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to Katharina

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Chapter I

Introduction

In 2002 the Bank of Sweden Prize in Economic Sciences in Memory of Alfred Nobel was awarded to Daniel Kahneman and Vernon Smith. It was not only a distinction for the work of the two laureates, but also for the field of experimental economics. Motivating the prize for the laureates the committee stated: *Controlled laboratory experiments have emerged as a vital component of economic research and, in certain instances, experimental results have shown that basic postulates in economic theory should be modified.*¹

The four studies in the work at hand demonstrate the variety of fields on which the methods of experimental economics can be applied to. The first study deals with culture and presentation effects, the second study reports on team incentives, the third study checks the performance of behavioral equilibrium concepts and the fourth study deals with learning behavior of populations and single individuals. Each study is self-contained and based on a discussion paper.

Chapter II is based on a discussion paper by Goerg and Walkowitz and investigates the impact of game presentations dependent on ethnical affiliation.²

Two continuous prisoner's dilemma games where decision makers can choose an individual level of cooperation from a given range of possible actions are introduced. Both games represent the same logical and strategical problem. In the first game, a

¹refer to http://nobelprize.org/nobel_prizes/economics/laureates/2002/public.html

²Sebastian J. Goerg and Gari Walkowitz, "Presentation Effects in Cross-Cultural Experiments - An Experimental Framework for Comparisons", *Discussion Paper No. 4/2008*, Bonn Graduate School of Economics, University of Bonn.

positive transfer creates a positive externality for the opposite player. In the second game, this externality is negative.

Accomplishing a cross-cultural experimental study involving subjects from the West Bank and Jerusalem (Israel) we test for a strategic presentation bias applying these two games. Subjects in the West Bank show a substantially higher cooperation level in the positive externality treatment than in the one with negative externality. In Jerusalem no presentation effect is observed.

Discussing our findings, we argue that a cross-cultural comparison leads to only partially meaningful and opposed results if only one treatment condition is evaluated. In our setting cooperation was significantly higher in the West Bank than in Jerusalem in the game with positive externality. In contrast cooperation was significantly higher in Jerusalem than in the West Bank in the game with negative externality. We therefore suggest a complementary application and consideration of different presentations of identical decision problems within cross-cultural research.

Chapter III is based on a paper by Goerg, Kube and Zultan and deals with the impact of reward schemes and production functions in teams.³

The importance of fair and equal treatment of workers is at the heart of the debate in organizational management. In this regard, we study how reward mechanisms, either egalitarian or discriminating, and production technologies, given by production functions of either complementarity or substitutability, affect effort provision in teams. Our experimental results demonstrate that unequal rewards can potentially increase productivity by facilitating coordination, and that the effect strongly interacts with the exact shape of the production function.

Our findings suggest that designing (production) tasks in a way that makes workers' efforts complements i.e., the impact of a worker's input increases in the size of the others' input, rather than substitutes may lead to a major cost advantage. Since peer

³Sebastian J. Goerg, Sebastian Kube and Ro'i Zultan, "Treating Equals Unequally - Incentives, Motivation and Production Technology in Teams.", *Journal of Labor Economics*, forthcoming.

pressure constitutes a complementarity in effort exertion, the mere strengthening of social ties amongst the workforce alone might have a strong impact on productivity.

We show that whenever the organizational technology is one of complementarity, the usage of a discriminating reward scheme might be potentially efficiency-enhancing. Thus equal treatment of equals is neither a necessary nor a sufficient prerequisite for eliciting high performance in teams.

Chapter IV is based on a paper by Goerg and Selten and tests the success of three stationary concepts in describing experimental data gathered in oligopoly markets.⁴

The concepts experimentally tested are Nash equilibrium, impulse balance equilibrium and payoff-sampling equilibrium. The latter two equilibria are behavioral concepts that either depend on tendencies to play the ex-post best strategy (impulse balance equilibrium) or on samples of payoffs for each strategy (payoff-sampling equilibrium).

In the experiment two different cyclic duopoly games were played and the aggregated frequencies of entering an occupied market were the test criteria to be described by the three concepts. The comparison of the three concepts with mixed strategies shows that the order of performance from best to worst is as follows: payoff-sampling equilibrium, impulse balance equilibrium, and Nash equilibrium. In addition our data exhibit a weak but significant tendency over time in the direction of coordination at a pure strategy equilibrium.

Chapter V is based on a discussion paper by Chmura, Goerg and Selten and examines learning behavior in repeated 2×2 games.⁵

In this study we introduce four new learning models: impulse balance learning, impulse matching learning, action-sampling learning, and payoff-sampling learning. With this models and together with the models of self-tuning EWA learning and

⁴Sebastian J. Goerg and Reinhard Selten, "Experimental Investigation of a Cyclic Duopoly Game", *Experimental Economics*, 12(3), 2009.

⁵Thorsten Chmura, Sebastian J. Goerg and Reinhard Selten, "Learning in Experimental 2×2 games", *Discussion Paper No. 18/2008* Bonn Graduate School of Economics, University of Bonn.

reinforcement learning, we conduct simulations over 12 different 2×2 games and compare the results with experimental data. Hereby, the learning rules have to meet two challenges: First, can they reproduce the aggregate behavior of a human population and second do they adequately describe the observed behavior of a single individual?

Our results are twofold: while our newly introduced models are able to capture the distribution of decisions on the aggregate level much better than self-tuning EWA does, self-tuning EWA describes the individual data in a more accurate way than our models do.

Chapter II

Presentation Effects in Cross-Cultural Experiments

II.A Introduction

Nowadays it is widely accepted - even by economists - that human behavior is not solely driven by the ratio of the homo economicus. Many experiments have shown that subjects' behavior can be influenced amongst others by their risk attitudes, fairness or and equity preferences, and even by the mere presentation of a decision problem¹. A vast body of literature demonstrates that differently framed descriptions of decision tasks can lead to divergent and non-rational behavior (refer to Tversky and Kahneman, 1981; Levin, Schneider and Gaeth, 1998²). Furthermore, other contributions have shown that subjects' performance can be influenced even by the mere presentation form of a decision problem (e.g., Pruitt, 1967; and Selten and Berg, 1970). In this broad field, studies dealing with public goods games creating either positive externalities (public good) or negative externalities (public bad) are well established (e.g., Andreoni, 1995; Sonnemans, Schram and Offerman, 1998; Willinger and Ziegelmeyer, 1999; Cookson, 2000; and Park, 2000). Results from these publications in general suggest that experimental designs enabling positive externalities are aligned with significantly higher cooperation levels compared to setups allowing for negative externalities³.

In this chapter we intend to analyze cultural affiliation as one factor leading to dif-

¹E.g., Kahneman and Tversky (1979), Selten (1978), Fehr and Schmidt (1999), Bolton and Ockenfels (2000), Konow (2000), Pruitt (1967), Selten and Berg (1970).

²See also Abbink and Hennig-Schmidt (2006) for a review on framing literature and framing types.

³Applying a more complex experimental design Brewer and Kramer (1988) and Sell, Chen, Hunter-Holmes, and Johansson (2002) found an effect that went in the opposite direction.

ferent levels of cooperation dependent on two game presentation forms with positive and negative externality. Since both cooperation mechanisms are crucial for human interaction from an individual perspective as well as from a societal point of view it is important to compare behavior under *both* conditions also on a cross-country level to evaluate the cross-cultural validity of findings on cooperative behavior under both conditions.

So far conducted cross-cultural experimental studies normally apply experimental designs with one form of presentation. Possible implicitly induced presentation effects - although not in focus of the study - are ignored (e.g., Roth, Prasnikar, Okuno-Fujiwara, and Zamir, 1991; Anderson, Rodgers and Rodriguez, 2000; Henrich, 2000; Henrich, Boyd, Bowles, Camerer, Fehr, Gintis, and McElreath, 2001; Buchan and Croson, 2004; Buchan, Croson, and Johnson, 2004⁴). To the best of our knowledge there exist only two studies taking a cross-cultural perspective of framing or presentation effects into account. The first work, a questionnaire study by Levin, Gaeth, Evangelista, Albaum, and Schreiber, (2001), involves Americans and Australians. Therein, American subjects stated to reduce a significantly higher amount of red meat consumption if the negative consequences of not reducing were stressed compared to a treatment in which the positive consequences of reducing were emphasized. Contrary, Australian subjects did not respond differently to the two frames. In a second study, Sell et al. (2002) investigated the consistency and direction of framing effects across different cultures. They found very similar patterns of cooperation both in the United States and in the People's Republic of China. In both countries group members were less cooperative in a standard public goods game compared to the situation of a public bad setting.⁵ We will extend the approach of Sell et al. (2002) with regard to a more extensive cross-cultural analysis and a discussion of the behavioral and methodological consequences of our findings. Formally identical bargaining and cooperation setups might be perceived differently in different countries and might unconsciously lead to unintended behavior. Knowing

⁴See for an specific international overview of public goods and commons dilemma studies Cardenas and Carpenter (2004a,b).

⁵Sell et al (2002) entitled the first situation as a public good game and the second situation as a resource goods dilemma.

the impact of diametral frames might be essential for the design of institutions built up to moderate the relationship between involved conflict parties.

The historical and political background of Israelis and Palestinians⁶ makes them a promising testbed for investigating the link between cultural affiliation and cooperative behavior. We will show that the awareness of the impact of culture on frame perception should have importance for practical applications.

For our study we conducted two series of experiments with Palestinians located in Abu-Dis (West Bank) and with Israelis from Jerusalem applying two continuous two-person prisoner's dilemma games which represent different presentations of the same - structurally and functionally equivalent - decision task. That is, in both cases individuals must choose between a maximization of their own profit or to cooperate at some personal cost to increase joint payoff. Individuals can give up an immediate benefit to sustain a resource for the other player's use. Thus, in one experimental treatment action creates a positive externality for the matched player. Contrary, in our second experimental treatment action results in a negative externality. Like a public goods dilemma our first treatment is a problem of contribution. Only with positive contributions an efficiency increase is achieved. Similarly, our second treatment, like a commons dilemma, is a problem of consumption. The lower the share of personal consumption the higher efficiency. Expected utility theory suggests these two types of presentations are equivalent since strategies and related payoffs are equivalent. However, giving and taking are psychologically different actions and findings from one set of studies may not be generalized to the other set (Brewer and Kramer, 1986; Fleishman, 1988). This holds especially true in a cross-cultural environment.

Our West Bank data show that the presentation can significantly influence decision makers' choices. In the positive externality condition substantially more cooperation is manifested than in the negative externality condition. In contrast, the experiment

⁶At the moment, a Palestinian state does not exist. Most of our subjects are formally citizens of the states of Israel and Jordan. Nevertheless, we will refer to them as Palestinians to ease the notation.

conducted in Jerusalem yielded different results. There, on an aggregate level, no significant presentation effect can be detected. In both societies our data show that neither the Nash equilibrium nor the social optimal strategy is reached.

Comparing the level of cooperation under each of our two conditions across the two locations yields opposite conclusions about country-dependent cooperative behavior. While behavior in the treatment condition with positive externality is more cooperative in the West Bank, behavior in the treatment condition with negative externality is more cooperative in Jerusalem. In contrast to this an evaluation of all data gathered from each of the two populations shows no significant difference in cooperation levels.

Our results shed new light on the impact of presentation conditioned by preferences and social norms in different habitats. Therefore, we will argue that for deriving a conclusion about a population's cooperative behavior, different presentations of logically identical experimental setups should be considered and evaluated adequately.

The remainder of this chapter is organized as follows: In the next part we will introduce our experimental framework consisting of two logically identical games. In the third section, we describe the method and procedure we applied conducting the cross-cultural experimental study in the Westbank and in Jerusalem. In part four, we present population-specific results. We compare data within and across populations. The final section five discusses our findings and their impact on cross-cultural research.

II.B Experimental Framework: Two new Games

The two applied games are both continuous prisoners' dilemma games (PD) and public goods games (PG) in which subjects can choose an individual level of cooperation from a given range of possible actions⁷. Thus, in contrast to the classical PD game, the question whether to cooperate or to defect is not a binary choice. In the first game (PDP) a player's decision creates a positive externality to the matched

⁷Refer to Appendix C.I. for further details on the PD- and PG-nature of the two games.

player's payoff, while in the second game (PDN) it induces a negative externality. In the next subsection we will describe both the PDP game and the PDN game in detail.

II.B.1 Continuous Prisoners' Dilemma with Positive Externality (PDP)

At the beginning of the game, two (randomly) matched players i and j obtain an initial endowment $X = X_i = X_j$. Each player then has the opportunity to transfer an integer part a of X , nothing, or the entire amount X to the opposite player. Both players choose $a \in [0, X]$ simultaneously. Each amount a , which is transferred to the paired player, will be multiplied by factor k yielding to an efficiency gain by transferring a positive amount a . Players' payoffs consist of the initial endowment X minus the transferred amount a plus the obtained and k -multiplied amount a transferred by the opposite player. Formally, player i 's payoff function is given by:

$$\pi_i^{PDP} = X_i - a_i^{PDP} + k \cdot a_j^{PDP}, \text{ with } X_i = X, a_i^{PDP}, a_j^{PDP} \in [0, X], \text{ and } k > 1$$

The payoff of the opposite player j is calculated analogously. The only Nash equilibrium is $a_i^* = a_j^* = 0$. Player i anticipates player j 's choice $a_j^{PDP} = 0$ and will therefore also choose $a_i^{PDP} = 0$. The collective optimal choice is $\hat{a}_i = \hat{a}_j = X$ since it maximizes the joint payoff $\Pi^{PDP} = \pi_i + \pi_j$.

II.B.2 Continuous Prisoners' Dilemma with Negative Externality (PDN)

The design of the PDN game is equivalent to the first game, but instead of choosing an amount a which is transferred to the opposite player, decision makers must choose an integer which is transferred from the other player. Again two players i and j simultaneously interact. Initially, both receive an endowment $X = X_i = X_j$. Each player then has the opportunity to transfer a part a , nothing, or the entire amount X from the matched player. Thus, again, both players simultaneously

choose $a \in [0, X]$. The difference $X - a$, which is respectively not transferred, will be multiplied with k . Hence, by transferring low amounts or nothing efficiency increases. In contrast to the PDP game, the amount a , which is transferred is not multiplied. Players' payoffs are determined by the multiplied difference of their initial endowments X and the amount a taken by the opposite player, and the amount a which players take away from the counterpart. Formally, player i 's payoff function is given by:

$$\pi_i^{PDN} = (X_i - a_j^{PDN}) \cdot k + a_i^{PDN}, \text{ with } X_i = X, a_i^{PDN}, a_j^{PDN} \in [0, X], \text{ and } k > 1$$

Player j 's payoff is calculated analogously. The only Nash equilibrium is $a_i^* = X_j$ and $a_j^* = X_i$. Player i anticipates player j 's choice $a_j^{PDN} = X_i$ and will therefore also choose $a_i^{PDN} = X_j$. The optimal collective choice is $\hat{a}_i = \hat{a}_j = 0$ since it maximizes the joint payoff $\Pi^{PDN} = \pi_i + \pi_j$.

II.B.3 Equivalence of the two Games

In both games player i 's payoff π_i consists of two parts - a self-determined component π_{iA} and a part π_{iB} resulting from player j 's actions. Therefore, the total payoff of player i can be stated as: $\pi_i = \pi_{iA} + \pi_{iB}$. Player i 's self-determined payoff fraction in the PDP game is the amount $X_i^{PDP} - a_i^{PDP}$ which is not given to the other player. In the PDN game it is the amount a_i^{PDN} that is taken away from the other player.

The foreign determined amount $k \cdot a_j^{PDP}$ for player i in the PDP game is the amount which he receives from the matched player. In the PDN game the foreign determined amount is the payoff fraction $k \cdot (X_i^{PDN} - a_j^{PDN})$ that the matched player leaves to him. In addition, each possible strategy combination in one game can be described by a strategy combination in the other game as well.

Figure 1 displays a graphical illustration of this equivalence. We will first turn our attention to the first quadrant of the figure.

The first quadrant illustrates the composition of player i 's self-determined payoff π_{iA} . In PDP π_{iA} is limited by player i 's own initial endowment X_i^{PDP} (given on the

If player i fixes his self-determined payoff as described in the first quadrant, the left over in PDN $X_j^{PDN} - a_i^{PDN}$ (thin line on the abscissa) equals the amount a_i^{PDP} transferred in PDP (thick line on the ordinate). These amounts are part of player j 's foreign-determined payoff π_{jB} and are multiplied with k which is shown in the second quadrant. The multiplier k is described as a straight line. The total amount of π_{jB} (including the multiplication with k) has to be taken from the ordinate in the second quadrant. Analogously, player i 's foreign-determined payoff is given in the fourth quadrant.

This illustrates that in each strategy space of the two games there exists a strategy a_i or a strategy-combination $(a_i; a_j)$ that also exists in the corresponding game in terms of cooperation, as well as individual and collective payoff.

II.C Experimental Procedure

The experiments were conducted in May 2006. The West Bank sessions were run at the AlQuds University located in the Westbank, close to the city of Jerusalem. Observations from Jerusalem were gained at the RatioLab of the Hebrew University in Jerusalem. In both universities students from different departments participated⁸.

Showing up for the experiment each student received a fixed payment of 25 NIS. At each university both games were played as one-shot games, applying the pen and paper method. We have chosen one-shot games to avoid confounding framing effects with strategical issues. Table II.1 displays the applied treatments.

Experiments were run by local helpers comprehensively instructed and supported by the authors, who stayed in the background. We are aware that this might result in an experimenter effect. We decided to choose this procedure to avoid self-presentation and face-saving effects (see, e.g., Bond & Hwang, 1986) of unexperienced subjects

⁸In Israel only subjects with very limited experimental experience were recruited (excluding previous collaborations in trust game, prisoner's dilemma, gift exchange, or public goods game experiments). Palestinian subjects had no experimental experience. The median age of Israeli subjects was 25 years and 22 for Palestinian subjects. In Jerusalem nearly 40% of the participants were female, in the West Bank nearly 30%. We checked with regression models for possible effects of age and gender. We could not find any significant influence, neither for each separate subject pool nor for the complete sample of observations.

Session	Game	Location	Independent observations
1	PDP	West Bank	20
2	PDN	West Bank	20
3	PDP	Jerusalem	20
4	PDN	Jerusalem	20

Table II.1: Treatment conditions.

resulting from the presence of people from foreign countries. Since we are interested in the pure presentation effect this procedure seems to be justified.

Instructions were written in neutral language avoiding terms like ‘give’ and ‘take’. According to the location, the instructions were either in Hebrew or Arabic⁹. They differed between treatments *only by the direction* of the conducted transfer. Accordingly, transfers were to be realized either *to* player j or *from* player j . This procedure ensured that only the technical presentation and not the wording or further frames could influence subjects’ behavior.

Subjects were initially endowed with $X = 10$ Talers in the opening of every game¹⁰. The multiplier k was fixed with $k = 2$. The individual payoff in the Nash equilibrium was 10 Talers, for each player. The Pareto optimal outcome generated 20 Talers, respectively. In the run of the experiment participants received no feedback on matched player’s decisions.

After running the experiment two questionnaires were passed out. In the first questionnaire we asked participants for their first-order beliefs on the behavior of the matched player¹¹. Correct beliefs were rewarded with addition of 1 Taler. The second questionnaire covered socio-demographic questions. At the end of the session the outcome for each participant was calculated, converted into NIS, and paid out.

⁹To avoid translation errors regarding the task and the procedure instructions were translated by natural speakers from German into the corresponding language and afterward translated back into German applying the back-translation method (Brislin 1970). For instructions see Appendix B.

¹⁰Taler=Experimental Currency. During the experiment all transfers were made in Taler. The exchange rate from Taler to NIS is 1 Taler = 2.5 NIS. We adjusted expected hourly payoffs to the average hourly wage of a local student helper.

¹¹We are aware of the fact that stated beliefs can be biased by prior decisions already undertaken. However, since actual unbiased decisions are more valuable for our analysis, we agreed upon this procedure.

II.D Results

In this section we present the results of our study. First, we start with our findings regarding the Palestinian subjects. Afterward we will present the Israeli data. Finally, we will merge and compare results from both societies. The basis of our analysis is the degree of cooperation exhibited by the participants. In the PDP game it is the transferred amount (a^{PDP}) and in the PDN game it is the amount left to the other player ($10 - a^{PDN}$).

II.D.1 Palestinian Choices

Table II.2 gives an overview on Palestinians' aggregated transfers and beliefs in both conditions:

	Actions		Beliefs	
	PDP	PDN	PDP	PDN
Mean	7.10	2.65	6.05	2.75
Median	7	2	5	2
Mode	5	2	5	0
SD	2.36	2.08	2.89	2.34

Table II.2: Descriptive statistics for Palestinian choices.

On average, under the PDP-condition 7.10 Talers are transferred to the opposite player, contrary to the PDN-treatment, where 2.65 Talers are left. The observed treatment effect is highly significant ($p < .001$, Mann-Whitney test, two-sided). Moreover, in the PDP-treatment the quadratic distance to the social optimum ($\Delta^2 = .137$) is significantly smaller than to the Nash equilibrium ($\Delta^2 = .557$, $p = .002$, Wilcoxon signed rank test, two-sided)¹². In the PDN-treatment the opposite holds. Here, the quadratic distance to the social optimum ($\Delta^2 = .582$) is significantly bigger than to the Nash equilibrium ($\Delta^2 = .112$, $p < .001$, Wilcoxon signed rank test, two-sided). Our findings get additional support evaluating median (7 vs. 2) and mode (5/10 vs. 2) values from both treatments. Results for beliefs are in line with

¹²The average quadratic distance is defined as $\Delta^2 = \frac{1}{n} \sum_{i=1}^n (r_i - t)^2$, with n being the number of participants, $r_i \in (0, 1)$ being the transfer rate of player i , and $t \in (0, 1)$ the predicted transfer rate. To apply the quadratic distance concept we calculated relative transfers.

the behavior. There is more cooperation expected in the PDP game (6.05 Talers) than in the PDN game (2.75 Talers). The observed treatment effect for the beliefs is also highly significant ($p < .001$, Mann-Whitney-test, two-sided). Comparing actions and beliefs we find no statistically significant difference. This holds for both treatments. According to this we conclude our first result:

Result 1: *The formal presentation of the game influences Palestinian subjects' actions and beliefs substantially. Cooperation (and its expectation) is significantly and economically higher under the PDP-condition than in the PDN-treatment.*

II.D.2 Israeli Choices

Israelis' aggregated actions and beliefs are presented in the following Table II.3:

	Actions		Beliefs	
	PDP	PDN	PDP	PDN
Mean	4.40	4.55	3.40	3.40
Median	4	5	4	4
Mode	2	5	4	0
<i>SD</i>	2.95	3.38	2.50	3.14

Table II.3: Descriptive statistics for Israeli choices.

On average, under the PDP-condition 4.40 Talers are transferred to the opposite player. Similarly, in the PDN-treatment on average 4.55 Talers are chosen not to be taken by the participants. There is no statistical significant difference in behavior across the two treatments ($p = .946$, Mann-Whitney-test, two-sided). Furthermore, we observe a weak tendency to play according to the Nash equilibrium - the quadratic distance to the Nash equilibrium (PDP: $\Delta^2 = .276$; PDN: $\Delta^2 = .316$) is smaller in both treatments than the distance to the social optimum (PDP: $\Delta^2 = .396$; PDN: $\Delta^2 = .406$). However, in both treatments the difference is not significant (PDP: $p = .404$; PDN: $p = .530$, both Wilcoxon signed rank test, two-sided). The mean beliefs for both games are identical. On average, under both conditions 3.40 Talers were expected to be contributed from the opposite player. No statistical evidence for a difference can be found ($p = .967$, Mann-Whitney-test, two-sided). These findings get further support considering median values from both treatments.

Contrasting actions and beliefs we find slightly higher amounts in actions compared to stated beliefs (4.40 Talers vs. 3.40 Talers) for the PDP-treatment ($p = .047$, Wilcoxon signed rank test, two-sided). No statistically significant difference is detected under the PDN-condition. We summarize this as our second result:

***Result 2:** No evidence is found that the formal presentation of the game influences Israeli subjects' behavior or beliefs in a significant way. Both conditions imply a similar level of cooperation (and its expectation).*

II.D.3 Comparison of Presentation Effect-Size and Merging the Data

Results 1 and 2 show that the difference in mean cooperation levels among the two treatments is higher in the West Bank than in Jerusalem. We refer to this difference as the effect-size caused by the two different presentations of the game.

In Jerusalem the impact of the presentation form is close to zero, on average, the observed cooperation level is 1.5% lower in the PDP-condition. Formed beliefs are exactly the same across the two games. In contrast, actions (beliefs) in the West Bank are 44.5% (33%) more cooperative under the PDP-condition.

We tested the absolute value of the difference between the two treatment effects with a Monte-Carlo approximation of a two-sided permutation tested with 50,000 draws. The test computed the probability for obtaining a sample with the same, or a larger difference between the two effect sizes by randomly assigning each single action (or belief) in PDP and PDN to one of the two locations, keeping the condition fixed at the same time. In at most 1% of the permutations an equal or higher difference was obtained for actions as well as for beliefs. This corresponds to a p -level of $p \leq .01$. This finding, together with Results 1 and 2, leads to our third result:

***Result 3:** Subjects in the West Bank are more sensitive to the game presentation than subjects from Jerusalem. The differences between observed behavior and beliefs in the two games are both significantly and economically higher in the West Bank compared to Jerusalem.*

We now want to compare our findings cross-culturally for each treatment condition in the two locations. We will start with the transfer behavior in the West Bank and Jerusalem in the PDP game. Afterward we turn our attention to the PDN game. Figure II.2 gives the mean level of cooperation for observed behavior beliefs in the two treatments.

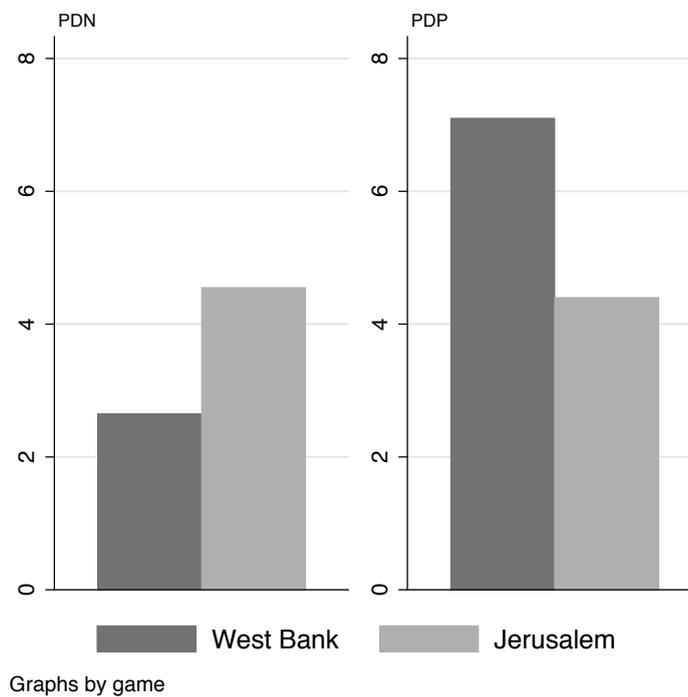


Figure II.2: Location specific mean cooperation levels in the 2 treatments.

In the PDP-condition, on average, Palestinian subjects have transferred 7.10 Talers to their counterparts, while Israelis choose 4.40 Talers in this treatment-condition. Similarly, on average subjects in the West Bank expect the matched player to transfer 6.05 Talers compared to 3.40 Talers which reflect Israelis' expectations toward their counterparts (see Tables II.2 and II.3). Both differences are highly statistically significant ($p < 0.01$ and $p < .01$, Mann-Whitney test, two-sided). Hence, we conclude our fourth result:

Result 4: *In the West Bank cooperation is significantly higher under the PDP-condition than in Jerusalem. Moreover, under this condition stated beliefs are substantially and significantly higher in the West Bank than in Jerusalem.*

In the PDN-treatment, on average, Israelis have left 4.55 Talers to their counterparts. Contrary, Palestinians choose to contribute only 2.65 Talers on average under this treatment condition. Similarly, Israelis expect the matched player not to transfer 3.40 Talers compared to 2.75 Talers which reflect Palestinian expectations toward their counterparts (see Tables II.2 and II.3). The difference in actions is weakly significant ($p < .10$, Mann-Whitney-test, two-sided). Comparing stated beliefs delivers no significant effect. Thus, our fifth result states:

Result 5: *Israelis cooperate more under the PDN-condition than Palestinians do. Furthermore, under this condition the mean belief on cooperation by Israelis is higher than the expectations quoted by Palestinians.*

Taken together, Results 4 and 5 directly lead us to a further stunning result:

Result 6: *Statistically robust results from different locations gathered under one presentation condition do not necessarily hold for other presentations of the same decision task applied in the same locations.*

Our results clearly show that depending on the presentation form we observe divergent levels of cooperation in the West Bank and Jerusalem.

	West Bank		Jerusalem	
	Actions	Beliefs	Actions	Beliefs
Mean:	4.88	4.40	4.48	3.40
Median:	5	5	5	4
Mode:	5	5	5	0
SD:	3.15	3.09	3.13	2.80
Δ^2 Nash:	0.334	0.287	0.296	0.192
Δ^2 Pareto:	0.359	0.407	0.400	0.512

Table II.4: Descriptive statistics and quadratic distances for aggregated data from the West Bank and Jerusalem.

In a next and final step we try to elicit whether cooperation in general is higher in one of the two subject pools involved. Hence we investigate all 80 independent observations (from PDP- and PDN-condition) gathered in the two societies. Table II.4 gives an overview on actions and beliefs from both samples.

On average, Palestinians contribute 4.88 Talers when both treatments are considered. Similarly, Israelis add 4.48 Talers. There is no evidence for a statistical difference among the involved subject-pools ($p = .547$, Mann-Whitney-test, two-sided). The same can be stated for merged beliefs. Here, Palestinians on average expect to receive 4.40 Talers, and Israelis expect 3.40 Talers from their counterpart. Again, no statistical difference can be detected across both subject-pools ($p = .1938$, Mann-Whitney test, two-sided). Moreover, we observe no substantial difference among the quadratic distances to the Nash-equilibrium ($\Delta^2 = .334$ and $\Delta^2 = .296$, $p = .547$, Mann-Whitney-test, two-sided) and to the Pareto optimum ($\Delta^2 = .359$ and $\Delta^2 = .400$, $p = .547$, Mann-Whitney-test, two-sided) of transfer amounts from both societies. Our results considering actions are supported by evaluating median (5 vs. 5) and mode (5 vs. 5) values from both treatments and samples. Equally, for stated beliefs we find that median (5 vs. 4) values do not substantially differ¹³.

For further insights into this similarity of aggregate behavior we calculated for each location the relative frequency of cooperation levels above the overall mean, which is the average cooperation level if all presentations and locations are considered. In both locations a similar fraction of transferred amounts is above the overall mean: 57 % in Abu Dis and 55% in Jerusalem. Binomial confidence intervals for these frequencies show with 95% of confidence that the relative frequency of transferred amounts above the overall mean is between 41% and 73% in Abu Dis and between 38% and 71% in Jerusalem.

Given these similarities in behavior and beliefs, our seventh and last result is:

Result 7: *In the aggregated data from both treatments no significant difference between the levels of cooperation (and its expectation) in the Westbank and Jerusalem can be found.*

¹³Mode values also support this finding. There, 5 is the amount chosen the *second* highest time by participants. This amount was chosen in 9 from 40 cases, contrary to the actual mode=0 which was chosen 10 times out of 40.

II.E Summary and Discussion

The aim of this work was to investigate the impact of game presentation dependent on cultural affiliation. Merging the experimental application of two logically and strategically identical decision problems in a cross-cultural study we demonstrated that data obtained from only one presentation form might lead to only partly valid results and conclusions on population-specific behavior. This finding holds especially true if results are compared and evaluated across ethnical borders.

Our results from the West Bank have shown that the formal presentation of a decision problem can influence subjects' choices and beliefs substantially. The cooperation level and associated beliefs are significantly higher when subjects can create positive externalities toward each other compared to a situation wherein resulting externalities are negative. In the positive condition subjects from the West Bank are more willing to transfer higher amounts to voluntarily increase mutual welfare. On average, this attitude is also expected from the opposite player. Contrary, in the negative condition subjects leave relatively less to the counterpart. In this interaction also more negative beliefs about the opponents' behavior are formed. These findings give support to prior work by Andreoni (1995), Sonnemans et al. (1998), Willinger and Ziegelmeyer (1999), and Park (2000).

The behavior of our Palestinian subjects is analogous with results from goal framing experiments (e.g., Meyerowitz and Chaiken, 1987; Levin, Schneider and Gaeth, 1998). In these experiments the negative formulation of an identical problem has an higher impact on subjects behavior than a positive one. The observed attitude could be connected to the concept of loss aversion and the so-called endowment effect as introduced by Kahneman and Tversky (1979), Thaler (1980) and Kahneman, Knetsch, and Thaler (1990). It is possible that, even if the technical presentation of the implemented game designs was kept strictly neutral, Palestinians perceive an amount taken away from them as a substantial loss, while they perceive an amount voluntarily given away not, or less, as a loss. Or, in other words, Palestinians are more sensitive to a loss induced by a second person compared to a loss induced

by themselves. As a consequence of this cognition, they might react much more sensitively to the threat of a possible loss induced by the right of the second player to take away any amount as compared to the situation where they can determine themselves which amount to give away. To avoid this expected loss induced by the matched player, players take more from the matched player and thus cooperation is on a lower level in the PDN game compared to the PDP game. This might deliver an explanation why Palestinians seem to obtain a higher benefit from doing a good rather than from not doing a bad deed¹⁴.

An alternative explanation refers to the action itself. In the PDP-game action leads to cooperation whereas under the PDN-condition the opposite holds. There, action results in competitive and less efficient behavior. The difference in the sensitivity toward the given frame might stem from a different attitude towards action depending on power in general. Galinsky, Gruenfeld, and Magee (2003) have shown that priming high power leads to increased action in a social dilemma regardless of whether that action had pro-social or anti-social consequences. Being primed with power brings participants to both give more to and to take more from a commonly shared resource. The different perception of own power of Palestinians - performing notably more action in the PDP-game - and Israelis - showing a similar degree of action in both conditions - may deliver an approach to explain behavioral differences across subject pools and cultures. Future research should address this issue by linking different concepts of self image (e.g., power perception, self esteem) and situational power to decisions.

Future studies have to analyze whether Palestinians' behavior is similar to Western subjects' behavior as the cited public goods game framing results suggest or whether and how it is specifically rooted in the Arabic culture. Herrmann, Thöni, and Gächter (2008) give evidence for the latter conjecture. They have found that Arabian participants are not - unlike most decision makers from Western populations who cooperate more under a punishment condition - very sensitive to the threat and

¹⁴Andreoni (1995) argues that utility of people increases if they perceive the act of transferring as doing something good ("warm-glow") and decreases when they perceive it as doing something bad ("cold-prickle").

enforcement of punishment in public goods game setups. As a consequence, although Palestinian choices in our framework appear to be similar to findings in Western societies the driving motives behind them could differ.

Although geographically not far away located from the West Bank, experiments run in Jerusalem yielded different results. There, aggregated subjects' actions and beliefs appear to be unaffected across treatments in terms of the measured outcome. No significant presentation effect can be verified. Israelis seem to show a similar behavioral attitude in both treatments. This evidence might be rooted in the structure of the Israeli society. The Israeli society is ethnically heterogeneous and consists of different subcultures. Furthermore, the gaps between these ethnic groups do not decrease. In fact, the segregation of the society increases further, especially since the breakdown of the Soviet Union¹⁵. As Knack and Kefer (1999) point out, cooperation on the national level of societies is negatively influenced by the degree of ethnic differences within these societies. Trust and cooperative norms are strong within ethnic groups but weak among different groups. Subjects in heterogeneous societies might be less influenced by the presentation of a problem since they already apply a certain pattern of thought on a decision problem. Further studies must address the cause for the similarity of behavior displayed under different presentation conditions. Do Israelis actually perceive the two games as presentation forms of the same decision problem, or do they apply different approaches leading to similar behavioral consequences and outcome?

As Levin et al. (2001), we observe that subjects in some regions might respond to framing effects, while others do not. In addition to this, we have shown that this might confront results from cross-cultural research with new challenges: Comparing levels of cooperation under each of the conditions across subject pools might lead to opposing conclusions about society-specific behavioral attitudes. Palestinians display a *relatively* higher cooperation level and more positive beliefs on opponent player's contributions than Israelis when only the positive externalities condition is considered. Contrary, Israelis cooperate *relatively* more and state substantially

¹⁵Compare Mark (1994), Cohen and Habersfeld (1998), and Fershtman & Gneezy (2001).

higher beliefs when only the negative externalities condition is regarded. However, when all available data gathered from each of the two populations are evaluated, we find no evidence that relative cooperation levels and associated beliefs are different. These striking results would not have been detected by the implementation of a mere one-sided experimental approach. Taking findings from different presentations into account might not only enrich socio-economic theory but also refine our experimental methodology.

To conclude, recognizing the impact of the presented frame might be essential for the design of culture-sensitive institutions or the conduct of international negotiations where foreign agents repeatedly interact for the first time in rapidly changing environments. Bargaining and cooperation setups might be perceived differently by decision makers depending on their ethnical background and some strategies may generate higher levels of cooperation and agreements than others. For example, to maintain peace in a border region of two conflict parties both sides could be asked to take efforts to reduce their hostile armed assaults by withdrawal of armed troops or to send more unarmed peace keepers into the region. This example shows that our findings and the awareness of them have potential importance for application.

Chapter III

Treating Equals Unequally - Incentives in Teams

III.A Introduction

A general feature of incentive schemes in organizations is a non-uniform distribution of benefits among its agents, which usually accounts for the heterogeneity in agents' ability and performance. As long as the discrimination is based on individual differences, i.e., as long as *unequal* agents are rewarded unequally, there should be little scope for fairness considerations to induce dissonance among the agents.¹ However, a recent theoretical model developed by Eyal Winter (2004) shows that it might even be optimal to treat *equal* agents unequally – depending on externalities given by the production function. This surprising result, derived under the standard assumptions of fully rational, self-centered and money-maximizing behavior, seems to stand in sharp contrast to the implications from research on fairness and equity preferences, whose bottom line is that *“even a small intrinsic concern for justice, .. may have significant effects on .. wage structure”* (Konow (2000), p. 1089; see also Bolton and Ockenfels (2000), Fehr and Schmidt (1999), Mowday (1991), Young (1994) or Selten (1978)). In the present paper, we experimentally explore the interaction in teams and test within the framework of Winter's model whether the psychological cost of the inequality induced by a discriminating mechanism deters from the efficiency of the theoretical optimal mechanism. Thus, to the best of our knowledge, we report the first empirical evidence on the interplay between equity, coordination and

¹A necessary assumption for this statement is that agents are aware of the individual differences and do not misperceive the direction of the differences; which might for example not hold true if agents are overconfident about their own performance (see Ross and Sicoly (1979) for early evidence on overconfidence about contribution to a joint project).

production function within teams.²

The general model as described in Winter (2004) features n risk-neutral agents who work on a project. Each agent i decides simultaneously whether to work ($e_i = 1$) or shirk ($e_i = 0$). Exerting effort is connected with costs c , with c being constant across all agents. Individual effort is assumed to be non-observable and non-contractible. Instead, agents' rewards are contingent on the success of the project, i.e., agents receive individual rewards $b = (b_1, \dots, b_n)$ if the project succeeds and 0 otherwise. The probability $p(k)$ of the project's success is specified as a function of the number k of agents exerting effort, mapping the effort profiles to $[0, 1]$. In this sense, $p(k)$ can be interpreted as the project's technology or production function. We assume $p(k)$ to be strictly increasing in k . Depending on the exact specification of $p(k)$, the production function can be modeled to have increasing or decreasing returns to scale. By increasing returns to scale we mean that the production function is one of complementarity, i.e., that $p(k+1) - p(k)$ increases in k ; whereas a production function of substitutability has decreasing returns to scale, i.e., $p(k+1) - p(k)$ is decreasing in k ($k \in [0, \dots, n-1]$).³ In the following, a reward vector b (i.e. a reward mechanism) is said to be strongly incentive-inducing if it induces all agents to exert effort as a unique Nash equilibrium, and it is optimal if it does so at minimal cost of rewards. The mechanism is symmetric if rewards are constant across all agents. It can be shown that such a *symmetric*, optimal, strongly incentive-inducing mechanism exists if and only if the production function is one of *substitutability*. Contrarily, a production function of *complementarity* implies the optimal, strongly incentive-inducing mechanism to be fully *discriminating* – even if all agents are perfectly symmetric!

Consider that a technology of increasing returns to scale is a sufficient, but not a

²The existing literature on team production and teamwork, e.g., Alchian and Demsetz (1972), Nalbantian and Schotter (1997) or Irlenbusch and Ruchala (2008), usually focusses on the problem of free-riders and provides means to organize and discipline selfish workers. Complementing this line of research, our paper points to the difficulties that can arise if incentive schemes originally designed for selfish agents are applied to other-regarding agents; thus, interestingly, in our setup it is the absence of selfish agents, and not their presence, that constitutes a potential source of inefficiency for work teams.

³For the sake of simplicity we only consider the two extreme cases of increasing or decreasing returns to scale here. In general, the production function could take any form, as long as it satisfies the assumption of $p(k)$ being strictly increasing in k .

necessary, condition for full discrimination. In fact, it is only necessary that an agent's incentive to exert effort increases with the number of other agents who do so, which for example might also be caused by some psychological effect like peer pressure (cp. Kandel and Lazear (1992), Barron and Gjerde (1997), Falk and Ichino (2006) or Mas and Moretti (2007) and the references therein).

The purpose of the present study is to experimentally test the key findings of Winter's model, namely whether subjects' behavior is indeed sensitive to the externalities given by the production technology, and whether a major incentive advantage really exists when discriminating among perfectly identical agents; or if the psychological cost of the unequal treatment of equals drives a wedge between the initially predicted and the actually observed efficiency.

Ideally, these questions would be examined with 'cloned' workers acting in 'cloned' work environments which differ only with respect to the production function and the reward schemes. To come close to this ideal world, we introduce a simple and parsimonious laboratory experiment that allows us to analyze the interaction between production function, equity considerations, and reward scheme, while at the same time ensuring that agents are perfectly identical. In the experiment, three players work on a joint project and exert costly efforts. Their total sum of effort determines the number of some goods produced by the joint project for a given production function. The payoff of a player is given by the productivity (i.e., the number of produced goods) multiplied by an individual reward, minus the cost of effort. We create four different treatments by manipulating the characteristics of the production function (either a function of complementarity or of substitutability) as well as of the reward scheme (either a symmetric or a discriminating mechanism).

We find that, as predicted by Winter's model, the subjects in our experiment respond to the shape of the production function. The discriminating reward scheme under the production function of complementarity achieves almost maximum efficiency, whereas it leads to significantly lower efficiency rates under the production function of substitutability. Moreover, our data suggest that subjects' effort choices are highly sensitive to their own reward, but largely unresponsive to the rewards of the other two subjects in their group: The disadvantaged player (receiving the

low reward) regularly exerts effort under the production function of complementarity, notwithstanding the unequal treatment of equals. Contrarily, the symmetric reward scheme significantly hampers efficiency, demonstrating that equal treatment of equals is not necessarily a prerequisite for eliciting high performance in teams, and that unequal treatment can facilitate coordination within the workforce.

The insights gained from our experiment are of significant importance for research on optimal mechanism design in general, but especially in the context of work contracts and organizations. As Winter puts it: *“A large number of models in personnel economics establishes that unequal treatment of unequal agents may have major incentive advantages. The particular importance of demonstrating the optimality of treating **equals** unequally is that it potentially implies an additional gain for inequality in each of these models”* (Winter (2004), p. 766). We complement this assertion by ascertaining it in an empirical way.

In this regard, we contribute to the question of “equality versus inequality”, which is at the heart of the debate in organizational management. Internal inequity is thought to have a tendency to lead to morale problems and to interfere with teamwork (cp. Akerlof and Yellen 1990, Milgrom and Roberts 1992, or Bewley 1999, chapter 6), whereas equal wages are usually associated with positive effects (e.g., increased peer monitoring or lower transaction costs, see Knez and Simester 2001 or Prendergast 1999). However, as Lazear (1989, p. 561) puts it, *“.. it is far from obvious that pay equality has these effects.”* For example, equal wages do not account for heterogeneity in agents’ ability and performance, and payment is not linked to the individual’s marginal product, which in turn can lead to free-riding among selfish agents (cp. Holmstrom 1982). Moreover, as we demonstrate in our setup, equal rewards make it hard to form exact beliefs about the others’ effort. In contrast, the asymmetry that is created by unequal rewards has the potential to facilitate coordination within the workforce, because it reduces strategic uncertainty about each others’ actions.

In real-life organizations, this discrimination is often implemented through non-monetary rewards, e.g., prestige, or by using artificial classifications or (job) titles

for seemingly similar tasks, e.g., ‘Project Head’ or ‘Team Captain’.⁴ It is often hidden to avoid negative reactions of inequality-averse workers, or fixed by an internal (pay) structure. For example, lawyers, consultants and accountants are paid according to seniority. This special form of *hidden* discrimination creates common knowledge about the stakes that everyone has in the project’s success, and thus fosters cooperation and coordination; while at the same time it does not invoke equity concerns because everyone knows that his turn will come to be senior partner. The experimental results in the present paper show that under a production function of complementarity even *transparent* discrimination contributes to efficiency, yet hidden discrimination is effective.

Our study differs from existing experimental studies that analyze the interaction between social preferences and reward schemes in several points. First, the evidence up to now mainly stems from bilateral gift-exchange games between a principal and a single agent (e.g., Fehr et al. (1993, 1997)). What is usually observed in this setup is a positive wage-effort relationship; if the principal shares a large part of the total output with the worker, the worker feels treated fairly and reciprocates by exerting a high effort. While this suggests that most workers care about fairness along a vertical dimension, our question about possible horizontal comparisons within the workforce is usually not addressed.⁵ Second, the existing studies are mainly conducted in an incomplete-contract framework where effort and/or wage is non-contractible, while we allow for complete contracts.⁶ Third, the usual experimental setup features a principal who can set wages anew in each round, but this introduces uncontrolled elements of intentionality and reputation. Agents can withhold effort to punish and enforce principals to pay higher wages in the future, which to us not only seems

⁴The ‘Team Captain’, as the one carrying the responsibility and possible blame for unsuccessful results, is highly motivated to exert effort. Therefore, he functions to incentivize the other team members in the same way as the high-reward agent in our model induces cooperation and high productivity. Cp. also Winter (2004), p. 769.

⁵Two exceptions are notable which feature a multi-agents setup. In Charness and Kuhn (2007), two workers differ in productivity. The authors find that co-workers’ wages do not matter much for agents’ decisions. Contrarily, Abeler et al. (forthcoming) demonstrate that paying equal wages to workers exerting different efforts leads to a strong decline in efficiency over time.

⁶In Keser and Willinger (2000) agents’ actions are hidden, but wage payments can be made contingent on the observed output. However, again the focus is on the vertical comparison between a principal and a single agent. Fehr et al. (2007) provide a direct comparison on the efficiency of incomplete and complete contracts in a bilateral setup.

difficult to reconcile with real-world work-relationships, but additionally is outside the scope of Winter's model. Fourth, to the best of our knowledge we are the first to pay attention to the important role of the production function in a labor market setting.⁷ Our finding that agents' behavior is sensitive to the shape of the production function should be taken into account in future empirical research on the interaction between social preferences and reward schemes.

The remainder of this paper is organized as follows: In the next section, we describe the experimental design and derive theoretical predictions. Subsequently, the experimental results are presented and discussed in Section 3, and Section 4 concludes.

III.B The Experiment

Experimental Design Exact control over players' risk-preferences and over the underlying cost- and production-functions is crucial for testing Winter's theoretical model. We therefore use a deterministic representation of his model for the experiment.⁸ In our game we have three agents working on a joint project. Each agent i individually decides whether to work (effort level $e_i = 1$) or shirk (effort level $e_i = 0$), and the individual cost of exerting effort is 90 Taler (our experimental currency). The individual payoff of agent i is given by the total number of goods produced multiplied by agent's individual reward per unit produced, minus his effort costs. The output of the project, i.e. the number of produced units, depends on the number of agents $\sum_i e_i$ choosing to work, and on our treatment variable **production function**:

production function	number of units produced if...			
	$\sum_i e_i = 0$	$\sum_i e_i = 1$	$\sum_i e_i = 2$	$\sum_i e_i = 3$
complementarity (COM)	20	40	65	100
substitutability (SUB)	20	55	80	100

⁷Normann et al. (2007) examine the relation between production function and the existence of large-buyers' discounts.

⁸The following game can easily be rewritten in a probabilistic way, which is the interpretation used by Winter (2004). We instead opt for the deterministic representation to impose risk-neutrality over the final outcome of the project, i.e., we pay the expected value of a lottery rather than to actually implement the lottery. This allows us to abstract from subjects' individual risk preferences.

The first case (COM) describes a production function of *complementarity*. The technology has increasing returns to scales, since the number of produced units (the output of the project) is $P(0) = 20$ if all agents shirk, $P(1) = 40$ if two agents shirk, $P(2) = 65$ if only one agent shirks and $P(3) = 100$ if all agents work, thus $P(3) - P(2) > P(2) - P(1) > P(1) - P(0)$. In the second case (SUB), we have a production function of *substitutability*. The technology has decreasing returns to scale, since $P(3) - P(2) < P(2) - P(1) < P(1) - P(0)$.

Agents' rewards are made contingent on the output of the project and the **reward scheme** or remuneration scheme, which we vary across treatments. The reward scheme in treatments 444COM and 444SUB is symmetric. Each agent in the group receives a reward of 4 Taler per produced unit. Contrarily, the mechanism implemented in treatments 345COM and 345SUB is a discriminating one: agents' reward per produced unit is either 3, 4, or 5 Taler (with each possibility occurring exactly once). At the same time, the sum of the individual rewards does not differ across the reward mechanisms. For example, the total reward costs in case that all agents shirk equals $3(4 \cdot 20) = 240$ under the *symmetric* reward scheme, and $3 \cdot 20 + 4 \cdot 20 + 5 \cdot 20 = 240$ under the *discriminating* reward scheme.

Implementation Our experiment was conducted in a labor market framing, avoiding loaded terms (e.g., 'shirk' or 'success'). We used the same procedure in each treatment condition. Upon arrival, participants were randomly divided into groups of three. In the treatments with a discriminating reward scheme, the three possible rewards were randomly assigned within each group. The written instructions were distributed and read out aloud. Afterwards, subjects could pose questions in private, and had to answer a set of computerized control questions to ensure that everybody had understood the game and to make subjects familiar with the operation of the program. Then subjects were told their own reward and the other players' rewards, and simultaneously had to decide between working or shirking. Afterwards, it was announced that we were additionally interested in their beliefs about the other subjects' behavior, and each subject had to state what they expected

the first and the second other player in their group to choose.⁹ In case that their belief fully matched the actual behavior, subjects were paid an additional 20 Taler. Only then we announced that five additional rounds of the game would follow, in which everything was kept constant (individual rewards, costs, production function and group composition). This was done to allow for possible learning to take place.¹⁰ After our experiment, subjects had to complete a social-value orientation test¹¹ and a socio-economic questionnaire.

The computerized experiments were run in 2007 and 2009 at the University of Bonn. Participants were randomly recruited via email invitation out of approximately 3000 persons from the BonnEconLab's subject pool (including mostly undergraduate students from a large variety of fields). For each treatment, we ran two sessions with 18 subjects each; totalling 12 independent matching groups (all rounds) or 36 independent decisions (only first round) per treatment.¹² A session lasted approximately 70 minutes. Subjects were paid for their decision and their belief in the first round, and additionally for one randomly selected round (which was constant across all subjects within a session) out of the subsequent five rounds. Talers earned in the experiment were converted at a rate of 80 Taler = 1 Euro. Subjects received a show-up fee of 4 Euros and earned on average approx. 7 Euro in the main experiment.

III.B.1 Behavioral Predictions

Figure III.1 shows players' payoffs as a function of his reward-type and his decision. As can be seen, the reward per unit produced that is needed to make an agent

⁹E.g., a player receiving a reward of 3 Taler per unit had to choose between '4' and '5' shirk, '4' and '5' work, '4' works and '5' shirks, or '4' shirks and '5' works. To keep the procedure constant, in 444COM and 444SUB we also asked separately for the behavior of the two other players in the group.

¹⁰We acknowledge that repeated play may have promoted reciprocal strategies, so that the results might have been different under random rematching. However, as will be shown in the next section, the results do not support this conjecture, as they are qualitatively in line with the baseline model, and remain stable following the announcement of the additional rounds

¹¹The 'ring test' is described for example in Griesinger and Livingston (1973) or Liebrand (1984); see also Beckenkamp (1995) for an early application in Economics.

¹²Subjects were recruited using ORSEE by Greiner (2003). The experiment was programmed in Pascal using RATimage by Abbink and Sadrieh (1995). The questionnaire and the ring test were conducted using zTree by Fischbacher (2007). Sessions for treatment 444SUB were added during the revision process in 2009. Unfortunately, in one session in treatment 444COM, only 15 subjects showed up, so that we are missing one of the twelve independent observations in this treatment.

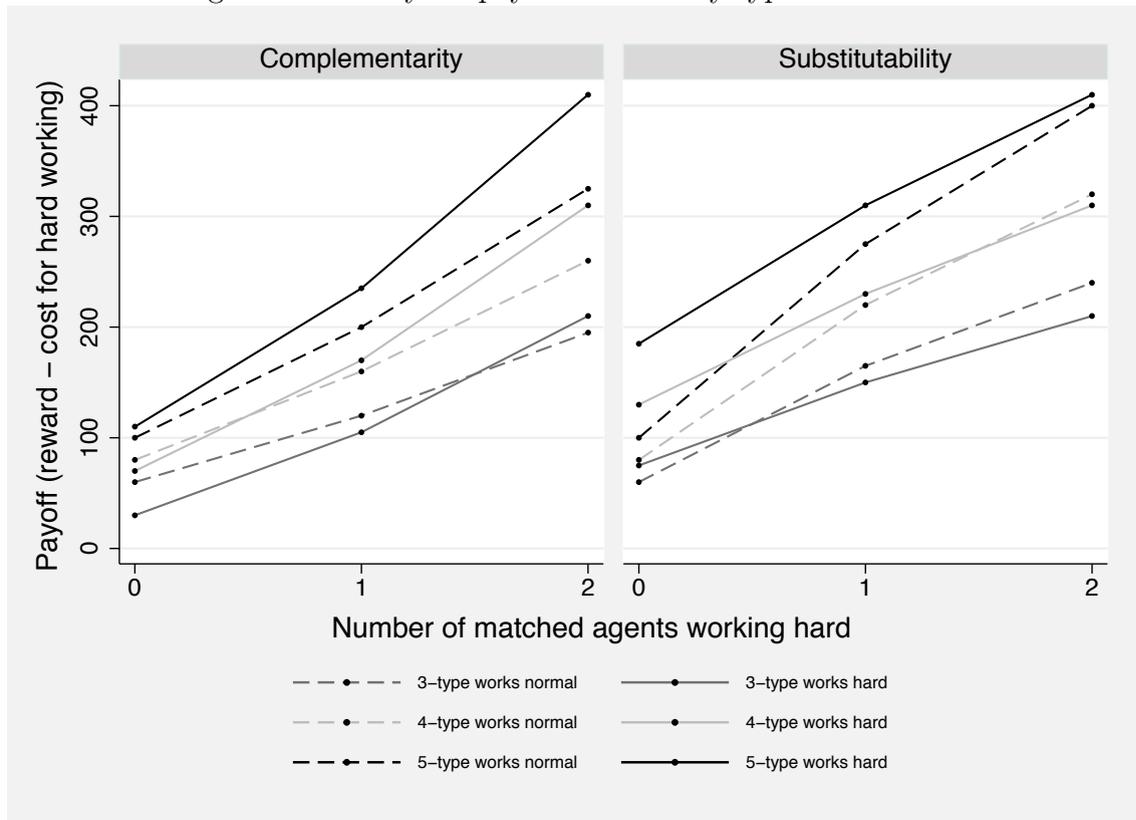
just indifferent between working and shirking depends on the (belief about the) decisions of the other two players in the group. Let X_0 denote the reward that is needed if an agent believes that both the other two agents in the group will shirk, and let X_1 and X_2 be the corresponding values when expecting one, resp. none of the others to shirk. Under a production function of *complementarity*, X_0 is given as $40X_0 - 90 = 20X_0 \Leftrightarrow X_0 = 4.5$, i.e., the payoff from working must equal the payoff from shirking under the belief that both the others shirk. Analogously, we find that $X_1 = 3.6$ and $X_2 = 90/35 \approx 2.6$.

This implies that the high-reward player in 345COM, receiving a reward of 5 per unit produced, will always work, irrespective of his beliefs (since $5 > X_0 > X_1 > X_2$). Anticipating this, the feasible beliefs for the medium-reward player are such that he also has an optimal strategy to work (since $4 > X_1 > X_2$). The only feasible belief of the low-reward player is thus to expect both the others to work, in which case his reward induces him to work as well (since $3 > X_2$). Hence the *discriminating* scheme enables players to form exact beliefs about the other players' decisions, although they move simultaneously – and repeated elimination of strongly dominated strategies leads to the unique Nash equilibrium of all players exerting effort.

Contrarily, this line of reasoning is not applicable when using the *symmetric* reward scheme. Each player works only if he has the belief that at least one other player exerts effort as well (since $X_0 > 4 > X_1 > X_2$). This implies that in 444COM we have two equilibria in pure strategies: Either all agents work, or all agents shirk (with all work being the payoff- and risk-dominant equilibrium). Besides that, also an equilibrium in mixed strategies exists in which the probability of shirking is approximately 0.77 (and all players know that each of the other players will shirk with this probability).

If we switch to the production function of *substitutability*, first consider that a naive principal might be tempted to prefer this technology over the previous one. For any given effort sum, the number of units produced is always equal or higher under substitutability than under complementarity. However, in 345SUB the *discriminating* reward scheme is not optimal anymore, because the threshold-order is reversed under a production function of *substitutability* (i.e., $X_0 \approx 2.6$, $X_1 = 3.6$ and $X_2 = 4.5$).

Figure III.1: Player's payoff function by type and decision



In both treatments, the payoffs for the 5-type players from working dominate the payoffs from shirking, and so the possibility of zero matched agents working can be eliminated for the other players. Now working dominates shirking for the 4-type players under complementarity, while the opposite is true for the 3-type players under substitutability. The remaining player in both treatments now maximizes her payoff by working. Thus the equilibria are derived through repeated elimination of dominated strategies. The multiple pure equilibria of the egalitarian treatments are revealed by the crossover of the payoff functions of the 4-type player under the corresponding production function. Note that the gain from working can be seen to increase (diminish) under complementarity (substitutability).

Thus, the low-reward player shirks in equilibrium, while the other two players work; and all players hold corresponding beliefs.

In 444SUB, an agent receives a higher payoff from exerting effort if no more than two of the other agents exert effort (since $X_2 > 4 > X_1 > X_0$). Hence there are three asymmetric equilibria in pure strategies in which one of the agents shirks while the other two agents exert effort. As in 444COM, an additional (symmetric) mixed strategies equilibrium exists, in which the probability of shirking is approximately .22.

The predictions above crucially depend on the assumption of subjects being *self-centered* money-maximizers. By contrast, part of the literature (not only) in Behavioral and Experimental Economics suggests that, beside pure money maximization,

a non-negligible fraction of subjects is strongly motivated by *other-regarding* considerations. In particular, subjects exhibit a basic desire for equity, including a preference for equal treatment of equals (cp. Selten (1978), Mowday (1991), Roemer (1996)), and a preference for equal payoff distributions (cp. Fehr and Schmidt (1999) or Bolton and Ockenfels (2000)).

In the presence of equity considerations, any discriminating reward scheme comes at some hidden costs which incentivize agents to shirk, even under an initially incentive-inducing mechanism! Slight equity preferences¹³ are already enough to let the superiority of the discriminating rewards vanish in 345COM. If agents' loss of utility from another agent receiving a higher payoff than their own is as low as 1/6 of the loss of utility of reducing their own payoff by the same amount, all-shirk becomes the unique equilibrium in 345COM.¹⁴ Even worse, due to the recursive nature of the equilibrium in Winter's model, the sheer belief that one or both of the other agents might have equity preferences can alone lead to a loss of efficiency — even if all agents themselves are strictly self-centered money-maximizers. By contrast in 444COM, equity preferences provide additional incentives *not* to shirk. If a subject expects the other two players in his group to work, shirking will reduce his payoff and lead to a less equitable payoff distribution ((260, 170, 170) instead of (310, 310, 310)); which is something that (not only) an inequality-averse subject would never prefer. Under substitutability, the effect of discrimination is rather robust to equity preferences. In 345SUB, a smaller number of agents is exerting effort in equilibrium as common envy increases. By contrast in 444SUB, the predictions crucially hinge on the exact shape of the assumed equity preferences.

The behavioral predictions are summarized in Table IV.2. It lists the possible equilibria in pure strategies for self-centered subjects in the first row, and the equilibria that might additionally emerge in the presence of equity-considerations in the second

¹³Throughout the paper, equity preferences are defined over payoffs rather than effort levels (cp. Mohnen et al., forthcoming).

¹⁴The intuition behind this hypotheses can easily be seen if we reconceive above equilibrium derivations using an extended utility function which incorporates equality preferences, e.g., the function described in Fehr and Schmidt (1999). Using their model, all-shirk is a possible equilibrium in 345COM if $\alpha \geq 1/3$ and $\beta = 0$ — which is a very conservative estimate in comparison with empirical estimations. Since the exact calculations are rather tedious and lengthy, they are available from the authors upon request.

row.

Table III.1: Treatment variations and equilibria

	Treatment			
	345COM	345SUB	444COM	444SUB
Production Function:	complementarity	substitutability	complementarity	substitutability
Reward scheme:	discriminating	discriminating	symmetric	symmetric
Equilibria:				
Self-centered	(1,1,1)	(0,1,1)	(1,1,1) (0,0,0)	(0,1,1) (1,0,1) (1,1,0)
Inequality-averse	(0,0,0) (0,0,1) (0,1,1)	(0,0,1)	<i>no additional equilibria</i>	(0,0,0) (0,0,1) (0,1,0) (1,0,0) (1,1,1)

III.C Experimental Results

In this section, first we show that workers' behavior is indeed sensitive to the type of production function they face in their joint project. The unequal treatment of equals does not necessarily hamper full effort provision. We then present data on a change in the reward scheme from a discriminating to an egalitarian one, which suggests that equal treatment of equals does not necessarily promote full effort provision within a team of agents. Nevertheless, as we finally show, signs of equity concerns are present in our data.

III.C.1 Sensitivity to the Production Function

Figure III.2 shows mean effort levels over all rounds, conditional on players' reward type and treatment. Table III.2 provides summary statistics and test results.

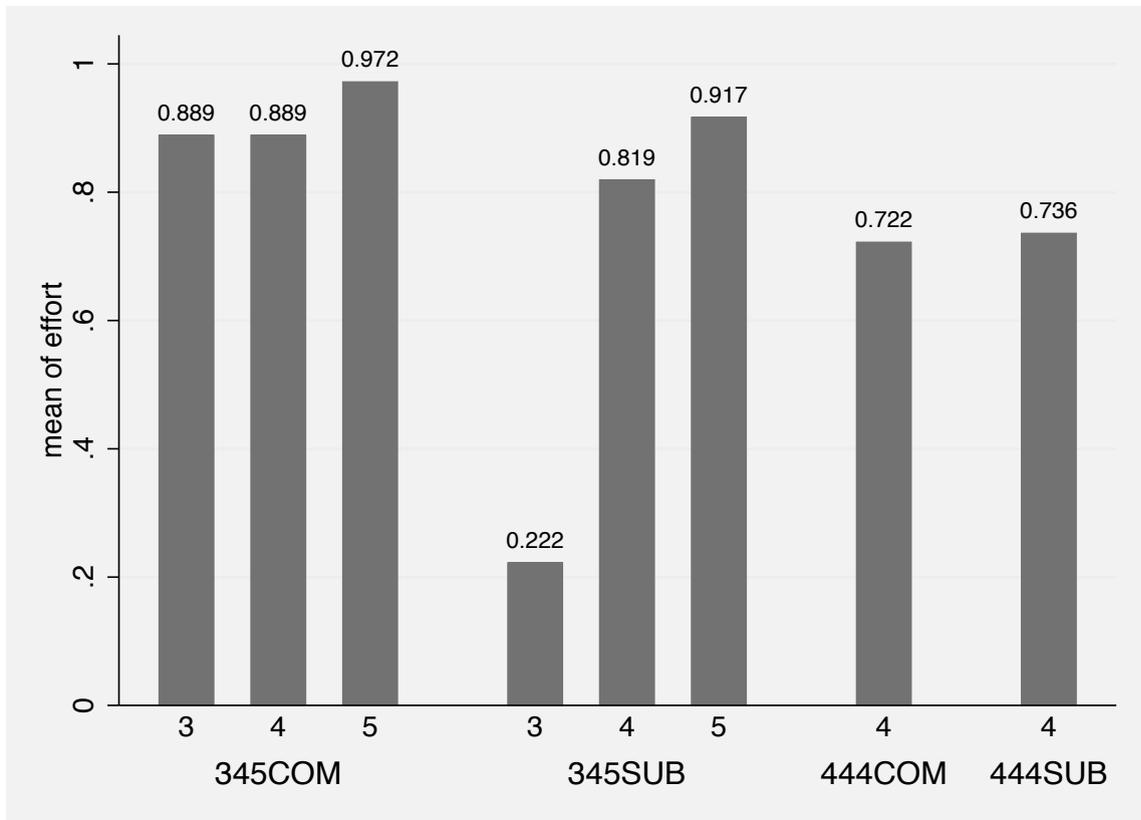


Figure III.2: Mean effort per treatment

Focussing on the discriminating reward scheme, overall effort levels are significantly higher under a production function of complementarity than under a production function of substitutability. 91.7% of all effort decisions in 345COM are to work, compared to only 65.3% in treatment 345SUB. In 345COM, 6 out of 12 groups exert full effort in all rounds (9/12 in all but one round), whereas the same is never observed in 345SUB.

The difference in efficiency between 345COM and 345SUB is predicted to stem from a difference in the behavior of the low-reward type in equilibrium. The average effort level of the low-reward type in 345SUB is significantly lower than that of the other two types (22.2% vs. 81.9% and 91.7%). It is also significantly lower than the effort level of the same type in 345COM (22.2% vs. 88.9%). Also in the first round, the number of low-reward players exerting effort is significantly higher in 345COM than in 345SUB (16.7% vs. 75%).¹⁵

¹⁵Fisher's exact test $p = .012$. Comparing the sums of effort per matching group in the first round and the last round, we find no indication of a significant time trend (two-sided sign-rank

Table III.2: Summary statistics and results of statistical comparisons

	Treatment			
	345COM	345SUB	444COM	444SUB
A. Summary statistic:				
Mean effort level round 1	88.9%	66.7%	78.8%	66.7%
Mean effort level rounds 1-5	91.7%	65.3%	72.2%	73.6%
SD round 1	.1641	.1421	.1681	.3482
SD rounds 1-5	.1580	.1421	.1681	.3482
B. Statistical comparison round 1 (p-values Fisher's exact)				
345COM		.0230	.2080	.0230
345SUB			.1960	.5990
444COM				.1960
C. Statistical comparison rounds 1-5 (p-values, rank-sum test)				
345COM		.0004	.0649	.0309
345SUB			.6850	.4410
444COM				1
D. Mean effort level per reward type:				
low-reward type (3)	88.9%	22.3%		
medium-reward type (4)	88.9%	81.9%	72.2%	73.6%
high-reward type (5)	97.2%	91.7%		
E. Comparison across treatments within reward type (p-values, rank-sum test)				
low-reward type (3)				
345COM		.001		
medium-reward type (4)				
345COM		.2058	.0260	.0127
345SUB			.2526	.2508
444COM				1
high-reward type (5)				
345COM		.3202		
F. Comparison within treatment across reward types (p-values, sign-rank test)				
low vs. medium (3 vs. 4)	.3930	.0074		
low vs. high (3 vs. 5)	.0261	.0039		
medium vs. high (4 vs. 5)	.1577	.1248		

NOTE: All reported p-values are two-sided. A: SD is given over the mean frequencies of work per matching group. B: Effort level of each subject is one independent observation. C: Mean effort level of each matching group is one independent observation. E: Mean effort level of each player is one independent observation. F: Players with different reward types in one matching group are treated as depended observations.

The effort levels of the medium- and high-reward types in 345COM (88.9% and 97.2%) do not differ significantly from the corresponding levels in 345SUB. Overall, when standard equilibrium predicts effort exertion, more than 80% do so. In the test in 345COM $p = .75$; and in 345SUB $p = .37$). For further details compare the corresponding time-series data of Figures C.1 and C.2 in the appendix.

one case (low-reward type in 345SUB) in which the equilibrium strategy is to shirk, almost 80% of the decisions are to shirk (cp. Table III.2-D).

Subjects' individual beliefs are in line with these findings. In 345COM, medium- and high-reward players believe that the low-reward player will work in 85% of all cases, while in 345SUB the low-reward player is expected to work in only 33% of all instances.¹⁶ 93% of the decisions in 345COM and 77% of the decisions in 345SUB are best responses to stated beliefs.

***Result 1:** In line with Winter's model, treating equals unequally by using a discriminating reward scheme leads to almost full efficiency under a production function of complementarity — whereas the same reward scheme does not perform well under a production function of substitutability.*

III.C.2 Sensitivity to the Reward Scheme

Given a production function of complementarity and keeping the total cost of the reward scheme constant, the mean efficiency in round one is lower under the symmetric reward scheme (78.9%) than under the discriminating one (88.9%). Over the course of the experiment, the difference grows larger and becomes significant (72.2% vs. 91.7%).¹⁷ On average, every reward type exerts more effort in the discriminating than in the symmetric treatment. Only 3 out of 11 groups exert full effort in all rounds, compared to 6/12 groups in 345COM (4/11 vs. 9/12 in all but one round). Moreover, the standard deviation of group efficiencies is significantly higher in 444COM than in 345COM.¹⁸

Our result suggests that equal treatment of equals does not necessarily promote full effort provision within a team of agents. A potential reason for the observed

¹⁶Two-sided rank-sum test, medium-reward: $p = .0004$; high-reward: $p = .0007$

¹⁷Note that although the difference becomes significant over time, we find no significant time trend in 444COM. Comparing the mean effort level of work per matching group between the first and the last round reveals no significant difference (two-sided sign-rank test, $p = .53$; cp. also the time-series data in Figure C.3).

¹⁸SD in 444COM (0.233) vs. SD in 345COM (0.158), Conover's squared-ranks test: $p = .0145$. Notice that the difference is not an artifact resulting from the high degree of efficiency in 345COM (which puts a bound on the variance), as the group efficiencies in 345SUB, in which the overall efficiency is similar to that in 444COM, show an even lower standard deviation of 0.068 (cp. Figure C.4).

difference in efficiency between the symmetric and the discriminating scheme under complementarity might be the introduction of the additional ‘all-shirk’-equilibrium in treatment 444COM. Even though it is payoff- and risk-dominated by the ‘all-work’-equilibrium, the multiplicity of equilibria introduces strategic uncertainty (cp. van Huyck et al., 1990). Players formulating beliefs are uncertain whether the other players in their group will work or shirk, which is visible in our data: 83% expect both other players to work in 345COM, whereas only 62% do so in 444COM.¹⁹ In 444COM, this translates into low efficiency rates and a high variance of group efficiencies, suggesting that strategic considerations shaped by the reward scheme are crucial, and outweigh possible equity preferences of the subjects.²⁰

The asymmetry of the reward scheme facilitates coordination among the agents under a production of complementarity. In case of the discriminating reward scheme, subjects can anticipate that the high-reward player will exert effort, which in turn incentivizes the medium- and low-reward players to do so as well. On the other hand, the identical rewards under the symmetric scheme make it hard for the subjects to form beliefs about the action of the other players, so that they are all in the dark. Also under a production function of substitutability, the symmetric reward scheme yields a higher degree of strategic uncertainty than the discriminating reward scheme. This is reflected by our data. In 40% of the rounds, at least one team member changes its effort level in 444SUB (32% in 345SUB). The observed standard deviation of group efficiencies is significantly higher in 444SUB than in 345SUB.²¹ However, all of the pure equilibria in 444SUB require exactly two out of three agents to exert effort, which is the same as in the unique equilibrium in 345SUB. Therefore, the lack of coordination should not decrease efficiency. In fact, in both treatments we observe exactly two-thirds of the subjects exerting effort in the first round. The proportion remains fairly stable in 345SUB throughout the experiment (65.3%) and

¹⁹two-sided rank-sum test, $p = .0979$

²⁰Note that strategic uncertainty might also be present in 345COM, because ‘all-work’ and ‘all-shirk’ are potential equilibria once we allow for equity considerations. Yet, we observe almost full efficiency in this treatment. One might consider that the result may be driven by a difference in the subject population between treatments. However, a comparison of the corresponding results of the social-value orientation test reveals no significant differences between treatments (Kruskal-Wallis test, $p = .19$).

²¹SD in 444SUB (0.215) vs. SD in 345SUB (0.068), Conover’s squared-ranks test: $p = .0011$

increases slightly in 444SUB (73.6%).²²

***Result 2:** Treating equals equally is neither a necessary nor a sufficient prerequisite for eliciting high performance in teams. Asymmetry facilitates coordination and increases efficiency under a production function of complementarity. The possible benefit of a discriminating reward scheme on efficiency levels strongly interacts with the production function — which is again in line with Winter’s model.*

III.C.3 Equity Concerns

Although we saw above that unequal rewards can potentially increase productivity, let us point out that this is not to say that equity considerations are absent in our experiment. For example, the average rate of effort provision over all rounds in 345COM is significantly different between the low- and the high-reward type (88.9% vs. 97.2%). This might reflect a slight reluctance of the low-reward players to work because the others then earn more than himself. Yet, in 5/8 instances where the low-reward player shirks, the behavior might also be explained by self-centered preferences, because subjects play a best response given their individual belief (in total, 93% of the decisions in 345COM are best responses to the stated beliefs). Speaking of beliefs, in 345COM also the beliefs of medium- and high-reward players about the low-reward player’s decision in the first round reveal some influence of equity concerns, because 42% (wrongly) expect him to shirk.

Also in 444COM, we observe signs of equity concerns. Players are very likely to exert effort if they expect both other players to work as well (in this situation 89% of the decisions were to work). This might just be playing the best reply on their stated belief (in total, 79% of the decisions in 444COM are best responses to the stated beliefs). But it might also be because they do not want to increase the payoff inequality in their group by shirking.

Exploring the same situation in 444SUB, we can actually distinguish between the two

²²The slight increase may be due to subjects trying to coordinate on one of the pure equilibria in the first round, but later approaching the symmetric mixed equilibrium through learning. Nevertheless, no significant time trend is observed in 444SUB. Comparing the mean effort level per matching group between the first and the last round reveals no significant difference (two-sided sign-rank test, $p = .87$; cp. also the time-series data in Figure ??). As noted earlier, the same holds true for 345SUB.

reasons because now they do not coincide. Here, if a player expects both the others to work, the best reply would be to shirk. Nonetheless, equity concerns might make him want to work so that players' payoffs are equitable. What we observe is that in this case only 18% of the decisions are a best reply to the stated beliefs (in the other cases in 444SUB, the rate is actually 55%) — which again is indicative of equity concerns. However, it is important to note that the discrepancy between beliefs and behavior could also result from rational selfish money-maximizing preferences. In the mixed equilibrium, agents exert effort with high probability. Thus, when asked for a point belief, expecting others to exert effort becomes optimal, which leads to behavior similar to what we observe.

Finally, the data from the social-value orientation test indicate that subjects have a general preference for equitable outcomes, because in all treatments the value-orientations do differ significantly from being strictly self-centered (two-sided rank-sum test, 345COM: $p \leq .001$; 345SUB: $p \leq .001$; 444COM: $p \leq .001$; 444SUB: $p \leq .001$).

III.D Conclusion

In this paper, we studied the interaction in teams. More specifically, we experimentally explored whether workers' behavior is sensitive to the externalities given by the production technology, and whether a major incentive advantage exists when discriminating among perfectly identical agents. In our experiment, three workers simultaneously decide on their individual provision of costly effort to a joint project. Treatments differ in the shape of the project's production technology and of the reward scheme. Under a production technology of complementarity, the use of a symmetric reward scheme elicits substantially lower efforts and efficiency than a cost-equivalent discriminating reward scheme. The same discriminating reward scheme underperforms when it is utilized under a production function of substitutability.

Our findings have important implications for the design of organizations in practice. First, they clearly point to the relevance of the production function for organization

construction – a factor which has so far received little attention in the literature.²³ Designing (production) tasks in a way that makes workers' efforts complements rather than substitutes may lead to a major cost advantage. Insofar as peer pressure constitutes a complementarity in effort exertion, the strengthening of social ties amongst the workforce alone might have a strong impact on productivity.

Second, and closely related, is our finding that unequal treatment of equals does not necessarily hamper efficiency. Whenever the organizational technology is one of complementarity, i.e., whenever the impact of a worker's input increases in the size of the others' input, the usage of a discriminating reward scheme might be potentially efficiency-enhancing. The main reason for this is that asymmetric rewards facilitate coordination, because workers can anticipate that those who have high stakes at hand will certainly exert effort – which in turn incentivizes the other workers to exert effort as well. Consider that discrimination must not necessarily be in monetary terms, but might also take the form of hierarchies. While a vast body of literature in personnel economics already promotes the implementation of hierarchies (e.g., Lazear and Rosen (1981)), our results suggest that hierarchies might enhance performance despite the absence of the existing literature's usual assumptions of monitoring or authority relations.

In this regard, we more generally contribute to the ongoing research on behavioral phenomena in organizations. As James Konow (2000) puts it: *“Many of the successes of economics can probably be attributed to its pushing the assumption of self-interest to the extreme. To proceed further, however, it may be necessary to incorporate richer behavioral assumptions that include fairness and other moral standards.”* (Konow (2000), p. 1089). While we agree in principle, it should be added that it is additionally necessary to identify the situations in which behavior is in line with the classical model – which is ultimately an empirical question. Only then can we really understand how to model the richer behavioral assumptions in a way to advance Economics.

The implications of our results can be extended beyond the labor context to addi-

²³The role of externalities between coworkers was studied by Gould and Winter (2009), who show that professional baseball players react to the technology in a way consistent with a related model to the one we study.

tional environments in which unequal treatment of equal is shown to be efficient. Relevant applications include differential tax rates (Atkinson & Stiglitz, 1976) and various trade contexts in which a 'divide and conquer' strategy maximizes gains (see Segal, 2003, and references therein). Thus, equity preferences may hinder the dynamics assumed in different domains. Our paper presents a step forward in understanding the boundaries of equity considerations and their potential implications. The results in this paper should not be taken as arguments against the importance of fairness considerations in general. For instance, they might be partially explainable by models incorporating social efficiency (e.g. Charness & Rabin, 2002). Still, our findings suggest that equal treatment of equals is neither a necessary nor a sufficient prerequisite for eliciting high performance in teams. Yet the relative importance of equity considerations is likely to depend on the exact details of the organizational setting and framework. In this paper, we presented experimental evidence for some of these settings, and stressed the interaction between production technologies and reward schemes. Future research could try to exacerbate the differences in payoffs in order to estimate some kind of metric for the strength of inequity preferences in our setting (we thank an anonymous referee for making this suggestion). Other interesting variations of the organizational settings include a change in the timing of effort choices, the introduction of heterogeneity among the workforce or the use of 'symbolic' instead of monetary differentiation. Extending our simple design allows for studying these and other interesting aspects in the future.

Chapter IV

Experimental Investigation of Cyclic Duopoly Games

IV.A Introduction

Several studies have demonstrated that the concept of mixed Nash equilibrium fails to explain observed behavior in experiments (e.g., Brown & Rosenthal, 1990, Erev & Roth, 1998, and Avrahami, Kareev & Güth, 2005). In a recent paper by Selten & Chmura (2008) on completely mixed 2×2 games played by small populations with random matching over 200 rounds, several behavioral stationary concepts beat the Nash equilibrium in predicting subjects' behavior. In that study the two behavioral concepts of impulse-balance equilibrium and payoff-sampling equilibrium proved to be successful but hard to differentiate.

The main goal of this paper is to examine the results from Selten & Chmura in a different environment. We therefore compare the predictive success of Nash equilibrium, impulse-balance equilibrium and payoff-sampling equilibrium in two cyclic games.

The notion of a cyclic game has been introduced by Selten and Wooders (2001). Cyclic games can be applied to simplified recurring situations with intertemporal competition. Similar situations are investigated by overlapping generations models (starting with Diamond 1965), but on the basis of market theory rather than game theory. In our study we applied the concept of a cyclic game to the market entry situation in a duopoly.

In our duopoly games exactly one potential entrant in each period can decide whether

he wants to enter the market or not. If he enters he stays in the market for exactly two periods and then exits. Imagine that this market is very narrow. A firm makes a negative profit if it has to share the market with another firm in both periods. A positive profit can be obtained if the firm is the only supplier in at least one of the two periods.

In these games it is always profitable to enter an empty market. However, a potential entrant who faces an occupied market in period t has to think about the consequences of entering the market. If he enters, the following potential entrant in period $t + 1$ will also face an occupied market and will find himself in the same decision problem. As we shall see this leads, for each of the three stationary concepts, to a different symmetric mixed equilibrium, in which every player facing an occupied market enters with the same probability.

We will investigate two different cyclic games, which share two features with the 2×2 games investigated by Selten & Chmura (2008): First, two types of players compete against each other and, second, both player types have two possible actions to choose from. However, the investigated cyclic games differ by three properties from the 2×2 games from Selten & Chmura (2008): First, in our cyclic games the payoffs of both players are symmetric, while in Selten & Chmura (2008) they were not. Second, players in cyclic games have perfect information in the sense that each information set consists of only one node. In cyclic games the players act sequentially in contrast to the 2×2 games with simultaneous decisions. Third, while in the mentioned 2×2 games only mixed equilibria existed there are two pure strategy equilibria in the cyclic duopoly games.

Because of the similarities and the differences we think that the cyclic game is a good starting point to observe the concepts investigated by Selten & Chmura in a different environment and a good way to identify potential reasons for alternative results.

Our results confirm the superior predictive power of impulse-balance equilibrium and payoff-sampling equilibrium in comparison to Nash equilibrium. Overall, both

behavioral concepts perform significantly better than Nash equilibrium does. Our results differ from Selten & Chmura (2008) regarding the equality of impulse-balance equilibrium and payoff-sampling equilibrium: In our study payoff-sampling equilibrium performs significantly better than impulse-balance equilibrium does. In our opinion this disadvantage of impulse-balance equilibrium in comparison to the mentioned 2×2 games is caused by the sequential move structure of the cyclic game.

As mentioned before, our experimental setup also permits asymmetric equilibria in which one of the two players, say player one, always enters and the other player never enters. In fact the data reveal a significant tendency towards convergence to pure strategies over time. This finding sheds some doubt on the comparison of the three stationary concepts in the long run.

The rest of the paper is organized as follows: in section 2 we will describe and explain the cyclic oligopoly game in more detail. Afterwards the three stationary concepts are introduced, applied to the games and their predictions are derived. In section 4 the experimental procedure is described and subsequently, section 5 gives our results. Finally, section 6 summarizes and concludes this paper.

IV.B The cyclic game

A cyclic game may be looked upon as a condensed description of an infinite game. In the following we shall describe the infinite game structure underlying our experiment. The game runs over periods $t = 1, 2, \dots$. In each period t a potential entrant t has to decide whether he enters the market or not in period t . If he enters he stays in the market for periods t and $t + 1$ and exits then. A potential entrant t may face an empty market, which is always true for $t=1$. For $t = 2, 3, \dots$ the market is empty at period t if the potential entrant $t - 1$ did not enter the market. The market is occupied for t with $t = 2, 3, \dots$ if the potential entrant $t - 1$ did enter the market.

The concept of a cyclic game permits a condensed description of game situations like the one investigated in our experiment. In our case, the cyclic game has only two players. These two players are roles of the potential entrants. The odd-numbered

members of an independent subject group are in the role of player 1 and the even-numbered are in the role of player 2.

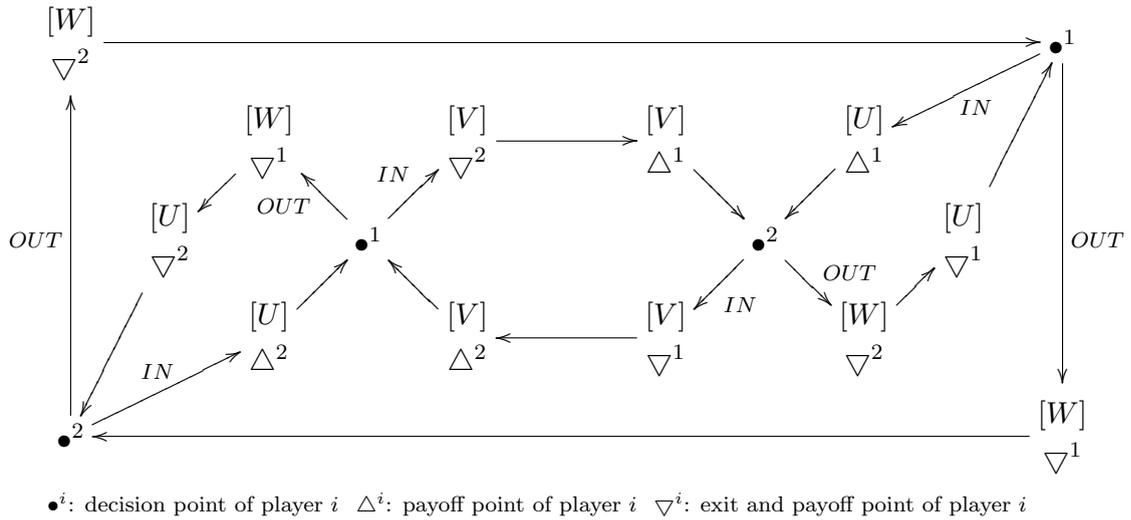


Figure IV.1: Structure of the cyclic duopoly game

Figure IV.1 illustrates the structure of the cyclic duopoly game as introduced by Selten & Wooders (2001). The figure has the structure of a directed graph with 3 types of nodes and additional information regarding player and payoff. Each point describes a situation of either player 1 or player 2. At a decision point a player has to decide between two alternatives in our case IN or OUT. Here IN means entering and OUT means not entering. At a payoff point or an exit and payoff point, the payoff of the concerning player is shown in rectangular brackets above this point. The arrows show the direction in which the game moves from one situation to the next.

At the upper right corner player 1 can decide between IN and OUT in the situation of an empty market. In the case OUT he receives a payoff of W at a payoff and exit point. If he chooses IN he receives a payoff of U in this period and the game moves to a decision point of player 2. If player 2 then chooses OUT first, a payoff and exit point is reached, at which player 2 receives W and then a payoff and exit point of player 1, where he receives U. From there the game moves back to the upper right corner. The other parts of the figure are to be understood in the same way.

In our cyclic oligopoly game U is the payoff for a period in which the entrant is alone in the market, V is the payoff for a period in which the entrant is not alone in the market, and W is the payoff for two periods if the market is not entered. The parameters U , V and W were chosen in such a way that the condition $U + V > W > 2V$ is satisfied and thus implies $U > V$. Therefore entering an empty market always leads to a higher payoff than not entering an empty market. In our experiments we applied two different sets of the parameters U, V and W , which are given in table IV.1.

	U	V	W
Game A	10	2	5
Game B	10	3	9

Table IV.1: Parameter for U, V and W in Game A and Game B

These different parameter sets lead to different equilibria and provide different attractiveness for not entering an occupied market.¹ In Game B the payoff for not entering the market is higher than in Game A; therefore it should lead to a smaller entry rate in Game B compared to the one in Game A.

IV.C Three stationary concepts for the cyclic game

We shall look at three stationary concepts: Nash equilibrium, impulse-balance equilibrium and payoff-sampling equilibrium. First, we will derive the Nash equilibria for the two games. Then we will explain the basic ideas behind the two behavioral concepts, impulse-balance equilibrium and payoff-sampling equilibrium.

As has been shown in Selten and Wooders (2001) the cyclic game has three **Nash equilibria**. A symmetric mixed-strategy equilibrium and two pure-strategy equilibria. In the symmetric mixed equilibrium the probability α for entering if the market is occupied is as follows:

¹In addition we chose the parameters to ensure that the distances between the resulting equilibria are big enough to determine the concept with the best fit to the data.

$$\alpha = \frac{U + V - W}{U - V}$$

In Game A this leads to the probability of entering the occupied market of $\alpha = 0.875$ and in Game B to the probability of $\alpha = 0.571$. If the market is empty the probability of entering is always one. This is also true for the two pure equilibria. However, there the probabilities α_1 and α_2 are

$$\alpha_1 = 1 \text{ and } \alpha_2 = 0$$

in the first pure-strategy equilibrium and

$$\alpha_1 = 0 \text{ and } \alpha_2 = 1$$

in the second pure-strategy equilibrium.

We now turn our attention to the **impulse-balance equilibrium**. Impulse-balance equilibrium is based on the idea of learning direction theory (Selten & Buchta, 1999), which looks at probabilities of decisions as behavioral tendencies. Selten and Buchta explain the concept by the example of a marksman aiming at a trunk: *"If he misses the trunk to the right, he will shift the position of the bow to the left and if he misses the trunk to the left he will shift the position of the bow to the right. The marksman looks at his experience from the last trial and adjusts his behavior [...]."* (p. 86 Selten & Buchta, 1999)

The concept of impulse-balance equilibrium (Selten, Abbink & Cox, 2005, and Selten & Chmura, 2008) models these adjustments with impulses received after the realization of payoffs. Suppose that the first of two strategies has been chosen in a period and this strategy was not the best reply to the strategy played by the other player. Then the player receives an impulse towards the second strategy. This impulse is the difference between the payoff the player could have received for his best reply minus the payoff actually received given the strategy used by the other player in this period. The player does not receive an impulse if his strategy was a best

reply against the strategy used by the other player.

To incorporate loss aversion, the impulses are not calculated with the original payoffs but with transformed ones. In games with two strategies and a mixed Nash equilibrium each strategy has a minimal payoff and the maximum of the two minimal payoffs is called the pure strategy maximin. This pure strategy maximin is the maximal payoff a player can obtain for sure in every round and it forms a natural aspiration level. Amounts below this aspiration level are perceived as losses and amounts above this aspiration level are perceived as gains. In the case of our cyclic games the payoff for not entering a market W forms this aspiration level. In line with prospect theory (Kahneman & Tversky, 1979) losses are counted double in comparison to gains.² Thus, gains (the part above W) are cut into half for the computation of impulses. Figure V.1 illustrates this transformation for the investigated cyclic oligopoly games.

The original payoffs			The transformed payoffs		
	Entrant $t + 1$			Entrant $t + 1$	
	IN	OUT		IN	OUT
IN	2V	V+U	⇒	2V	$\frac{V+U-W}{2} + W$
OUT	W	W		W	W

Figure IV.2: Entrant t 's original and transformed payoffs for an occupied market, assuming that $U + V > W > 2V$ is fulfilled.

Impulse-balance equilibrium is reached at a point in which the expected impulses in both directions are equal. Let α be the probability of entering an occupied market at impulse-balance equilibrium. If the potential entrant enters the market he receives

²We consider impulse-balance equilibrium as a concept, which is free of parameters. Keeping the loss-aversion fixed to 2 allows impulse-balance equilibrium to be used for predictions in different games without estimating a parameter. This is a big advantage over parametric concepts for which the parameter must be adjusted, to the whole population or parts of it, after the behavior has been observed. However, one might want to use impulse-balance equilibrium to organize the data ex-post and therefore it might be appropriate to estimate the loss-aversion directly from the data.

no impulse if the next player does not enter, since in this case entering proved to be the best choice, ex-post. If the other player also enters he receives an impulse of $W - 2V$ towards OUT. Since α is both players' probability for entering, he receives an impulse for OUT with probability α^2 .

We now consider the case that the player does not enter. In this case he does not receive any feedback. Of course he knows that the next player will enter the market since it is a dominant strategy, but this is not the relevant feedback impulse-balance equilibrium relies on. In the original concept of impulse-balance equilibrium impulses are formed with players deciding simultaneously. The sequential move structure of the cyclic game leads to the problem that the next player can condition his decision on the previous player's decision and thus an ex-post reflection keeping the matched player's decision fixed is impossible. The potential entrant is interested in what the next player would hypothetically have done if he, the potential entrant, had entered the market. Therefore he assumes that the next player finds himself in the same situation of an occupied market as he himself did and performs the same action as he did in this case.

For the proportion of cases in which the potential entrant did not enter and the following player would not have entered given that the potential entrant had entered, he receives an impulse of $(W + \frac{V+U-W}{2}) - W = \frac{V+U-W}{2}$ towards IN. This happens with probability $(1 - \alpha)^2$. Figure IV.3 illustrates the possible impulses.

At equilibrium the mathematical expectation of impulses in the direction of not entering is equal to the one towards entering. This is expressed by the following impulse-balance equation:

$$\alpha^2(W - 2V) = (1 - \alpha)^2 \frac{V + U - W}{2}$$

Thus, the probability of entering an occupied market can be stated as:

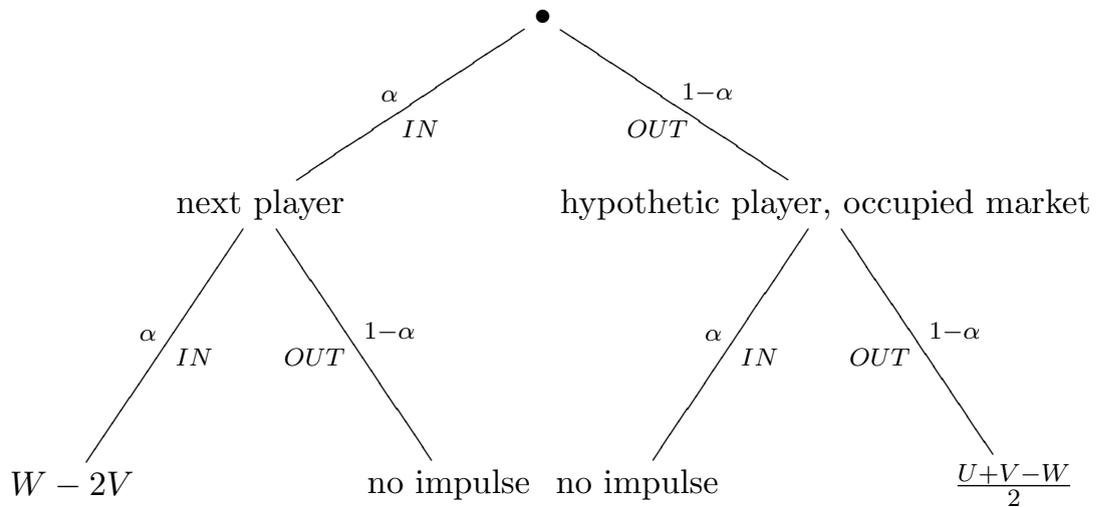


Figure IV.3: Impulses in the direction of the other strategy

$$\alpha = 1 - \frac{\sqrt{2(W - 2V)}}{\sqrt{V + U - W} + \sqrt{2(W - 2V)}}$$

At equilibrium a player enters an occupied market with probability $\alpha = 0.622$ in Game A and with $\alpha = 0.449$ in Game B. In the case of a free market, impulse-balance leads to the same dominant strategy IN as the Nash equilibrium does. In addition the pure-strategy Nash equilibria are also impulse-balance equilibria, since in a pure strategy equilibrium nobody receives any impulse and therefore does not change his strategy.

The last stationary concept we will report on is the **payoff-sampling equilibrium**. Osborne & Rubinstein (1998) introduced this concept. The concept assumes that a player acts in accordance with previous experiences. Therefore he accesses experience in his memory made for each possible action. Thereby the number of recalled experiences is limited and the number of sampled experiences can be interpreted as the intensity used to search through the memory.³ In addition, the selection of experiences is done randomly. The order how they come to mind is haphazard and not deterministic. Afterwards the player chooses the action, which has the highest

³Osborne & Rubinstein (1998) interpret the sample size as the detailedness of *the players' reasoning process* or as the *players' sophistication*.

outcome given the sampled experiences. This procedure describes behavioral patterns exhibited by subjects who do not make use of information about the actions and payoffs of their opponents.

Applied to our cyclic games this means that the player draws two samples of equal sizes n from previous periods, one for the strategy IN and one for the strategy OUT. He then forms the payoff sums in the two samples and compares them and plays the strategy with the highest payoff sum. If both payoff sums are equal he flips a coin and thus chooses a pure strategy with probability $\frac{1}{2}$. This rule is not part of the original concept; Osborne & Rubinstein (1998) did not discuss the case of equal payoffs.

The probability α for entering in the cyclic games is determined as follows. Consider a sample of n cases in which the player has played IN. Let k be the number of cases in this sample in which the next player entered. Let S_k be the payoff sum of the sample. Then we have

$$S_k = (V + U)(n - k) + 2Vk.$$

This payoff sum S_k must be compared to the payoff sum $W \cdot n$ obtained for not entering n times. The player does not enter if the payoff sum difference

$$D_k = Wn - S_k = (U - V)k - (V + U - W)n$$

is positive. In the case $D_k = 0$ the probability of **not entering** is $\frac{1}{2}$. The conditional probability of not entering if there are k cases of next players entering in the sample for IN is as follows

$$\eta(n, k) = \begin{cases} 0 & \text{for } (V + U - W)n > (U - V)k \\ \frac{1}{2} & \text{for } (V + U - W)n = (U - V)k \\ 1 & \text{for } (V + U - W)n < (U - V)k \end{cases}$$

With the help of this notation we now can derive an equation for the entry probability α :

$$\alpha = \max\left[1 - \sum_{k=0}^n \eta(n, k) \binom{n}{k} \alpha^k, 0\right]$$

The sum on the right-hand side of this equation is the total probability of not entering. The probability of not entering if there are exactly k cases with next players entering in the sample for IN is $\eta(n, k)$ times the binomial probability for k out of n players entering.

Figure IV.4 gives the functions of α for both cyclic games and shows that in both games the equation for α has exactly one solution in $0 \leq \alpha \leq 1$.

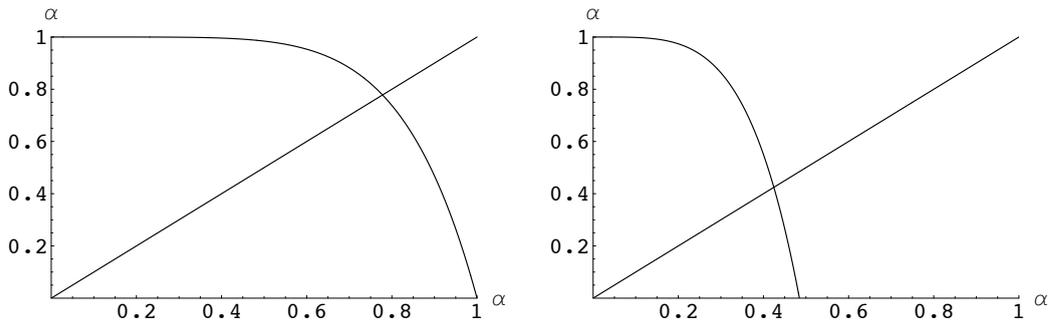


Figure IV.4: Probability α for the payoff-sampling equilibrium in Game A (left) and Game B (right).

It is not immediately clear whether a strict pure-strategy equilibrium can be considered a payoff-sampling equilibrium. If really always only the equilibrium strategy has been played in the past, there is no sample for the other strategy. On the other hand, a learning process applying the idea of payoff-sampling may very well converge towards the pure-strategy equilibria.

Table IV.2 gives the equilibria of the different concepts for both games.⁴ In the following we will use this probabilities as predictions for the average entry rates.

⁴The probabilities for payoff-sampling equilibrium are already given for the optimal sample size as determined in section IV.E.1

	Game A	Game B
Nash equilibrium	0.875	0.571
Impulse-balance equilibrium	0.622	0.449
Payoff-sampling equilibrium	0.778	0.424

Table IV.2: Predicted probabilities for entering an occupied market by the three different concepts, for even and uneven players

IV.D Experimental design

The experiments were carried out in 2005 (Game A) and 2008 (Game B) at the Laboratory for Experimental Economics of the University of Bonn (BonnEconLab). Seven sessions were conducted, in two sessions there were 24 participants, in four sessions there were 18 participants and in one session only twelve. In each session subjects were subdivided into independent matching groups of six. Thus we gathered a total of 22 independent observations with 11 observations per game.

Altogether 132 subjects participated in our experiment. The participants, all students, were invited via the ORSEE⁵ database of the laboratory. The participants came from different faculties with most of them majoring in economics (around 37%) and law (around 21%).

The theoretical game situation described above extends over an infinite number of time periods. However, in an experiment one cannot play for infinite time. Therefore, our experiments run over 200 rounds. The calculation of somebody's payoff, who enters in the last period, requires the decision of a potential entrant in the next period. This creates an "end-problem". We solved this problem by substituting a randomly-chosen decision of an earlier entrant facing an occupied market for the decision in the next round.

Although the experiment lasted over 200 rounds each subject had to make only 100 decisions. This is due to the fact that only one half of the subjects decided in uneven rounds and the other half in even rounds.

⁵see Greiner (2004).

At the beginning of the experiment the participants were briefed with written instructions,⁶ which were read out to them. They were informed about the duration of the experiment and that one half would decide in uneven and the other in even rounds. Furthermore they were told that before each decision each subject would be randomly matched to a market. The participants did not know that they were subdivided into independent subject groups of six. Therefore they were led to believe that there were more markets to which they could be assigned. After the introduction the participants were separated into cabins with computer terminals and the experiment was started.⁷

On the screens⁸ participants first received the current status of the matched market, i.e., if the market was free or occupied. Given the status of the market they were asked whether they wanted to enter this market or not. After their decision and the decision of the next matched player they were shown their payoff for the two rounds. If they entered the market they additionally received the information whether the next matched player had entered the market or not. If they had not entered the market this information was not provided.

The payoffs in the game were given in the fictitious currency *Taler* and at the end of the game transferred into Euro with an exchange rate of 1 Taler equals 1 EuroCent. In addition to the cumulated payoffs subjects received a show-up fee of 5 Euro. To guarantee anonymity of the decisions participants were separately payed. Overall one session lasted about one hour and the payoffs were between 10 and 23 Euros.

IV.E The experimental results

The three concepts serve as predictions for the frequencies for entering a free market and an occupied market. In the following we do not assume that the theories can predict the behavior of a single player, but we will compare the predictive power of the three concepts for the average behavior in independent subject groups. For each

⁶A translated version of the instructions can be found in the Appendix.

⁷The experiment was programmed with z-Tree (Fischbacher, 2007).

⁸Screenshots are shown in the Appendix.

independent subject group i we will use the quadratic distance

$$Q_i = (\alpha - f_i)^2$$

between the theoretical probabilities α and the observed mean relative frequency f_i as the measure of predictive success. The overall predictive success is measured by the mean of all these quadratic distances over the 22 subject groups.

$$Q = \frac{1}{22} \sum_{i=1}^{22} Q_i$$

In the following we will first search for the sample size n of the payoff-sampling equilibrium with the best fit to the data. Then we will compare the predictive success of the three theories. We will compare the overall predictive success and whether this success changes over time. Afterwards we will analyze tendencies of convergences towards the pure-strategy equilibria.

IV.E.1 Comparison of Sample Sizes for Payoff-sampling Equilibrium

In the study by Selten and Chmura (2008) the sample size 6 yielded the best fit for the data in the twelve 2×2 games. However, it is not clear whether this sample size would lead to the predictions with the best fit to the data in our cyclical game. Therefore, we compared the predictive success of different sample sizes. We searched for one sample size, which minimizes the quadratic distance over both games.

Figure IV.5 shows the quadratic distances for the payoff-sampling equilibrium with the sample sizes $n=2, \dots, 10$. It can be seen that, as in Selten & Chmura (2008), the sample size 6 yields the best fit to the data. Therefore we will base our comparison of the stationary concepts on the payoff-sampling with the sample size of 6.⁹

⁹Estimating the best-fitting parameter for each game separately leads to an optimal sample size of $n = 5$ for Game A and to an optimal sample size of $n = 9$ for Game B. Table 1 in the Appendix gives the quadratic distances for each game and for each sample size.

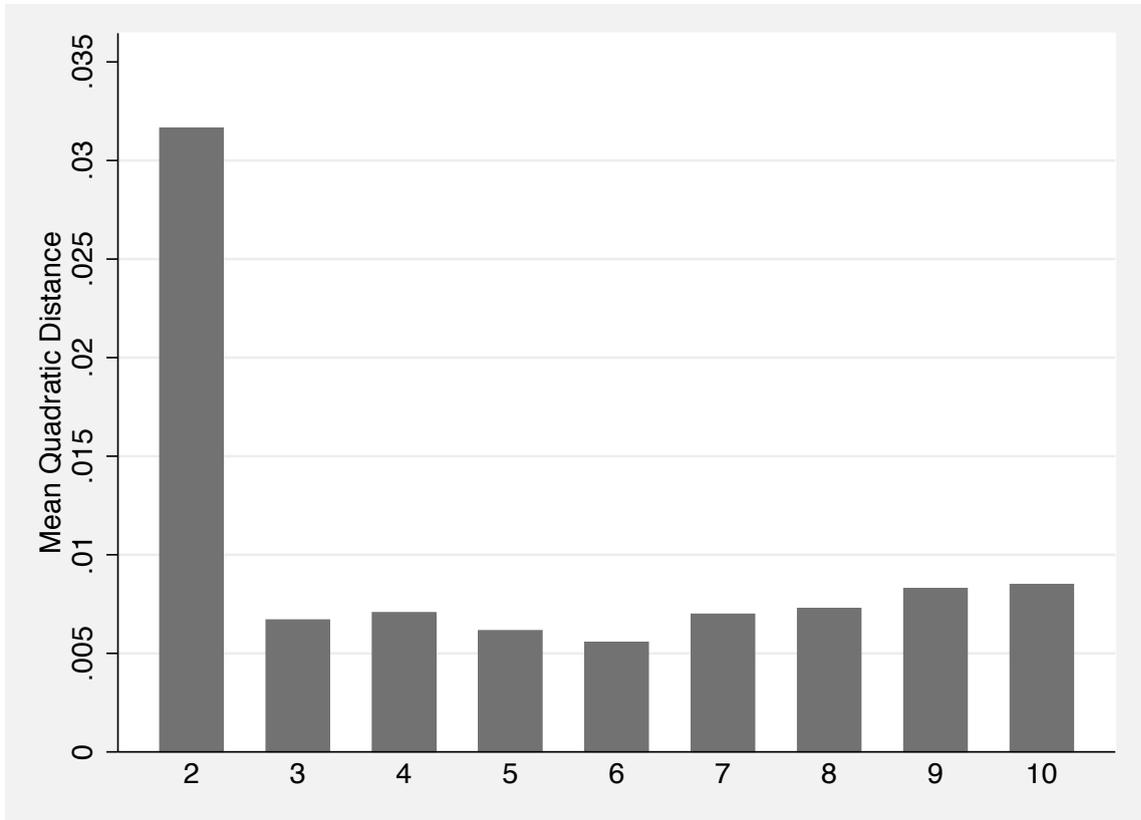


Figure IV.5: Mean quadratic distance for different sample sizes

IV.E.2 Predictive Power of the three Concepts

We will start with the comparison of the relative frequencies obtained in our experiment with the predictions of the three concepts in the case of an empty market. In this case all three concepts predict a frequency of 1 for entry. In nine of the 22 observations this prediction is correct and all potential entrants join the markets when they are empty. In the other 13 observations the relative frequencies for entry are very high, too. The smallest entry rate is 0.9506. It is not surprising that the participants realize that the strategy of not entering the market is dominated in this case by the strategy of entering the market. The numerical values for all observations are shown in Table 3 in the Appendix.

If the market is occupied, entry is no longer the dominant strategy and different frequencies of entering are observed. In Game A the mean frequency of entering an occupied market is 0.7415 and in Game B it is 0.4224. In the case of an occupied

market the three stationary concepts predict different relative frequencies of entry. Therefore they perform differently in describing the experimental data. To measure the predictive power of each concept we use the mean quadratic distance. Figure IV.6 gives the mean quadratic distances to the data for each of the three stationary concepts in both games.

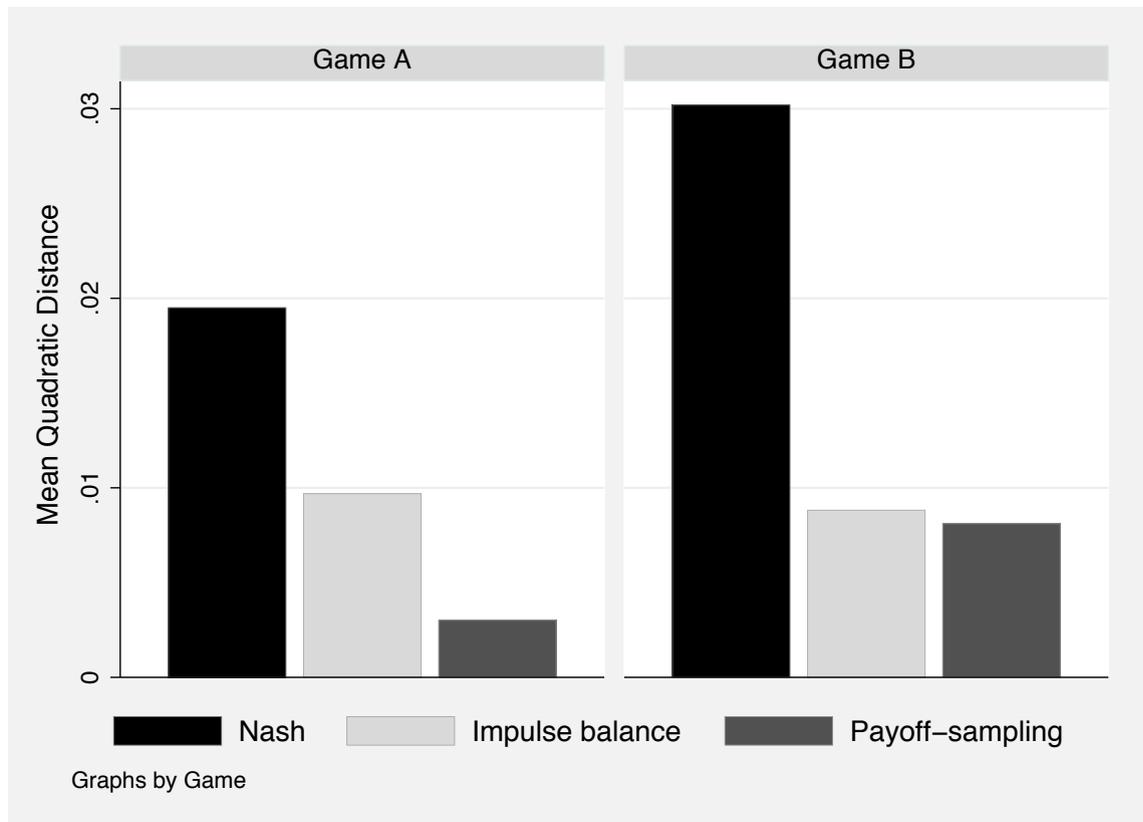


Figure IV.6: Quadratic distances in occupied markets

Obviously payoff-sampling equilibrium has the highest predictive success: In both games, payoff-sampling equilibrium has the smallest mean quadratic distance. Impulse-balance equilibrium, has in both games, the second highest quadratic distance and Nash equilibrium always has the highest quadratic distance. Table 4 in the Appendix shows the observed frequencies and the quadratic distances of the three concepts for each observation in both games.

In 15 of the 22 observations the quadratic distance to payoff-sampling equilibrium is the smallest, in five observations the quadratic distance to impulse-balance equi-

librium is the smallest and in two observations the quadratic distance to the Nash equilibrium is the smallest. In addition to this, the quadratic distance to the Nash equilibrium in three observations is smaller than the quadratic distance to the impulse-balance equilibrium, but nevertheless larger than the quadratic distances to the payoff-sampling equilibrium. In 17 out of 22 observations the quadratic distance to the Nash equilibrium is the largest of all three concepts. Taking the mean quadratic distance over both games we receive a clear order of predictive success: Payoff-sampling performs the best (0.0056), impulse-balance equilibrium performs second-best (0.0092) and Nash equilibrium has the worst performance (0.0248).

Testing the quadratic distances of the three concepts with the two-sided Wilcoxon signed-rank test, we obtain the results given in Table IV.3. The significances are in favor of the row concept. The first row in each cell shows the results only if the predictive power in Game A is compared, the second row only if the predictive power in Game B is compared and the third row if the predictive power over both games is compared.

	Nash Equilibrium	Impulse-balance equilibrium
Payoff	1%	5%
-sampling	2.5%	n.s.
equilibrium	1%	5%
Impulse-	n.s.	
balance	1%	-
equilibrium	1%	

Table IV.3: p-values of the two-sided Wilcoxon signed-rank test with the quadratic distances to the data in favor of the row concept. The first row gives the comparison for Game A, the second row for Game B and the last row over both games.

No statistically significant difference between the predictive power of the impulse-balance equilibrium and the Nash equilibrium could be observed for Game A. But for Game B and the overall comparison, impulse-balance equilibrium fits the data significantly better than the Nash equilibrium does. Payoff-sampling equilibrium has a significantly higher predictive success than Nash equilibrium over all games

and in each of the two games. The comparison between payoff-sampling equilibrium and impulse-balance equilibrium is not statistically significant in the case of Game B. In case of Game A and for the overall comparison, payoff-sampling equilibrium has a significantly higher predictive success than impulse-balance equilibrium.

But how sensitive is this order with respect to the sample size of payoff-sampling equilibrium? The comparison of payoff-sampling equilibrium and Nash equilibrium is very robust across different sample sizes. Thus, for each sample size $10 \geq n > 2$, payoff-sampling equilibrium performs significantly better than Nash equilibrium in the overall comparison and in Game A. In Game B, payoff-sampling equilibrium performs significantly better than Nash equilibrium for all sample sizes except for $n = 2$, $n = 5$ and $n = 10$.

In Game A, the comparison of payoff-sampling equilibrium with impulse-balance equilibrium is robust with respect to the sample size: for each sample size $10 \geq n > 2$ payoff-sampling equilibrium performs significantly better than impulse balance equilibrium. In Game B, all comparisons with impulse-balance equilibrium for $10 \geq n > 2$ are insignificant.¹⁰ Taking both games into account, payoff-sampling equilibrium has a significant higher predictive success than impulse-balance equilibrium for $\frac{1}{3}$ of the investigated sample sizes, namely $n = 3$, $n = 6$, and $n = 9$. The other investigated sample sizes do not yield significant differences.¹¹

IV.E.3 Changes over Time

Up to here we have analyzed the data on an aggregated basis and could elicit an order for the predictive success for 200 periods. We now investigate whether this order changes over time. In our experiment players had to decide whether to enter or not to enter the market 100 times. Thus, our analyses are limited to these 100 decisions. We compare the first 50 decisions with the second 50 decisions. On

¹⁰For $n=2$ impulse-balance equilibrium performs always significantly better than payoff-sampling equilibrium and in Game B even Nash equilibrium performs significantly better than payoff-sampling with $n = 2$.

¹¹The results for all comparisons with the Wilcoxon signed-rank test are given in table 2 in the Appendix.

average, in Game A entry rates for an occupied market are rather stable over time (first half: 73%; second half: 74%), while they drop in Game B over time (first half: 46%; second half: 37%). Figure IV.7 gives the mean quadratic distance of the three theories to the observed frequency of entering the market for the first 50 decisions, for the second 50 decisions, and for all 100 decisions.

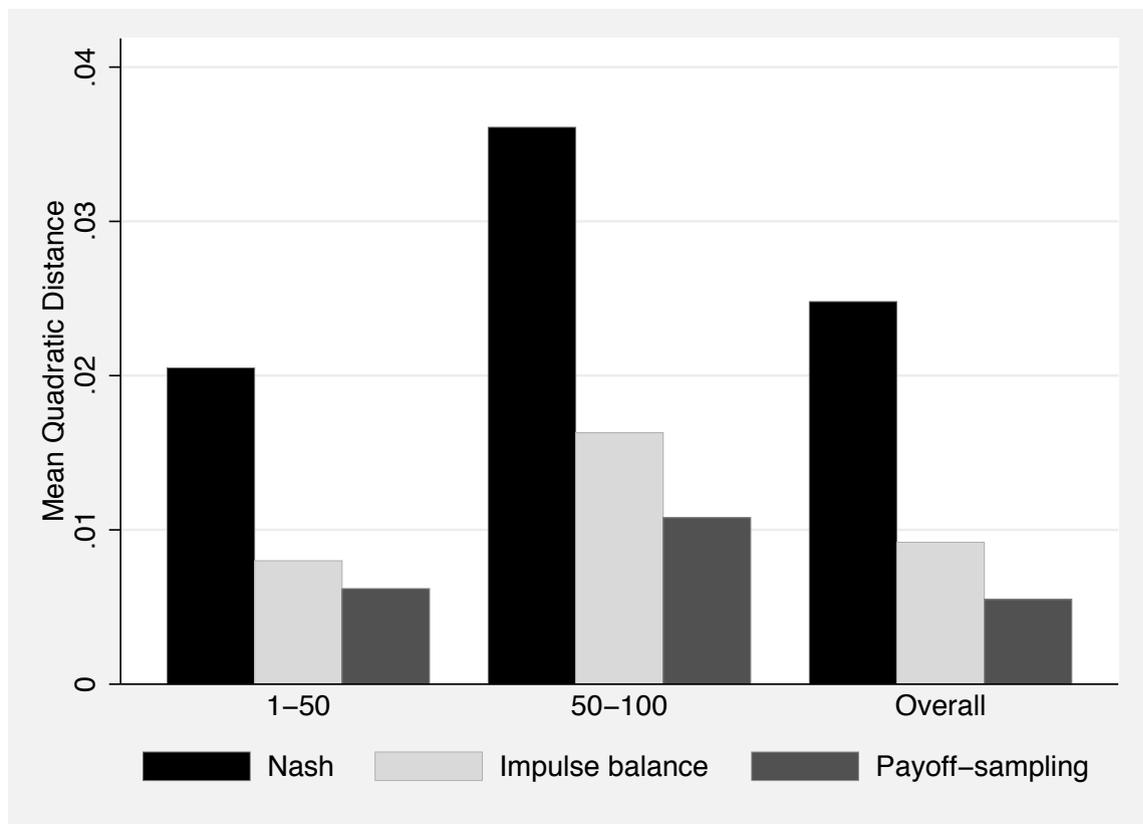


Figure IV.7: Quadratic distances to the data for the first 50 decisions, the second 50 decisions, and overall

The mean quadratic distance of all three concepts increases over time. The increase of the quadratic distance over time of impulse-balance equilibrium and the payoff-sampling equilibrium is not significant, neither for one of the two games nor for all 22 observations (Wilcoxon signed-rank test). The declined predictive success over time of the Nash equilibrium is neither significant over all games and in Game A,¹² but in Game B it is weakly significant ($p=0.1$, two-sided Wilcoxon signed-rank test).

¹²In fact, the quadratic distance of the Nash equilibrium decreases over time in Game A, but it is only a minor effect and not statically robust.

The increased quadratic distances of the three stationary concepts to the experimental data is at least partly caused by an inertia. The number of strategy changes between periods decreases over time. For the first 50 decisions in Game A 25.97% (Game B 22.67%) of the chosen action differed from the round before. In the second 50 decisions this fraction dropped in Game A to 19.18% (Game B 13.39%). There is only one independent observation group in Game A and two in Game B in which the number of strategy changes increases over time. Overall, there are significantly less changes of actions in the second half of the game ($p < 0.01$, two-sided Wilcoxon signed-rank test).

We now turn our attention to the comparison between the three concepts over time. Table IV.4 shows the two-sided significances of the Wilcoxon signed-rank test in favor of the row concept. The first value in a cell is the level of significance in the first 50 decisions and the second value is the level of significance in the second 50 decisions.

	Nash equilibrium	Impulse balance equilibrium
Payoff-sampling equilibrium	0.005 0.001	n.s. 0.05
Impulse-balance equilibrium	0.025 0.01	-

Table IV.4: p-values of the two-sided Wilcoxon signed-rank test with the quadratic distances of the data in rounds 1-50 (top) and rounds 51-100 (bottom) in favor of the row concept

Comparing the behavioral concepts with the Nash equilibrium, the significance levels are a little bit weaker in the first 50 decisions than in the second, but tendencies are the same as in the overall comparison. The prediction of the Nash equilibrium has a significantly weaker predictive success than the predictions of impulse-balance equilibrium and of the payoff-sampling equilibrium. No significant difference can be found for the comparison of the predictive success of impulse-balance equilibrium and payoff-sampling equilibrium for the first 50 rounds. Over time the difference

between higher predictive success of the payoff-sampling equilibrium in comparison to the one of impulse-balance equilibrium becomes significant.

IV.E.4 Convergence to Pure Strategies?

Altogether, 7 out of 66 subjects in Game A and 6 out of 66 subjects in Game B always entered the market. If only the last 50 decisions are analyzed, the number of participants who always entered the market increases to 18 participants in Game A and 15 in Game B.

In the above analysis we compared the mean entrance frequencies with the prediction of the three concepts in mixed strategies. However, there are also further asymmetric equilibria in pure strategies. In these equilibria one player always enters an occupied market whereas the other never does. Of course at equilibrium the first type of player never gets an opportunity to enter an occupied market but nevertheless it is his strategy to do this if he can. In our experimental setup coordination at an asymmetric pure equilibrium is possible, since one type of players decides to enter a market or not in odd periods and the other one in even periods.

As mentioned there exist a remarkable portion of players who always enter the market, but the number of players who never enter is extremely small. Over all periods there is no single player who never entered an occupied market and for the last 50 decisions only 1 player in Game A and 3 players in Game B did so. Not enough players choose such low entry rates that the predictive power of the pure-strategy equilibria can compete with the mixed Nash equilibria, mixed impulse-balance equilibria and the mixed payoff-sampling equilibria. But nevertheless it is quite possible that learning processes produce a tendency towards a coordination at an asymmetric pure equilibrium. In the following we shall argue that a tendency in this direction can be observed in our data and that eventually in longer experiments this process might lead to the pure-strategy equilibria.

The decrease of changes, as discussed in the previous section, might be a sign for a convergence towards the pure-strategy equilibria, in which one player type always

enters an occupied market and the other one never does. Of course it cannot be predicted how the roles in the asymmetric equilibria will be distributed to the players deciding in odd and even rounds. However, we can compare the relative frequencies of entries into occupied markets for players deciding in odd and even periods in the first 50 and the second 50 decisions. Therefore we form the quadratic distance between the entrance rates in even and odd periods. Table IV.5 gives these quadratic distances for the first and second 50 rounds per observation and game.

Observation	Game A		Game B	
	1-50	51-100	1-50	51-100
1	0.0007	0.0067	0.0536	0.6834
2	0.0002	0.1444	0.3155	0.8711
3	0.0097	0.0940	0.0678	0.2008
4	0.0025	0.1182	0.3642	0.6765
5	0.0125	0.0072	0.1326	0.4799
6	0.0465	0.1764	0.0518	0.0700
7	0.0312	0.0933	0.0360	0.3202
8	0.1044	0.0614	0.0526	0.1729
9	0.0021	0.0982	0.2136	0.0209
10	0.0044	0.0281	0.3141	0.3184
11	0.0405	0.0058	0.0463	0.2872
Mean	0.0231	0.0758	0.1498	0.3728

Table IV.5: Quadratic distance between entry in odd and even periods

In 18 of the 22 observations the quadratic distance of entries in odd and even rounds increased over time, as the mean distance over all observations did. A tendency towards coordination to a pure-strategy equilibrium would lead to such an increase. The two-sided Wilcoxon signed-rank test between the quadratic distances in the first and second 50 decisions over both games reveals a highly significant difference with $p = 0.002$.

One realizes that the quadratic distances between even and odd rounds are higher in Game B than in Game A. Recall that in Game B, not entering an occupied market is more attractive than in Game A and therefore results in lower entry rates. Lower entry rates in case of an occupied market enhance the coordination and the crowding

out of potential entrants, respectively. Nevertheless, in both games the tendencies are the same and statistically significant (Game A: $p = 0.04$; Game B: $p = 0.01$, both two-sided Wilcoxon signed-rank test).

IV.F Summary and Discussion

In this paper three stationary concepts, namely mixed Nash equilibrium, impulse-balance equilibrium, and payoff-sampling equilibrium, have been compared in an experimental setting. The three stationary concepts had to describe the cumulated behavior in two market entry games, which were based on the structure of a cyclic game introduced by Selten & Wooders (2001).

Altogether 22 independent subject groups, eleven per game, participated in the experiment. Each independent subject group consisted of 6 participants, three deciding in odd rounds and three deciding in even rounds. Each subject group played over 200 rounds with random matching. In the case of an empty market all three theories predicted entry and nearly all participants acted accordingly.

In the case of an occupied market the three stationary concepts predict different probabilities for entry. We used the mean squared distance between predicted and observed frequencies as the measurement of the predictive success of a theory. The comparison of the mean squared distances reveals the following order, from best to worst: payoff-sampling equilibrium, impulse-balance equilibrium and mixed Nash equilibrium. Pairwise testing shows that this order is statistically robust.

In addition to the mixed equilibrium the game also has two pure equilibria, in which players deciding in odd periods always enter and those deciding in even periods never enter, or vice versa. We observe a weak tendency towards these equilibria, as the quadratic distance between the relative frequencies of entering in odd and even periods is significantly higher in the second half of the experiment than in the first one.

A further sign for this tendency is the number of strategy changes, which decreases significantly over time. This inertia leads to a decreasing predictive success of the

three stationary concepts over time. For the second 50 decisions payoff-sampling equilibrium performs significantly better than impulse-balance equilibrium. This is connected to the inertia and a pronounced drop of the entry rates in Game B, in which payoff-sampling equilibrium predicts the lowest entry rates.

Nevertheless, the observed frequencies are far from those predicted by the pure equilibria and all mixed stationary concepts describe the data more accurately than the pure-strategy equilibria. Our findings give support to the results of Selten & Chmura (2008) where impulse-balance equilibrium and payoff-sampling equilibrium outperformed the mixed Nash equilibrium. In contrast to Selten & Chmura (2008) payoff-sampling performs significantly better in our cyclic duopoly game than impulse-balance equilibrium.

A plausible reason for this result might be the sequential move structure, which makes the calculations of impulses for the case of not entering a market not as intuitive as the general calculation of impulses in the 2×2 games. A player never experiences an impulse, if he does not enter. In this case only hypothetical impulses can be constructed on the basis of the idea that the other player follows the same decision process as one does oneself. Therefore the partial lack of feedback makes impulse-balance theory less applicable to cyclic games. While the calculation of impulses is no longer as intuitive as for the 2×2 games, the drawing of payoff-samples is not affected by the sequential move structure. Therefore payoff-sampling equilibrium might be the favorable approach to games with sequential moves. This line of reasoning is supported by our observations from Game A, in which payoff-sampling equilibrium performed significantly better than impulse-balance equilibrium for all sample-sizes $n > 2$.

A second reason for the better performance of payoff-sampling might be the parameter of the sample sizes, which represents the detailedness of, or the effort for, the underlying process of memorization. The free parameter might work in favor of the payoff-sampling equilibrium. This thesis is supported by our overall comparison and by the fact that over both games, payoff-sampling equilibrium performed significantly better with only one third of the investigated sample sizes than impulse

balance equilibrium.

Besides this, the question arises why the models with bounded rationality outperform the concept of Nash equilibrium. While it is known that learning dynamics based on Bayesian updating might lead to a Nash equilibrium (e.g., Kalai and Lehrer, 1993) it is by no means clear that actual human learning mechanisms must converge to Nash equilibrium. Our results suggest that at least for the short term of 200 rounds human learning processes approach different points.¹³

We believe that our results might enrich various economic fields working with stationary concepts to describe, for example, the behavior of market participants, the behavior in industrial organizations, the behavior in binary decisions and the behavior in bargaining situations. After all, behavioral stationary concepts might give models a higher accuracy in describing the distribution of human behavior.

¹³Of course, stationary concepts are not the optimal approach to individual period-by-period behavior, but the underlying ideas of impulse-balance equilibrium and payoff-sampling equilibrium contain precise descriptions of behavior. Therefore they are predestined to be used as the basis of learning models. Further studies should investigate whether those learning models are able to capture subjects' tendency towards the equilibria in pure strategies.

Chapter V

Learning in experimental 2×2 games

V.A Introduction

It is known that rational learning, in the sense of Bayesian updating, leads to the stationary points of the Nash equilibrium (e.g. Kalai and Lehrer, 1993). But it also known that actual human behavior not necessarily converges to Nash equilibrium. In fact, a vast body of literature indicates situations in which standard theory performs not as a good predictor for subjects' behavior in experiments (e.g. Brown & Rosenthal, 1990, Erev & Roth, 1998).

A recent publication by Selten & Chmura (2008) documents the predominance of behavioral stationary concepts regarding the descriptive power . In the paper the concepts of impulse balance equilibrium (Selten & Chmura, 2008), payoff-sampling equilibrium (Osborne & Rubinstein, 1998) and action-sampling equilibrium (Selten & Chmura, 2008) outperform Nash equilibrium in describing the decisions of a population in twelve completely mixed 2×2 games. Moreover, payoff-sampling equilibrium and action-sampling equilibrium perform better than quantal response equilibrium (McKelvey & Palfrey, 1995) does. In addition does the parameter-free concept of impulse-balance equilibrium perform equally well as the parametric concept of quantal response equilibrium does.¹

The three behavioral stationary concepts of action-sampling equilibrium, payoff-sampling equilibrium and impulse balance equilibrium yield precise predictions of

¹For further discussions please refer to Brunner, Camerer & Goeree (2010) and Selten, Chmura & Goerg (2010).

stationary behavior. Presumably stationary behavior is a result of a learning process converging to a stationary distribution of actions for both players which is not necessarily Nash equilibrium. It suggests itself to construct and to test simple learning models with the predicted stationary states of the three concepts.

The main purpose of this chapter is to introduce four new learning models which are based on the behavioral reasoning of payoff-sampling equilibrium, action-sampling equilibrium and impulse balance equilibrium and test them in the environment of twelve repeated 2×2 games. Hereby, the learning rules have to meet two challenges: First, do they reproduce the aggregate behavior of a human population and second do they adequately describe the observed behavior of a single individual? For comparison we include the models of reinforcement learning (Erev & Roth, 1998) and self-tuning experience weighted attraction learning (EWA) (Ho, Camerer & Chong, 2007) into our study.

We conduct simulations with the learning models and the twelve 2×2 games experimentally investigated in Selten & Chmura (2008). The simulations replicate the exact situation of the 2×2 experiments. In each simulation run, eight agents, four deciding as row players and four deciding as column players, are randomly matched each round over 200 rounds. In each simulation run one game is played and one learning model is applied. To judge the predictive power on the aggregate level we compare the distribution of choices in the simulation runs with the data from Selten's & Chmura's 2×2 experiments.

In addition we evaluate the explanatory power of the learning models for each participant of the 2×2 experiments, separately. For each of the 864 subjects we compared the actual decision in every round with the decision predicted by the learning model given the subject's history. To judge the power of the learning models we introduce a benchmark which all learning models should beat. This benchmark is the inertia rule, which predicts for each round the same choice as executed in the round before.

Our results are twofold, while our newly introduced models are able to capture the distribution of decisions on the aggregate level much better than self-tuning EWA

does, self-tuning EWA describes the individual data in a more accurate way. On the aggregate level the learning models of impulse matching learning and action-sampling learning have the smallest distance to the experimental data, while the concepts of self-tuning EWA and reinforcement learning have biggest ones. On the individual level self-tuning EWA and impulse-matching have the highest scores.

The rest of the chapter is organized as follows: In section II we will introduce the models impulse balance learning, impulse matching learning, action-sampling learning and payoff-sampling learning. In addition we will briefly deal with reinforcement learning and self-tuning EWA. Afterwards, in section III, we will recapitulate the experiment conducted in Selten & Chmura and introduce our measurements of predictive success for the aggregate data and for the individual data. Subsequently, section IV gives our results and section V summarizes and concludes the chapter.

V.B The Learning Models

In this section we will introduce four new learning models, which are based on the behavioral stationary concepts discussed in Selten & Chmura (2008). The concepts to be introduced are: impulse balance learning, impulse matching learning, action-sampling learning and payoff-sampling learning. In addition to the new learning models, the more established concepts of reinforcement learning (c.p. Erev & Roth, 1998) and self-tuning EWA (Ho, Camerer & Chong, 2007) are briefly explained.

Three of the discussed models, namely action-sampling learning, payoff-sampling learning and self-tuning EWA are parametric concepts. In case of action sample learning and payoff sample learning the parameter is the sample size. Self-tuning EWA is based on the multi-parametric concept of experience weighted attraction learning (Camerer & Ho, 1999). Self-tuning EWA replaces two of the parameters with numerical values and two with experience functions. The remaining "*parameter λ measures sensitivity of players to attractions*" (p. 835 Camerer & Ho, 1999). The version of reinforcement learning theory examined here does not have any parameter and the initial propensities are not estimated from the data.

For the sampling learning models we will not determine the optimal sample size, but apply the sample sizes which determined the best fit for the related stationary concepts to the data in Selten & Chmura (2008). In case of the action-sampling learning this is the action-sampling equilibrium and in case of the payoff-sampling learning this is the payoff-sampling equilibrium. The parameter of self-tuning EWA is determined in such a way that it leads to the best fit over all data and over all games.

In the literature parametric concepts are usually fitted for each game separately. We believe that this gives an unfair advantage to one-parameter theories over parameter free ones, especially in the case of 2×2 games where only two relative frequencies are predicted. Adjusting one parameter separately for each game so to speak does half the job. Therefore we base our analysis on one estimate for all games in case of the self-tuning EWA and in case of the sampling learning rules we take the parameter for the stationary concepts estimated in Selten & Chmura (2008) over all games.

V.B.1 Impulse Balance Learning

Impulse balance learning relates to the concepts of impulse balance equilibrium (Selten, Abbink & Cox 2005 and Selten & Chmura 2008) and learning direction theory (Selten & Buchta, 1999). After a decision and after the realization of the payoffs the behavior is adjusted to experience. Selten and Buchta explain the concept by the example of a marksman aiming at a trunk: *"If he misses the trunk to the right, he will shift the position of the bow to the left and if he misses the trunk to the left he will shift the position of the bow to the right. The marksman looks at his experience from the last trial and adjusts his behavior [...]."* (p. 86 Selten & Buchta, 1999).

Suppose that the first of two actions has been chosen in a period and this action was not the best reply to the action played by the other player. Then the player receives an *impulse* towards the second action. This impulse is the difference between the payoff the player could have received for his best reply minus the payoff actually

received given the decision by the other player in this period. The player does not receive an impulse if his action was a best reply against the other player's decision.

To incorporate loss aversion, the impulses are not calculated with the original payoffs but with transformed ones. In games with two pure strategies and a mixed Nash equilibrium each pure strategy has a minimal payoff and the maximum of the two minimal payoffs is called the pure strategy maximin. This pure strategy maximin is the maximal payoff a player can obtain for sure in every round and it forms a natural aspiration level. Amounts below this aspiration level are perceived as losses and amounts above this aspiration level are perceived as gains. In line with prospect theory (Kahneman & Tversky, 1979) losses are counted double in comparison to gains. Thus, gains (the part above the aspiration level) are cut to half for the computation of impulses. Figure 1 is taken from Selten & Chmura (2008) and illustrates the transformation of the payoffs by the example of game 3.

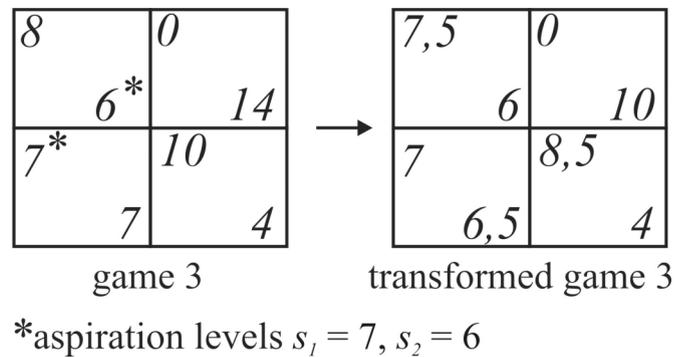


Figure V.1: Example of matrix transformation as given in Selten & Chmura (2008)

Impulse balance learning can be described as a process in which a subject builds up impulse sums. The impulse sum $R_i(t)$ is the sum of all impulses from j towards i experienced up to period $t - 1$. The probabilities for playing action 1 and 2 in period t are proportional to the impulse sums $R_1(t)$ and $R_2(t)$:

$$p_i(t) = \frac{R_i(t)}{R_1(t) + R_2(t)}, \text{ for } i = 1, 2 \quad (\text{V.1})$$

The impulses from action j towards action i in period t is as follows:

$$r_i(t) = \begin{cases} \max[0, \pi_i - \pi_j] & , \text{ if the chosen action is } j \\ 0 & \text{ else.} \end{cases} \quad (\text{V.2})$$

for $i, j = 1, 2$ and $i \neq j$. Here, π_i is the payoff for action i given the matched agents decision and π_j the one for action j . Afterwards the impulse sums are updated with the new impulses:

$$R_i(t+1) = R_i(t) + r_i(t) \quad (\text{V.3})$$

In the first round all impulse sums are zero $R_1(1) = R_2(1) = 0$ and until both impulse sums are higher than zero the probabilities are fixed to $p_1(t) = p_2(t) = 0.5$.

V.B.2 Impulse Matching Learning

This learning model is very similar to impulse balance learning. In fact, in our 2×2 setting the resulting stationary point of impulse matching learning is the same as of impulse balance learning. But for other types of games both concepts do not necessarily lead to the same stationary points.² Therefore we treat the impulse matching learning as a self contained model. As in the case for the impulse balance learning impulse matching learning is applied to the transformed matrix, described in section A.

The idea of an impulse is different in impulse matching. Here it is assumed that after a play a player always receives an impulse to his ex-post optimal strategy, the best reply to the pure strategy chosen by the other player. Thus an impulse from j towards i is defined as a payoff differences, regardless of the player's own action. This means that (V.2) has to be replaced by the equation (V.2).

$$r_i(t) = \max[0, \pi_i - \pi_j] \quad (\text{V.2})$$

The equation (B.1.) and (B.3.) are identically to (V.1) and (V.3) respectively. As before π_i is the payoff of action i and π_j is the payoff of action j given the matched

²For a formal illustration of this point refer to the Appendix.

player's decision.

The name impulse matching is due to the fact that this kind of learning leads to probability matching by player one if the probabilities p_1 and $(1 - p_1)$ on the other side are fixed and the payoffs for the player is one if both players play the strategy with the same number (one or two) and zero otherwise. Probability matching has been observed in early learning experiments, e.g. Estes (1954).

V.B.3 Payoff-Sampling Learning

Payoff-sampling learning relates to the stationary concept of Osborne & Rubinstein (1998) which was first applied to experimental data in Selten & Chmura (2008). The behavioral explanation of the stationary concept is that a player chooses her action after sampling each alternative an equal number of times, picking the action that yields the highest payoff.

To implement this behavior payoff-sampling learning is based on samples from earlier periods. The samples are randomly drawn with replacement and a fixed sample sizes of $n = 6$.³ The agent draws two samples $(s_1(t), s_2(t))$ of earlier payoffs, one sample with payoffs from rounds in which she chose action 1 and one with payoffs from rounds in which she chose action 2. In the following $S_1(t)$ and $S_2(t)$ denote the payoff sums in $s_1(t)$ and $s_2(t)$, respectively.

After the drawing of the samples, the cumulated payoffs $S_1(t)$ and $S_2(t)$ are calculated and the action with the higher cumulated payoff is played, if there is one. If the samples of both possible actions have the same cumulated payoff the agent randomizes with $p_1 = p_2 = 0.5$.

$$p_i(t) = \begin{cases} 1 & \text{if } S_i(t) > S_j(t) \\ 0.5 & \text{if } S_i(t) = S_j(t) \\ 0 & \text{else} \end{cases} \quad (\text{V.3})$$

³Recall that $n = 6$ leads to the optimal fit for the payoff-sampling equilibrium to the experimental data in Selten & Chmura (2008).

for $i, j = 1, 2$ and $i \neq j$.

As before $p_i(t)$ is the probability of playing action i in period t . At the beginning and until positive payoffs for each action have been obtained at least once, the agent chooses both actions with equal probabilities, i.e. $p_1 = p_2 = 0.5$.

V.B.4 Action-Sampling Learning

Action-sampling learning relates to the idea of the action-sampling equilibrium of Selten & Chmura (2008). According to action-sampling equilibrium a player takes in the stationary state a fixed size sample of the pure strategies played by the other players in the past and optimizes against this sample.

In the process of action-sampling learning the agent randomly takes a sample $A(t)$ with replacement of n earlier actions a_1, \dots, a_n of the other player. In the following we are keeping n fixed to 12.⁴ Let $\pi_i(a_j)$ be the payoff of action i if the opponent plays action a_j . For $i = 1, 2$ let $P_i(t) = \sum_{j=1}^7 \pi_i(a_j)$ be the sum of all payoffs of the player for using her action i against the actions in this sample.

Therefore, in period t the player chooses her action 1 or 2 according to

$$p_i(t) = \begin{cases} 1 & \text{if } P_i(t) > P_j(t) \\ 0.5 & \text{if } P_i(t) = P_j(t) \\ 0 & \text{else} \end{cases} \quad (\text{V.4})$$

for $i, j = 1, 2$ and $i \neq j$.

At the beginning the probabilities are set to $p_1 = p_2 = 0.5$ until both possible actions were played by the opponent agents.

⁴As mentioned above $n = 12$ leads to the highest fit of the action-sampling equilibrium to the data in Selten & Chmura (2008). There was an error in the calculation of the optimal sample-size in the original paper by Selten & Chmura, which yielded a sample-size of $n = 7$. For a detailed discussion refer to Brunner, Camerer & Goeree (2010) and Selten, Chmura & Goerg (2010).

V.B.5 Reinforcement Learning

The reinforcement learning is one of the oldest and well established learning models in the literature, refer to Harley (1981) for an early application in the field of theoretical biology.

In our reinforcement model a player builds up a payoff sum $B_i(t)$ for each of his actions 1 and 2 according to the following formula:

$$B_i(t+1) = \begin{cases} B_i(t) + \pi(t) & \text{if action } i \text{ was chosen in } t \\ B_i(t) & \text{else.} \end{cases} \quad (\text{V.5})$$

Here $\pi(t)$ is the payoff obtained in period t . After an initial phase in which both possible actions are used with equal probabilities the probability of choosing action i in period t is given by:

$$p_i(t) = \frac{B_i(t)}{B_1(t) + B_2(t)} \quad (\text{V.6})$$

This model presupposes that all payoffs in a player's payoff matrix are positive with the possible exception of one. All twelve games considered here have this property. In the first round the initial payoff sums $B_i(t)$ are zero. The initial phase ends as soon as each of both possible actions has been used at least once. The player chooses both possible actions with equal probabilities $p_1 = p_2 = .5$. Only from then on rule V.6 is applied.

For games with negative payoffs this approach is not adequate. For example in the model used by Erev & Roth (1998) the payoff $\pi(t)$ in E.1 was replaced by $\pi(t) - \pi_{\min}$, where π_{\min} is the smallest possible payoff of the player. Moreover they estimated initial values $B_i(0)$ from the data. We did not do this since we are only interested in models with at most one parameter.

V.B.6 Self-Tuning EWA

Self-tuning EWA was introduced by Ho, Camerer & Chong. It is based on the experience weighted attraction model, but estimates the parameter of this model with several functions. Of all models discussed in the chapter at hand, self-tuning EWA is the most complex one.

The decisions are made according to *attractions* $A_i(t)$ for each strategy. The attractions depend on an experience weight, a change-detector function and an attention function. For more details on the attraction updating function refer to the appendix.

The probability of playing action i in period t depending on the attractions is calculated as a logit response function:

$$p_i(t) = \frac{e^{\lambda A_i(t-1)}}{\sum_{j=1}^2 e^{\lambda A_j(t-1)}}$$

Here, λ is the response sensitivity and this parameter must be specified to fit to the empirical data. We searched for one λ to yield the best fit over all 12 games. Our measurement of the predictive success is the quadratic distance Q , which will be explained in more detail in the next chapter. Figure V.2 gives the quadratic distance for the different values of lambda.

Each point in the graph represents the mean quadratic distance over all twelve games with 500 simulations runs per game with one specific lambda value. The value leading to the smallest quadratic distance is $\lambda = 0.28$.

To be consistent with the other models we have chosen not to estimate any additional values. Therefore the initial attractions were set to $A_1 = A_2 = 0$.

V.C Design

V.C.1 Games and Experiments

The experimental data, which are compared with the simulations, are those on which the paper by Selten & Chmura (2008) is based. In their study twelve 2×2 games

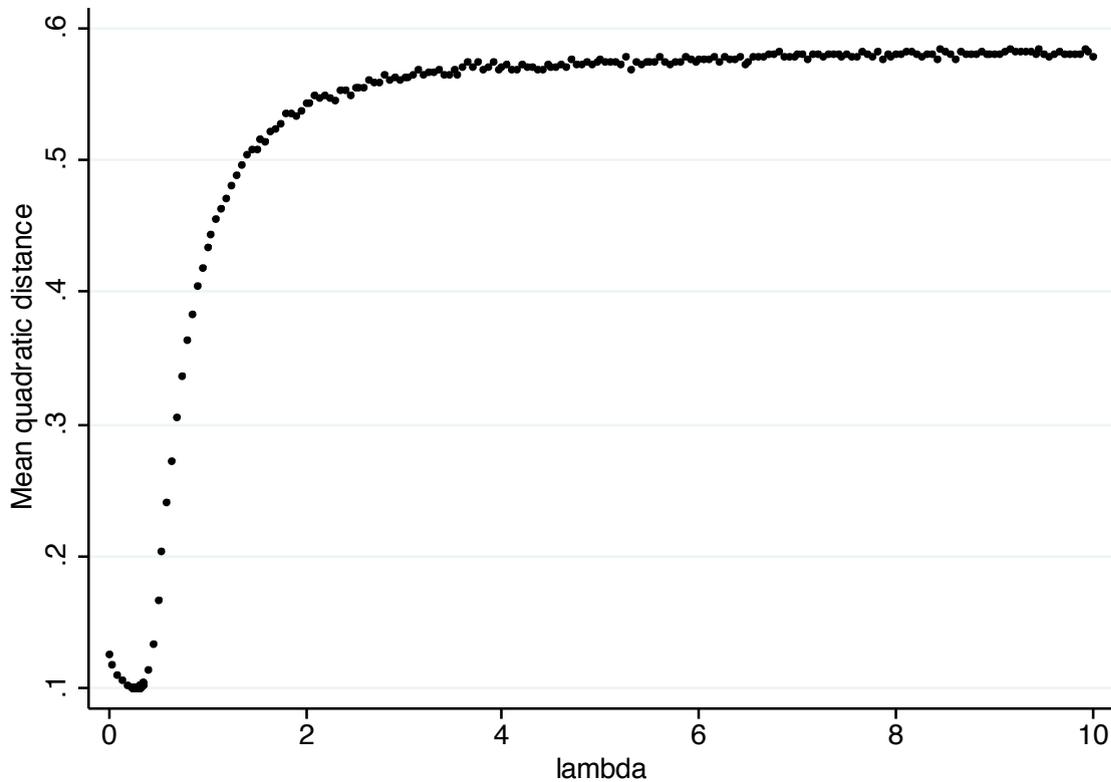


Figure V.2: Quadratic distances of self-tuning EWA for different lambdas, each point represents the mean quadratic distance over 500 simulations.

were experimentally investigated. To cover a broad field of games, six constant and six non-constant sum games were played. Figure C.5 shows the twelve games used in the experiment. The constant sum games are shown on the left side of the figure and the non-constant sum games on the right side.

Note that the first six games have the same best response structure as the second six games and that the concepts of action-sampling equilibrium and Nash equilibrium only depend on this best response structure. Thus the predictions of Nash equilibrium are the same for the first and the second six games. The same holds true for the action-sampling equilibrium.

Each game was played by matching groups consisting out of eight subjects. The role of the subjects were fixed for the whole experiment, thus four subjects decided as column players and the other four as row players. At the beginning of each round row and column players were randomly matched. After each of the 200 rounds subjects received feedback about the other player's decision, their own payoff, the

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The payoffs for the column-players are shown in the lower right corner, the payoff for the row-players are shown in the upper left corner.
Abbreviations used: L Left, R Right, U Up, D Down

Figure V.3: The twelve 2×2 -games taken from Selten & Chmura (2008).

period number and their own cumulative payoff. The game played was known by all subjects.

For each constant sum game twelve independent matching groups were gathered, for each non-constant sum game six independent matching groups were gathered. Overall 864 subjects participated.

The main goal of the present chapter is to find learning algorithms which can replicate the human behavior in this twelve games. To evaluate this problem we compare the simulations with the experiments on the aggregate level and on the individual basis.

V.C.2 Measure of Predictive Success on the Aggregate Level

On the aggregate level everything is kept the same as in the experiment except that instead of real participants now computer agents interact. Each agent interacts according to her history and to one learning model over 200 rounds. In each round eight agents with fixed roles, four deciding as row players and four as column players are randomly matched.

After each round they receive feedback about the matched agent's decision and their payoff. Since none of the learning models makes use of the round number and since the calculation of the cumulated payoff can be done by the agents themselves this information is not provided to the agents. It is crucial that the agents do not receive more information than the subjects in the experiment did.

All learning models include stochastic elements. To avoid the influence of statistical outliers 500 simulation runs per game are conducted. In each simulation run all agents act in accordance with one learning model, thus our data set obtained by the simulations consists out of 500 simulations per game and learning model.

To measure the predictive success on the aggregate basis, we will compare the mean frequencies of U and L in the simulations with the mean frequencies obtained in the experiments by means of the quadratic distance.

The mean quadratic distance Q is the average quadratic distance over all 12 games and over all 500 simulations for each of these

$$Q = \frac{1}{12} \sum_{i=1}^{12} \left(\frac{1}{500} \sum_{n=1}^{500} (s_{in}^L - f_i^L)^2 + (s_{in}^U - f_i^U)^2 \right),$$

whereas s_{in} is the frequency for L or U in game i and simulation run n and f_i the mean frequency for L or U observed in the experiments with game number i .

The predictive success of a learning model increases with a decrease of the mean quadratic distance, i.e. the smaller the mean quadratic distance is the better does the learning theory fit the experimental data on the aggregate level.

V.C.3 Measure of Predictive Success on the Individual Level

To judge the performance on the individual level we compare the individual decisions in every round with the predicted decisions or predicted probability by the learning rule, given the history of the subject.

To measure the predictive success of the learning theories describing the behavior of a single individual we apply the quadratic scoring rule. It was first introduced by Brier (1950) in the context of weather forecasting. The rationale behind the quadratic scoring rule is that for each round a score is determined which evaluates the nearness of the predicted probability distribution to the observed outcome.

In Selten (1998) the quadratic scoring rule is axiomatically characterized. The characterizing properties of the quadratic scoring rule as described in Selten (1998) are: symmetry, elongational invariance, incentive compatibility and neutrality. Symmetry means that the score of a theory must not depend on the numbering on the names of the decision alternatives. Elongational invariance assures that the score of a theory is not influenced by adding or leaving an alternative which is predicted with a probability of zero. Incentive compatibility requires that predicting the actual probabilities yields the highest score. Finally, neutrality means that in the comparison of two theories among which one is right in the sense that it predicts the actual probabilities and the other is wrong the score for the right theory does not depend on which of the two theories is the right one. This means that the score does not prejudice one of the theories depending on the location of the theory in the space of probability distribution.

We apply the quadratic scoring rule to measure the predictive success of a theory for every period and subject separately and then add up over subjects, rounds and games. Accordingly a score depending on the predicted probabilities and the actually observed action is computed. In order to compute the score the observation is interpreted as a frequency distribution where for the chosen action the relative frequency is one and for the not chosen action zero. Thus the quadratic score $q(t)$ of a learning theory for subject choosing action i in period t is given as:

$$q(t) = 2p_i(t) - p_i(t)^2 - (1 - p_i(t))^2$$

Here $p_i(i)$ is the predicted probability of the learning theory. The predicted probability of the learning theory is calculated by applying the theory's learning algorithm on the whole playing history of this player. If no history is available we assume that the player randomizes with .5.

The concepts of action-sampling learning and payoff-sampling learning always yield probability 1, 0 or $\frac{1}{2}$ for one of the possible actions. Which action is chosen depends on the randomly drawn sample. Therefore we calculate the probability of drawing a sample that commands playing action 1 or action 2 as the predictions of these two concepts.

If a player decides completely in line with the prediction of the theory he receives a score of 1 if he decides in complete contrast to the prediction the theory he receives a score of -1 .

The mean score \bar{q} is given as the mean of $q(t)$ over all 200 rounds, 12 games and 108 subjects groups of 8 subjects each. Of course \bar{q} must be in the closed interval between -1 and $+1$.

V.D Results

In this section we will first take a look at the simulations and the experiments on the aggregate level. We will start with the relative frequencies for U and L observed in the simulations with the different learning models and compare them with the experimental data. Then we will take a closer look at the simulations and start by comparing the results obtained in the constant sum games with the results in the non-constant sum games. Afterwards we will investigate how the learning models perform in the original matrices and in the transformed matrices. Thereafter we will compare the overall mean quadratic distances to the experimental data. We will conclude our examination on the aggregate level by testing the robustness of

the overall result over time and therefore compare the performance of the learning rules in the first and second 100 rounds.

The second part of this section deals with the individual behavior. There we will check for the subjects in the 2×2 experiments how well they conform in the average to each of the learning theories.

V.D.1 Aggregate Behavior

Table V.1 gives the observed mean frequencies for each game and simulation type and as well as the observed ones in the experiments. For the experimental games 1 to 6 the mean frequency observed in a game is based on the observed frequencies in twelve independent matching groups, for games 7 to 12 it is based on the observed frequencies in six independent matching groups. Each matching group consists out of eight subjects. For each learning type and game the mean is based on 500 simulation runs, which produced 500 independent matching groups per game. Each matching group consists of eight agents.

Game		Impulse balance learning	Impulse matching learning	Action- sampling learning	Reinforce- ment learning	Payoff- sampling learning	self-tuning EWA learning	Experiment Selten & Chmura (2008)
1	L	0.416	0.574	0.710	0.345	0.746	0.499	0.690
	U	0.164	0.063	0.095	0.121	0.054	0.499	0.079
2	L	0.417	0.495	0.571	0.333	0.519	0.477	0.527
	U	0.282	0.169	0.193	0.161	0.070	0.502	0.217
3	L	0.593	0.770	0.763	0.503	0.893	0.541	0.793
	U	0.227	0.157	0.211	0.128	0.169	0.492	0.163
4	L	0.581	0.714	0.711	0.587	0.854	0.548	0.736
	U	0.309	0.259	0.295	0.190	0.312	0.494	0.286
5	L	0.535	0.632	0.639	0.566	0.798	0.524	0.664
	U	0.350	0.296	0.323	0.241	0.370	0.495	0.327
6	L	0.540	0.602	0.596	0.666	0.767	0.527	0.596
	U	0.419	0.400	0.422	0.265	0.466	0.497	0.445
7	L	0.475	0.637	0.709	0.380	0.781	0.564	0.564
	U	0.198	0.098	0.094	0.170	0.099	0.485	0.141
8	L	0.485	0.563	0.572	0.396	0.753	0.540	0.586
	U	0.336	0.258	0.193	0.217	0.287	0.494	0.250
9	L	0.601	0.767	0.762	0.525	0.862	0.600	0.827
	U	0.248	0.185	0.212	0.165	0.177	0.489	0.254
10	L	0.602	0.726	0.711	0.640	0.852	0.587	0.699
	U	0.335	0.303	0.295	0.219	0.309	0.487	0.366
11	L	0.560	0.648	0.640	0.609	0.790	0.572	0.652
	U	0.382	0.354	0.324	0.289	0.369	0.492	0.331
12	L	0.557	0.605	0.596	0.560	0.623	0.578	0.604
	U	0.459	0.466	0.422	0.342	0.595	0.494	0.439

Table V.1: Relative frequencies observed in simulations and experiments for Up and Left

As mentioned before games 1 to 6 and games 7 to 12 have the same best response structure. The concept of action-sampling equilibrium depends only on this structure and therefore leads in Selten & Chmura to the same predictions in the constant and an non-constant sum games. Since action-sampling learning is based on best replies, it does not surprise, that the frequencies in the simulations with games 1-6 are very similar to those with games 7-12. For all other learning models different frequencies are observed in the constant and non-constant sum games.

It is surprising that self-tuning EWA yields relative frequencies very near to .5 for each of the twelve games. This is probably connected to the fact, that we estimate the free parameter of this model jointly for all games. However as we have already pointed out estimating parameters for each game separately would not be adequate.

V.D.1.1 Constant Sum and Non-Constant Sum Games

Table V.1 shows that the behavior of the subjects in the experiments differ in the constant (games 1 - 6) and non-constant sum games (games 7 - 12). Therefore, we will start comparing the predictive success of the learning models in constant and non-constant sum games. Figure V.4 gives the mean quadratic distance in constant and non-constant games for each learning theory.

The models of self-tuning EWA, reinforcement learning and impulse balance learning perform much better in the non-constant sum games. The concept of impulse matching learning performs slightly better in the non-constant sum games. In contrast, the two learning rules relying on samples, namely action-sampling learning and payoff-sampling learning, perform better in the constant sum games.

V.D.1.2 Original Versus Transformed Games

The concepts of impulse balance learning and impulse matching learning are applied to the transformed game rather than the original one. But the ideas behind these concepts could also be applied directly to the original games as well as the other concepts could be applied to the transformed games. Figure V.5 shows the overall mean quadratic distances for self-tuning EWA learning, reinforcement learning,

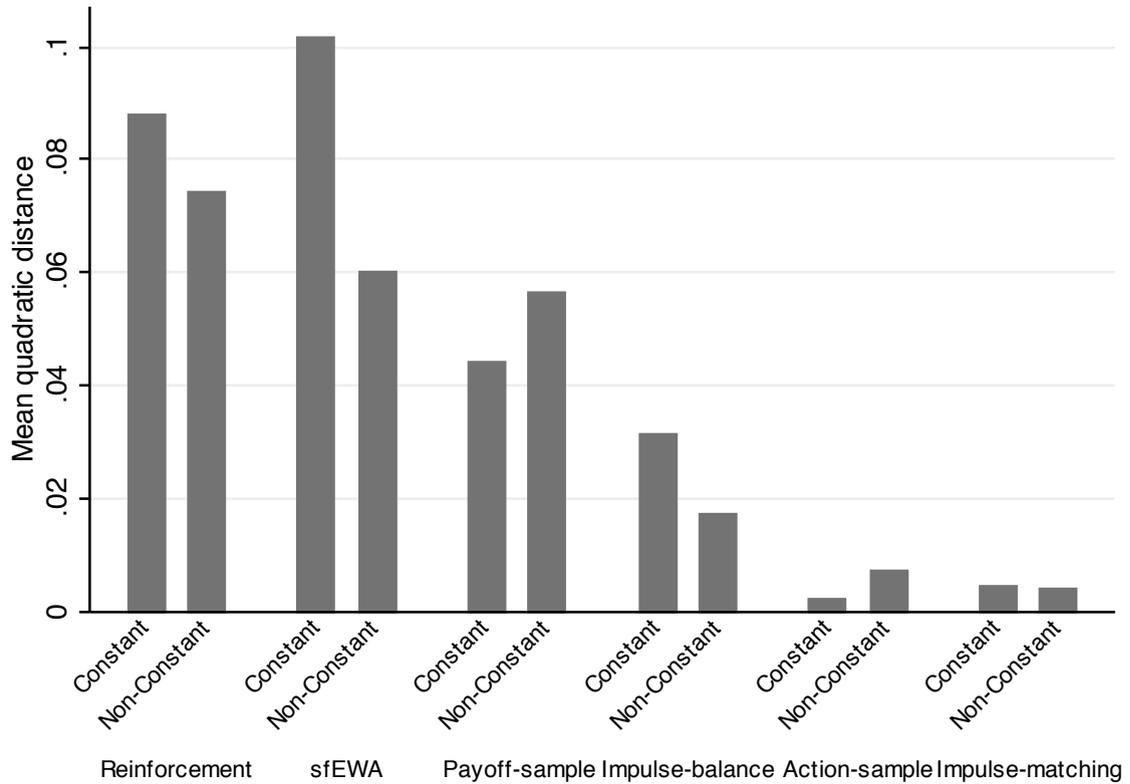


Figure V.4: Mean quadratic distance in constant and non-constant sum games

payoff-sampling learning, impulse balance learning, action-sampling learning and impulse matching learning applied to the original games and to the transformed games.

For the original as well as for the transformed matrices the results are based on 500 simulation runs per game and learning model.

It can be seen that impulse balance learning, impulse matching learning and reinforcement learning perform better when applied to the transformed games whereas self-tuning EWA learning, payoff-sampling learning and action-sampling learning do less well. While the improvement of impulse balance learning and impulse matching learning in transformed games is expected, the benefit of applying reinforcement learning to transformed games is unexpected. This improvement is substantial, in the original game the quadratic distance is 22% higher than in the transformed ones.

The theory of Roth and Erev (1998) already applies a transformation of the original

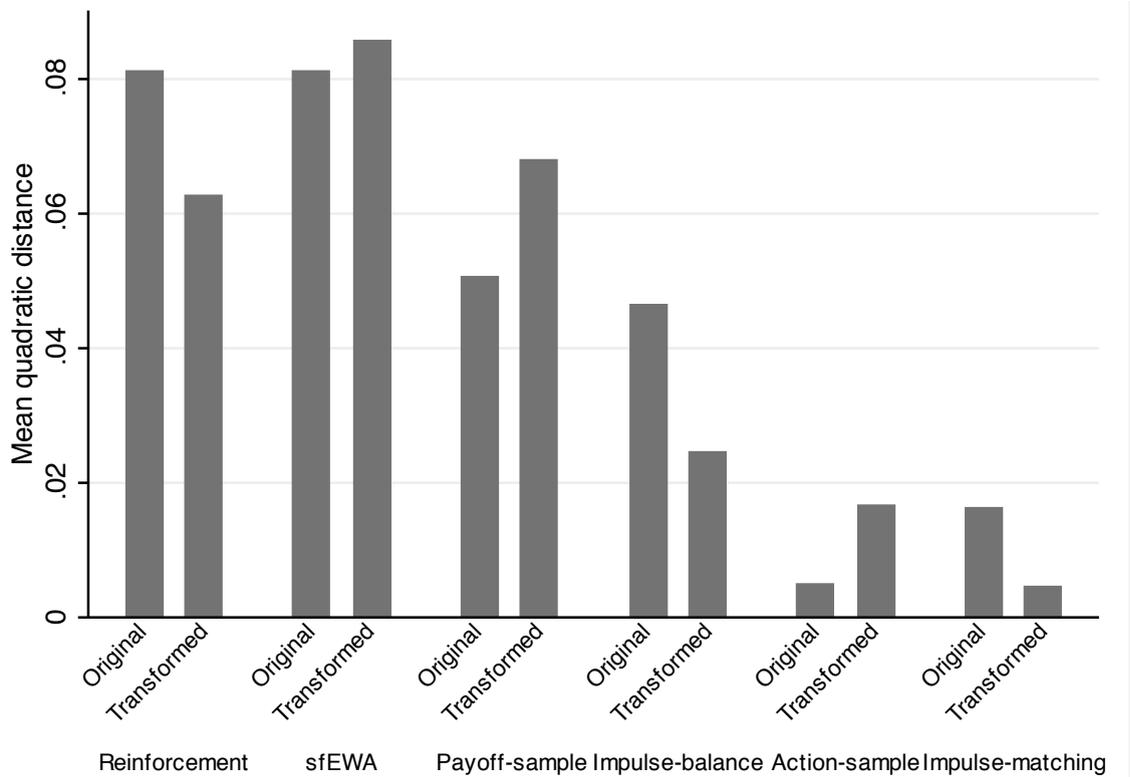


Figure V.5: Mean quadratic distance in original and transformed games

game by replacing the payoff of a player by its difference to the minimal value in her matrix. The transformation used here is different since it involves double weights for losses with respect to the pure strategy maximin. Nash equilibrium is the stationary concept corresponding to the reinforcement learning theory. However, in Selten & Chmura (2008) we did not observe an improvement of the predictive power of the Nash equilibrium applied to the transformed game rather the original one. It is interesting that the picture looks different for the simulations over 200 rounds.

V.D.1.3 Overall Comparison

Figure V.6 gives the mean of the quadratic distance between the experiment and simulations over all games and rounds for self-tuning EWA learning, reinforcement learning, payoff-sampling learning, impulse balance learning, action-sample learning and impulse matching learning.

The figure reveals an order of explanatory power. The order from worse to best

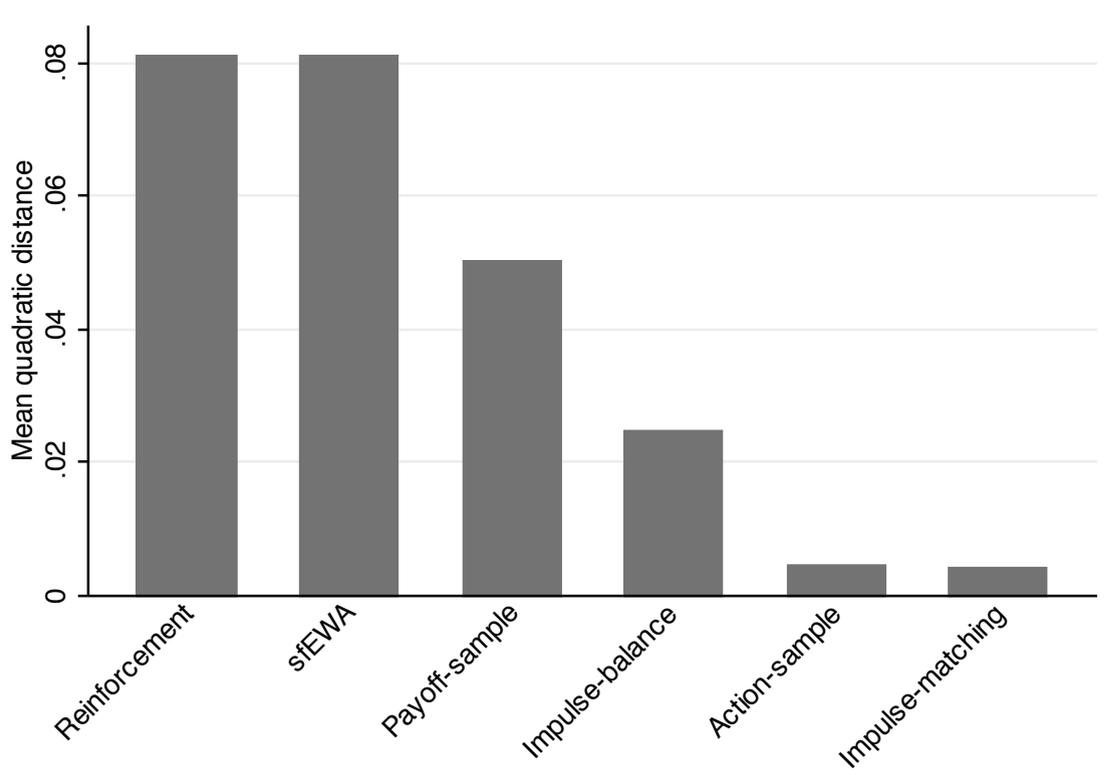


Figure V.6: Overall mean quadratic distance over all games

(highest quadratic distance to lowest quadratic distance) is as follows: reinforcement learning, self-tuning EWA learning, payoff-sampling learning, impulse balance learning, action-sampling learning and impulse matching learning.

The difference between self-tuning EWA and reinforcement is very small and irrelevant. However the small difference between the two quadratic deviations does not mean that both theories make similar predictions. This can be seen in table V.1. Recall figure V.4, which demonstrates that self-tuning EWA performs better than reinforcement learning in the non-constant sum games, while reinforcement learning performs better in the constant-sum games.

The figure demonstrates that the concepts of self-tuning EWA and reinforcement fail to describe the aggregate behavior in the 2×2 experiments in contrast to the other concepts. Out of these new concepts especially the processes of action-sampling learning and impulse matching learning lead to results which are very close to subjects' behavior. Already the concept of payoff-sampling learning has a nearly 40%

lower quadratic distance than self-tuning EWA and the quadratic distance of impulse matching is over 18 times smaller.

The order given by figure V.6 is statistically robust. Because of the high number of observations, 6000 per learning type, all differences (even the slight ones between self-tuning EWA and reinforcement) are statistically significant on a high level (for all $p < 0.001$ two-sided Man-Whitney u-test).

V.D.1.4 Changes over Time

Learning processes are always dependent on time and history and therefore it is of interest to check whether our above results remain stable over time. To check stability of the order of explanatory power over time we compare the first hundred periods with the second hundred periods. Figure V.7 gives the mean quadratic distances for periods 1-100 (left) and 101-200 (right) for the six learning models. Basis of the comparison is always the observed mean frequencies for the corresponding rounds (either round 1-100 or 101-200) in the experiments.

It is easy to recognize that in the second half of the simulation runs the explanatory power of self-tuning EWA, reinforcement learning and impulse balance learning decreases. For payoff-sampling learning and impulse matching learning the performance is improved in the second half. The concept of action-sampling learning is rather stable over time and no relevant differences are observed over time.

For all theories the quadratic distance in the first and second half of the experiment differs significantly (two-sided Wilcoxon signed-rank test $p < 0.0000$). For the negligible disimprovement of action-sampling learning the high level of significance is caused by the high number of observations.

The comparison over time confirms the order of explanatory power obtained in the overall comparison. This order is stable over all concepts.

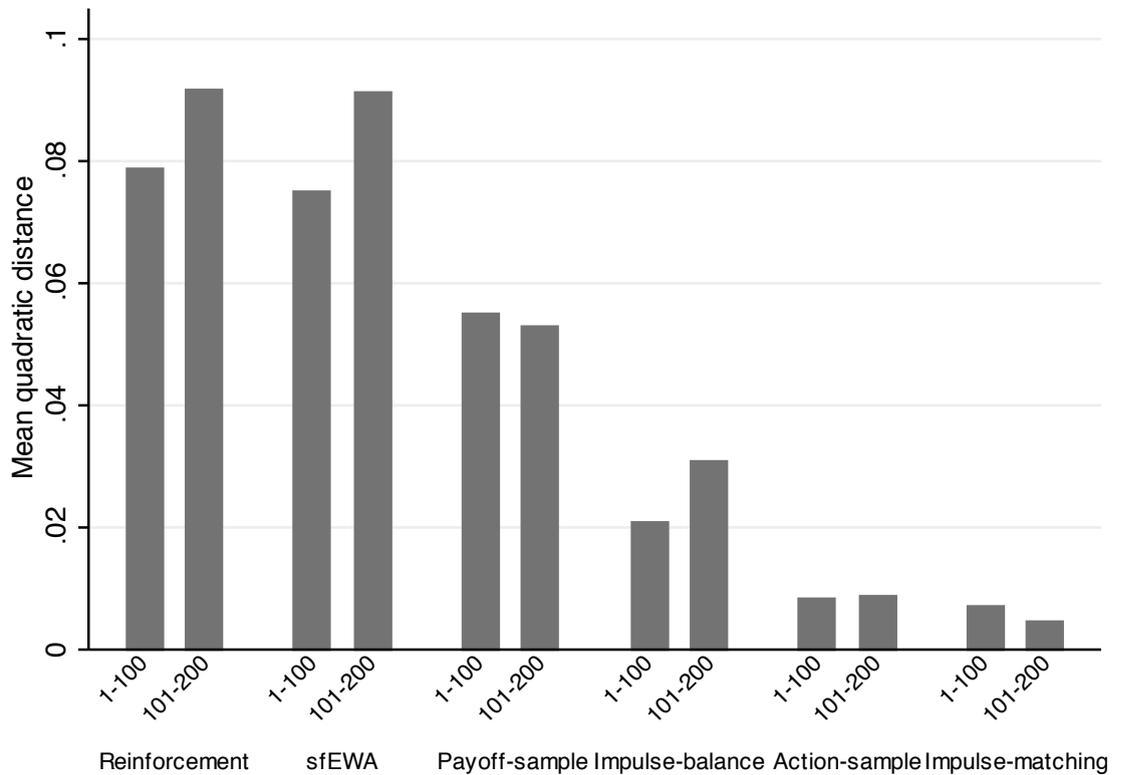


Figure V.7: Mean quadratic distance over time

V.D.1.5 Comparison with the stationary concepts

To conclude the analyses on the aggregate level the learning models are compared with their corresponding stationary concepts.

Of all learning models only impulse matching learning and action-sampling learning are quite close to their stationary counterparts after 200 periods. The quadratic distances between impulse matching learning and impulse balance equilibrium as well as between action-sampling learning and action-sampling equilibrium are smaller than 0.001. The other distances between a learning rule and the related equilibrium are much greater: impulse balance learning (0.019), payoff-sampling learning (0.048), and reinforcement learning (0.158). Self-tuning EWA has a much higher distances towards all stationary concepts.

It is striking that the order of the quadratic distance between a learning rule and its corresponding concept is exactly the same as the order of the predictive success. In other words: the lower the quadratic distance to the corresponding concept the

higher the predictive success of the learning rule as given in section V.D.1.3. A Spearman rank-correlation confirms this connection as highly significant ($\rho = 0.8418$ and $p < 0.0001$).⁵

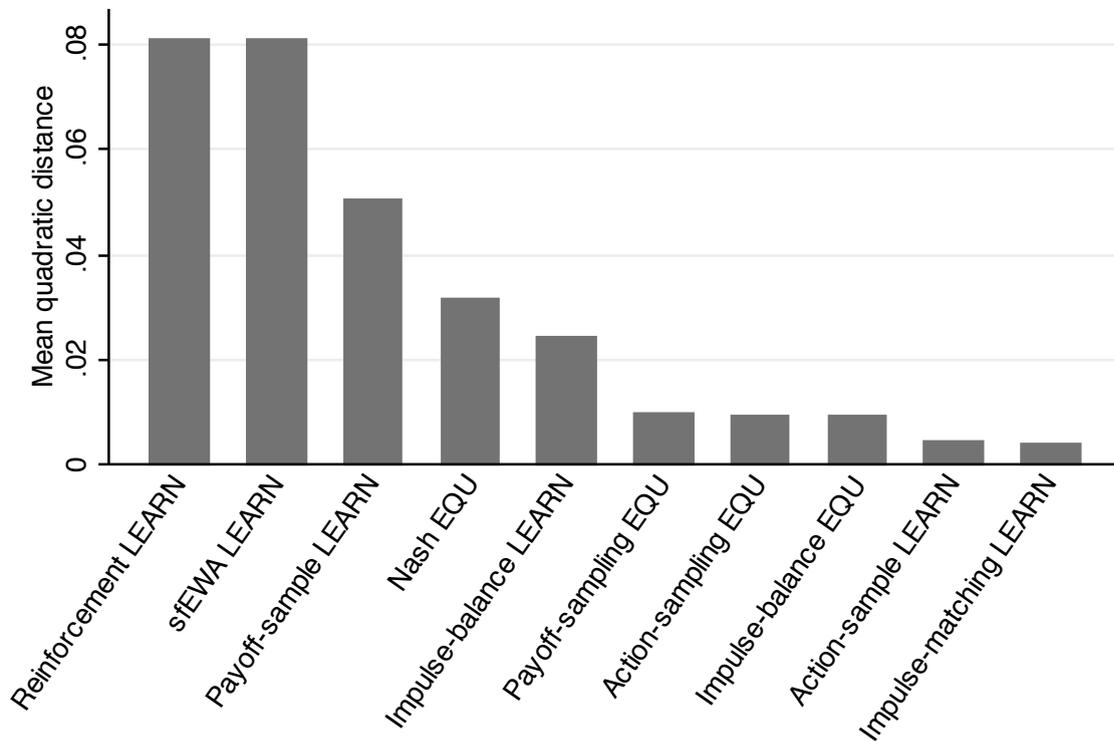


Figure V.8: Mean quadratic distances of the stationary concepts and the learning models to the observed behavior

But how well do the learning models describe the experimental data compared to the stationary concepts? Figure V.8 gives the mean quadratic distances between the investigated learning rules and the data and, if existing, the quadratic distances between the stationary counterparts and the data. The mean quadratic distances of the stationary concepts are either taken from Selten & Chmura (2008) or from Brunner, Camerer & Goeree (2010).⁶

The learning models of self-tuning EWA, reinforcement and payoff-sampling are

⁵The correlation is positive since the quadratic distance to the data is used as the measurement of predictive success. Self-tuning EWA is not included into this analysis, because there exists no corresponding stationary concept.

⁶There were some flaws in the paper by Selten & Chmura (2008). For a detailed discussion refer to Brunner, Camerer & Goeree (2010) and Selten, Chmura & Goerg (2010).

clearly outperformed by all stationary concepts. Impulse balance learning performs only better than Nash equilibrium and worse than the other equilibria. In contrast to these four models, the learning models of action-sampling and impulse matching perform very well. Both learning models have a higher predictive success than the other learning models and additionally a higher predictive success than all stationary concepts. Impulse matching learning does not only perform better than its corresponding stationary concept but also as the related concept of impulse balance learning.

V.D.2 Individual Behavior

In this section we will take a closer look at subjects' decisions and whether they are in accordance with one of the learning theories. Therefore we will use the quadratic scoring rule, as introduced in section V.C.3. Recall, that in contrast to the quadratic distance the higher the value of the quadratic score the better the fit is. The analysis for the three parametric concepts are either based on the parameters calculated in Selten & Chmura (2008) (payoff-sampling and action-sampling) or the one with the best fit on the aggregate level (self-tuning EWA).

In addition to the investigated learning rules we introduce one heuristic which we call the inertia rule. This rule commands to *"do exactly the same as in the preceding round"*. Of course this does not apply to the first period in which both possible actions are chosen with equal probabilities. The player is required to repeat the decision of the preceding period even if he deviated from this rule in the past. Obviously, the inertia rule is not a serious decision rule, but it serves as a benchmark that every learning rule should beat. A second benchmark is the score, which an agent would receive if he decides randomly between the two actions with $p = 0.5$. In this case the score would be 0.5 and again every learning rule should beat this benchmark.

Figure V.9 gives the mean quadratic scores in the 108 independent observations for each learning model and the inertia benchmark. The dark line represents the 0.5 benchmark.

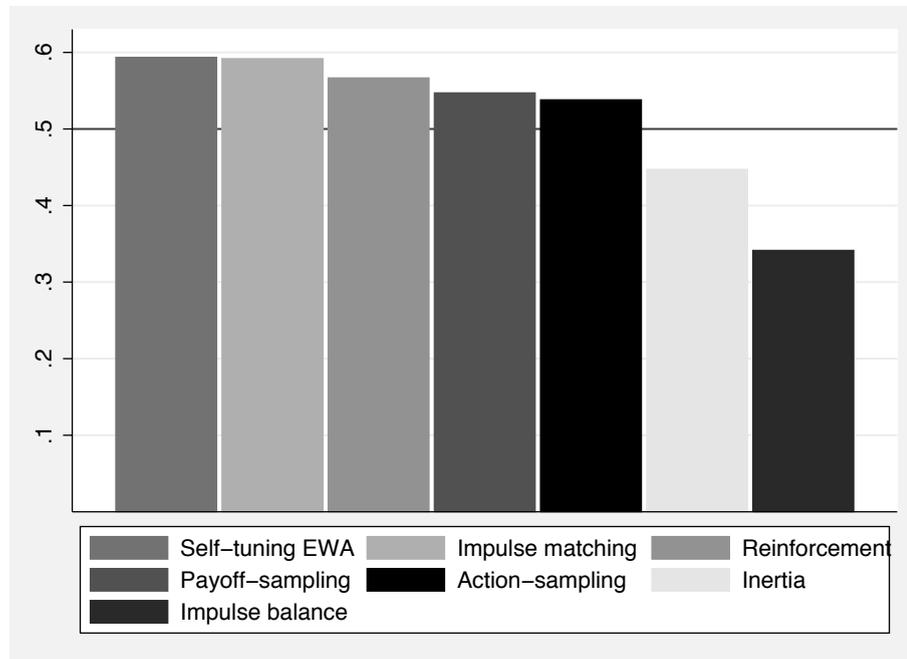


Figure V.9: Mean quadratic scores in the 108 observations with different learning models

The figure reveals a clear order of predictive success, from best to worst: self-tuning EWA, impulse matching learning, reinforcement learning, payoff-sampling learning, action-sampling learning, the inertia benchmark and impulse balance learning. The plot shows that all models, except impulse balance learning, perform better than the inertia benchmark and the 0.5 benchmark.

In 62 observations out of 108 independent observation groups self-tuning EWA has the highest score, in 36 observations impulse-matching is the concept that describes the data best and in 9 observations reinforcement has the highest score. Applying a two-sided Wilcoxon signed-rank test for the pairwise comparison of the mean scores over the independent observations reveals that the order given by the plot is statistically robust. All pairwise comparisons between two models are at least significant on the 1% level.

V.E Discussion

In this chapter the models of impulse matching learning, impulse balance learning, action-sampling learning and payoff-sampling learning have been introduced and together with reinforcement learning and self-tuning EWA applied and tested in the environment of repeated 2×2 games.

The newly introduced learning models are based on the behavioral reasoning of payoff-sampling equilibrium, action-sampling equilibrium and impulse balance equilibrium, which had been successfully tested in experimental 2×2 games by Selten & Chmura (2008). Therefore the experimental dataset obtained by Selten & Chmura (2008) were used as a testbed for the learning models. The experimental data comprises aggregate and individual behavior in 12 completely mixed 2×2 games, 6 constant sum games with 12 independent subject groups each, and 6 nonconstant sum games with 6 independent subject groups each. Each subject group consists of eight participants being randomly matched over 200 periods.

The learning models had to prove whether they can replicate the aggregate behavior of the experimental population and whether they can explain the individual behavior of single subjects. For the comparison with the aggregate behavior 500 simulation runs per game and learning model were conducted. As in the experiment, 200 rounds with random matching and four agents deciding as row players and four agents as column players were simulated. Our measure of predictive power for the aggregate is the quadratic distance between observed relative frequencies in simulation runs and the mean frequencies observed in the experiments. For the comparison with the individuals' behavior the models were applied to the history of each participant. Then the actual decisions of every round were compared with the predictions of the learning models given the subject's history. For each subject and round a quadratic score, a measurement for the accuracy of a prediction, was calculated and averaged over rounds, subjects and games.

For our comparisons with the aggregate and the individual behavior we can conclude two main results:

Main Result 1: *The models of learning are able to replicate the aggregate behavior in our 2×2 -games. In our study the models of impulse matching learning and action-sampling learning prove to be especially successful.*

The comparison of the six models yields the following order of predictive success from best to worst: Impulse matching learning, Action-sampling learning, Impulse balance learning, Payoff-sampling learning, Reinforcement learning, Self-tuning EWA learning. Due to the high number of simulation runs, this order is statistically robust, all pairwise comparisons with the two-sided Man-Whitney u-test are at least significant on the 0.1% level.

The predominance of the new models, impulse matching learning, action-sampling learning, impulse balance learning and payoff-sampling learning, over the established models of reinforcement learning and self-tuning EWA is stable over time and across the different game types (constant sum and non-constant sum games). One possible reason for the predominance of the new models, especially over self-tuning EWA is that we insisted on adjusting parameters as less as possible. A further interesting result is that for reinforcement learning the quadratic distance to the data is round about 22% lower if applied to the transformed matrixes instead to the original ones.

Main Result 2: *Nearly all investigated models of learning describe the individual behavior in our 2×2 games better than a simple inertia rule and simple randomization with 0.5 does. The highest score is observed for the model of self-tuning EWA.*

Overall, all models, except impulse balance learning, perform better than simple randomization with .5 and the inertia benchmark does. The new models are outperformed, on the individual level, by self-tuning EWA. Only impulse matching learning performed similarly good, but nevertheless with a significantly smaller score than self-tuning EWA.

For the models action-sampling learning and payoff-sampling learning we did not adjust the sample sizes to the data, but applied the sample sizes which were determined in Selten & Chmura (2008). The parameter of self-tuning EWA was determined in such a way that it lead to the best fit over all data and over all games on the

aggregate level. It remains to be shown how good the new parametric concepts of action-sampling and payoff-sampling learning perform if we allow for additional adjustments to the data.

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B Instructions

B.I Presentation Effects in Cross-Cultural Experiments

Introduction

Thank you for taking part in this experiment. Please read these instructions very carefully. It is very important that you do not talk to other participants for the time of the entire experiment. In case you do not understand some parts of the experiment, please read through these instructions again. If you have further questions after this, please give us a sign by raising your hand out of your cubicle. We will then approach you in order to answer your questions personally.

To guarantee your anonymity you will draw a personal code before the experiment starts. Please write this code on top of every sheet you use during this experiment. You will later receive your payment from this experiment by showing your personal code. This method ensures that we are not able to link your answers and decisions to you personally.

During this experiment you can earn money. The currency within the experiment is ‘Taler’. The exchange rate from Taler to NIS is:

$$\boxed{1 \text{ Taler} = 2.5 \text{ NIS}}$$

Your personal income from the experiment depends on both **your own** decisions and on the decisions of **other** participants. Your personal income will be paid to you in cash as soon as the experiment is over.

During the course of the experiment, you will interact with a randomly assigned other participant. The assigned participant makes his/her decisions at the same point in time as you do. You will get no information on who this person actually is, neither during the experiment, nor at some point after the experiment. Similarly, the other participant will not be given any information about your identity. You will receive information about the assigned participant’s decision after the entire experiment has ended.

After the experiment, please complete a short questionnaire, which we need for the statistical analysis of the experimental data.

Description of the experiment (PDP)

In this experiment you are randomly matched with another participant. You act as **Person A**, and the randomly assigned other participant acts as **Person B**. You and Person B must simultaneously make a similarly structured decision.

Person A and Person B first receive an initial endowment of **10 Talers**.

You now have the opportunity to transfer any part of your endowment to Person B. You can only transfer integer amounts - thus, you can only choose amounts $a_A \in [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]$.

The amount you transfer to Person B is **doubled**. That means that Person B receives **twice the amount you have transferred** to him/her.

The randomly assigned participant acting as Person B is given exactly the same alternatives as you have. He/she also has the possibility to transfer any amount to you. The amount Person B transfers to you is also doubled. That means that **you receive twice the amount Person B has transferred** to you.

You will make your decisions **simultaneously**. During the course of the experiment neither person receives any information concerning the decision of the other person.

How the income is calculated

Your personal income can be calculated as follows:

Initial endowment
- amount you choose to transfer to Person B
+ twice the amount b Person B transferred to you
= your personal income

Description of the experiment (PDN)

In this experiment you are randomly matched with another participant. You act as **Person A**, and the randomly assigned other participant acts as **Person B**. You and Person B must simultaneously make a similarly structured decision.

Person A and Person B first receive an initial endowment of **10 Talers**.

You now have the opportunity to transfer any part of Person B's endowment to yourself. You can only transfer integer amounts - thus, you can only choose amounts $a_A \in [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]$.

The remaining amount - that is the amount that you do not transfer from Person B's endowment to yourself - is **doubled**. This means that Person B receives **twice the amount that you do not transfer** from him/her.

The randomly assigned participant acting as person B is given exactly the same alternatives as you have. He/she also has the possibility to transfer any amount to himself/herself. The remaining amount that he/she does not transfer from your endowment to himself/herself is **doubled**. This means that you receive **twice the amount that he/she does not transfer** from you.

You will make your decisions **simultaneously**. During the course of the experiment, neither person receives any information concerning the decision of the other person.

How the income is calculated

Your personal income can be calculated as follows:

+ amount you choose to transfer from Person B to yourself
+ twice the amount Person B did not transfer from your endowment to himself/herself
= your personal income

B.II Treating Equals Unequally - Incentives in Teams

This is the English translation of the instructions used in treatments 345COM and 444COM. In treatment 345SUB, the table and examples were adjusted to fit the production function.

Welcome to this decision-making experiment. Please read the following instructions carefully. The experiment will be conducted anonymously, that is to say you will not learn with whom of the other participants you are interacting. Please keep in mind that from now on and throughout the experiment you are **not allowed to talk to the other participants**. If you **have any questions**, please give a signal with your hand and we will come to you. During the experiment you can earn Taler. How much you earn depends on your decisions and the decisions of the other participants in your group. At the end of the experiment these Taler will be converted to Euro at an exchange rate of **80 Taler = 1 EURO**. The Euro amount will be paid out to you. You will be called to collect your earnings. Please turn in all instruction sheets when you collect your earnings.

In this experiment you will be randomly divided into groups of three persons. Together with two other participants you form a group. Each participant decides whether he wants to **work normal or hard**. The more participants choose to work hard, the more units of goods will be produced.

Number (#) of hard working participants	0	1	2	3
Produced units of goods	20	40	65	100

Examples: In case that all participants of the group work normal, 20 units will be produced altogether in your group. If you work hard and another participant in your group works hard as well, 65 units will be produced altogether in your group. etc... good

For each unit of goods produced, you receive a certain amount of Taler. At the beginning of the experiment you are informed how many Taler you earn per unit produced. Additionally, you learn how many Taler per unit the other two participants in your group earn. Examples: In the beginning of the experiment you

are told that you receive 5 Taler for each unit produced. In case that all participants in your group work hard, 100 units will be produced and you receive 500 Taler. In case that 40 units are produced, you receive $40 \cdot 5 = 200$ Taler. etc...

Costs: If you decide to **work hard**, the amount you receive is reduced by 90 Taler. If you **work normal**, no additional costs arise. Examples: You and another participant in your group work hard, so 65 units are produced. Accordingly, you receive $65 \cdot 5 = 325$ Taler. Since you worked hard, 90 Taler are taken away. Hence, your final payment is $325 - 90 = 235$ Taler. If instead you worked normal, 40 units would be produced. You would receive $40 \cdot 5 = 200$ Taler. Since you worked normal, no Taler are subtracted from this amount. Hence, your final payment would be 200 Taler. etc...

In order to facilitate the decision-making process, each participant is informed in detail about his own possible payoffs and the payoffs of the other two participants in his group. The corresponding information is given in table form. For every participant, a table lists all possible payments dependent on the own decision (to work normal or hard) and the decisions of the other two participants in the group (none, one or both work hard). In these tables, the corresponding costs for working hard have already been subtracted. Below, you see an example with fictional data:

<p>Ihre Auszahlungstabelle:</p> <p>Für jede produzierte Einheit erhalten Sie A Taler, d.h.:</p> <table border="1"> <thead> <tr> <th># der hart Arbeitenden (ohne Sie)</th> <th>Sie arbeiten NORMAL</th> <th>Sie arbeiten HART</th> </tr> </thead> <tbody> <tr> <td>0</td> <td>10</td> <td>11</td> </tr> <tr> <td>1</td> <td>12</td> <td>13</td> </tr> <tr> <td>2</td> <td>14</td> <td>15</td> </tr> </tbody> </table>	# der hart Arbeitenden (ohne Sie)	Sie arbeiten NORMAL	Sie arbeiten HART	0	10	11	1	12	13	2	14	15	<p>Auszahlungstabelle Tln. 2:</p> <p>Für jede produzierte Einheit erhält er B Taler, d.h.:</p> <table border="1"> <thead> <tr> <th># der hart Arbeitenden (ohne ihn)</th> <th>Er arbeitet NORMAL</th> <th>Er arbeitet HART</th> </tr> </thead> <tbody> <tr> <td>0</td> <td>16</td> <td>17</td> </tr> <tr> <td>1</td> <td>18</td> <td>19</td> </tr> <tr> <td>2</td> <td>20</td> <td>21</td> </tr> </tbody> </table>	# der hart Arbeitenden (ohne ihn)	Er arbeitet NORMAL	Er arbeitet HART	0	16	17	1	18	19	2	20	21	<p>Auszahlungstabelle Tln. 3:</p> <p>Für jede produzierte Einheit erhält er C Taler, d.h.:</p> <table border="1"> <thead> <tr> <th># der hart Arbeitenden (ohne ihn)</th> <th>Er arbeitet NORMAL</th> <th>Er arbeitet HART</th> </tr> </thead> <tbody> <tr> <td>0</td> <td>22</td> <td>23</td> </tr> <tr> <td>1</td> <td>24</td> <td>25</td> </tr> <tr> <td>2</td> <td>26</td> <td>27</td> </tr> </tbody> </table>	# der hart Arbeitenden (ohne ihn)	Er arbeitet NORMAL	Er arbeitet HART	0	22	23	1	24	25	2	26	27
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<p>Anzahl der produzierten Einheiten, wenn...</p> <table border="1"> <tbody> <tr> <td>0 hart arbeiten:</td> <td>20</td> </tr> <tr> <td>1 hart arbeitet:</td> <td>40</td> </tr> <tr> <td>2 hart arbeiten:</td> <td>65</td> </tr> <tr> <td>3 hart arbeiten:</td> <td>100</td> </tr> </tbody> </table>	0 hart arbeiten:	20	1 hart arbeitet:	40	2 hart arbeiten:	65	3 hart arbeiten:	100	<p>Berechnung für den Fall, dass Tln. 2 <input type="checkbox"/>normal / <input type="checkbox"/>hart arbeitet</p> <p>Berechnung für den Fall, dass Tln. 3 <input type="checkbox"/>normal / <input type="checkbox"/>hart arbeitet</p>																													
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<p>Die möglichen Auszahlungen für den Fall, dass Tln. 2 tatsächlich NORMAL und Tln. 3 tatsächlich HART arbeitet, betragen:</p> <table border="1"> <thead> <tr> <th>Wenn Sie..</th> <th>Ihre Auszahlung</th> <th>Auszahlung Tln. 2</th> <th>Auszahlung Tln. 3</th> </tr> </thead> <tbody> <tr> <td><input type="checkbox"/>NORMAL arbeiten</td> <td>12</td> <td>18</td> <td>24</td> </tr> <tr> <td><input type="checkbox"/>HART arbeiten</td> <td>13</td> <td>20</td> <td>26</td> </tr> </tbody> </table>			Wenn Sie..	Ihre Auszahlung	Auszahlung Tln. 2	Auszahlung Tln. 3	<input type="checkbox"/> NORMAL arbeiten	12	18	24	<input type="checkbox"/> HART arbeiten	13	20	26																								
Wenn Sie..	Ihre Auszahlung	Auszahlung Tln. 2	Auszahlung Tln. 3																																			
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In the lower right part of the screen, you can see another table. At the beginning, the table is empty. In order to display data, you first have to create a hypothetical situation: In the table of participant number 2, click on the corresponding button what you think how he will decide (to work normal or hard). Furthermore, in the

table of participant number 3, click on the corresponding button what you think about his decision (to work normal or hard). In the lower table you will then be shown in the first row what the payment for you and the other two participants would be, in case that your chosen situation actually occurs - and that you decide to work normal. The second row lists the possible payments that you and the other two participants would receive, in case that your chosen situation actually occurs - and that you decide to work hard. At any time, you can display data for a different situation. Simply change the situation by clicking on a different button underneath the payment tables of participant number 2 and 3. Below you see another example with fictional data:

Ihre Auszahlungstabelle:			Auszahlungstabelle Tln. 2:			Auszahlungstabelle Tln. 3:		
Für jede produzierte Einheit erhalten Sie A Taler, d.h.:			Für jede produzierte Einheit erhält er B Taler, d.h.:			Für jede produzierte Einheit erhält er C Taler, d.h.:		
# der hart Arbeitenden (ohne Sie)	Sie arbeiten NORMAL	Sie arbeiten HART	# der hart Arbeitenden (ohne ihn)	Er arbeitet NORMAL	Er arbeitet HART	# der hart Arbeitenden (ohne ihn)	Er arbeitet NORMAL	Er arbeitet HART
0	10	11	0	16	17	0	22	23
1	12	13	1	18	19	1	24	25
2	14	15	2	20	21	2	26	27
Anzahl der produzierten Einheiten, wenn...			Berechnung für den Fall, dass Tln. 2 <input type="checkbox"/> normal / <input type="checkbox"/> hart arbeitet			Berechnung für den Fall, dass Tln. 3 <input type="checkbox"/> normal / <input type="checkbox"/> hart arbeitet		
0 hart arbeiten:	20		Die möglichen Auszahlungen für den Fall, dass Tln. 2 tatsächlich NORMAL und Tln. 3 tatsächlich HART arbeitet, betragen:					
1 hart arbeitet:	40		Wenn Sie..	Ihre Auszahlung	Auszahlung Tln. 2	Auszahlung Tln. 3		
2 hart arbeiten:	65		<input type="checkbox"/> NORMAL arbeiten	12	18	24		
3 hart arbeiten:	100		<input type="checkbox"/> HART arbeiten	13	20	26		

Your decision: As soon as you have decided on whether you want to work hard or normal, please click on the according button in the lower right table (on the left hand side). The program will ask you to confirm your decision. Afterwards, your decision will be transferred. Please remain in your cubicle and wait until all participants have reached a decision. Afterwards, you will be informed about the number of units produced in your group and about your payoff. This amount will be paid to you in cash and anonymously at an exchange rate of 80 Taler = 1 EURO.

If you have any questions please give a signal with your hand!

The following instructions were distributed and read out aloud only after the first period.

In the following, the previous procedure will be repeated five times within the same group of persons and with the same numerical values for production function and

effort costs. In each of these five periods, you again have to choose between working normal or working hard. In the end, we randomly select one of these five periods. You will receive the payoff for the randomly selected period in addition to your present payoff.

If you have any questions please give a signal with your hand! Otherwise, please click to continue!

B.III Experimental Investigation of Cyclic Duopoly Games

Thank you very much for participating in today's decision experiment. Please read the following instruction carefully. If you do not understand something and have some questions you can ask them at the end of this introduction. As soon as the experiment has started no more questions will be answered. If you still have questions please take a look at these instructions. For the conduction of this experiment it is necessary that you do not communicate with other participants. Please do not talk with the other participants.

In this experiment you can earn money. Your payoff depends on your decisions and other participant's decisions.

The Experiment

The experiment consists out of 200 rounds. Decisions are done alternating, that means that everyone decides every two rounds. To which half of the participants you belong is only known to you.

In the rounds in which you make your decisions you are assigned to a market. Then you will receive the status of the market, as the market is either free or occupied. Then you can decide whether you want to enter the market or not. If you enter the market you stay in the market for two rounds. If you do not enter the market you stay outside the market for two rounds. After these two rounds and while the 200 rounds of the experiment are not exhausted you can decide again. After your decision the first round is over and the second round begins in which players from the other half of participants decide. After this player have decided the second round is over and you will again be allocated to a market (mostly a new one). This is repeated 100 times, thus there are 200 rounds to play.

Payoffs in the Experiment

In every round you receive a payoff.

If you do not enter the market you receive 5 Taler in the first round and 0 Taler in

the second round.

If you enter the market you receive an amount in the first round which depends on the status of the market. If the market is empty you receive in the first round a payoff of 10 Taler. If the market is occupied you receive a payoff in the first round of 2 Taler. In the second round your payoff depends on the decision made by the next participant from the other group randomly allocated to this market. If this participant enters the market you receive a payoff of 2 Taler, if he does not enter you receive a payoff of 10 Taler.

The payoffs from this rounds are summed up and form your round payoffs. This round payoffs are summed up over all rounds and form your total payoff at the end of the experiment. Your payoff of this experiment is payed to you in Euro, where 1 Taler is 1 EuroCent.

The following tables should illustrate your payoffs:

Your payoffs in an empty market:

		Next player	
		Enter	Not Enter
You	Enter	$10 + 2$	$10 + 10$
	Not Enter	5	5

Your payoffs in an occupied market:

		Next player	
		Enter	Not Enter
You	Enter	$2 + 2$	$2 + 10$
	Not Enter	5	5

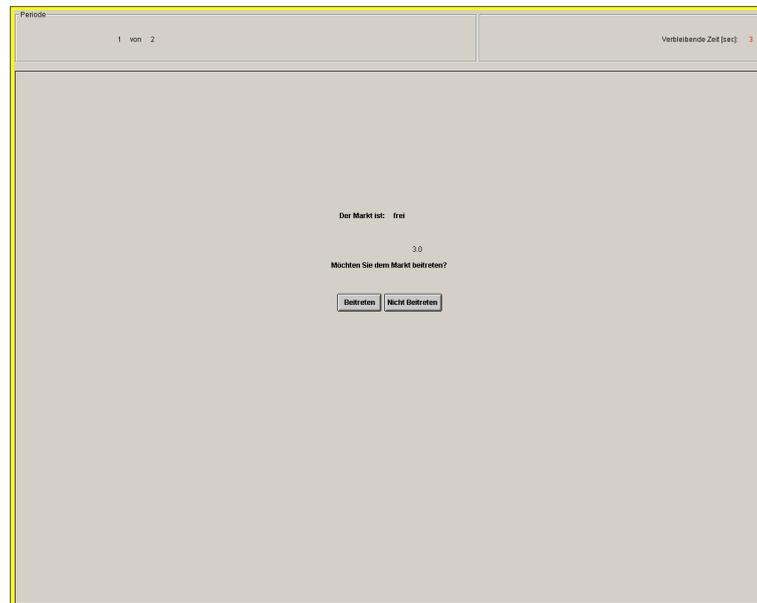


Figure B.1: Screenshot decision screen

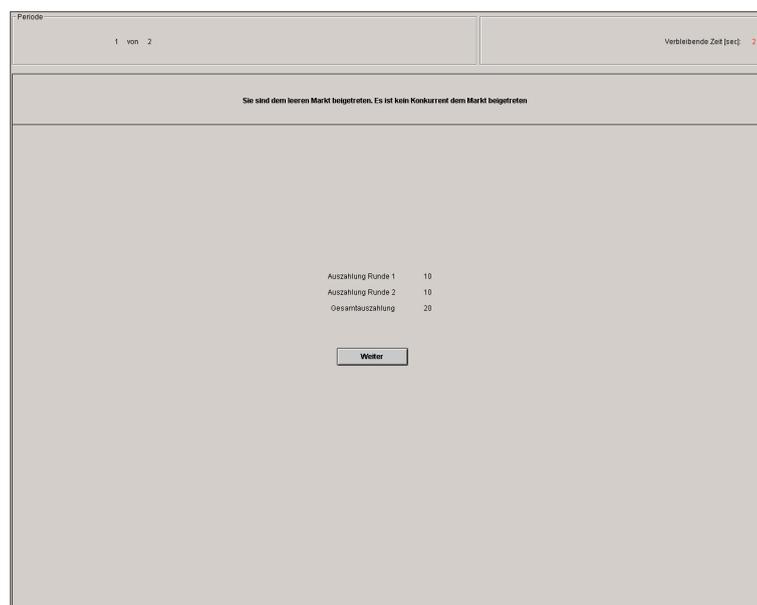


Figure B.2: Screenshot payoff screen

C Supplementary Material

C.I Presentation Effects in Cross-Cultural Experiments

C.I.1 External analogy with the Classical PD and PG Games

To show external analogy of our continuous games with a classical binary-choice PD we write down the 2×2 -payoff matrix form of both designs including only the extreme points of total (e.g., $a_i^{PDP} = 10$; $a_i^{PDN} = 0$) and no cooperation (e.g., $a_i^{PDP} = 0$; $a_i^{PDN} = 10$):

π_1, π_2	C₂	D₂
C₁	$k \cdot X, k \cdot X$	$0, X + k \cdot X$
D₁	$X + k \cdot X, 0$	X, X

Table 6: 2×2 -matrix, representing the prisoner's dilemma game.

The PD condition $(1+k) \cdot X > k \cdot X > X > 0$ is satisfied for all $k > 1$ in both games. In our experiment this condition is fulfilled, with $k = 2$. Given these parameters, by linear interpolation payoffs from the discrete payoff matrix can be obtained¹. Having a freely pre-determined range of possible actions a allows to obtain a non-binary measure of cooperation.

We now show external analogy of both games with a typical PG-design. The payoff function of a common 2-person PG is given by:

$$\pi_i^{PG} = X_i - a_i + k \cdot \frac{a_i + a_j}{2}, \text{ with } i \neq j, \text{ and } k > 1$$

X_i represents player i 's initial endowment. The parameter a_i is the investment into the public good. Accordingly, $X_i - a_i$ represents the investment into the private good. All investments made to the public good are multiplied by the factor k . The fraction of one half of the increased public pie is returned to both players i and j by the addition to their investments into the private good. For $k < 1$ it is rational for both players to invest nothing into the public good since the public pie shrinks. In

¹See also Verhoeff (1998).

the case of $k > 1$ both players can increase their personal income by investing into the public good. However, in this case each player has a strong incentive to free-ride hoping to reach even higher returns caused by a positive investment of the second player.

From the initial PG-equation we get:

$$\pi_i = X_i - \left(1 - \frac{k}{2}\right) \cdot a_i + k \cdot \frac{a_j}{2}$$

$$\iff \pi_i = X_i - \theta \cdot a_i + k^* \cdot \theta \cdot a_j, \text{ with } \theta = 1 - \frac{k}{2}, \text{ and } k^* = \frac{k}{2 \cdot \left(1 - \frac{k}{2}\right)}$$

The payoff-function of the PDP-game was given in equation by:

$$\pi_i^{PDP} = X_i - a_i^{PDP} + k \cdot a_j^{PDP}$$

It is evident that both games are of the same type: A PG-game with parameter k^* is formally similar to the PDP-game with parameter k . Because of internal equivalence among PDP and PDN it is obvious that the PDN-game is a PG too. Contrary to the PG-game, in PDP and PDN there is no back flow of own investments. Thus, each $a_i > 0$ is transferred directly to the opposite player thereby providing a lower individual incentive to cooperate.

C.II Treating Equals Unequally - Incentives in Teams

C.II.1 Additional Tables

Player type	Treatment		
	345SUB n=12	345COM n=12	444COM n=33
3	22.2% (9.3)	88.9% (4.3)	-
4	81.9% (6.6)	88.9% (8.3)	72.2% (5.6)
5	91.7% (4.4)	97.2% (1.2)	-
Mean	65.3%	91.7%	72.2%

Observations reflect individual subjects, for each of whom the percentage of 'work hard' decisions out of the six periods was calculated. The standard errors are given in parentheses.

Table C.1: Mean efficiencies (first row) and standard deviation (second row) for all rounds per player type over the treatments

Player type	345COM vs. 345SUB	345COM vs. 444COM
3	.0001	n.a.
4	n.s.	n.a.
5	n.s.	n.a.
Means	.0004	.0649

Table C.2: Comparison of mean efficiencies by player types between different treatments with two-sided rank-sum test.

C.II.2 Additional Graphs

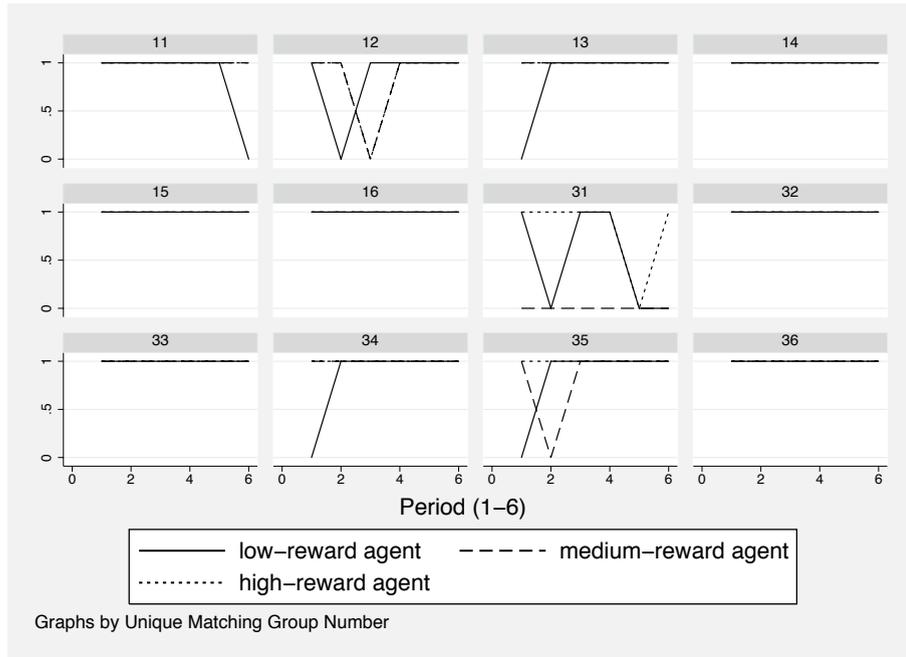


Figure C.1: Effort per reward type over time in 345COM

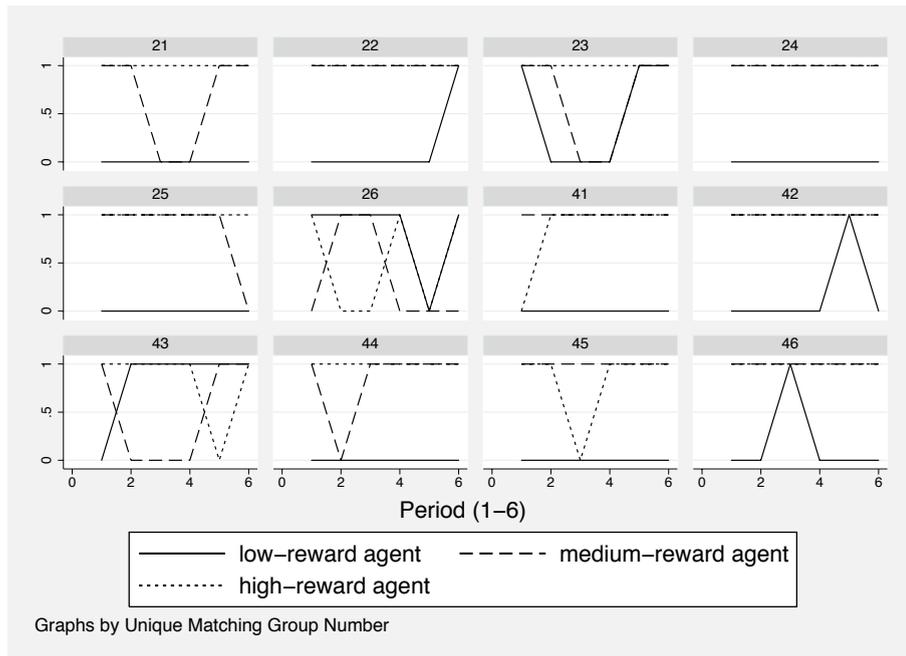


Figure C.2: Effort per reward type over time in 345SUB

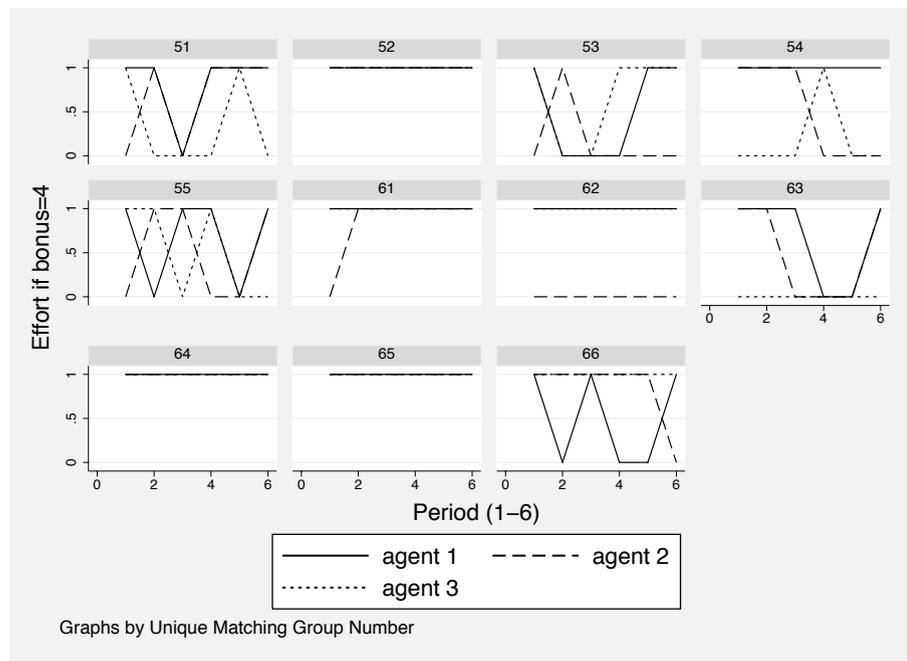


Figure C.3: Effort per agent over time in 444COM

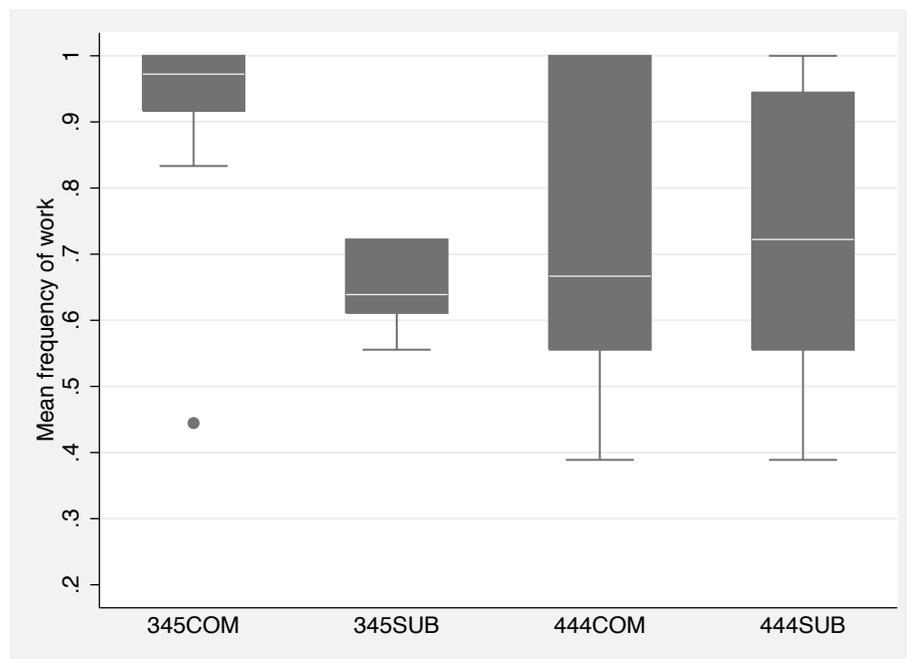


Figure C.4: Boxplots of average group efficiency rates

C.III Experimental Investigation of Cyclic Duopoly Games

C.III.1 Additional Tables

Game A			
Observation	Market Empty	Market Entries	Relative Frequency
1	103	99	0.9612
2	109	109	1
3	131	130	0.9924
4	129	129	1
5	124	123	0.9919
6	131	131	1
7	126	121	0.9603
8	140	138	0.9857
9	104	103	0.9904
10	133	131	0.9850
11	162	154	0.9506

Game B			
Observation	Market Empty	Market Entries	Relative Frequency
1	324	320	0.9806
2	373	370	0.9943
3	356	355	0.9962
4	373	373	1
5	331	330	0.9960
6	366	364	0.9957
7	315	313	0.9921
8	352	348	0.9881
9	323	321	0.9929
10	348	346	0.9925
11	352	343	0.9727

Mean:			0,9798
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Table C.3: Frequency of entries into an empty market

Game A				
Observation	Relative Frequency Entry	Mean quadratic distance		
		Nash Equilibrium	Impulse balance Equilibrium	Payoff-sampling Equilibrium
1	.8068	.0046	.0240	.0008
2	.7841	.0083	.0174	.0000
3	.7292	.0213	.0060	.0023
4	.7325	.0203	.0065	.0020
5	.7479	.0161	.0092	.0009
6	.7271	.0219	.0056	.0026
7	.7447	.0170	.0086	.0011
8	.7065	.0284	.0030	.0051
9	.7963	.0062	.0208	.0003
10	.7259	.0222	.0054	.0027
11	.6552	.0483	.0000	.0151

Game B				
Observation	Relative Frequency Entry	Mean quadratic distance		
		Nash Equilibrium	Impulse balance Equilibrium	Payoff-sampling Equilibrium
1	.4222	.0221	.0007	.0000
2	.2262	.1189	.0496	.0391
3	.408	.0265	.0017	.0002
4	.3146	.0657	.0181	.0120
5	.4809	.0081	.0010	.0032
6	.3643	.0427	.0071	.0035
7	.5450	.0007	.0092	.0146
8	.4639	.0115	.0002	.0016
9	.4331	.0190	.0002	.0001
10	.4441	.0161	.0000	.0004
11	.5439	.0007	.0090	.0144

Table C.4: Frequency of entries into an occupied market and the quadratic distances to the three concepts

C.IV Learning in Experimental 2×2 Games

C.IV.1 Impulse Matching and Impulse Balance

To show that the concepts of impulse balance equilibrium and impulse matching equilibrium lead to the same stationary points in case of the 2×2 games, we take a look at the structure of the investigated experimental 2×2 games, as introduced by Selten & Chmura (2008).

	L	R
U	$a_L + c_L$ b_U	a_R $b_U + d_U$
D	a_L $d_D + d_D$	$a_R + c_R$ b_D

Figure C.5: The Structure of the Experimental 2x2-Games

The figure shows the transformed payoffs, the payoffs for the column-players are shown in the lower right corner and the payoff for the row-players are shown in the upper left corner. The following equations must be fulfilled: $a_L, a_R, b_U, b_D \geq 0$ and $c_L, c_R, d_U, d_D > 0$. In the following p_U and p_D are the probabilities of the row player for U and D and q_L and q_R are the probabilities for L and R by the column player. In the following we will only look at the row player, the behavior in equilibrium of the column player is calculated analogously.

In case of impulse balance equilibrium the expected impulses for each of both strategies must be the same. Hereby, the row player receives only an impulse towards U for the proportion of plays in which he would choose down (given by p_D) and the other player at the same time would have chosen L (given by q_L). Therefore the expected impulse for U is given by $p_D q_L c_L$. Applying the same reasoning leads to $p_U q_R c_R$ as the expected impulse for D of the row player. Thus the impulse balance equation, which must be fulfilled in equilibrium is given as:

$$p_D q_L c_L = p_U q_R c_R$$

In case of impulse matching equilibrium, the row player receives always an impulse

of c_L towards U if the column player plays L. The column player does so with a probability of q_L . In addition the row player always receives an impulse of c_R towards D if the column player chooses R. The column player plays R with a probability of q_R . Impulse matching equilibrium is reached if the ratio of the two probabilities of U and D is the same as the ratio of expected impulses for U and D.

$$\frac{p_U}{p_D} = \frac{q_L c_L}{q_R c_R}$$

By transforming we obtain the impulse balance equation of impulse balance equilibrium:

$$p_D q_L c_L = p_U q_R c_R$$

Therefore, impulse matching equilibrium and impulse balance equilibrium have the same mixed stationary points in case of the described 2×2 games.