MAO is given simply as the value M for which $M - \phi M(50 - M\tilde{\theta}) = 0$. The key feature of this condition is that M does not depend on the responder's expectation of proposer behavior. Thus this model, combined with a reasonable theory of adaptively formed expectations, would still not explain our results.

Similarly, in Falk and Fischbacher's (2006) model, a straightforward extension of (19) in their Appendix 3, shows that $U_{2A} - U_{2R}$, the relative gain from accepting versus rejecting an offer a, is given by

$$U_{2A} - U_{2R} = a + \phi\tilde{\theta}(300 - 3a - a)(100 - a) \tag{B.2}$$

Again, this shows that the acceptance decision does not depend on beliefs $\tilde{F}$.

It is possible that past experiences might shape the second order belief $\tilde{\theta}$. However, there are no models of learning that posit how past experiences shape second-order beliefs, and there is not a clear hypothesis about how our phase 1 experiences should shape it. Moreover, intention based reciprocity models do not make a robust prediction about how $\tilde{\theta}$ affects M. In Dufwenberg and Kirchsteiger (2004), M is decreasing in $\tilde{\theta}$ while in Falk and Fischbacher (2006) M is increasing in $\tilde{\theta}$ (note that the utility from accepting is decreasing in $\tilde{\theta}$ in equation (B.2) while it is increasing in equation (B.1)).

C Salience Theory

C.1 Set up

The true utility function is $U_i = \Pi\left[\mu_i - \beta\max(r - \mu_i, 0) - \alpha\max(\mu_i - r, 0)\right]$, where $\mu_i = \pi_i/\Pi$ is player i's share of the pie, and $r = 1/N$ is the fairness norm in an N-player game.

How a responder trades off payoffs and fairness, however, depends on which is more salient. We let $\Delta_i := \mu_i - r$ denote how much the responder's share of the pie deviates from the fairness norm, and we let (μ_i, Δ_i) denote the pair consisting of the responder's payoff and the fairness deviation. The salience of payoffs versus fairness deviations depends on how those attributes depart from payoff and fairness values in the responder's evoked set. The evoked set $\mathcal{E}$ includes 1) the option corresponding to the proposer's offer, $(\mu(a_i), \Delta(a_i))$, where $\mu(a_i) = \frac{a_i}{3(100 - a_i) + a_i} = \frac{a_i}{300 - 2a_i}$ and $\Delta(a_i) := \frac{a_i}{3(100 - a_i) + a_i} - r = \frac{a_i}{300 - 2a_i} - r$. It includes 2) the option corresponding to the responder rejecting, $(0, 0)$. And it includes 3) a historical average of payoffs and fairness values either experienced or observed by the responder, (μ_i^H, Δ_i^H). We discuss the construction of the historical averages later.

Given the evoked set $\mathcal{E}$, the salience is determined by comparison to the reference good $(\bar{\mu}, \bar{\Delta})$ given by $\bar{\mu} = \frac{\mu_i + 0 + \mu_i^H}{3}$ and $\bar{\Delta} = \frac{\Delta(\mu_i) + 0 + \Delta^H}{3}$. The salience of a payoff π_i is given by $\sigma(\mu_i, \bar{\mu})$ and the salience of a fairness deviation Δ_i is given by $\sigma(\Delta_i, \bar{\Delta})$. As in BGS, we assume that the salience

3

function $\sigma(\cdot, \cdot)$ satisfies

1. Scale invariance. $\sigma(\alpha x, \alpha y) = \sigma(x, y)$

2. Diminishing sensitivity. If $x \geq 0$, then for any $\epsilon > 0$, $\sigma(x + \epsilon, y + \epsilon) \leq \sigma(x, y)$, with the inequality strict if $y > 0$.

3. Reflection. $\sigma(x, y) = \sigma(-x, -y)$.

A salience function that satisfies these properties for $x, y \neq 0$ is $\sigma(x, y) = \frac{|x-y|}{|x|+|y|}$. Note that the maximum value of this salience function is 1, and that $\sigma(x, 0) = \sigma(0, y) = 1$ for $x, y \neq 0$. To define $\sigma(0, 0)$, we thus make the more general fourth assumption that $\sigma(0, y) = \sigma(x, 0) = 1$ for all x, y.

As in BGS, the responder evaluates the option (μ_i, Δ_i) as follows:

$$
U_i^s = \begin{cases} \Pi\left[\mu_i - \delta\left(\beta \max(r - \mu_i, 0) + \alpha \max(\mu_i - r, 0)\right)\right] & \text{if } \sigma(\mu_i, \bar{\mu}) > \sigma(\Delta_i, \bar{\Delta}) \\ \Pi\left[\mu_i - (\beta \max(r - \mu_i, 0) + \alpha \max(\mu_i - r, 0))\right] & \text{if } \sigma(\mu_i, \bar{\mu}) = \sigma(\Delta_i, \bar{\Delta}) \\ \Pi\left[\delta\mu_i - (\beta \max(r - \mu_i, 0) + \alpha \max(\mu_i - r, 0))\right] & \text{if } \sigma(\mu_i, \bar{\mu}) < \sigma(\Delta_i, \bar{\Delta}) \end{cases}
$$

where $\delta \in (0, 1]$. To ensure that the responder does not reject offers that give him more than half of the pie, we make the reasonable assumption that $\alpha/\delta < 2$.

C.2 Explaining Experiment 1 results

The perceived utility of rejection is always zero. How does the responder evaluate the utility of accepting the action? We first begin with the case in which $(\mu_i^H, \Delta_i^H) \in \{(0, -1/3), (1, 2/3)\}$. These two cases correspond to the equilibrium outcomes in the PC and RC markets, respectively.

Case 1. $(\mu_i^H, \Delta_i^H) = (1, 2/3)$ In this case, $\bar{\mu} = (1 + \mu_i)/3$ and $\bar{\Delta} = ((\mu_i - 1/2) + 2/3)/3$. Thus payoff salience is given by $\sigma(\mu_i, (1 + \mu_i)/3) = \sigma(3\mu_i, \mu_i + 1)$, while fairness salience is given by $\sigma(\mu_i - 1/2, (\mu_i + 1/6)/3) = \sigma(3\mu_i - 3/2, \mu_i + 1/6)$. Now because the proposer makes an offer that gives the responder a payoff smaller than his own, $\mu_i < 1/2$, and thus the combination of the scale invariance and diminishing sensitivity assumptions implies that fairness is always more salient than payoffs in this case. The smallest share μ_i a responder is willing to accept in this case must satisfy

$$
\delta\mu_i - \beta(1/2 - \mu_i) = 0
$$

and thus $\mu_i = \frac{\beta}{2(\beta+\delta)}$. Since $\mu_i = \frac{a_i}{300-2a_i}$ by definition, this shows that smallest offer a responder is willing to accept in this case is thus $M = \frac{150\beta}{\delta+2\beta}$.

Case 2. $(\mu_i^H, \Delta_i) = (0, -1/3)$ In this case, $\bar{\mu} = \mu_i/3$ and $\bar{\Delta} = (\mu_i - 5/6)/3$. Thus payoff salience is given by $\sigma(\mu_i, \mu_i/3) = \sigma(3, 1)$, while fairness salience is given by $\sigma(\mu_i - 1/2, (\mu_i - 5/6)/3) = \sigma(3\mu_i - 3/2, \mu_i - 5/6)$. Now because the proposer makes an offer that gives the responder a payoff smaller than his own, $\mu_i < 1/2$ and thus Δ_i and $\bar{\Delta}$ are negative. In this case, payoffs will be more salient than payoffs if and only if $\frac{\mu_i - 5/6}{\mu_i - 3/2} < 3$, which happens when $\mu_i < 11/24$. When payoffs are salient, the smallest acceptable share is the solution to

$$\mu_i - \delta\beta(1/2 - \mu_i) = 0$$

and thus is $\mu_i = \frac{\delta\beta}{2(1+\delta\beta)}$. Now since $\mu_i = \frac{a_i}{300 - 2a_i}$, the smallest offer that a responder is willing to accept in this case is $M_1 = \frac{150\delta\beta}{1+2\delta\beta}$. When fairness is salient, the smallest acceptable offer is given by $M_2 = \frac{150\beta}{\delta + 2\beta}$ as before. Because $M_1 < M_2$, it follows that the proposers will offer M_1 iff $\frac{\delta\beta}{2(1+\delta\beta)} ¡ 11/24$ or, equivalently, iff $\delta\beta < 11$. If, however, $\delta\beta \geq 11$ then proposers offer M_2. Note, however, that $\delta\beta < 11$ is a very general condition that is extremely unlikely to be violated. In the standard ultimatum game without salience considerations, a $\beta > 11$ would imply that responders reject all offers that give them less than 42.3% of the total pie.

Proposition 3. *Suppose that $\delta\beta ¡ 11$. Then $MAO_{RC} = \left(\frac{\delta^2 + 2\delta\beta}{1 + 2\delta\beta}\right) MAO_{PC} < MAO_{PC}$.*

C.3   The Mixture Model and the Role Switch and Full Information experiments

Is it observational experience or personal payoff experience that enters into the evoked set $\mathcal{E}$ as (μ^H, Δ^H)? While this does not affect our experiment 1 interpretation, since the two are essentially identical, this can affect behavior in the Role Switch and the Full Information experiments. We suppose that a fraction q relies on observational experience, and a fraction $1 - q$ relies on personal payoff experience. Out of those who rely on observational experience, we suppose that in the Full Information Experiment, a fraction ω relies on what they observe in their own market, while a fraction $(1 - \omega)$ rely on what they observe in the other market. In this mixture model of the evoked set, the distribution of the option (μ^H, Δ^H) in the evoked set is thus as follows:

- For responders who were responders in the PC market and observed only that market, $(\mu^H, \Delta^H) = (1, 2/3)$ with probability 1.

- For responders who were responders in the RC market and observed only that market, $(\mu^H, \Delta^H) = (0, -1/3)$ with probability 1.

- For responders who were proposers in the PC market, $(\mu^H, \Delta^H) = (1, 2/3)$ with probability q and $(\mu^H, \Delta^H) = (0, -1/3)$ with probability $1 - q$.

- For responders who were proposers in the RC market, $(\mu^H, \Delta^H) = (1, 2/3)$ with probability $1 - q$ and $(\mu^H, \Delta^H) = (0, -1/3)$ with probability q.

- For responders who were in the PC market but observed both markets, $(\mu^H, \Delta^H) = (1, 2/3)$ with probability $1 - q + q\omega$ and $(\mu^H, \Delta^H) = (0, -1/3)$ with probability $q(1 - \omega)$.

5

- For responders who were in the RC market but observed both markets, $(\mu^H, \Delta^H) = (0, -1/3)$ with probability $1 - q + q\omega$ and $(\mu^H, \Delta^H) = (1, 2/3)$ with probability $q(1 - \omega)$.

We now have the following result:

Proposition 4. *Suppose that $\delta\beta < 11$. Define $M_h = \frac{150\beta}{\delta + 2\beta}$ and $M_l = \bar{\delta}^2 M_l$, where $\bar{\delta}^2 := \frac{\delta^2 + 2\delta\beta}{1 + 2\delta\beta} < 1$. Then*

1. *For responders who were responders in the PC market and observed only that market, the average MAO is M_h*

2. *For responders who were responders in the RC market and observed only that market, the average MAO is $M_l = \bar{\delta}^2 M_h$*

3. *For responders who were proposers in the PC market, the average MAO is $qM_h + (1-q)M_l = M_h\left[q + (1-q)\bar{\delta}^2\right]$*

4. *For responders who were proposers in the RC market, the average MAO is $(1-q)M_h + qM_l = M_h\left[1 - q + q\bar{\delta}^2\right]$*

5. *For responders who were in the PC market but observed both markets, the average MAO is $(1 - q + q\omega)M_h + q(1-\omega)M_l = M_h\left[1 - q + q\omega + q\bar{\delta}^2 - q\omega\bar{\delta}^2\right]$*

6. *For responders who were in the RC market but observed both markets, the average MAO is $(1 - q + q\omega)M_l + q(1 - \omega)M_h = M_h\left[q - q\omega + \bar{\delta}^2 - q\bar{\delta}^2 + q\omega\bar{\delta}^2\right]$.*

D   Convergence results

In this appendix, we show that if players enter the same environment with different experiences, then preferences will eventually converge. We make several simplifications: we assume that $\alpha = 0$, and we assume that the effect of past experience is solely through the reference point . We consider play in periods $t = -T, \ldots, 0, 1, 2, \ldots \infty$. In periods $t = -T, \ldots, 0$, players participate in some n player game (possibly one of the market games), while in periods $t = 1, 2, \ldots$ players participate in a non-competitive ultimatum game. As in section 3.3, we let μ_i^t denote the share of the pie that player i received in period t, and set $\mu_i^t = 0$ if all n players received zero payoffs in the respective period. We assume that the proposer's payoff in periods $t > 1$ is given by $k(Y - a)$, while the responder's payoff is given by a, where a is the offer.

In period $t = -T$, player i's reference point in an n person game is given by $\mu_i^{-T} = 1/n$. In periods $t > -T$, the reference point of player i in an n-player game is given by

$$r_i^t = (1 - \gamma)(1/2) + \gamma\frac{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}\mu_i^\tau}{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}}.$$

where $w_0, w_1, \ldots\ldots$ is an infinite sequence given by $w_0 = 1$ and $w_j = \delta^j$ for some $\delta \in [0, 1]$

In the simple specification adopted here, the reference point is a convex combination of the "neutral reference point" $1/n$ and the weighted average of past personal payoff experience. Augmenting the specification to allow for observational experience would not change our results.

We consider the evolution of play between a proposer and a responder in periods $t > 0$. We let r_P^t and r_R^t denote the proposer's and responder's period $t > 0$ reference points. We assume that each period, proposers and responders have perfect information about each others' reference points, and play an SPE of the non-competitive ultimatum game. We let M^t denote the minimal acceptable offer of a responder i in period $t > 0$, and let a^t denote the proposer's period $t > 0$ offer.

Throughout this analysis, we will be concerned with steady state preferences and strategies:

Definition 5. A steady state is a pair of strategies (a^*, M^*) and reference points (r_P^*, r_R^*) such that

(a^*, M^*) is an SPE of the ultimatum game in which players have the fairness reference points (r_P^*, r_R^*)

$r_P^* = (1-\gamma)(1/2) + \gamma \frac{\pi_P^*}{\pi_P^* + \pi_R^*}$ and $r_R^* = (1-\gamma)(1/2) + \gamma \frac{\pi_R^*}{\pi_P^* + \pi_R^*}$, where π_P^* and π_R^* are the proposer's and responder's steady state SPE payoffs

Our first result in this section is that there is a unique steady state to which play always converges:

Proposition 6. *Assume that* $\gamma < 1$. *Then there is a unique steady state* $\langle (a^*, M^*), (r_P^*, r_R^*) \rangle$. *In the steady state,* $a^* > 0$, $a^* < k(Y - a^*)$, *and* $a^* = M^*$. *Moreover, this steady state is globally stable. That is, for any set of initial experiences* $\{\mu_i^t\}_{t=-T}^0$, *preferences and strategies converge to the steady state:*

$$\lim_{t \to \infty} r_P^t = r_P^* \quad and \quad \lim_{t \to \infty} r_R^t = r_R^*$$

$$\lim_{t \to \infty} a^t = a^* \quad and \quad \lim_{t \to \infty} M^t = M^*$$

Proposition 6 shows that if players have enough experience in the ultimatum game environment, then their fairness preferences in that environment can be characterized as a fixed point of an adjustment dynamic. In fact, Proposition 6 shows that our model uniquely pins down what the steady-state fairness preferences can be—the steady state is unique. The only assumption needed to guarantee uniqueness is that $\gamma < 1$: that is, that players' fairness preferences are not completely (though perhaps arbitrarily close to) determined by past experience.

A second prediction of the model is that when players have extreme past experiences as in our market conditions, convergence to the steady state will be monotonic. That is, PC responders should monotonically decrease their MAOs, while RC responders should monotonically increase their MAOs:

Proposition 7. *Assume that* $\gamma < 1$ *and that* $\frac{\sum_{t=-T}^0 \mu_R^t}{T+1} + \frac{\sum_{t=-T}^0 \mu_P^t}{T+1} \leq 1$.

1. If $\frac{\sum_{t=-T}^{0} \mu_R^t}{T+1} < r_R^*$, then for all $t > 0$, $M^t < r_R^*$ but is strictly increasing in t.

2. If $\frac{\sum_{t=-T}^{0} \mu_R^t}{T+1} > r_R^*$, then for all $t > 0$, $M^t > r_R^*$ but is strictly decreasing in t.

Proposition 7 simply says that even though responders' MAOs should not reach steady state levels in a finite number of periods, the effect of past market experience should still diminish over time.

Proof of Proposition 6

Step 1: We first show that there is a unique steady state. In any steady state, we must have

$$M^* - \beta[r_R^*(k(Y - M^*) + M^*) - M^*] = 0, \tag{D.1}$$

which can be rearranged to show that

$$\frac{M^*}{k(Y - M^*) + M^*} = \frac{\beta r_R^*}{1 + \beta}. \tag{D.2}$$

Offering $a^* = M^*$ is clearly optimal for the proposer, conditional on making an offer that the responder will accept. Moreover, since $r_P^* + r_R^* = 1$ by definition, some algebra shows that

$$r_P^*[k(Y - M^*) + M^*] < k(Y - M^*),$$

from which it follows that the proposer derives positive utility from making an offer $a^* = M^*$. Thus the proposer's optimal strategy is to offer $a^* = M^*$ in any steady state.

Plugging in $a^* = M^*$ into (D.2), and using the definition of r_R^*, we now have that

$$r_R^* = (1 - \gamma)(1/2) + \gamma \frac{\beta}{1 + \beta} r_R^*. \tag{D.3}$$

Equation (D.3) is a linear equation in r_R^* with a unique solution given by

$$r_R^* = \frac{(1 - \gamma) + \beta(1 - \gamma)}{2 + 2\beta(1 - \gamma)}. \tag{D.4}$$

Thus there can be at most one steady state. We now show that the unique solution does, indeed, correspond to a steady state. First, examination of equation (D.4) shows that $r_R^* \in (0, 1)$: since $(1 - \gamma) < 2$, it is clear that the numerator is smaller than the denominator. Next, by definition of M^*, accepting an offer of $a^* = M^*$ is weakly optimal for the responder. And as we have already established, offering $a^* = M^*$ is also optimal for the proposer.

Step 2: We now show that for each $\epsilon > 0$, there exists a $t \geq 1$ such that $r_R^t + r_P^t \leq 1 + \epsilon$. To

see this, notice that $\mu_R^t + \mu_P^t \leq 1$ for $t \geq 1$, regardless of the outcome in period t. Thus

$$
\begin{aligned}
r_R^t + r_P^t \;&=\; (1-\gamma) + \gamma \left(\frac{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}\mu_R^\tau + w_{t-1-\tau}\mu_P^\tau}{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}} \right) \\
&\leq\; (1-\gamma) + \gamma \left(\frac{\sum_{\tau=-T}^{0} w_{t-1-\tau}\mu_R^\tau + w_{t-1-\tau}\mu_P^\tau}{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}} + \frac{\sum_{\tau=1}^{t-1} w_{t-1-\tau}}{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}} \right) \\
&=\; 1 + \gamma \left(\frac{\sum_{\tau=-T}^{0} w_{t-1-\tau}\mu_R^\tau + w_{t-1-\tau}\mu_P^\tau}{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}} - \frac{\sum_{\tau=-T}^{0} w_{t-1-\tau}}{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}} \right)
\end{aligned}
$$

But

$$
\frac{\sum_{\tau=-T}^{0} w_{t-1-\tau}\mu_R^\tau + w_{t-1-\tau}\mu_P^\tau}{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}} \leq \frac{\sum_{\tau=-T}^{0} 2 w_{t-1-\tau}}{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}}
$$

and

$$
\frac{\sum_{\tau=-T}^{0} w_{t-1-\tau}}{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}} \to 0
$$

as $t \to \infty$. Thus for each $\epsilon > 0$, there exists a $t \geq 1$ such that $r_R^t + r_P^t \leq 1 + \epsilon$.

Step 3: We now show that there is some $t^\dagger \geq 1$ such that $a^t = M^t$ for all $t \geq t^\dagger$; that is, for all $t \geq t^\dagger$, the proposer derives positive utility from offering M^t and having that offer accepted.

Set $r_P^t = 1 - r_R^t + \epsilon^t$. As in the proof of Proposition 6, we have that $r_R^t[k(Y-M^t)+M^t] > M^t$. Thus

$$
\begin{aligned}
r_P^t[k(Y-M^t)+M^t] \;&=\; (1 - r_R^t + \epsilon^t)[k(Y-M^t)+M^t] \\
&<\; [k(Y-M^t)+M^t] - M^t + \epsilon^t[k(Y-M^t)+M^t] \\
&=\; k(Y-M^t) + \epsilon^t[k(Y-M^t)+M^t].
\end{aligned}
$$

This means that the proposer's utility from offering M^t is such that

$$
u_P^t \geq k(Y-M^t) - \beta \max(\epsilon^t, 0).
$$

Moreover, because $r_R^t \leq (1-\gamma)/2 + \gamma = (1+\gamma)/2$, it easily follows that

$$
M^t = \frac{k\beta r_R^t Y}{1 + \beta(1 - r_R^t) + k\beta r_R^t}
$$

is bounded away from Y (for all possible β) as long as $\gamma < 1$. Thus we have that for all t, there is some $c > 0$ such that $k(Y-M^t) \geq c$. By step 2, there is a $t^\dagger$ such that $\beta\epsilon^t < c$ for all $t \geq t^\dagger$. Thus there is a $t^\dagger$ such that $k(Y-M^t) - \beta\max(\epsilon^t, 0) > 0$ for all $t \geq t^\dagger$.

Step 4: We now strengthen step 2 to show that $|r_P^t + r_R^t - 1| \to 0$. By step 3, we now have that

9

$\mu_R^t + \mu_P^t = 1$ for all $t \geq t^\dagger$. Thus for $t > t^\dagger$,

$$
\begin{aligned}
r_R^t + r_P^t &= (1-\gamma) + \gamma\left(\frac{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}\mu_R^\tau + w_{t-1-\tau}\mu_P^\tau}{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}}\right) \\
&= (1-\gamma) + \gamma\left(\frac{\sum_{\tau=-T}^{t^\dagger-1} w_{t-1-\tau}\mu_R^\tau + w_{t-1-\tau}\mu_P^\tau}{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}} + \frac{\sum_{\tau=t^\dagger}^{t-1} w_{t-1-\tau}}{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}}\right) \\
&= 1 + \gamma\left(\frac{\sum_{\tau=-T}^{t^\dagger-1} w_{t-1-\tau}\mu_R^\tau + w_{t-1-\tau}\mu_P^\tau}{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}} - \frac{\sum_{\tau=-T}^{t^\dagger-1} w_{t-1-\tau}}{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}}\right)
\end{aligned}
$$

But since

$$
\frac{\sum_{\tau=-T}^{t^\dagger-1} w_{t-1-\tau}\mu_R^\tau + w_{t-1-\tau}\mu_P^\tau}{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}} \to 0
$$

and

$$
\frac{\sum_{\tau=-T}^{t^\dagger-1} w_{t-1-\tau}}{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}} \to 0
$$

as $t \to \infty$, it follows that $r_R^t + r_P^t \to 1$ as $t \to \infty$.

Step 5: We now finish off the proof of the proposition by proving that the steady state identified in Step 1 is globally stable.

Define $\nu_R^t = \frac{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}\mu_i^\tau}{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}}$. Define the map $\xi : \mathbb{R} \to \mathbb{R}$ as follows:

$$
\xi(\nu) = (1-\gamma)/2 + \gamma\nu.
$$

Define the map $\psi : \mathbb{R} \to \mathbb{R}$ as follows:

$$
\psi(\nu) = \frac{\beta\xi(\nu)}{1+\beta}.
$$

Notice that ψ is linear in ν and has slope $\gamma\beta/(1+\beta) < 1$; thus ψ is a contraction and has a unique fixed point. In a steady state, $r_R^* = \xi(\nu_R^*)$, and thus equation (D.2) implies that

$$
\frac{M^*}{k(Y-M^*)+M^*} = \psi(\nu_R^*). \tag{D.5}
$$

But since $\nu_R^* = \frac{M^*}{k(Y-M^*)+M^*}$ by definition, it follows that the unique fixed point of ψ corresponds to the unique steady state.

Now for $t^\dagger$ defined as in step 3, $r^t = \xi(\nu^t)$ and $\frac{M^t}{k(Y-M^t)+M^t} = \psi(\nu_R^t)$ for all $t \geq t^\dagger$. Because ξ is strictly increasing, each value of ν_R^t corresponds to a unique value of M^t. Because ψ is strictly increasing and because $\frac{M^t}{k(Y-M^t)+M^t}$ is strictly increasing in r_R^t, each value of ν_R^t also corresponds to a unique value of M^t. Because ξ and ψ are both continuous functions of ν, showing that $\nu_R^t \to \nu_R^*$ will thus imply that $M^t \to M^*$ and $r_R^t \to r_R^*$. Moreover, since $|r_R^t + r_P^t - 1| \to 0$ by Step 4, convergence of r_R^t will also imply convergence of r_P^t. And finally, since Step 3 shows that $a^t = M^t$

10

for all $t \geq t^\dagger$, $\nu_R^t \to \nu_R^*$ will thus also imply that $a^t \to a^*$.

Because ψ is an increasing and linear function of ν^t that crosses the 45-degree line exactly once, it thus follows that $\psi(\nu) \in (\nu^*, \nu)$ for $\nu > \nu^*$ and $\psi(\nu) \in (\nu, \nu^*)$ for $\nu < \nu^*$. By definition,

$$\nu_R^{t+1} = \frac{w_0}{\sum_{\tau=-T}^t w_{t-\tau}} \mu_R^t + \left(1 - \frac{w_0}{\sum_{\tau=-T}^t w_{t-\tau}}\right) \nu_R^t \tag{D.6}$$

is a convex combination of ν_R^t and $\psi(\nu_R^t) = \frac{M^t}{k(Y-M^t)+M^t} = \mu_R^t$, which implies that $\nu_R^{t+1} \in (\nu_R^*, \nu_R^t)$ if $\nu_R^t > \nu_R^*$. Similarly, it follows that $\nu_R^{t+1} \in (\nu_R^t, \nu_R^*)$ if $\nu_R^t < \nu_R^*$.

For $t^\dagger$ defined as in step 3, a simple induction thus implies that if $\nu_R^{t^\dagger} < \nu_R^*$, then ν_R^t will be strictly increasing for $t \geq t^\dagger$ and bounded from above by ν^*. Similarly, if $\nu_R^{t^\dagger} > \nu^*$, then ν_R^t will be strictly decreasing for $t \geq t^\dagger$ and bounded from below by ν_R^*. Because any monotonic and bounded sequence converges, ν_R^t must converge to some $\nu^{**} \in [0,1]$. Because each value of ν_R^t corresponds to a unique value of M^t, and because ψ is continuous in ν, there must, therefore, exist some M^{**} such that $M^t \to M^{**}$. Thus

$$\lim_{t\to\infty} \mu_R^t = \lim_{t\to\infty} \frac{M^t}{k(Y-M^t)+M^t} = \frac{M^{**}}{k(Y-M^{**})+M^{**}}.$$

It is then easy to show that

$$\nu^t = \frac{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}\mu_i^\tau}{\sum_{\tau=-T}^{t-1} w_{t-1-\tau}} \to \frac{M^{**}}{k(Y-M^{**})+M^{**}}.$$

On the other hand,

$$\psi(\nu_R^t) = \frac{M^t}{k(Y-M^t)+M^t} \to \frac{M^{**}}{k(Y-M^{**})+M^{**}}.$$

But since ψ is continuous, we therefore have that $\psi(\nu^{**}) = \nu^{**}$. And because ψ has a unique fixed point, it must be that $\nu^{**} = \nu_R^*$, thus completing the proof.

Proof of Proposition 7

Since $r_P^t + r_R^t \leq 1$ for all $t \geq 1$, the reasoning of Step 3 in the proof of Proposition 6 implies that the proposer will offer $a^t = M^t$ in all periods $t \geq 1$. Thus for $t \geq 1$, $r^t = \xi(\nu_R^t)$ and $\frac{M^t}{k(Y-M^t)+M^t} = \psi(\nu_R^t)$.

As in the proof of Proposition 6, a simple induction thus implies that if $\nu_R^1 < \nu_R^*$, then ν_R^t will be strictly increasing for $t \geq 1$ and bounded from above by ν^*. Similarly, if $\nu^1 > \nu_R^*$, then ν_R^t will be strictly decreasing for $t \geq 1$ and bounded from below by ν_R^*. But since M^t is a monotonic function $\zeta(\cdot)$ of ν_R^t such that $M^* = \zeta(\nu_R^*)$, the result follows.

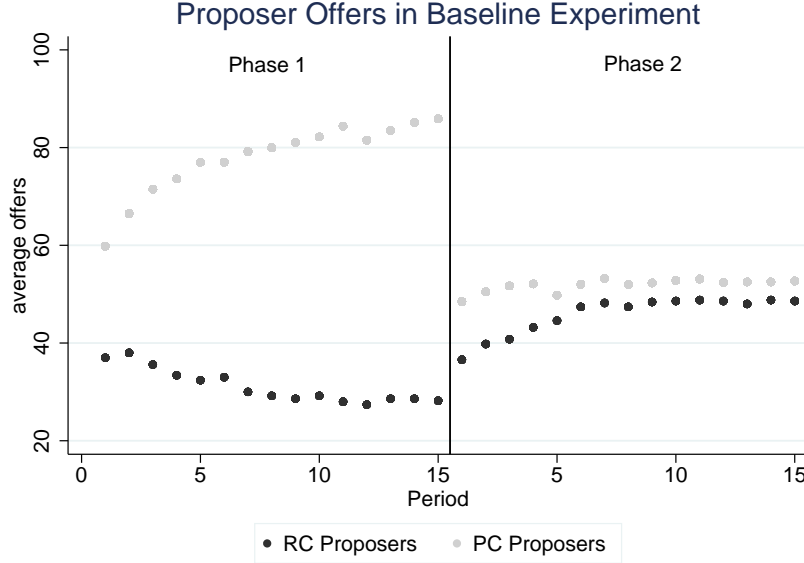# E Comparing Phase 1 and Phase 2 proposer offers

Figure E.1: Proposer offers in phase 1 and phase 2 of the Baseline Experiment.

F Regressions with differently coded experiences

In this section, we analyze whether our results on the effect of observational experience and personal payoff experience are sensitive to their respective definitions. First, we have measured observational experience and personal payoff experience simply as the respective average over all 15 periods of phase 1. As an alternative to plain averaging, we consider weighted averages, $G(\boldsymbol{\mu}^\tau, \boldsymbol{\nu}^\tau) = g\left(\sum \delta^t \mu^t / \sum \delta^t, \sum \delta^t \nu^t / \sum \delta^t\right)$, which give more weight to more recent periods in phase 1 of the experiment. Second, we have made assumptions about observational experience in the Full Information treatment experiment as well as about personal payoff experience in case of rejection, and we would like to check whether our results are robust to changes in these assumptions.

Table F.1 shows results of the same IV GMM regression that is presented in columns (5) and (6) of table ?? of the paper, but uses alternative measures of personal payoff experience and observational experience.

Two different weights have been used to construct the geometric averages: $\delta = 0.9$ and $\delta = 0.95$. It can be seen that using geometric averages does not qualitatively alter our results. Observational experience and personal payoff experience remain significant determinants of responders minimum acceptable offers in phase 2 of the experiment. Also, the magnitude of the estimated coefficients remains quite stable. Consequently, our results on the impact of observational experience and personal payoff experience are robust to alterations in the construction of these measures.

Second, we had to make assumptions on experienced payoff shares in case of rejections, i.e.,

Table F.1: The effect of discounted experiences on minimum acceptable offers

	(1) MAO	(2) MAO	(3) MAO	(4) MAO
Observational experience ($\delta = 0.9$)	23.84***	23.73***		
	(6.33)	(8.43)		
Personal payoff experience ($\delta = 0.9$)	11.76**	20.12**		
	(5.14)	(9.93)		
Observational experience ($\delta = 0.95$)			24.85***	21.75***
			(6.67)	(7.44)
Personal payoff experience ($\delta = 0.95$)			12.15**	17.17**
			(5.32)	(8.45)
Constant	32.03***	34.32***	31.89***	35.76***
	(4.74)	(3.42)	(4.79)	(3.34)
Adj. R^2	0.02	0.03	0.02	0.04
Observations	222	3330	222	3330

Instrumental variables regressions estimating the impact of phase 1 personal payoff experience and observational experience on phase 2 MAOs. Estimates computed using the iterative GMM estimator. All regressions are IV GMM regressions, similar to those in columns (5) and (6) of table 6 of the paper. However, here observational experience and personal payoff experience are geometric means of first period offers and payoffs. The discount rate is either $\delta = 0.9$ or $\delta = 0.95$. Observational experience and personal payoff experience are instrumented using 6 dummies, one for each market treatment and experiment. Columns (1) and (3) contain period 1 observations of phase 2 only. Columns (2) and (4) use data from all 15 periods. All regressions also contain dummy variables for high proposer personal payoff experience and for high proposer observational experience. Robust standard errors are clustered by phase 1 market matching group (30 clusters). Significance levels: * $= 10\%$, ** $= 5\%$ and *** $= 1\%$.

when the total sum of payoffs is 0. In the paper, we have assumed that in these cases, the personal payoff experience is equal to 0. An alternative intuition is that in an N-player group, $\mu_i^t = 1/N$ when $\Pi^t = 0$, to reflect the possibility that when everyone gets the same payoff (even when it's zero) the player feels like it was such an equitable outcome that his subsequent feelings of entitlement move towards him getting an even share of the surplus. Additionally, in the Full Information experiment, all subjects received feedback about the average offer in the RC and in the PC market. We have assumed that all subjects correctly weight the information from the PC market twice as much as the information from the RC market, reflecting the fact that there are twice as many offers comprised in the average offer of the PC market. Alternatively, it is possible that subjects weigh these two pieces of information equally. Consequently, we test the robustness of our results with regard to the assumed observational experience of subjects in the Full Information experiment.

Table F.2 replicates columns (5) and (6) of table ?? from the main paper using these alternative codings of personal payoff experience and observational experience. Personal payoff experience2 is the recoded personal payoff experience variable and observational experience2 is the recoded observational experience variable. Columns (1)-(6) replicate the original estimations in table ?? of the paper using different combinations of the recoded variables. Again, it can be seen that our estimates are robust to these changes in the definition of observational experience and personal payoff experience. The magnitude of the estimated coefficients is remarkably stable, and observational

Table F.2: Alternative codings of observational experience and personal payoff experience

	(1) MAO	(2) MAO	(3) MAO	(4) MAO	(5) MAO	(6) MAO
Observational experience2	26.00***	15.96***			26.72***	16.43***
	(7.06)	(5.11)			(6.93)	(4.97)
Personal payoff experience	12.59**	10.84**				
	(5.52)	(5.36)				
Observational experience			26.72***	16.43***		
			(6.93)	(4.97)		
Personal payoff experience2			12.40**	10.92**	12.41**	10.92**
			(5.48)	(5.34)	(5.48)	(5.33)
Constant	31.71***	39.16***	31.26***	38.83***	31.26***	38.83***
	(4.84)	(3.19)	(4.74)	(3.15)	(4.74)	(3.15)
Adj. R^2	0.025	0.047	0.030	0.050	0.030	0.051
Observations	222	3330	222	3330	222	3330

Instrumental variables regressions estimating the impact of phase 1 personal payoff experience and observational experience on phase 2 MAOs. Estimates computed using the iterative GMM estimator. All regressions are IV GMM regressions, similar to those in columns (5) and (6) of table 6 of the paper. However, observational experience2 differs from observational experience (as used in the paper) in how observed offers in the Full Information experiment are weighted. Observational experience gives 2/3 weight to the average offer in the PC market and 1/3 weight to the average offer in the RC market, reflecting the fact that there are twice as many proposers in the PC market. Observational experience2 weighs the average offers in the RC market and PC market equally in each period. Personal payoff experience2 codes personal payoff experience as 1/3 in case an offer is rejected by all subjects. Personal payoff experience, on the other hand, codes rejections as a personal payoff experience of 0. Observational experience and personal payoff experience are instrumented using 6 dummies, one for each market treatment and experiment. Columns (1), (3) and (5) contain period 1 observations of phase 2 only. Columns (2), (4) and (6) use data from all 15 periods. Standard errors are clustered at the phase 1 market matching group level (30 clusters). Significance levels: * = 10%, ** = 5% and *** = 1%.

experience and personal payoff experience remain significant determinants of responders' minimum acceptable offers independent of the precise definition of these terms.

G Ruling out Anchoring

As we note in section 4.3 of the paper, experimental evidence has shown that individuals can be influenced by arbitrary anchors (Lichtenstein and Slovic, 2006; Kahneman and Tversky, 2000; Ariely et al., 2003; Simonson and Tversky, 1992), and that behavior that appears to be consistent with expressing a particular preference can in fact be the result of arbitrary anchoring.[2] On the face of it, our path-dependence account may seem very similar to anchoring. However, there is one crucial difference. We posit that past experience affects *preferences,* and we further show that differences in preferences will affect behavior in environments such as the Ultimatum Game, but that they will not affect behavior in competitive market games as in phase 1 of our experiment (see Appendix A). In contrast, standard anchoring and adjustment theory (Tversky and Kahneman, 1973) does not make such a prediction. This theory states that subjects' choice of action (e.g., offer) starts at some anchor, and then is incompletely adjusted toward the optimal choice of action. Formally, the choice of action is given by $a = (1 - \kappa)\vartheta + \kappa a^*$ where ϑ is the anchor, a^* is the optimal action, and $\kappa \in [0, 1]$ is the degree of adjustment away from the anchor. Such anchoring and adjustment theory would predict that anchors should also have an effect in the market games.

Here, we provide evidence that suggests that behavior in our experiment is not driven by the mere provision of arbitrary anchors. To show this, we exploit a design feature in the Full Information experiment. In this experiment, all subjects received feedback about the average offers in both the PC and the RC markets after every period during phase 1 of the experiment. If responders' acceptance behavior were influenced by the provision of arbitrary anchors, we should observe that responders in the RC market in the Full Information experiment show higher acceptance rates than Responders in the RC market in the Baseline or in the Role Switch experiment.[3] This is the case because in the Full Information experiment, they are subjected to higher anchors than in the Baseline experiment or in the Role Switch experiment, in which responders only get to observe the offers made by their matched proposer.

Table G.1 contains information that tests whether the information provided in the Full information experiment indeed provides an alternative anchor and consequently changes proposers' offers. Moreover, table G.2 provides results from a probit regression that test whether responders' acceptance behavior is affected by the altered anchor in the Full Information experiment. It turns out that neither proposers' offers nor responders' acceptance behavior in the Full Information experiment is statistically different from the respective behavior in the Baseline or the Role Switch experiment. Interacting a Full Information experiment dummy with both an RC market dummy and a PC market dummy yields insignificant and economically very small coefficients, implying that proposer and responder behavior in neither the RC nor the PC market was affected by the altered anchor in the Full Information experiment. Consequently, anchoring does not seem to be a

---

[2]See, however, Fudenberg et al. (2012) and List et al. (2013) for evidence questioning the robustness of these anchoring effects.

[3]We restrict attention to the RC market because in the PC market, responders almost never reject both offers, and hence there is not enough variance in the data to identify a potential impact.

Table G.1: OLS regressions on proposer offers

	(1)	(2)
Full info * PC Market	1.32	1.76
	(0.98)	(1.40)
Full info * RC Market	−3.73	2.11
	(3.61)	(3.77)
PC Market	41.34***	46.73***
	(3.07)	(3.40)
Constant	36.99***	31.15***
	(2.99)	(3.17)
Adj. R^2	0.69	0.72
Observations	3330	2430

OLS regression of proposer offers on treatment dummies and interactions. PC Market indicates observations from the Proposer Competition market. Full info*PC Market is an interaction between a Full Information experiment dummy and a proposer competition market dummy. Equivalently, Full info*RC Market is an interaction between a Full Information experiment dummy and a responder competition market dummy. Column (1) contains data from all 3 experiments. Column (2) only compares the Full Information experiment and the Baseline experiment. Standard errors are clustered at the phase 1 market matching group level (30 clusters in columns (1) and (3), 22 clusters in columns (2) and (4)). Significance levels: $^* = 10\%$, $^{**} = 5\%$ and $^{***} = 1\%$.

Table G.2: Probit regressions on responder acceptance decisions

	(1)	(2)
	Accept	Accept
Maxoffer	0.01***	0.01***
	(0.00)	(0.00)
Full info * PC Market	−0.05	−0.01
	(0.05)	(0.04)
Full info * RC Market	−0.00	−0.04
	(0.03)	(0.04)
PC Market	0.02	−0.04
	(0.04)	(0.08)
Adj. R^2	0.23	0.21
Observations	3330	2430

Marginal Effects of a Probit regression of responder acceptance decisions on treatment dummies and interactions. PC Market indicates observations from the Proposer Competition market. full info*PC Market is an interaction between a Full Information experiment dummy and a proposer competition market dummy. Equivalently, Full Info*RC Market is an interaction between a Full Information experiment dummy and a responder competition market dummy. Maxoffer contains the best offer made to responders in a particular round. In responder competition, there is only one offer. In proposer competition, it is the higher of the two offers made. Column (1) contains data from all 3 experiments. Column (2) only compares the Full Information experiment and the Baseline experiment. Standard errors are clustered at the phase 1 market matching group level (30 clusters in columns (1) and (3), 22 clusters in columns (2) and (4)). Significance levels: $^* = 10\%$, $^{**} = 5\%$ and $^{***} = 1\%$.

driving force of behavior in our experimental setting.

H The Full Information Experiment

Table H.1: Minimum Acceptable Offers in the Full Information Experiment

	OLS		IV	
	(1)	(2)	(3)	(4)
	MAO	MAO	MAO	MAO
PC Responder	11.55*	5.64		
	(6.11)	(5.64)		
Personal payoff experience			19.69 **	9.62
			(9.97)	(9.27)
Constant	48.45***	47.58***	47.17 ***	46.95 ***
	(4.67)	(3.90)	(4.81)	(3.98)
Adj. R^2	0.01	0.03		
Observations	87	1305	87	1305

Columns (1) and (2) show results of an OLS regression. Regressions include a dummy for proposer phase 1 market experience. Column (1) uses data from period 1 of phase 2 only. Column (2) uses all data. Columns (3) and (4) show IV GMM regressions, in which payoff experience is instrumented using 6 dummies, one for each market treatment and experiment. Observational experience cannot be included here because it is constant across treatments in the Full Information experiment. Column (3) contains data from period 1 only. Column (4) contains data from all 15 periods. Standard errors are clustered at the phase 1 market matching group level (18 clusters). Significance levels: * $= 10\%$, ** $= 5\%$ and *** $= 1\%$.

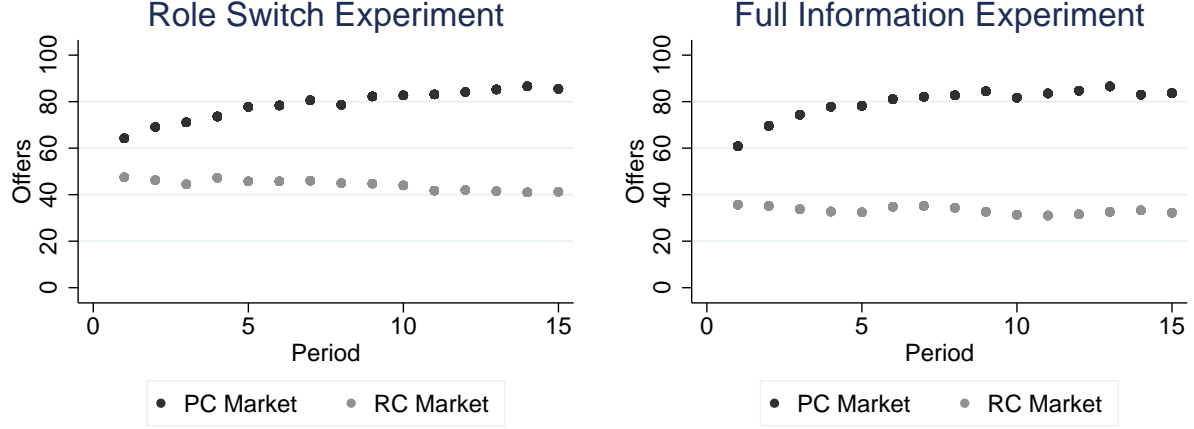# I Phase 1 of the Role Switch and the Full Information Experiments

Figure I.1: Left Panel: Average offers over time under responder competition and under proposer competition in phase 1 of the Role Switch experiment. Right Panel: Average offers over time under responder competition and under proposer competition in phase 1 of the Full Information experiment

The exogenous assignment to either the PC market or the RC market also had strong effects on market outcomes and personal payoff experiences in the Role Switch and the Full information experiment. Figure I.1 shows average offers in phase 1 of both experiments for all 15 periods. Not surprisingly, a very similar pattern to phase 1 of the Baseline experiment emerges. In both experiments, the difference in average offers between the RC market is large. In an OLS regression of offers on a PC market dummy, offers on average differ by 35 chips in phase 1 of the Role Switch experiment and by 46 chips in the Full Information experiment. Both differences are highly significant ($p < 0.001$).

References

Ariely, Dan, George Loewenstein, and Drazen Prelec, ""Coherent arbitrariness": Stable demand curves without stable preferences," *The Quarterly Journal of Economics*, 2003, *118* (1), 73–106.

Bowman, David, Deborah Minehart, and Matthew Rabin, "Loss aversion in a consumption–savings model," *Journal of Economic Behavior & Organization*, 1999, *38* (2), 155–178.

Dufwenberg, Martin and Georg Kirchsteiger, "A Theory of Sequential Reciprocity," *Games and Economic Behavior*, 2004, *47* (2), 268–298.

Falk, Armin and Urs Fischbacher, "A theory of reciprocity," *Games and Economic Behavior*, 2006, *54* (2), 293–315.

Fudenberg, Drew, David K. Levine, and Zacharias Maniadis, "On the Robustness of Anchoring Effects in WTP and WTA Experiments," *American Economic Journal: Microeconomics*, 2012, *4* (2), 131–145.

Kahneman, Daniel and Amos Tversky, *Choices, Values, and Frames*, 1st ed., New York: Cambridge University Press, 2000.

Kőszegi, Botond and Matthew Rabin, "A Model of Reference-Dependent Preferences.," *Quarterly Journal of Economics*, 2006, *121* (4), 1133–65.

Lichtenstein, Sarah and Paul Slovic, *The construction of preference*, 1st ed., New York: Cambridge University Press, 2006.

List, John A., Zacharias Maniadis, and Fabio Tufano, "One Swallow Doesn't Make a Summer: New Evidence on Anchoring Effects," *American Economic Review, forthcoming*, 2013.

Rabin, Matthew, "Incorporating Fairness into Game Theory and Economics," *American Economic Review*, 1993, *83* (5), 1281–1302.

Simonson, Itamar and Amos Tversky, "Choice in context: tradeoff contrast and extremeness aversion.," *Journal of Marketing Research*, 1992.