BARGAINING BEHAVIOR

Edited by

HEINZ SAUERMANN

1 9 7 8

J. C. B. MOHR (PAUL SIEBECK) TÜBINGEN

REFERENCES

Harnett, D.L./ Cummings, B.L. (1972): Bilateral Monopoly Bargaining: An International Study, in: *Sauermann, H.* (Ed.): Contributions to Experimental Economics, Vol. 3, Tübingen: J.C.B. Mohr, p. 100-129.

Harsanyi, J.C./ Selten, R. (1972): A Generalized *Nash* Solution for Two-Person Bargaining Games with Incomplete Information, 18, p.

Hoggatt, A. (1969): Response of Paid Subjects to Differential Behavior of Robots in Bifuncated Dupoly Games, in: Review of Economic Studies, 36, p. 417-432.

Hoggatt, A.C./ Esherich, J./ Wheeler, J.T. (1969): A Laboratory to Facilitate Computer-Controlled Behavioral Experiments, in: Administrative Science Quarterly, 14, p.

Selten, R. (1975): Bargaining under Incomplete Information - A Numerical Example, in: *Becker, O./ Richter, R.* (Eds.): Dynamische Wirtschaftsanalyse, Tübingen: J.C.B. Mohr, p. 203-232.

ROBOTS AS INSTRUMENTAL FUNCTIONS IN THE STUDY OF BARGAINING BEHAVIOR

by

AUSTIN C. HOGGATT, HERMANN BRANDSTÄTTER,

PETER BLATMAN

University of California, Universität Augsburg
University of California

Experimental studies of Harsanyi-Selten bargaining under uncertainty have been extended to include robots which were based on frequency analysis of the play of student subjects. Logit analysis is employed to measure a second generation of robots based on play among businessmen, university administrators, and first generation robots. These more advanced robots are employed in the study of the implications of the play of human subjects in the extensive form of the game. We have extended the study of the situation defined by Turing in the "immitation game" by adding to the question "is the robot player detectable?" the additional question, "Does the presence of a robot player effect the play of the game?" We have a marginal "no" answer to the first question and a strong "no" answer to the second question. The study of the experimental results is further extended by computer simulation of the play of the second generation robots.

INTRODUCTION

In a joint paper also presented at this conference (*HOGGATT/SELTEN/CROCKETT/GILL/MOORE*, 1978) *Selten* reports on the first experiments which were performed to test the *HARSANYI/SELTEN* (1972) theory of bargaining under uncertainty with regard to the state of the opponent. The work which we report here is an extension of that primary experiment in two major directions. First, probabilistic robot players which were developed from observations of human play in the primary experiment were implemented on the Laboratory computer of the Center for Research in Management Science. We refer to these robots in the sequel as *Selten* robots. They were embedded in a control program so that they could play the role of subjects in a bargaining experiment.[1)] Second, Professor *Hermann Brandstätter* became interested in these experiments as a new situation in which to study the use of social-psychological measurements to provide instrumental variables to aid in the understanding of human behavior. *Blatman, Brandstätter* and *Hoggatt* jointly worked during July 1976 to expand the experimental protocol to include these psychological instruments. This work, including the invention of the experimental design, was the primary responsibility of *Brandstätter*. The analysis of the usefulness of these instruments to the analysis of bargaining is to be reported elsewhere so we shall not discuss this phase of the experiment in detail.[2)] The game theoretic analysis of the bargaining situation and a detailed description of the primary experiment are reported elsewhere in this volume (*HOGGATT/SELTEN* et. al. 1978). We shall assume that the reader is familiar with that paper and concentrate here on the extensions which we have made to it.

Hoggatt recruited business men and educators known to him and on June 27, 28, 29, and 30 of 1977, *Hoggatt* and *Blatman* ran the four experimental sessions required for the *Brandstätter* design and transmitted the data to the campus computer facility via remote data entry from the laboratory. Data reduction necessary to provide inputs for *Brandstätter*'s analysis was completed by *Hoggatt* on July 7, 1977. The analysis for this paper was begun and completed during July 1977.[3)]

1) This work was largely done by *Peter Blatman*. For details of this work, see *Blatman/Brandstätter/Hoggatt* (1977), available from the Center for Research in Management Science, University of California, Berkeley. Response probabilities for these robots were taken from Figures 32-37 of *Hoggatt* et al. (1978).
In the current experiment players had the opportunity to select one of 9 messages from a predefined list (see Appendix). Since we had no observations of human play on which to base this decision, we specified *a priori* a random message emission function with the following structure:

Conditions		Probability of Emitting Message									
LIKING	OPPONENTS' LAST YIELD	0	1	2	3	4	5	6	7	8	9
yes	0	.5	0	0	0	0	.25	.25	0	0	0
yes	>0	.1	.1	.2	.2	.2	.2	0	0	0	0
no	0	.1	0	0	0	0	.2	.2	.2	.2	.1
no	0	.5	0	0	.0	.25	.25	0	0	0	0

It has the property that messages tend to be less friendly under the not liking condition than under the liking condition and messages tend to be less friendly under yield zero for the opponent and more friendly under yields greater than zero for the opponent.

2) In the Appendix we present the Instructions for Participants. The two instruments, *Kuhlman*-test and *Mach*-test, have been deleted to save space. In the instructions the subjects are informed that in 8 games they will meet robots 4 times.

Our major task is to perform logit analysis on the observations obtained on the play among humans and *Selten* robots in order to measure the coefficients of a stochastic difference equation, ROBOT, with which to further our understanding of this extremely complex situation. We shall proceed as follows: In *section 1* there is a short discussion of logit models and the new logit estimation procedures which have been developed at Berkeley.[4)] In *section 2* we present the structure of the data and sketch the flow diagram of the dynamic-stochastic robot which is to be measured employing the data and logit algorithms. In *section 3* we present 19 independent binomial and multinimial logit functions which uniquely specify a "*Brandstätter* robot". Inasmuch as there are 263 coefficients and their associated standard deviations and *t*-statistics, we shall have to be content with a general discussion of this part of our work. We will see that the instrumental variables (cost, liking) and the instrumental function (ROBOT) evoke strong behavioral responses. In *section 4* we investigate responses to the question: "Were you playing a person or a robot"? which was put to each subject after each round. Our analysis treats the *structure* of responses to that question. In *section 5* we employ simulation to examine the implications of our stochastic-dynamic robot with respect to conflict and agreement in extensive play of the game. We conclude, in *section 6*, with a discussion of the role that instrumental functions may play in studying the extensive form of interactive human behavior.

1. DIGRESSION ON LOGIT ESTIMATION

The statistical model which we employ assumes that there are a limited number of discrete alternatives available at each decision. These may be completely specified by the rules; for example, only one from a list of 10

3) Support of the Campus Computing Facility was essential to the completion of the analysis. Funds to pay subjects were provided by ACHFEB, a partially anonymous donor to whom the authors are personally indebted. The administrative assistance of *F.E. Balderston* and his helpful comments on an earlier draft are gratefully acknowledged. Comments of *Reinhard Selten* and *James Friedman* on an earlier draft were also very helpful.

4) *Daniel McFadden* has spearheaded this development. See *Berkman* et al. (1976), *McFadden* (1973).

messages may be sent. Or the response may be defined by a combination of rules and the current state of the bargaining as in the situation of a high cost player whose previous demand is 11 and who is restricted to the set of alternatives {11,10,9} when choosing his next demand. We shall employ only two simple models. The first involves two alternatives and it is assumed that P, the *probability of choosing the first alternative,* is given by

$$P = 1/(1 + e^{-\beta x+u}),$$

where x is an independent vector variable with one value for each case and u is assumed to be drawn from a logistic distribution. The program QUAIL employs modified *Newton-Raphson* search for the maximization of the log likelihood function since a closed form for the estimators is not known. All of our predictor variables are *not* differentiated by alternatives: so the *probability of the second alternative* is given by (1-P).

We shall also wish to fit a multinomial logit of the form

$$P_i = e^{\beta^i x} / \sum_{j=1}^{J} e^{\beta^j x}$$

where, P_i is the probability of selecting the i-th alternative;

x is the vector of independent variables *not* differentiated by alternative;

β^i $i = 1,\ldots,J$ are parameter vectors.

By virtue of the predictors not being differentiated by alternative, the model is underdetermined. We may introduce the arbitrary assumption:

$$\sum_{j=1}^{J} \beta^i = 0 .$$

Then we may estimate $\beta^1,\ldots,\beta^{J-1}$ and obtain $\beta^J = -(\beta^1+\ldots+\beta^{J-1})$. Individual coefficients may be tested for significance by the usual t-tests. LRS, the likelihood ratio statistic,[5] has a χ^2 distribution with number of degrees

5) LRS = 2(log likelihood at convergence - log likelihood at zero).

of freedom equal to the number of parameters estimated and may be used to test the hypothesis that all parameters are zero. Since memory requirements are related to the product of number of independent variables, number of alternatives, and the number of observations, we must be careful to keep this in bounds since computing requirements go up very rapidly with this number and it is easy to decimate any budget. In order that we may live within our means and the available computer memory, we have limited our alternatives to at most three.

Notice that the logit function is non-linear in the estimated parameters. In order to fully understand the response of a logit function it is necessary to examine the probabilities associated with various points in the domain. We employ simple FORTRAN programs to accomplish these tabulations.

2. STRUCTURE OF THE BRANDSTÄTTER DATA FILE

Table 1 lists the treatment variables which were determined by the experimental design and the endogenous variables which were determined by the rules of the game. The lag structure was determined by the extensive form of play. For example, the communication from the other player is received after guessing cost, so guess switching is not dependent on the message sent in the current period.

For comparability, the alternatives for demand and yield are kept the same as in *HOGGATT* et al. (1978). Our only encoding decision was where to divide the list of message numbers. We decided to place 5, "We will see what happens next", in alternative 3, "unfriendly". This is subjective classification.

There were 2168 stages of play recorded for human players in the *Brandstätter* design. A unit record was produced for each of these. Unit records were also produced at each stage for robot players; however, since robot structure and its implications for robot dynamics are known, we have not performed dynamic analysis on robot performance.

Response latencies were recorded for each guess and each demand. Regressions to relate these to the state variables and treatment variables

Table 1: Variables Used in the Analysis Program

Variable	Definition	Range
Treatment Variables		
MCOST	my cost	0 low; 1 high
IHCOST	his cost	0 low; 1 high
LIKING	liking	0 opponents do not like each other; 1 opponents do like each other
Endogenous Variables		
JROUND	round	integer 1-8
JSTAGE	stage	integer 1-15
MFDRM1	my first demand in previous round	-0 missing data for ROUND1 integer 1-20
JDEMM1	my demand in previous stage	non-negative integer
JHDEM	his demand	non-negative integer
JGUESS	guess his cost	0 guess low; 1 guess high
IGSM1	JGUESS in previous stage	0-1
MCOMM1	my message in previous stage	integer 0-9
JHCOM1	his message in previous stage	integer 0-9
MYLD	my yield in current stage	non-negative integer
MYLDM1	MYLD in previous stage	non-negative integer
IHYLD	his yield in current stage	non-negative integer
IHYDM1	IHYLD in previous stage	non-negative integer
MFDMHD	my first demand minus his first demand	integer
CT	strategic situation	1: (JDEMM1<JHDEM1) and (JHDEM1>10) 2: (JDEMM1>JHDEM1) and (JHDEM1<10) 3: (JDEMM1=JHDEM1) 4: (JDEMM1<JHDEM1) and (JDEMM1≥10) 5: (JDEMM1<JHDEM1) and (JDEMM1<10)
Dependent Variables for Logit Analysis		
IFDEM	first demand	1: MFD = 20 2: MFD = 19 3: MFD ≤ 18
IGSW	guess switch	1: switch guess 2: do not switch guess
IDCOM	message	1: no message 2: JCOM ∈ {1,2,3,4} 3: JCOM ∈ {5,6,7,8,9}
IDYLD	yield	1: MYLD = 0 2: MYLD = 1 3: MYLD ≤ 2

Table 2: Subject Frequency Response by Strategic Situation*

	First Demand		Guess His Cost		Communication	
Stage 1 N = 256	20	.41	Low	.30	No message	.60
	19	.20	High	.70	Friendly	.30
	≤ 18	.40			Unfriendly	.18
	Yield		Guess Switch		Communication	
Stage 2 N = 256	0	.21	No	.91	No message	.28
	1	.60	Yes	.09	Friendly	.48
	≥ 2	.19			Unfriendly	.24
CT1 N = 526	0	.27	No	.88	No message	.22
	1	.67	Yes	.12	Friendly	.47
	≥ 2	.06			Unfriendly	.31
CT2 N = 45	0	.60	No	.98	No message	.20
	1	.29	Yes	.02	Friendly	.58
	≥ 2	.11			Unfriendly	.22
CT3 N = 390	0	.14	No	.91	No message	.19
	1	.81	Yes	.09	Friendly	.59
	≥ 2	.05			Unfriendly	.22
CT4 N = 619	0	.36	No	.95	No message	.29
	1	.53	Yes	.05	Friendly	.38
	≥ 2	.10			Unfriendly	.33
CT5 N = 76	0	.21	No	.95	No message	.26
	1	.70	Yes	.05	Friendly	.36
	≥ 2	.09			Unfriendly	.38

*) The relative frequency of yields in condition CT4 does not include the data for 38 moves in which the player had high cost and a previous demand of 10. He could not then choose to yield more than 1. In these 38 moves the yield of 1 was chose 4 times.

are trivial. (We have computed one case and it is well behaved.) Latencies will be needed to specify the delay functions for these robots when they in their turn are called on to play against subjects. We eliminate latencies from consideration in this paper in order to concentrate on questions related to strategic choices.

In order for reader to have some feel for the data, we present in Table 2 the marginal frequencies of our dependent variables grouped by STAGE = 1, STAGE = 2, and the five strategic conditions (see *HOGGATT* et al., 1978):

CT1 my demand is greater than his demand and his demand is at least 10

CT2 my demand is greater than his demand and his demand is smaller than 10

CT3 my demand is equal to his demand

CT4 my demand is smaller than his demand and my demand is at least 10

CT5 my demand is smaller than his demand and my demand is smaller than 10.

The frequencies in Table 2 are plausible and suggest that our data reduction has not been grossly in error. For example, our old friend "H-bias" shows up in that 70 percent of the first guess of cost is "high"; guess inertia is large; and modal yields are 1 (except in condition CT2 where yielding is nonsense), so we see similarity between the behavior of student subjects in the *Selten* games and the behavior of businessmen and administrators in the *Brandstätter* games. We shall not pursue the detailed study of cross comparisons between these two groups.

Our primary goal is to achieve a computer program for a robot based on the *Brandstätter* data. A sketch of the flow diagram for such a robot is shown in Figure 1. In the diagram we see the various strategic relations which must be specified in order to construct a robot player in extensive form. The dependent variables at each point are determined by the rules of the game. The few independent variables are selected in each function from the large list of Table 1. The lag structure in each round has been kept short (the largest lag involves yield which is dependent on yield at the

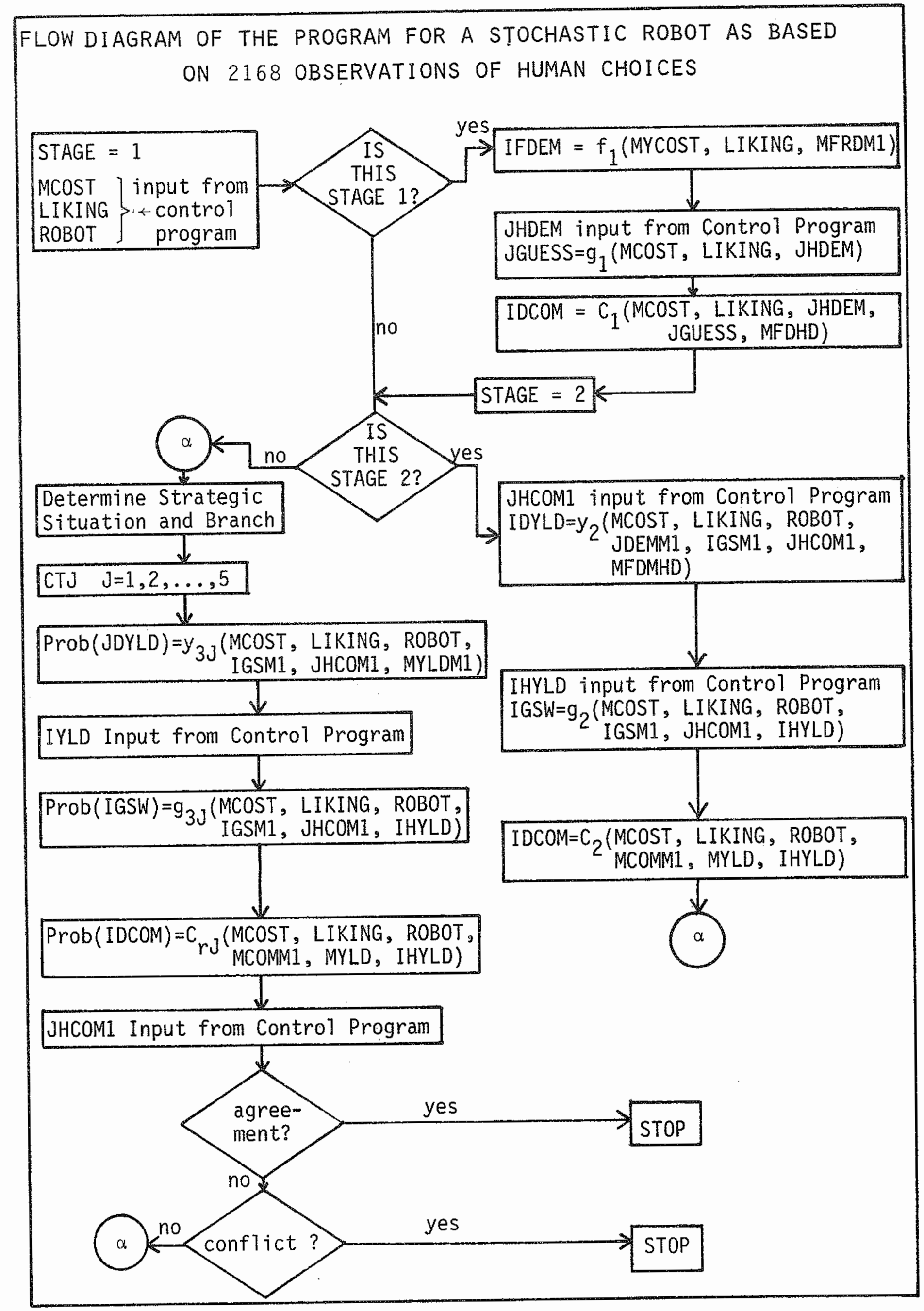

Figure 1

previous stage, thus making yield dependent on demand two stages back). So from a huge set of potential models we have selected a very restricted class to estimate. The highly subjective nature of this solution process is obvious when it is presented in this way. The laboratory produces large data bases for complex situations but we do not have objective methods at our disposal which can be used to aid the activity of variable selection and model reduction. With limited resources we could only investigate a single model.

3. ESTIMATES OF A PLAYER RESPONSE FUNCTION FOR THE BRANDSTÄTTER EXPERIMENT

Twenty-one independent logits were attempted and 19 of these were successfully computed. These are presented in Tables 3, 4, 5 and 6. Our first impression is that there is a lot of structure which has been caught in our net. The likelihood ratio statistics are outliers often beyond 10 times as large as $\chi^2_{.001}$. Only for messages do we have one weak relation and that for CT5 which has only 76 cases. Our second impression is that the treatments have been successful. Large *t*-values are associated with MCOST, LIKING and ROBOT throughout these tables. Messages matter! In Table 6 we see that they are being emitted as functions of the state space of the game and in particular as functions of *his* yield. In Table 4 we see that my yield is a function of his message so we may conclude that the messages are received and that they influence demands.

We cannot begin to explore all of these functions in detail. However, let us examine the probabilities of first demand.
Let,

$$F1 = .2396 \times MCOST + (-.1685 \times LIKING) + .0165 \times MFDRM1$$

$$F2 = .1358 \times MCOST + (-.1942 \times LIKING) + (-.0225 \times MFDRM1)$$

Table 3: Coefficients of Response Functions for Stages 1 and 2 as Based on Logit Analysis*

STAGE1

IFDEM	MCOST	LIKING	MFDRM1	LIKELIHOOD RATIO STAT.
20	.2396	-.1685	.0165	29.6
	(1.49)	(-1.01)	(2.31)	$\chi^2_{.001}=22.5$
19	.1358	-.1942	-.0225	
	(0.72)	(-1.00)	(-2.47)	
≤18	-.3754	.3627	.0060	

JGUESS	MCOST	LIKING	JHDEM	LRS
high	-.0094	-.2960	.0572	48.9
	(-.03)	(-1.07)	(4.35)	$\chi^2_{.001}=16.3$

IDCOM	MCOST	LIKING	JHDEM	JGUESS	MFDMHD	LRS
no mes.	.0125	-.0230	.0259	.1208	-.0279	66.5
	(.07)	(-.13)	(2.26)	(.60)	(-.90)	$\chi^2_{.001}=29.6$
friendly	-.0111	.4062	.0055	-.4301	.1163	
	(-.05)	(2.02)	(.43)	(7.95)	(3.07)	
unfriendly	-.0014	-.3832	-.0314	.3093	-.0884	

STAGE2

IDYLD	MCOST	LIKING	ROBOT	JDEMM1	IGSM1	IHCOM1	MFDMHD	LRS
0	.3857	-.3004	.2588	-.0163	-.4502	-.0762	-.2807	153.6
	(1.42)	(-1.18)	(.97)	(-.84)	(-1.61)	(-1.30)	(-5.59)	$\chi^2_{.001}=36.1$
1	-.4546	.0512	.1301	.0685	-.0846	-.0362	.1625	
	(-2.27)	(.27)	(.64)	(4.67)	(-.38)	(-.87)	(3.85)	
≥2	.0689	.2492	-.3889	-.0522	.5348	.1124	.0182	

IGSW	MCOST	LIKING	ROBOT	IGSM1	JHCOM1	IHYLD	LRS
switch	-.2818	-1.1496	-.8132	-1.1640	-.1120	.0837	174.3
	(.77)	(-3.06)	(-1.88)	(-3.19)	(-1.38)	(.6207)	$\chi^2_{.001}=22.5$

IDCOM	MCOST	LIKING	ROBOT	MCOMM1	MYLD	IHYLD	LRS
no mes.	.2298	-.0274	-.3122	-.2455	-.0435	.3845	87.5
	(1.24)	(-.14)	(-1.66)	(-4.18)	(-.69)	(3.21)	$\chi^2_{.001}=29.6$
friendly	-.1923	.2020	-.0223	.0412	-.0162	.5150	
	(-1.17)	(1.23)	(-.14)	(1.01)	(-.30)	(4.60)	
unfriendly	-.0375	-.1746	.3345	.2043	.0597	-.8995	

*) The t-statistic associated with each independently estimated coefficient is shown in parenthesis directly below it. This convention is also employed in Tables 4, 5 and 6.

Table 4: Coefficients of the Probability for Yielding (Stage > 2) as Based on Logit Analysis

Strategic Condition	IDYLD	MCOST	LIKING	ROBOT	IGSMI	JHCOMI	MYLDMI	LIKELIHOOD RATIO STAT†
CT 1 N = 526	0	.7564	-.0768	.3867	-.1453	-.0042	-.5519	379.0
		(4.85)	(-.50)	(2.20)	(-.85)	(-.17)	(-3.94)	$\chi^2_{.001} = 32.9$
	1	-.0561	.2583	.3654	.0291	.0361	.99o3	
		(-.40)	(1.88)	(2.27)	(.14)	(1.56)	(8.34)	
	≥ 2	-.7003	-.1815	-.7521	.1162	-.0319	-.4384	
CT 2* N = 45		P(0) = .60; P(1) = .29; P(≥2) = .11						
CT 3 N = 390	0	.4685	.5882	.2015	-.4920	-.0822	-.4045	372.9
		(2.02)	(2.65)	(.88)	(-2.01)	(-1.86)	(-2.14)	$\chi^2_{.001} = 32.9$
	1	-.1291	.1570	.0015	.4624	.0789	1.0018	
		(-.68)	(.84)	(.0079)	(2.35)	(2.23)	(6.72)	
	≥ 2	-.3394	-.7452	-.2030	.0296	.0033	-.5973	
CT 4** N = 581	0	.4512	.4140	.1051	-.3691	.0558	-.0721	228.4
		(3.38)	(3.41)	(.84)	(-2.83)	(2.18)	(-1.06)	$\chi^2_{.001} = 32.9$
	1	-.0012	.1623	.0240	.9213	.0088	-.1310	
		(-.0093)	(1.37)	(.20)	(7.35)	(.35)	(-1.93)	
	≥ 2	-.4500	-.5763	-.1291	-.5522	-.0646	.2031	
CT 5*** N = 76	0		.5461	-.4200	-.0069	-.0606	.0685	49.7
			(1.13)	(-.88)	(-.02)	(-.46)	(.72)	$\chi^2_{.001} = 29.6$
	1		-.5966	1.1734	.7437	.1342	-.1811	
			(-1.33)	(2.76)	(1.84)	(1.15)	(-1.70)	
	≥ 2		.0505	-.7534	-.7368	-.0736	.1126	

*) This logit failed to convergence under several configurations of independent variables because of small sample size and skewness of choice distribution. In this case P(IDYLD) is set to the marginal probabilities for CT 2.

**) Excluding 38 moves for high cost players with previous demand of 10. In this situation IDYLD = 1 occured 4 times. Therefore CT 4 has a single sub-case which is identified by MCOST = 1 and MDEMM1 = 10. In this situation P(0) = 34/38, P(1) = 4/38, P(≥2) = 0.

***) The logit would not convergence for the full complement of independent variables. With the elimination of MCOST, convergence was achieved.

†) The logit would not convergence for the full complement of independent variables. With the elimination of MCOST, convergence was achieved.

Table 5: Coefficients of the Probability Functions for Guess Switching (Stage > 2) as Based on Logit Analysis

Strategic Situation	IGSW	MCOST	LIKING	ROBOT	IGSM1	JHCOM1	IHYLD	Likelihood Ratio Statistic
CT1 N=526	switch	-.9172	-.5405	-.5374	.0746	-.1245	-.4638	293.9
		(-4.03)	(-2.44)	(-2.15)	(.29)	(-2.89)	(-2.41)	$\chi^2_{.001}=22.5$
CT2*		P(switch) = .022		P(no switch) = .978				
CT3 N=390	switch	-.5691	-.4379	-.5478	-.1464	-.3054	-.7141	292.3
		(1.60)	(-1.31)	(-1.62)	(-.44)	(-3.42)	(-2.69)	$\chi^2_{.001}=22.5$
CT4 N=619	switch	-.7780	-.7396	-1.4961	-1.5844	-.1692	.0978	578.9
		(-2.28)	(-2.49)	(-4.27)	(-5.44)	(-2.61)	(.52)	$\chi^2_{.001}=22.5$
CT5† N=76	switch		-2.3261	-.7172	-1.7735	-.0614	.2246	69.9
			(-1.85)	(-.93)	(-2.36)	(-.31)	(.81)	$\chi^2_{.001}=20.5$

*) This logit failed to convergence because of small sample and skewness of choice distribution. In this case P(IGSW) is set as the marginal probabilities for CT2.

†) The logit would not convergence for the full complement of independent variables. With the elimination of MCOST, convergence was achieved.

Table 6: Coefficients of the Probability Functions for Message Types (Stage ≥ 2) as Based on Logit Analysis

Strategic Situation	IDCOM	MCOST	LIKING	ROBOT	MCOMMI	MYLD	IHYLD	LIKELIHOOD RATIO STATISTIC
CT 1 N = 526	No Message	.1406	.3330	-.6075	-.1794	-.1491	.2296	231.7
		(.95)	(2.24)	(-3.75)	(-4.90)	(-1.38)	(1.82)	$\chi^2_{.001}=32.9$
	Friendly	-.1792	-.3049	.4902	.0217	-.0083	.8197	
		(-1.46)	(-2.44)	(3.93)	(.78)	(-.10)	(7.69)	
	Un-friendly	.0386	-.0281	.1173	.1577	.1574	-1.0493	
CT 2 N = 45	No Message	-.0797	-.5093	1.5874	-.5073	.4644	-.1062	29.23
		(-.08)	(-.80)	(1.58)	(-2.05)	(1.94)	(-.19)	$\chi^2_{.001}=32.9$
	Friendly	.2358	.4171	-.3192	.1904	.0411	.3236	
		(.34)	(.91)	(-.43)	(1.26)	(.20)	(.83)	$\chi^2_{.005}=28.3$
	Un-friendly	-.1561	.0922	-1.2682	.3169	-.5055	-.2174	
CT 3 N = 390	No Message	.2699	.3176	.1366	-.3991	.1697	.0566	290.2
		(1.40)	(1.69)	(.73)	(-6.34)	(1.72)	(.31)	$\chi^2_{.001}=32.9$
	Friendly	-.0980	.1162	-.6540	.1148	-.1527	1.3038	
		(-.61)	(.75)	(-4.04)	(2.75)	(-1.59)	(8.24)	
	Un-friendly	-.1719	-.4338	.5174	.2843	-.0170	-1.3604	
CT 4 N = 619	No Message	.2686	.2334	.0322	-.1946	-.0511	.3405	269.9
		(2.21)	(1.95)	(.25)	(-7.41)	(-.58)	(2.98)	$\chi^2_{.001}=32.9$
	Friendly	-.2950	-.3489	-.1766	.0052	-.3583	1.0032	
		(-2.50)	(-3.01)	(-1.47)	(.23)	(-4.09)	(9.09)	
	Un-friendly	.0264	.1155	.1444	.1894	.4094	-1.3437	
CT 5 N = 76	No Message	.6989	-.1141	-.0990	-.0936	.1003	-.0606	16.82
		(1.25)	(-.31)	(-.26)	(-1.35)	(.30)	(-.39)	$\chi^2_{.10}=18.5$
	Friendly	-.5180	.0380	.1566	-.0637	.3756	.1109	
		(-.84)	(.12)	(.47)	(-1.06)	(1.32)	(.91)	$\chi^2_{.25}=14.8$
	Un-friendly	-.1809	.0761	-.0576	.1573	-.4759	-.0503	

(where the coefficients are taken from the first three lines of Table 3) then,

$$\text{Prob}\left\{\begin{matrix}20\\19\\\le 18\end{matrix}\right\}=\left\{\begin{matrix}(e^{F1})/(e^{F1}+e^{F2}+e^{F3})\\(e^{F2})/(e^{F1}+e^{F2}+e^{F3})\\(e^{F3})/(e^{F1}+e^{F2}+e^{F3})\end{matrix}\right\}$$

In the case MCOST = 0, LIKING = 0, MFDRM1 = 18, we have F1 = .30, F2 = -.40, F3 = .11 with

$$\text{Prob}\left\{\begin{matrix}20\\19\\\le 18\end{matrix}\right\}=\left\{\begin{matrix}.43\\.21\\.46\end{matrix}\right\}$$

If we move to high cost we have MCOST = 1, LIKING = 0, MFDRM1 = 18 and

$$\text{Prob}\left\{\begin{matrix}20\\19\\18\end{matrix}\right\}=\left\{\begin{matrix}.53\\.24\\.24\end{matrix}\right\}$$

So we see that the probability distribution of first demand is strongly dependent on treatment conditions. Reader may wish to explore the other functions using a hand calculator and this illustration as a guide.

In a highly interrelated structure such as the one we are dealing with, it is not possible to think through all of the effects to arrive at conclusions about important questions such as the overall impact of message activity on the outcomes of the game. Experiments could be designed in which message sending and/or receiving was differentially restricted. This would be a costly effort. Alternatively, the simulator which is described in section 6 could be simply modified to include some players who could only send or receive "no message". We illustrate this extension of the concept of a "Gedanken-experiment" at the end of section 6 where we simulate players who always send "no message". In the simulation there are instrumental dummy variables which may be set to override message generating routines so that "no message" is sent. Such a dummy then enters the analysis at the same level as an experimental treatment variable.

4. CAN SUBJECTS DISCRIMINATE BETWEEN ROBOT AND HUMAN OPPONENTS?

We now turn to the question, "Were the subjects able to discriminate between human and robot opponents?" We drop payoff dependency from this regression on grounds that there was no direct feedback about bonus awards during play. Correct guesses occurred in 140 out of 256 cases. The logit is displayed in Table 7. That estimate includes a dummy variable specific

Table 7: Logit Estimates of the Dependence of Correct Guess as to Whether Opponent is Robot or Person as a Function of Treatment Variables, Whether or not Game Ended in Conflict and Alternative 1

Independent Variable	β	t
MCOST	.1866	.67
IHCOST	.05347	.19
LIKING	.009419	.04
IROBOT	-.6719	-2.55
ICONF	-.1692	-.57
ALT1	.4866	1.68
Likelihood ratio statistic = 10.5		
$\chi^2_{.10}$ = 10.6		

to alternative 1. (In a binary logit this introduces a constant into the linear form of the estimator.) The likelihood ratio statistic falls on the 10 percent point of the χ^2 distribution. Here only the alternative specific dummy and IROBOT are significant. The prediction of correctness of the guess is shown in Table 8. These subjects tended to guess that the opponent was a person (150 guesses out of 256 were "person") and this bias accounts for the significance of IROBOT in the model. We conclude that our subjects as a group were not able to detect robots differentially under the treatment or outcome conditions of the experiment. The robots are well hidden.

Table 8: Logit Prediction of the Probability of Correct Guess as to Whether Opponent is a Person or a Robot as Dependent on my Cost and Opponent's Cost and Alternative 1*

Opponent is Robot			Opponent is Person		
MYCOST	HISCOST	PROB COR. GUESS	MYCOST	HISCOST	PROB COR. GUESS
Low	Low	.45	Low	Low	.62
Low	High	.47	Low	High	.63
High	Low	.50	High	Low	.66
High	High	.51	High	High	.67

We may now turn to an investigation of the implications of the robots which were developed in Tables 3, 4, 5 and 6.

5. DEPENDENCE OF PROBABILITY OF CONFLICT ON THE TREATMENT CONDITION, COST, LIKING, ROBOTS AND PAYOFF DEPENDENCY

In his work *Brandstätter* will apply a powerful analysis of variance program to the data. This will provide a detailed analysis of the structure of his complex experiment. However, we may employ logit analysis to our data to look for first order dependency. For this analysis the independent variables are:

MCOST	=	0	low cost
		1	high cost
HCOST	=	0	low cost
		1	high cost
LIKING	=	0	players do not like each other
		1	players do like each other
IROBOT	=	0	opponent is a person
		1	opponent is a robot
PAYDEP	=	0	no payoff dependency[6)]
		1	payoff dependency

*) LIKING = no and ICONF = no in this tabulation. Since the t-statistics associated with cost conditions are small, we are not surprised that the range of variation associated with cost conditions is small.

6) With payoff dependency players award to the opponent a bonus of 0, 1

The dependent variable is:

CONFLICT = 0 the bargaining resulted in agreement
1 the bargaining resulted in conflict .

The data involve 256 observations, one for each game in which at least one player was a human. In those cases where both players were human there is an observation for each subject. We have not introduced the refinement of restricting the analysis to dyads in order to eliminate dependency.

Table 9: Logit Estimates of the Dependence of Conflict Probability on Treatment Variables and the Conflict Alternative

Independent Variable	β	t
MCOST	1.6963	5.49
IHCOST	1.6295	5.28
LIKING	.2945	1.00
IROBOT	.9514	3.18
PAYDEP	.2945	1.00
ALT1	-2.5385	-6.01
Likelihood ratio statistic = 73.3		
$\chi^2_{.001} = 22.5$		

This logit is shown in Table 9 and it is strong. We also find that IROBOT is highly significant. The predictions for this logit are shown in Table 10. These results are reasonable with the conflict probabilities falling in the range of the data. The person-person games have a lower conflict probability than the person-robot games. Since these robots are based on the behavior of the student subjects, we have indirect evidence that the students were more "competitive" than our "executives". Unfortunately, LIKING and PAYDEP are not significant in this model and we shall have to await *Brandstätter*'s analysis for definitive conclusions about the treatment effects of these variables.

6) continued:

or 2 money units after each round. Subjects get no feedback about their bonus award until the debriefing at the end of the session.

Table 10: Logit Prediction of the Probability of Conflict as Dependent on my Cost, Opponent's Cost, Irobot, Liking, Payoff Dependency and Alternative 1

MYCOST	HISCOST	LIKING*	PAYDEP*	PROB(CONF)	
				IROBOT=0	IROBOT=1
low	low	no	no	.07	.17
low	low	yes	no	.10	.12
low	low	no	yes	.17	.22
low	low	yes	yes	.12	.27
low	high	no	no	.29	.51
high	low	no	no	.30	.53
low	high	yes	no	.35	.58
high	low	yes	no	.37	.60
low	high	no	yes	.35	.58
high	low	no	yes	.37	.60
low	high	yes	yes	.42	.65
high	low	yes	yes	.44	.67
high	high	no	no	.69	.75
high	high	yes	no	.75	.88
high	high	no	yes	.75	.88
high	high	yes	yes	.88	.91

6. ON THE BEHAVIOR OF HOGGATT-BRANDSTÄTTER ROBOTS

The robot which has been developed from the *Brandstätter* data is a very complex mechanism. Our method for studying its behavior is to construct a computer program which embodies the rules of the bargaining game and embed two of our robots in it and have them compete with each other. The FORTRAN program which provides for the simulated play of *Brandstätter* robots in the *Brandstätter* design is available from the first author.[7)]

*) Note that t-statistic associated with LIKING and PAYDEP is not significant.

7) Since our analysis was developed on the Berkeley campus CDC 6400 computing facility, it was easiest to implement the simulator on that facility also. FORTRAN is the language of choice in this situation. The robot procedures could be translated into APL, the language implemented on our laboratory system. This would be a single day's work for a competent programmer. The programs are available from *A.C. Hoggatt*, Center for Research in Management Science, University of California, Berkeley, Cal. 94720, U.S.A.

The simulation of a game begins with the reading of a card which determines the values of treatment variables. For players in a session, the program has memory for FDRM1 (this is initialized at 19 for round 1).[8)] The same response functions are now used in a "closed loop" in which the iteration proceeds through the stages of play until agreement or conflict results. A simulation of four sessions which are parallel to the play of *Brandstätter*'s subjects was achieved by reading in the 256 cards which provided the input data for the logit analysis of conflict shown in Table 9. At the end of each game a similar card is produced (ID = "Z") with three added fields for the final simulated demands and whether conflict occurred or not. For statistical tests, which we may later wish to perform, this assures us that we have precisely matched pairs between the laboratory-experiment and the simulation. In the simulation 132 of our 256 cases ended in conflict. This is close to what we would expect from draws of the distribution of Table 9 in which 123 of 256 cases ended in conflict.

It should be borne in mind that the logit program also estimates the standard error of the distribution of the coefficients but in this simulation we do not perturb the coefficients in the response functions to produce individual variations. Hence, we would expect the data from the simulator to display less variability at the local level. We do not conjecture as to the effects this might have at the global level.

As a test of the simulator we reran the logit analysis of Table 9 using conflict in the simulated game as the dependent variable. These results are reported in Table 11.

There is the suggestion that payoff dependency may produce a stronger effect in the simulator than it does in actual play. This is reasonable

8) This is a compromise. ROUND1 value of MFDRM1 was missing data for the logit. Strictly, we should estimate the first round response separately, excluding MFDRM1, then we could not have to make any assumption about the value of this independent variable in round 1.

since *Selten-robots* ignored this nuance and *Brandstätter-robots* have been measured from humans who did not. In other respects the results of simulated play and actual play are similar.

Table 11: Logit Estimates of the Dependence of Conflict on Treatment Variables and the Conflict Alternative for 256 Simulated Cases in a Brandstätter Statistical Design

Independent Variable	β	t
MCOST	1.0430	3.8027
IHCOST	.9782	3.5683
LIKING	0	-
IROBOT	.5705	2.0927
PAYDEP	-.5003	-1.8368
ALT1	-.9738	-2.8818
Likelihood ratio statistic = 35.5		
$\chi^2_{.001} = 22.5$		

Finally, we may turn to the question, "What impact do messages have on the play"? To explore this question we modified the simulator to introduce two additional treatment variables, viz.,

$$\text{MEDUMB} = \begin{cases} 0 & \text{with probability } 3/4 \\ 1 & \text{with probability } 1/4 \end{cases}$$

$$\text{HEDUMB} = \begin{cases} 0 & \text{with probability } 3/4 \\ 1 & \text{with probability } 1/4. \end{cases}$$

In any game if MEDUMB = 1, player 1 can emit only "no message" and if HEDUMB = 1, player 2 can emit only "no message". The logit which measures the dependency of conflict probability on treatment variables in this simulation is shown in Table 12. In this case, introducing the alternative specific dummy made no essential change in the logit result. The effects are stronger than in Table 11 (the likelihood ratio statistic is more than double that of Table 11). "Robot" players behave differently than "human" players. MEDUMB, associated with "human" players, is very weak, but this is not surprising since half of the opponents of player 1 are "robots" which are deaf (they were not programmed to react to messages). Interac-

Table 12: Logit Estimates of the Dependence of Conflict Probability on Treatment Variables, Messages, and Pure Conflict Aversion for 256 Simulated Cases in a Brandstätter Statistical Design

Independent Variable	β	t
MCOST	1.2206	4.16
IHCOST	.6968	2.42
LIKING	.006790	.02
IROBOT	.6969	2.38
PAYDEP	-.8723	-2.96
MEDUMB	.07928	.24
HEDUMB	.4633	1.18
ALT1	-.3344	-.94
Likelihood ratio statistic = 58.4		

tion effects are not measured, but it is likely that this accounts for the large coefficient on IROBOT. These two positive coefficients move the probability of conflict upwards for "robot" players or "dumb" players. This strongly suggests that message exchanges induce more cooperative play on the part of human players and that this has been captured in the *Brandstätter-robots*. This is also consistent with the results in Table 9 which show the *Selten-robots* to have significantly higher conflict probabilities than do their human opponents.

7. COMMENT ON OUR METHODOLOGY

We have constructed a recursive procedure which moves from a model (in this case *Harsanyi-Selten* bargaining under uncertainty) to a laboratory experiment (*Hoggatt-Selten* primary experiment). The data from the experiment are used to measure the parameters of a robot whose structure was

determined by considerations taken from the theory (i.e., the switching parameter, CT $\in$ {1,2,3,4,5} employs the threshold "demand less than 10" which divides situations into those in which cost of the demander is known to the opponent with certainty or not). In a secondary experiment the robots play against human players and *Turing*'s test (*TURING*, 1950) is employed to determine whether they are transparent or not. In the case at hand this process was not followed completely since the *Brandstätter* experiment involved activity (messages) which provided feedback to the other player for which we did not have experimental data on which to model the robot behavior. Now we are in possession of a much more sophisticated robot which has been based on a large set of observations. With a small additional effort to "tune" the robot we would be ready to perform the definitive experiment by entering another laboratory series in which the subjects in the *Brandstätter* experiment are brought back into a replication of the experiment with *Brandstätter*-robots substituted for the *Selten*-robots.[9] My conjecture is that these robots will not be detectable (subjects will not be able to discriminate) and the test for this would be that in the logit parallel to that of Table 9 the likelihood ratio statistic would be large and the t-statistics associated with the coefficient of IROBOT would be nonsignificant. A first test of whether or not our robots had captured the essentials of human play would be run the logit parallel to Table 7. We would conjecture that the t-statistic for the coefficient IROBOT would be nonsignificant. A strong test would be to run again the logits of Tables 3, 4, 5 and 6 on the *subject* responses and test the null hypotheses that

9) In tuning the robot I have in mind two tasks. First, the latency functions have to be measured and placed in the programs. This is all straightforward. The demand latency was done for CT2 and held no surprises. Second, the message emitting structure should be refined. It can be done as follows: run a multinomial logit with four possibilities, viz.,
0 no message
1 messages 1, 2, 3, 4 (the friendly ones)
2 5 "we will see what happens next"
3 messages 6, 7, 8, 9 (the unfriendly ones).
Then run two more logits which, given either "friendly" or "unfriendly" choice, discriminate among the four alternatives in each case.

In this paper we have not considered learning. This was treated in the *Hoggatt-Selten* paper under the heading "round effects". This should be investigated with the current data base. However, it would be efficient to do so only after *Brandstätter* runs the analysis of variance in which ROUND may be a concomitant variable.

they were drawn from the same distributions. Were this successful, we would argue that we have adequately measured the behavior relevant to human strategic choice in the play of the game.

Once this is accomplished we would then proceed to study the construction of artificial players who "take advantage" of ROBOT. Recall that this task was relatively easy for *Selten* modal robots and led to uninteresting quiet games. It is a much more difficult undertaking to do this with a *Brandstätter* robot. We would propose to pursue this question with learning programs which modified the parameters of ROBOT to produce ROBOTPRIME. Under fictitious play with ROBOT playing ROBOTPRIME, we could search for robots which were better players than ROBOT. If superior robots emerged (we think it likely), we would return to the laboratory once more with SUPERROBOT replacing ROBOT.[10] Assuming that subjects do "event-match", it is not too much to hope for that humans would learn to emulate better play, and in this way we would begin to *teach* good play to humans - that would be consistent with the goals of the university and with the idea that interaction between research and teaching was desirable.

It bears mention that we seem to have made an extension to the situation defined by *Turing* with the immitation game. In our case we have asked two questions: first, "Can the robot (computer) player be detected by the human"? Subjects guessed correctly 140 out of 256 trials which falls *inside* the .05 critical level of a one-tailed test[11] under the null hypothesis that probability of a correct guess is 1/2. Not much better than chance! Then we ask the further question, "Whether detected or not, does the presence of a robot player affect the play"? We transform this to an objective test, "Does it alter the probability of conflict"? And the answer is "YES" for businessmen and academic administrators in a *Brandstätter* design (t_{IROBOT} = 3.18 in Table 9). Robots based on student behavior have significantly higher conflict probabilities than their executive opponents.

10) This would not be a costly procedure. The full simulation of the *Brandstätter* design took 17 seconds on the 6400 and cost $2.69. The three logits for Tables 7, 9 and 11 cost $2.56.

11) Under the normal approximation to the binomial $\mu = 128$ and $\sigma = \sqrt{256 \times 1/2 \times 1/2} = 8$, our observation falls 1.5σ above the mean.

The robots which are embodied in the FORTRAN functions of the program are rather formidable - there is a super abundance of parameters. Well, no one promised us that effective behavioral models would be simple! For those dedicated to simplicity there is the hope that routines with fewer parameters could adaptape the behavior of these robots. These could be searched for very simply:

(1) Eliminate variables from the response functions which have smallest t-values;
(2) reestimate the logits and modify the robot response functions; and
(3) simulate with the modified response functions in place of *robot players only*.

If the t-value (either tail) for IROBOT is not critical and conflict probability has not been significantly altered, repeat the procedure. Should simple, effective robots emerge from this process, then science wins. Were this done first, it could aid the search for SUPERROBOT by reducing the dimensionality of the search space.

With these comments we have finished. Clearly a lot remains to be investigated with regard to our *Brandstätter* robots which we intend to follow up on immediately. We know that they are cooperative and much more reliable than humans and we are looking forward to the association.

REFERENCES

Berkman, J./ Brownstone, D./ Duncan, G.M./ McFadden, D. (1976): QUAIL Users Manual, Urban Travel Demand Forecasting Project, Working Paper No. 7402, Berkeley: University of California.

Blattman, P./ Brandstätter, H./ Hoggatt, A.C. (1977): Operations Manual for the *Brandstätter* Bargaining Game, Center for Research in Management Science, Berkeley, Cal.: University of California.

McFadden, D. (1973): Conditional Logit Analysis of Qualitative Choice, in: *Zarembka, P.* (Ed.): Frontiers in Econometrics, New York: Academic Press.

Harsanyi, J.C./ Selten, R. (1972): A Generalized *Nash* Solution for Two-Person Bargaining Games with Incomplete Information, in: Management Science, 18, p.

Hoggatt, A.C./ Selten, R./ Crockett, D./ Gill, S./ Moore, J. (1978): Bargaining Experiments with Incomplete Information, in: *Sauermann, H.* (Ed.): Contribution to Experimental Economics, Vol. 7, Tübingen: J.C.B. Mohr.

APPENDIX

INSTRUCTIONS AND EXPERIMENTAL PROTOCOLLS

In this appendix we briefly describe how sessions were managed and present the instructions for participants.

Hoggatt called associates known to him and after a brief introduction to the lab and the experiment they were invited to participate. Positive respondents were asked to assemble at 6:30 p.m. in the conference room about a round table. They had a preliminary discussion, read instructions, and performed ratings. Rating sheets were typed into the computer which assigned cubicles. Each person had filled out a door tag which was affixed to the door of the cubicle. The group leader informed them that they were free to move about and talk except they were not to go into other cubicles or to discuss the game until the debriefing.

The group was then led into the terminal area and a brief description of the lab was given. Then they found their cubicles and took the *Kulman*-test. When they finished *Kulman* they found a buffet meal waiting in the conference room. After dinner they watched the *Brandstätter* briefing tape, in which he read the Instructions to Participants. They asked the usual questions and then played the game. The *Mach*-test was run at the end and they were debriefed.

One participant forgot to come and could not be located. After 40 minutes of frantic search, an alternate was found who arrived at 8:00 p.m. In this group dinner was served first.

INSTRUCTIONS FOR PARTICIPANTS*

As you read these instructions you are seated around a table with 7 other participants. In addition to their names, participants are designated by letters from A to H. A main activity during this session is the Bargaining Game which is discussed below. Prior to playing the game you will introduce yourself briefly to the other participants by talking a

*) Note: With no payoff dependency, the paragraph labeled "Bonus" on the end of the appendix was deleted.

MUTUAL RATING OF ATTRACTION

You have been able to form a first impression of one another. Please mark on the scale how close you feel yourself to each of the other participants by writing their letters below the scale in the order of liking. Don't give any two persons exactly the same position on the scale. Please write your own letter in the square at the left side of the scale. Look at this example:

Very Close — Indifferent — Very Remote

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
N		R	M			K	L	Q					P					O		

Participant N, who has written his letter into the square at the left side of the scale, feels himself closest to R, and just a little bit less close to M. To the next cluster of people (K, L, Q), N feels a larger distance. He feels remote from P, and very remote from O.

How close do you feel to the other participants? Please write their letters below the scale in the proper order and distance.

Very Close — Indifferent — Very Remote

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20

Be sure that you have related all of the other participants. You may use the row of letters at the lower right corner of this sheet to check this.

A B C D E F G H

little about your work and leisure activities. Based on the first impression you form of each other in that way, you will indicate on a scale how close you feel to one another. Then you will perform some simple decision tasks before you start the main part of the experiment, namely, the bargaining game. After that game you will complete a short opinion survey.

For the bargaining game, money units are worth 10¢. You will be paid in cash for all of your money units at the end of the last game.

THE BARGAINING EXPERIMENT

There are eight persons participating in your session and they will all play the same bargaining game. Sometimes you will play one of the other persons, and sometimes you will play a robot. You will play exactly eight games. In any game, two players may divide 20 money units between themselves if they reach agreement. If they reach conflict neither receives any money units. At the beginning of a bargaining game, the computer decides for each player whether he has high or low cost. High cost = 9 money units, and low cost = 0 money units. These costs are deducted from the payments in the event that agreement is reached. If no agreement is reached, the net payoffs to both players are zero regardless of whether they are high or low cost players.

You will not know the cost of the other player, but will know your own cost. The cost of the other player was evenhandedly chosen high or low and independently from the selection of your costs. In any one game you will not know which of the other participants you are playing against. The other player (person or robot) will find himself in exactly the same general situation.

Your bargaining is done via terminals and proceeds in discrete stages.

Liking, between you and the next player you will encounter, will be reported to you before each game. In the case where the player is a person, this report is correctly based on the results of the liking form which you have just filled out. In the case your play is with a robot, the liking intensity is determined in an evenhanded way by the computer. At the end of each game, you will rate your partner again on the liking scale. This allows us to learn how liking based on first impressions is affected by further interaction in a bargaining situation.

At the first stage the terminal will accept your demand for a share which must be an integer no lower than your cost and not higher than 20. In succeeding stages your demand must not be higher than the demand in the previous stage and no lower than your cost. The demand payment will be reported as soon as both bargainers have made demands. If a player's move is not completed within the decision time for a stage, the computer will take the demand of that player in the previous stage. The decision time for both bargainers is limited to, at most, 2 minutes for each stage.

Remarks at each stage of the play may be sent to the other player. We have programmed the machine to facilitate the typing of remarks to the other player. After the terminal prompts with ":" you then

TYPE	THE COMPUTER PRINTS
0	NO MESSAGE
1	IT IS FUN TO BE YOUR PARTNER
2	I APPRECIATE YOUR COOPERATIVENESS
3	YOU ARE A PERSON ONE CAN GET ALONG WITH
4	YOU SEEM TO BEHAVE RATIONALLY
5	WE WILL SEE WHAT HAPPENS NEXT
6	YOU PRESS HARD FOR YOUR POSITION
7	I AM IRRITATED BY YOUR STUBBORN BEHAVIOR
8	YOU DO NOT CARE AT ALL ABOUT FAIR PLAY
9	YOU ARE A GREEDY AND SELFISH PERSON .

After you and the other player have selected a phrase, it will be transmitted to the other and the play will continue. If you type a number or character not on this list the terminal will "beep", indicating that you have not selected a legitimate code. If you have not selected a legitimate message after 30 seconds, the computer will select "NO MESSAGE" and proceed.

Conflict occurs at any stage for which neither player makes a concession, i.e., both demands remain at the levels set in the previous stage; therefore, if you decide not to make a concession you take the risk of conflict since the other player also might not make a concession. In case of conflict (see above) both players have a net payoff zero.

Agreement is reached should a stage occur in which the sum of both demands is at most 20 money units. If your demand in the agreement stage is D_1 and the other player's demand is D_2, then your gross agreement payoff is:

$$D_1 + 1/2[20 - (D_1 + D_2)] \ .$$

This means that each player gets his demand; then the amount by which the sum of demands falls short of 20 is split evenly.

If an agreement is reached, your *net payoff* is your gross payoff minus your cost. You will receive a report of this net amount in money units at the end of each play.

At the end of each stage, after the demand of the other player is reported to you. You will be required to make a guess about the cost of the other player. If you think he is high cost, type "H", and if you think he is low cost, type "L". The terminal will not proceed before you have made this guess. It will periodically remind you if you forget to guess his cost.

Guessing about robot players will be done after each game. The computer will query you as to whether you think that you have just played a person or a robot. After the session is over, we will show you the actual conditions in each game and you will learn how often you guessed correctly; however, we can tell you now that you will play an equal number of robots and persons.

Examples of how the teletype printout will look are given on the next page.

We expect you to be motivated by profit, and it should be your goal to play in such a way as to earn as much money as you can.

Bonus payments are awarded at your discretion to the other player at the end of each game. You award him 0 or 1 or 2 money units when the computer asks you to type in the bonus payment for the other player. Only after the end of all games will you find out about the bonus that you receive.

EXAMPLE 1

ROUND 3 - YOUR COST IS: L - YOU AND THE OTHER PLAYER LIKE EACH OTHER

STAGE	YOUR DEMAND	HIS DEMAND	GUESS	YOUR REMARKS	HIS REMARKS
1	19.	17	L	:NO MESSAGE	NO MESSAGE
2	18.	17	L	:YOU PRESS HARD FOR YOUR POSITION	YOU ARE A PERSON ONE CAN GET ALONG WITH
3	17.	16	H	:YOU ARE A PERSON ONE CAN GET ALONG WITH	NO MESSAGE
4	17.	16	H	:I AM IRRITATED BY YOUR STUBBORN BEHAVIOR	YOU PRESS HARD FOR YOUR POSITION

CONFLICT: YOUR NET PAYOFF IS Ø

DO YOU THINK YOU WERE PLAYING A PERSON OR A ROBOT? (P/R): P

TYPE IN YOUR CLOSENESS SCALE VALUE FOR THE OTHER PLAYER (FOLLOWED BY RETURN): 9

IS [9] CORRECT? (Y/N): Y

EXAMPLE 2*

ROUND 3 - YOUR COST IS: H - YOU AND THE OTHER PLAYER LIKE EACH OTHER

STAGE	YOUR DEMAND	HIS DEMAND	GUESS	YOUR REMARKS	HIS REMARKS
1	17.	12	L	:I APPRECIATE YOUR COOPERATION	NO MESSAGE
2	17.	11	L	:YOU ARE A PERSON ONE CAN GET ALONG WITH	I AM IRRITATED BY YOUR STUBBORN BEHAVIOR
3	16.	8	L	:IT IS FUN TO BE YOUR PARTNER	WE WILL SEE WHAT HAPPENS NEXT
4	16.	4	L	:I APPRECIATE YOUR COOPERATION	YOU DO NOT CARE AT ALL ABOUT FAIR PLAY

AGREEMENT: YOUR NET PAYOFF IS 7

DO YOU THINK YOU WERE PLAYING A PERSON OR A ROBOT? (P/R): R

TYPE IN YOUR CLOSENESS SCALE VALUE FOR THE OTHER PLAYER (FOLLOWED BY RETURN):
25

IS [25] CORRECT? (Y/N):
Y

INVALID RESPONSE - VALUE NOT ON SCALE

TYPE IN YOUR CLOSENESS SCALE VALUE FOR THE OTHER PLAYER (FOLLOWED BY RETURN):
18

IS [18] CORRECT? (Y/N): Y

*) Note: You must type a "." after each demand you input. To recover from a typing error, press the "RETURN" key. Once you inout the "." you cannot change your demand. For illegal inputs, the message INPUT IGNORED will be typed out and the line will be repeated.

THE INFLUENCE OF THE ASPIRATION LEVEL, OF THE LEVEL OF INFORMATION AND BARGAINING EXPERIENCE ON THE PROCESS AND OUTCOME IN A BARGAINING SITUATION*

by

HELMUT W. CROTT, GÜNTER F. MÜLLER, PETER L. HAMEL
Universität Mannheim

This experiment was conducted to study the influence of the aspiration level, information level and experience on the behavior of Ss in a symmetrical bargaining situation (both Ss have the same gain possibilities). Ss with a high aspiration level had higher gain expectations, made higher initial demands and were able to achieve higher gains. Increasing experience in dealing with the experimental bargaining situation also led to a significant increase of gain expectations, initial demands and the gains obtained by bargaining. With a high level of aspiration as well as with increasing experience the number of bid exchanges and the bargaining time increased. As an analysis of the first ten bargaining trials showed, the opponent's aspiration level had no obvious effect on the participant's behavior. Level of experience, however, influenced the observed concession process.

The results of this study are discussed with regard to motivational bases of bargaining behavior.

INTRODUCTION

In which way the aspiration levels (ALs) of bargaining participants influence the process and outcome of a dyadic conflict will depend, among other things, on the relation of their ALs. *FOURAKER* (1964) distinguishes the following conflict levels:

(1) Overlapping ALs: There are *many* mutually satisfactory solutions for both participants.

*) This study was conducted at the Sonderforschungsbereich 24, sozial- und wirtschaftspsychologische Entscheidungsforschung, Universität Mannheim (West Germany), financed by the Deutsche Forschungsgemeinschaft, with support from the Government of Baden-Württemberg.