Web Appendix for "Fatal Attraction:
Salience, Naiveté, and Sophistication in Experimental 'Hide-and-Seek' Games"

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This appendix provides background and more detail for the paper.

Labels with Positive or Negative Connotations and/or Focally Labeled End Locations

Table A1 lists the choice frequencies from five additional RTH Treasure treatments with the same payoff structure as RTH-4 (Table 1), but labels with positive or negative connotations and/or focally labeled end locations. RTH-2 and RTH-5 are analogous to RTH-4 except for the connotations of the focal label. RTH-1 and RTH-3 are like RTH-4 except that the focal label is at an end position, and in RTH-3 it has a negative connotation. RTH-6 is like RTH-5 except that the focal label is in the third rather than second position; and is like RTH-2 and RTH-4 except for this difference in position and that the focal label has a positive connotation in RTH-6 but negative or neutral connotations in RTH-2 or RTH-4. The choice frequencies for these treatments echo those for the ones we analyze, with shifts in expected directions, and so provide additional evidence of the robustness of the patterns in RTH's data. It seems likely that our analysis could be extended to them by introducing and estimating payoff perturbations and/or new *L0* choice probabilities.

Table A1. Aggregate Choice Frequencies in RTH's Experiments with Non-neutral Connotations

RTH-1	***Triangle***	**Circle**	**Circle**	**Circle**
Hider (53)	23%	23%	43%	11%
Seeker (62)	29%	24%	42%	5%
RTH-2	**Polite**	***Rude***	**Honest**	**Friendly**
Hider (53)	15%	26%	51%	8%
Seeker (62)	8%	40%	40%	11%
RTH-3	**Smile**	**Smile**	**Smile**	***Frown***
Hider (53)	21%	26%	34%	19%
Seeker (62)	7%	25%	34%	34%
RTH-5	**Frown**	***Smile***	**Frown**	**Frown**
Hider (53)	15%	40%	34%	11%
Seeker (62)	16%	55%	21%	8%
RTH-6	**Hate**	**Detest**	***Love***	**Dislike**
Hider (53)	11%	23%	38%	28%
Seeker (62)	20%	21%	55%	14%

Sample sizes in parentheses; salient labels in italics; order of presentation of locations to subjects as shown.

Data Adjustments

In Table 1, we made minor adjustments to RTH's published data to reconcile reported frequencies and sample sizes. Hiders' choice frequencies in RT-AABA-Treasure and RT-1234-Treasure, and seekers' frequencies in RT-AABA-Mine, all sum to 101%; and hiders' frequencies in RT-AABA-Mine and hiders' and seekers' frequencies in RT-1234-Mine sum to 99%. We deal with this by translating the percentages into integer numbers of subjects and then rounding as needed. In RT-AABA-Treasure, for example, RT's reported percentages for hiders are 22%, 35%, 19%, and 25%, with reported sample size 189. Applying the rounded percentages to the sample size yields numbers of subjects 41.58, 66.15, 35.91, and 47.25, which round to 42, 66, 36, and 47, which sum to 191 > 189. We rounded 41.58 down to 41 and 35.91 down to 35, which is the only way to reconcile the sample size and the rounded reported percentages. Similarly, in RT-AABA-Mine we rounded 0.39×132 = 51.48 up to 52, which allows us to reconcile the sample size and reported percentages. Finally, in R-ABAA the reported percentages for hiders are 16%, 18%, 45%, and 22%, which add to 101%, with a sample size of 50. This yields numbers of subjects 8, 9, 22.5, and 11, which add to 50.5. The only way to reconcile this with one typo is to adjust the 45% to 44% as in Table 1, yielding numbers of subjects 8, 9, 22, and 11.

Symmetry of Payoff Perturbations Across Roles for Equilibrium and QRE with Perturbations Models

Here we discuss, in more detail than in Section II, the issue of symmetry of payoff perturbations across player roles. We focus on the equilibrium with perturbations model, but our discussion also applies to the QRE with perturbations model.

There is no logical reason why a role-asymmetric payoff structure should not evoke instinctive aversions or attractions that differ in magnitudes as well as signs. The issue here is slightly different than for the symmetry across roles of *L0* in our level-*k* model, discussed below, because we allow the signs of the perturbations to differ in keeping with Bacharach and Stahl's (1997ab) intuition, without which equilibrium with perturbations fits the data extremely poorly; the only question is whether to assume that their magnitudes are the same across roles. If anything the case for equal magnitudes is weaker than the case for a role-symmetric *L0*, because hard-wired payoff perturbations presumably stem from an evolutionary or learning process that is surely influenced by payoffs as well as framing. These a priori considerations are reinforced by our strong rejection of the restriction to perturbations of equal magnitudes in RTH's dataset (Table 3) and by the qualitatively perverse behavior of the analogous QRE with restricted perturbations model (web appendix below).

The problem with equilibrium with unrestricted perturbations, as we see it, is that there is no theory that could explain (or even restrict the specification of) such differences in magnitudes. This makes "explaining" the role-asymmetry in RTH's subjects' behavior (via an unexplained twofold role difference in magnitudes) an empirical dead end. Our overfitting and portability analyses make this subjective judgment more concrete, by showing that equilibrium with unrestricted perturbations, which has the best fit of all the models we consider in RTH's dataset (Table 3), does worst of all in our within-sample overfitting test (Table 4); does worse than equilibrium without perturbations under the natural restrictions on hiders' and seekers' instinctive reactions to salience in O'Neill's game; and is not well-defined for Rapoport and Boebel's game.

Quantal Response Equilibrium ("QRE") with and without Payoff Perturbations

Here we discuss the QRE with payoff perturbations models mentioned in Section II. In a QRE players' choices are noisy, with the probability of each choice increasing in its expected payoff given the distribution of others' choices; a QRE is thus a fixed point in the space of players' choice distributions. QRE describes the patterns of deviations from equilibrium in some other experiments, and so has the potential to explain RTH's results better than equilibrium does. Its specification is completed by a response distribution, whose noisiness is represented (inversely) by a precision parameter. Some of our results are independent of this distribution, but for others we adopt the standard assumption of logit responses and study the special case called "logit QRE".

Because QRE responds only to the payoff structure, it ignores the framing of the Hide-and-Seek game without payoff perturbations. In that game, for any error distribution, there is a unique QRE, which yields the same choice probabilities as equilibrium. To see this, suppose to the contrary that in a QRE the most probable location for Hiders, call it P, has probability greater than 1/4. Because QRE choice probabilities increase with expected payoffs and the game is constant-sum, P must then have the highest expected payoff for Seekers, thus probability greater than 1/4 for them. But then some location other than P has higher expected payoff for Hiders, a contradiction.

We therefore consider explanations that combine logit QRE with payoff perturbations as in Section II's equilibrium with perturbations analysis (Figure 2), which make QRE sensitive to the framing and give it the potential to explain RTH's results by responding asymmetrically to the asymmetries in the perturbed game's payoff structure. As usual, such models must be solved computationally.

QRE with perturbations does no better than equilibrium with perturbations in explaining RTH's results. Figure A1 illustrates logit QRE with payoff perturbations restricted to be equal in magnitude but opposite in sign across player roles, as a function of the precision λ, with $e = 0.2187$ and $f = 0.2010$, the values that best fit RTH's data for the equilibrium with restricted perturbations model. (The maximum likelihood estimate of λ in the QRE with restricted perturbations model is effectively infinite, reducing the model to the analogous equilibrium model.) For all combinations of $e, f = 0.1$, 0.2, 0.3, or 0.4 (all consistent with a totally mixed equilibrium), as in Figure A1, the logit QRE probability of central A dips below 0.25 for low values of λ for seekers but never for hiders; and it is always higher for hiders, reversing the patterns in RTH's data. There is enough structure to suggest that this result is symptomatic of a theorem, but we have been unable to prove it. Thus, logit QRE can explain the prevalence of central A for Hiders and Seekers with perturbations of equal magnitudes but opposite signs across player roles. But the main difficulty is explaining the greater prevalence of central A for seekers, and in this case logit QRE robustly predicts that central A is more prevalent for hiders.

Like equilibrium with payoff perturbations, logit QRE can only explain RTH's results by postulating large differences across player roles in the magnitudes of the perturbations e and f as well as their signs. But this again yields an effectively infinite estimate of λ, reducing logit QRE, in terms of its substantive implications, to Section II's equilibrium with unrestricted perturbations model. (With payoff perturbations restricted to have equal magnitudes across player roles, the estimated $\lambda \rightarrow \infty$. With perturbations allowed to differ in magnitude across roles, for any sufficiently large but finite λ QRE can adjust the perturbations to match the observed frequencies exactly. Thus λ and the perturbations are not identified, but all parameter values that maximize the likelihood are equivalent to those obtained when $\lambda \rightarrow \infty$. With finite λ the estimated perturbations for hiders (seekers) are higher (lower) than those estimated for equilibrium with perturbations.) Figure A2 illustrates logit QRE with $e_H = 0.2910$, $f_H = 0.2535$, and $e_S = f_S = 0.1539$, the values that give the best fit for this model.

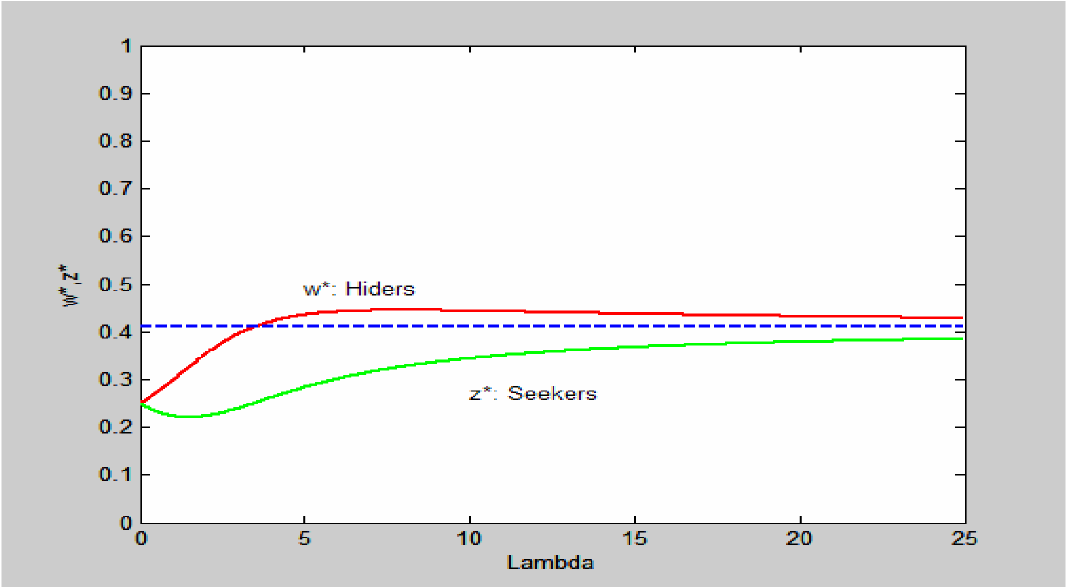

Figure A1. QRE with Payoff Perturbations of Equal Magnitudes Across Player Roles

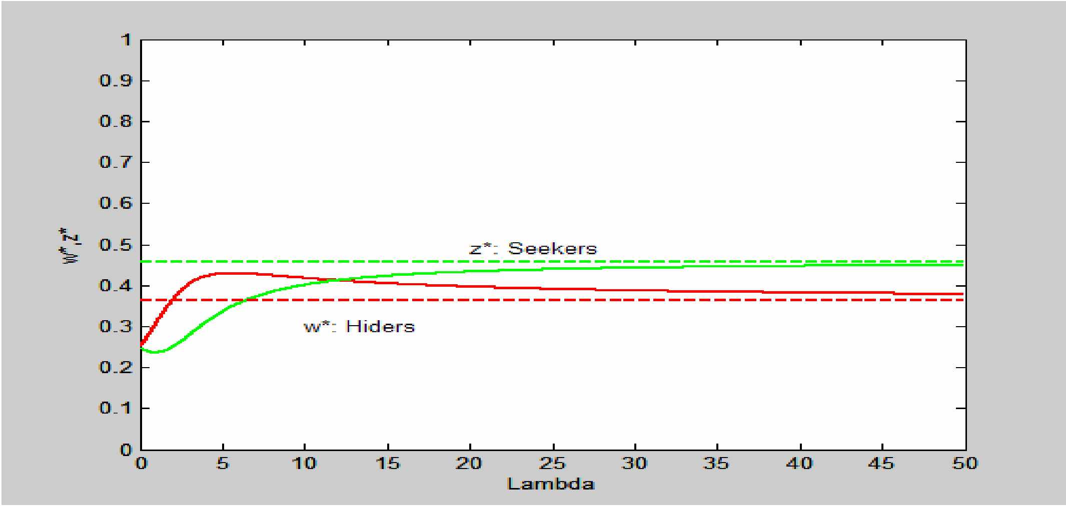

Figure A2. QRE with Payoff Perturbations of Differing Magnitudes Across Player Roles

Symmetry of *L0* Across Roles for Level-*k* Models

Here we discuss, in more detail than in Section III, the issue of symmetry of *L0* across player roles for level-*k* models.

In our view the case for a role-symmetric *L0* is partly an empirical question and partly rests on behavioral plausibility. Assuming for the sake of argument that some kind of level-*k* model is correct, the issue is how best to describe a player's strategic thinking with regard to the order in which he processes information about the game. One can imagine a model in which a player first reacts, all at once, to the game's framing, feasible decisions, and payoffs, and so forms a payoff-sensitive, role-asymmetric (though perhaps nonstrategic) *L0*; and then reacts further to the payoffs and strategic structure via a best-responding *L1*, *L2*, etc. But one can equally well imagine a compartmentalization of the thought process in which a player reacts first to the framing and feasible decisions, which are arguably more primitive than payoffs even in games where the strategic structure is as transparent as in hide-and-seek; and to payoffs only in later stages.

The latter compartmentalization is more in keeping with the spirit of the nonstrategic *L0*s in most of the previous level-*k* literature. See the uniform random *L0* in Stahl and Wilson (1994, 1995) and several subsequent analyses; the *truthful* and *credulous L0*s in Crawford (2003); and the *truthful* and *random L0*s in Crawford and Iriberri (2005). The role-symmetric, non-uniform random *L0* in Ho, Camerer, and Weigelt (1998) implicitly allows payoffs to matter by not imposing uniformity, but does so only for symmetric games where the distinction between nonstrategic and payoff-insensitive doesn't matter, and doesn't try to model payoff-sensitivity or connect *L0*s across games. The one *L0* in the literature that is clearly payoff-sensitive is Bacharach and Stahl's (1997ab), which favors salience for seekers and avoids it for hiders.

A Bacharach and Stahl-style model fits slightly better than our favored model, and does 10% better within RTH's sample in our overfitting test (Table 4). But it does poorly beyond sample in O'Neill's game (Table 5), and it is not even well-defined for Rapoport and Boebel's game. The simplicity of a payoff-insensitive *L0* and the fact that its specification can be based on decision-theoretic evidence about reactions to framing are (together with the simplicity and generality of the iterated best responses that define *L1*, etc.) the key to our level-*k* model's portability, because different games are much more likely to have compelling analogies between their sets of feasible decisions and framing than between strategic structures, as would be required to transport a Bacharach and Stahl-style *L0*.

Overfitting

This section gives more detail on the overfitting test discussed in Section V. Table A2 gives the treatment by treatment parameter estimates on which the overfitting comparisons in Table 4 are based. The estimated type frequencies for our proposed level-*k* model in Table A2, particularly those of *L4*, vary widely across RTH's six treatments, which is disturbing because level-*k* types are meant to be general strategic decision rules. The estimated type frequencies for *L1* and *L2* are actually very stable. The type frequencies for *L3* and *L4* are less stable, but mainly for RTH-4 and RT-AABA-Mine. Even so, we cannot reject the constraint that in our proposed level-*k* model, the type frequencies are the same in all six RTH treatments, despite RTH's large samples (*p*-value 0.9873). This failure to reject despite the varying point estimates is due mainly to two factors: (i) The designs, with only one observation per subject in the games we study, are not well suited to identifying subjects' decision rules; and (ii) *L4*'s and to a lesser extent *L3*'s frequency estimates are weakly identified in RTH's data because *L4* never chooses central A and *L3* seldom does (Table 2), so they are not much involved in either of the major, robust patterns in the data.

As Table A2 shows, the parameter estimates for the other models also vary widely across treatments. Like the instability of the type frequencies for *L3* and *L4*, this is probably due to differences in observed frequencies other than the larger ones involving central A that our analysis focuses on. The two treatments that differ the most from the others are RTH-4, in which B is chosen more than in any other treatment (Table 1, footnote 7) and RT-AABA-Mine, in which hiders' and seekers' frequencies of central A differ the least.

Table A2. Treatment by Treatment Parameter Estimates in RTH's Games

Treatment	**Level-*k* with symmetric *L0* favoring salience**						**Equilibrium with unrestricted perturbations**			
	r	*s*	*T*	*u*	*v*	*e*	e_H	f_H	e_S	f_S
RTH-4	0	0.2499	0.2643	0.4858	0.0000	0	0.3307	0.1451	0.2736	0.0377
RT-AABA-Treasure	0	0.1577	0.3265	0.2257	0.2901	0	0.3648	0.2941	0.1164	0.1640
RT-AABA-Mine	0	0.1566	0.3393	0.0686	0.4355	0	0.1818	0.2121	0.1028	0.2192
RT-1234-Treasure	0	0.1572	0.3810	0.1421	0.3197	0	0.3035	0.2976	0.1471	0.1390
RT-1234-Mine	0	0.2066	0.3153	0.2603	0.2178	0	0.2669	0.2406	0.1667	0.1111
R-ABAA	0	0.1933	0.3743	0.2683	0.1641	0	0.4141	0.3594	0.2500	0.2600
Treatment	**Level-*k* with symmetric *L0* avoiding salience**						**Level-*k* with asymmetric *L0***			
	r	*s*	*T*	*u*	*v*	*e*	*r*	*s*	*t*	*ε*
RTH-4	0	0.2897	0	0.4911	0.2192	0	0	0.7940	0.2060	0.7312
RT-AABA-Treasure	0	0.4184	0.0668	0.3265	0.1883	0	0	0.5408	0.4592	0.6588
RT-AABA-Mine	0	0.2176	0.4239	0	0.3585	0	0	0.8032	0.1968	0.8081
RT-1234-Treasure	0	0.3761	0.0822	0.3816	0.1601	0	0	0.6091	0.3909	0.6984
RT-1234-Mine	0	0.3797	0.0334	0.4745	0.1124	0	0	0.6804	0.3196	0.7419
R-ABAA	0	0.3925	0.0337	0.3326	0.2412	0	0	0.7300	0.2700	0.6042

Portability

This section gives background on Section VI's portability analysis. Figure A3 and Tables A3-A4 give the details of types' choices in the best-fitting regions for our proposed level-*k* model in O'Neill's game, just as Figure 3 and Table 2 did for RTH's games. Table A5 gives the details of types' choices in the best-fitting regions for our proposed model in Rapoport and Boebel's game.

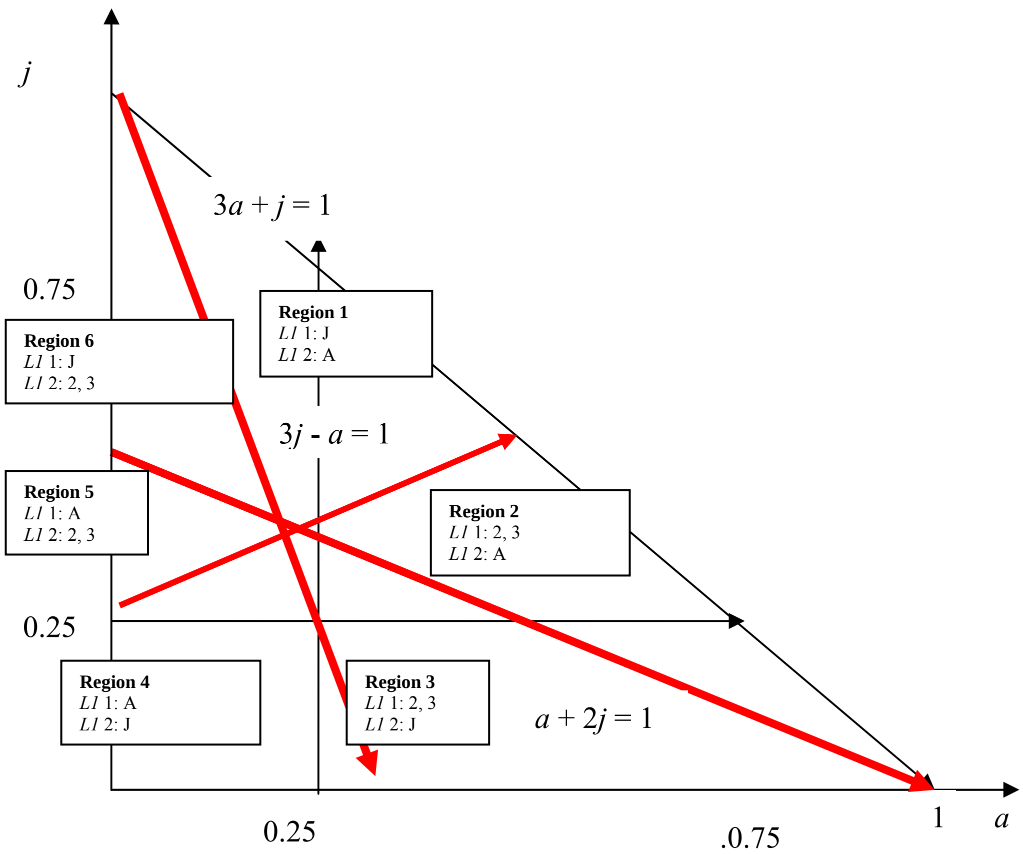

Figure A3. *L1*'s Choices in O'Neill's Game as Functions of *L0*'s Choice Probabilities *a* and *j*

Table A3. Types' Expected Payoffs and Choice Probabilities in O'Neill's Game when $3j - a < 1$

Player 1	Exp. Payoff $A+2j<1$	Choice Pr. $a+2j<1$	Exp. Payoff $a+2j>1$	Choice Pr. $a+2j>1$	Player 2	Exp. Payoff $a+2j<1$	Choice Pr. $a+2j<1$	Exp. Payoff $a+2j>1$	Choice Pr. $a+2j>1$
***L0* (Pr. *R*)**					***L0* (Pr. *r*)**				
A	-	a	-	A	**A**	-	a	-	a
2	-	$(1-a-j)/2$	-	$(1-a-j)/2$	**2**	-	$(1-a-j)/2$	-	$(1-a-j)/2$
3	-	$(1-a-j)/2$	-	$(1-a-j)/2$	**3**	-	$(1-a-j)/2$	-	$(1-a-j)/2$
J	-	j	-	J	**J**	-	j	-	j
***L1* (Pr. *s*)**					***L1* (Pr. *s*)**				
A	$1-a-j$	0	$1-a-j$	0	**A**	$a+j$	0	$a+j$	1
2	$(1+a-j)/2$	1/2	$(1+a-j)/2$	1/2	**2**	$(1-a+j)/2$	0	$(1-a+j)/2$	0
3	$(1+a-j)/2$	1/2	$(1+a-j)/2$	1/2	**3**	$(1-a+j)/2$	0	$(1-a+j)/2$	0
J	J	0	J	0	**J**	$1-j$	1	$1-j$	0
***L2* (Pr. *t*)**					***L2* (Pr. *t*)**				
A	0	0	0	0	**A**	0	0	0	0
2	0	0	1	1/2	**2**	½	0	1/2	0
3	0	0	1	1/2	**3**	½	0	1/2	0
J	1	1	0	0	**J**	1	1	1	1
***L3* (Pr. *u*)**					***L3* (Pr. *u*)**				
A	0	0	0	0	**A**	1	1/3	0	0
2	0	0	0	0	**2**	1	1/3	1/2	0
3	0	0	0	0	**3**	1	1/3	1/2	0
J	1	1	1	1	**J**	0	0	1	1
***L4* (Pr. *v*)**					***L4* (Pr. *v*)**				
A	2/3	1/3	0	0	**A**	1	1/3	1	1/3
2	2/3	1/3	0	0	**2**	1	1/3	1	1/3
3	2/3	1/3	0	0	**3**	1	1/3	1	1/3
J	0	0	1	1	**J**	0	0	0	0
Total	$a+2j<1$		$a+2j>1$		**Total**	$a+2j<1$		$a+2j>1$	
A	$ra+(1-\varepsilon)[v/3] + (1-r)\,\varepsilon/4$		$ra+(1-r)\,\varepsilon/4$		**A**	$ra+(1-\varepsilon)[u/3+v/3]+(1-r)\,\varepsilon/4$		$ra+(1-\varepsilon)[s+v/3]+(1-r)\,\varepsilon/4$	
2	$r(1-a-j)/2+(1-\varepsilon)[s/2+v/3]+(1-r)\,\varepsilon/4$		$r(1-a-j)/2+(1-\varepsilon)[s/2+t/2]+(1-r)\,\varepsilon/4$		**2**	$r(1-a-j)/2+(1-\varepsilon)[u/3+v/3]+(1-r)\,\varepsilon/4$		$r(1-a-j)/2+(1-\varepsilon)[v/3]+(1-r)\,\varepsilon/4$	
3	$r(1-a-j)/2+(1-\varepsilon)[s/3+v/3]+(1-r)\,\varepsilon/4$		$r(1-a-j)/2+(1-\varepsilon)[s/2+t/2]+(1-r)\,\varepsilon/4$		**3**	$r(1-a-j)/2+(1-\varepsilon)[u/3+v/3]+(1-r)\,\varepsilon/4$		$r(1-a-j)/2+(1-\varepsilon)[v/3]+(1-r)\,\varepsilon/4$	
J	$Rj+(1-\varepsilon)[t+u]+(1-r)\,\varepsilon/4$		$rj+(1-\varepsilon)[u+v]+(1-r)\,\varepsilon/4$		**J**	$rj+(1-\varepsilon)[s+t]+(1-r)\,\varepsilon/4$		$rj+(1-\varepsilon)[t+u]+(1-r)\,\varepsilon/4$	

Table A4. Types' Expected Payoffs and Choice Probabilities in O'Neill's Game when 3*j* – *a* > 1

Player 1	Exp. Payoff	Choice Pr.	Player 2	Exp. Payoff	Choice Pr.
***L0* (Pr. *R*)**			***L0* (Pr. *r*)**		
A	-	a	**A**	-	a
2	-	$(1-a-j)/2$	**2**	-	$(1-a-j)/2$
3	-	$(1-a-j)/2$	**3**	-	$(1-a-j)/2$
J	-	j	**J**	-	j
***L1* (Pr. *S*)**			***L1* (Pr. *s*)**		
A	$1-a-j$	0	**A**	$a+j$	1
2	$(1+a-j)/2$	*0*	**2**	$(1-a+j)/2$	0
3	$(1+a-j)/2$	*0*	**3**	$(1-a+j)/2$	0
J	j	1	**J**	$1-j$	0
***L2* (Pr. *T*)**			***L2* (Pr. *t*)**		
A	0	0	**A**	1	1/3
2	1	1/2	**2**	1	1/3
3	1	1/2	**3**	1	1/3
J	0	0	**J**	0	0
***L3* (Pr. *U*)**			***L3* (Pr. *u*)**		
A	2/3	1/3	**A**	0	0
2	2/3	1/3	**2**	1/2	0
3	2/3	1/3	**3**	1/2	0
J	0	0	**J**	1	1
***L4* (Pr. *V*)**			***L4* (Pr. *v*)**		
A	0	0	**A**	1/3	0
2	0	0	**2**	1/3	0
3	0	0	**3**	1/3	0
J	1	1	**J**	1	1
Total			**Total**		
A	$Ra+(1-\varepsilon)[u/3]+(1-r)\,\varepsilon/4$		**A**	$ra+(1-\varepsilon)[s+t/3]+(1-r)\,\varepsilon/4$	
2	$r(1-a-j)/2+(1-\varepsilon)[t/2+u/3]+(1-r)\,\varepsilon/4$		**2**	$r(1-a-j)/2+(1-\varepsilon)[t/3]+(1-r)\,\varepsilon/4$	
3	$R(1-a-j)/2+(1-\varepsilon)[t/2+u/3]+(1-r)\,\varepsilon/4$		**3**	$r(1-a-j)/2+(1-\varepsilon)[t/3]+(1-r)\,\varepsilon/4$	
J	$Rj+(1-\varepsilon)[s+v]+(1-r)\,\varepsilon/4$		**J**	$rj+(1-\varepsilon)[u+v]+(1-r)\,\varepsilon/4$	

Table A5. Types' Expected Payoffs and Choice Probabilities in Rapoport and Boebel's Game

Player 1	Exp. Payoff $3m/2+n>1$	Choice Pr. $3m/2+n>1$	Exp. Payoff $3m/2+n<1$	Choice Pr. $3m/2+n<1$
***L0* (Pr. *r*)**				
C	-	$m/2$	-	$m/2$
L	-	$(1-m-n)/2$	-	$(1-m-n)/2$
F	-	n	-	n
I	-	$(1-m-n)/2$	-	$(1-m-n)/2$
O		$m/2$		$m/2$
***L1* (Pr. *s*)**				
C	$m/2$	0	$m/2$	0
L	$1/2+n/2$	1	$1/2+n/2$	1
F	$1/2-n/2$	0	$1/2-n/2$	0
I	$1-m-n$	0	$1-m-n$	0
O	$(1-m+n)/2$	0	$(1-m+n)/2$	0
***L2* (Pr. *t*)**				
C	0	0	1	1
L	1	1/2	0	0
F	0	0	0	0
I	1	1/2	0	0
O	0	0	0	0
***L3* (Pr. *u*)**				
C	½	1/4	1/2	1/4
L	0	0	0	0
F	½	1/4	1/2	1/4
I	½	1/4	1/2	1/4
O	½	1/4	1/2	1/4
***L4* (Pr. *v*)**				
C	1	1	0	0
L	0	0	3/4	1
F	0	0	1/2	0
I	0	0	1/2	0
O	0	0	1/2	0
Total	$3m/2+n>1$		$3m/2+n<1$	
C	$rm/2+(1-\varepsilon)[u/4+v]+(1-r)\varepsilon/5$		$rm/2+(1-\varepsilon)[t+u/4]+(1-r)\varepsilon/5$	
L	$r(1-m-n)/2+(1-\varepsilon)[s+t/2]+(1-r)\varepsilon/5$		$r(1-m-n)/2+(1-\varepsilon)[s+v]+(1-r)\varepsilon/5$	
F	$rn+(1-\varepsilon)[u/4]+(1-r)\varepsilon/5$		$rn+(1-\varepsilon)[u/4]+(1-r)\varepsilon/5$	
I	$r(1-m-n)/2+(1-\varepsilon)[t/2+u/4](1-r)\varepsilon/5$		$r(1-m-n)/2+(1-\varepsilon)[u/4](1-r)\varepsilon/5$	
O	$rm/2+(1-\varepsilon)[u/4]+(1-r)\varepsilon/5$		$rm/2+(1-\varepsilon)[u/4]+(1-r)\varepsilon/5$	

Player 2	Exp. Payoff $3m/2+n>1$	Choice Pr. $3m/2+n>1$	Exp. Payoff $3m/2+n<1$	Choice Pr. $3m/2+n<1$
***L0* (Pr. *r*)**				
C	-	$m/2$	-	$m/2$
L	-	$(1-m-n)/2$	-	$(1-m-n)/2$
F	-	N	-	n
I	-	$(1-m-n)/2$	-	$(1-m-n)/2$
O		$m/2$		$m/2$
***L1* (Pr. *s*)**				
C	$1-m/2$	0	$1-m/2$	1
L	$1/2-n/2$	0	$1/2-n/2$	0
F	$1/2+n/2$	0	$1/2+n/2$	0
I	$m+n$	1	$m+n$	0
O	$(1+m-n)/2$	0	$(1+m-n)/2$	0
***L2* (Pr. *t*)**				
C	1	½	1	1/2
L	1	½	1	1/2
F	0	0	0	0
I	0	0	0	0
O	0	0	0	0
***L3* (Pr. *u*)**				
C	1	1	0	0
L	½	0	1	1/4
F	½	0	1	1/4
I	0	0	1	1/4
O	1/2	0	1	1/4
***L4* (Pr. *v*)**				
C	3/4	¼	3/4	1/4
L	0	0	1/4	0
F	3/4	¼	3/4	1/4
I	3/4	¼	3/4	1/4
O	3/4	¼	3/4	1/4
Total	$3m/2+n>1$		$3m/2+n<1$	
C	$rm/2+(1-\varepsilon)[t/2+u+v/4]+(1-r)\varepsilon/5$		$rm/2+(1-\varepsilon)[s+t/2+v/4]+(1-r)\varepsilon/5$	
L	$r(1-m-n)/2+(1-\varepsilon)[t/2]+(1-r)\varepsilon/5$		$r(1-m-n)/2+(1-\varepsilon)[t/2+u/4]+(1-r)\varepsilon/5$	
F	$rn+(1-\varepsilon)[v/4]+(1-r)\varepsilon/5$		$rn+(1-\varepsilon)[u/4+v/4]+(1-r)\varepsilon/5$	
I	$r(1-m-n)/2+(1-\varepsilon)[s+v/4]+(1-r)\varepsilon/5$		$r(1-m-n)/2+(1-\varepsilon)u/4+v/4]+(1-r)\varepsilon/5$	
O	$rm/2+(1-\varepsilon)[v/4]+(1-r)\varepsilon/5$		$rm/2+(1-\varepsilon)[u/4+v/4]+(1-r)\varepsilon/5$	