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THE ADAPTIVENESS OF PUNISHING BEHAVIOR: A BASELINE STUDY

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THE ADAPTIVENESS OF PUNISHING BEHAVIOR: A BASELINE STUDY

by

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A THESIS

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THE ADAPTIVENESS OF PUNISHING BEHAVIOR: A BASELINE STUDY

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This study sheds light on the current patterns of punishing behavior. Experimental work with ultimatum bargaining shows that individuals have a high sensitivity to fairness, and when taken advantage of, are willing to endure costs to punish deviant behavior. Third party observers of the unfair behavior asked to represent ultimatum recipients are more hesitant to engage in such punishment. This becomes ever more puzzling when we consider individuals’ high value of their own reputation in similar settings. This leaves both rational choice modelers and political psychologists puzzled. This study presents the baseline model for a research agenda proposing a multi-agent modeling approach that allows for analysis of the observed behavior’s adaptiveness from an evolutionary perspective. Understanding discrepancies between individual and representative third party behavior is crucial for understanding issues of political representation.
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Chapter 1

Introduction

The goal of social science is to understand behavior, to figure out why people do what they do. Of course such a question cannot be tackled in its entirety. Punishment is a foundational behavioral trait. Though at first glance we would expect an analysis of punishing behavior to come from other disciplines, I would argue that observed patterns of punishment have relevance to political science.

A preliminary experimental study which recently persuaded the NSF to fund further analysis, conducted by Hibbing and Alford, showed that people subjected to unfair treatment are willing to endure high costs to punish their persecutors [1]. Recent science article presented neuro-scientific evidence that punishers of deviant behavior derive satisfaction from punishment and the anticipation of punishment [2]. But when a third party is asked to represent the mistreated, they are not likely to make the same decision, at least in cases where the cost of punishment is borne by the mistreated and not the representative [1]. To complicate the matter further, studies have also concluded that participants of such experiments have a high sensitivity to what non-participants, like the experimenter and other observing parties, will think about their actions. According to Larimer, the level of anonymity significantly
influences participants’ actions within an experiment [3] [4]. Simply put, while third parties are more reluctant to punish deviant behavior than parties involved in the interaction, decision makers in such settings still care about how non-participants will perceive them.

Representation is one of the most basic behavior that interests political scientists. Scenarios similar to the abstraction described above are played out in real life every day, in the courts and among elected and appointed decision makers representing the public. This lack of fit between the behavioral tendencies of the mistreated and their representatives should interest political scientists. Understanding these behavioral traits will allow us to better understand representation and misrepresentation.

Hibbing and Alford’s study took an experimental approach and used ultimatum bargaining to study punishment. Ultimatum bargaining is a popular experimental design in the field of experimental game theory and behavioral economics. In its classic form, it is a game with two players: an allocator (or offerer), and a receiver (or recipient). The allocator receives a predetermined amount\(^1\) from an outside source (usually an experimenter) to divide between him/her self and the receiver. The receiver can either accept this allocation and both parties will walk home with the amount in hand, or reject it, in which case neither player gets anything.

Ultimatum bargaining was first utilized by Güth et al. [5]. Their design was frequently used by social scientists as their findings were elaborated on. The initial and consequent experiments have one thing in common - they all show inconsistency with the microeconomic or rational choice model that assumes full profit maximization for all individuals. Based on this unrealistic assumption any player would gladly accept \(\epsilon\) regardless of how much the other player would get or how fair the division.

\(^1\)This amount is usually money, but some studies, like Larimer’s, have involved extra credit points for class; another study used candy with children.
In Hibbing and Alford’s experiment the recipient had no power to accept or reject, but one of his/her peers, whose role was to represent the recipient, was vested with the power to accept or reject the allocator’s offer. This third party’s decision did not influence his/her own well being, only the outcome for the other two parties. In their experimental design the offer was a rigged $3/$17 (15%) allocation in favor of the offerer. Both the literature and common sense show that this offer is highly unfair, and would be rejected most of the time, as was the case with Alford and Hibbing’s control group where the experiment was conducted in the traditional manner. With the third party decision maker, the rejection rate was substantially lower [1].

From a rational profit maximizing point of view $3 is clearly better than nothing, therefore a rational profit maximizer should accept it. Most people would object that profit maximization is not the top preference of people. In this study I propose that an evolutionary approach to the problem will lead us to a better understanding of the phenomenon and explain the observed behavior without abandoning the principles of rationality and scientific rigor.

Though the post-hoc nature of evolutionary psychology casts shadows over its scientific soundness, I have always found asking the classic question: “what made this behavior adaptive in a hunter gatherer setting?” to be a useful intellectual guide. Punishment is understandable from this perspective. When resources are scarce, everyone helping everyone else in the group as they gain access to resources increases everyone’s chance of survival. But if this is the case, the discrepancy between the behaviors of mistreated individuals and third party observers should not exist.

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2\(\epsilon\) - Epsilon - the lowest possible allocation.
3In their survey of ultimatum literature, Nowak et al. concluded that offers 30% or less are rejected over 50% of the time [6].
4Evolutionary psychology assumes that all behavioral traits have evolved slowly over time to serve a specific purpose. Since people spent most of their evolutionary history in a hunter gatherer setting, all behavior must be analyzed based on its adaptiveness in such a setting.
The problem with evolution is that it is difficult to recreate for testing purposes. With multi level modeling, a simplified version of reality can be reproduced and changes both in the properties of the system and in behavioral patterns that can be observed over time. These observations shall lead to a better understanding of why certain behaviors evolved. This study proposes a simple research design in the hopes that it will either shed light on why punishment deviates so much from rational expectations, or show how the model needs to be refined to conduct a more realistic analysis. The results will serve as a useful baseline for future analyses with more complex models.
Chapter 2

Multi-Agent Modeling

Methodological individualism is foundational to scientific soundness within most of the social sciences. Unfortunately this principle is violated all too often in political science. Waltz’s three levels of analysis have been the foundation of international relations research, but two of the three levels argue for a level of analysis higher than the individual [7]. Theories like Modelski’s long cycle theory [8] or Huntington’s three waves of democratization [9] are just a few examples of theories that explain systems on higher levels without making the connection to the actions of individuals. Solber and Wilson lays out a hypothesis that evolution occurs on a group level [10]. Though both Waltz and Solber and Wilson argue for a multi-level approach to the analysis of human behavior, none of the works cited offer appropriate methodology. Multi-agent modeling is the most promising tool to provide the link between the individual and the group level [11]. The other advantage of social simulation is that time can be sped up, and therefore interactions can be observed over entire generations [12]. This is the exact reason why the approach is appropriate to analyze the evolution and the evolutionary adaptiveness of a phenomenon.

To better understand the discrepancies of punishing behavior between the repre-
presented and the representer I propose a multi-agent modeling approach. A multi-agent model is a simulation of society. An “agent” is a self contained piece of software that controls its own actions (based on pre-set rules which should represent the real world) based on its perception of its artificial environment. In the case of this study an agent is an artificial person. These agents are placed inside an artificial space where they can interact with each other. The sum of these interactions simulate social phenomena. Realizing that simplifications are unavoidable, the designs of both the agent’s abilities, and the environment they interact in, have to represent the real world.

Simulations have been around since the mid 60’s, when von Neumann created his self-reproducing automata [13]. The fields where the approach was widely applied included studies of cellular automata, genetic programming, individual based modeling in biology, etc. But simulations were rarely applied to the social sciences [14]. The earliest account was the 1969 Thomas Schelling article on the simulation of de-facto segregation [15]. Though this article created much excitement, simulations did not become widely used in the social sciences until the 90’s and even for the time period in between the only considerable work utilizing simulations was political scientist Robert Axelrod’s work on cooperation. This piece basically redefined how cooperation was viewed by modelers [16]. One of the reasons for this is the recent advancement in computational power and the rise of personal computers, giving social scientists better access to the tools required to design simulations. Advances in the fields of artificial intelligence and artificial life have also helped social scientists to gain more access to better tools to create better agents [14].

Simulations have been used in the past to study punishing behavior. Boyd et al.’s model shows why punishment is rational even with one-shot interactions in larger groups [17]. Ultimatum bargaining has also appeared in the simulation literature, though much to my surprise I was only able to find one instance. Zhong et al. con-
ducted extensive analysis of learning models and the impact of memory on agent’s behavior, but did it solely in dyadic interactions between predefined agents [18].

These studies lead to little understanding of why third parties are less likely to choose punishment when they have to make a decision for someone else - that is, why there is a lack of fit between the behavior of the representer and the represented. To better understand the problems with representation, especially in the context of the courts whose job is specifically to punish deviant behavior, we need to understand why punishment is adoptive, and why third party punishment is less substantial than retaliation by the mistreated. The research agenda proposed here attempts to explain this. Understanding the reasons for such discrepancies between the representer and the represented will help us design better institutions that offer better representation, a better fit between the wishes of the representer and the represented. Such findings will be applicable to both legislative designs and judicial studies.
Chapter 3

Simulation Design

3.1 Systemic Settings

In this simulation\(^1\) social interaction between agents will be proxies by ultimatum bargaining. This study will focus on behavior within homogeneous groups. Each agent’s behavioral functions will be the same as every other agent’s in the group. Groups consist of 150 agents unless otherwise noted.\(^2\) Simulation will proceed for several rounds\(^3\), in each round agents are randomly paired up and will play the ultimatum game with each other. Every time the game is played, chance decides which agent becomes the decision maker, with the wealthier agent having a higher probability of being in the high power, allocator position. The probability function of an agent (let us say agent 1) becoming the allocator is \(\frac{w_1}{w_1 + w_2}\).\(^4\)

\(^1\)Technical specifications are described in Appendix A
\(^2\)I picked 150 because it most resembles the real world. Anthropological evidence suggests that hunter gatherer tribes had about 150-155 individuals on average [19]
\(^3\)For most of the analysis presented in this study, the number of rounds in a simulation was set to 10000.
\(^4\)Where \(w_1\) is the wealth of an agent 1, \(w_2\) is the wealth of agent 2.
3.2 Allocation Function

Regardless of the properties of the group, the allocation function is the same for all agents. Each round, allocating agents are given $10 to divide between themselves and the recipient. For the sake of simplicity only integer allocations are possible. Initial allocation is calculated based on a random number generated with an expected mean of 2.5 and a standard deviation of 1. \( \hat{x} = 2.5, \sigma = 1 \) This number is then rounded to determine the allocation. Allocators also have a learning function, with which they adjust their offers given their past experiences. If the allocator’s offer is accepted the agent will adjust its offer function by decreasing \( \hat{x} \) by 0.1 (thinking they can probably get away with a lower offer next time), if the allocation is rejected, the agent will increase the \( \hat{x} \) of their allocation function by 0.1 (thinking they should offer a higher amount next time, if they want their offer to be accepted). Limits are placed at 0 and 5, making these the lowest and highest possible offers.

3.3 The Recipient

The recipients’ behavior differs depending on which group they are in. Rational agents will accept all allocations above 0. (If \( a > 0 \) then accept)\(^5\) Realistic agents have a linear acception function \( f(p) = (0.2)a \)\(^6\), also presented in Figure 3.1. For example, a realistic agent will accept a $5 offer all the time, a $4 offer 80% of the time, etc., and like rational counterparts, never accept a $0 offer.

\(^5\)where \( a \) is the allocation.
\(^6\)where \( p \) is the probability of offer \( a \) being accepted.
Figure 3.1: Acception Function for Realistic Agents
3.4 Punishment and Grudge

Beyond the round to round ultimatum game played, agents (realistic ones, but not the rational ones) also engage in punishing behavior. Agents have a memory and remember members of the group who gave them an unacceptable offer. Simply speaking, realistic agents hold grudges. The literature suggests that parties not directly affected by the transaction are reluctant to punish parties who engage in unfair behavior [1]. On the other hand people do worry about what others (third parties) will think of their behavior [3]. For this reason I created two distinct groups: (1) where only the individual who was low-balled holds a grudge against the allocator who treated him/her unfairly, and (2) where everyone else in the group will be aware of a member’s unfair actions and will engage in punishing behavior acting as third parties in an interaction between two agents. Punishment is simply refusing to play the game, thus denying the punished agent all financial benefits of the transaction and enduring the cost of any possible payoff.

The extent of punishment will be measured by either rounds or encounters. Punishment for \( t \) number of rounds means that agent 1 holding a grudge against agent 2 will punish agent 2 if they meet within the following \( t \) rounds. Punishment for \( e \) number of encounters means that agent 1 a holding grudge against agent 2 will punish agent 2 for the next \( e \) times they meet, regardless of how many rounds have passed since the transaction that made agent 1 angry. Simply speaking, when the grudge is measured by rounds agents are angry for a set amount of time and then they forget. When the grudge is measured by encounters, agents stay angry until they get back at the social deviant.

Due to hardware constraints\(^7\), I was limited in the number of simulations that I was able to run. For this reason, I only ran the simulations with \( t \) and \( e \) set to 3,

\(^7\)see Appendix A
25, and 150. Agents in the simulations presented punishment for 3, 25, 150 rounds, and similarly for 3, 25, 150 encounters. Note that separate simulations were run for groups where only the individual punished unacceptable offers, and for groups where the whole group punished deviant behavior.
Chapter 4

Evaluation Criteria

Simulations were run 25 times, and after making sure that no arbitrary threshold existed that modified properties of the group at arbitrary times, results were averaged across the 25 simulations, within all groups. The distributions of observations were evaluated at random time slices and appeared to be normal.¹

One of the reasons the simulation approach was chosen for this study is that it serves us with a proper mechanism to infer group behavior as an aggregate of individual behavior. For this reason I am predominantly interested in the properties of the group, and not the individuals. Groups will be evaluated based on:

- the number of offers accepted in each round (measuring the amount of conflict within a group.)
- the total wealth of the group
- the level of equality within the group (measured by the Gini index.)

¹For normal distributions, the rule of thumb is to have a minimum of 30 observations. I initially planned to run all simulations 30 times and evaluate the distribution at random time slices, but the computer decided that such analysis was beyond its capabilities, limiting me to 25 runs.
Chapter 5

Expectations

When I started working on this project the goal was to try to show why rational behavior is not observed in the real world as much as the neoclassical microeconomic model would expect. I wanted to show why rational behavior is not adaptive in certain group settings and therefore will not evolve. After thinking about the model, I realized that such results cannot be expected from this design until the additional complexity of heterogeneous groups and procreation/survival of fit agents are added. The purpose of simulations is to reveal findings that cannot be logically predicted due to model complexities. If we knew why the current observable behavioral patterns evolved, we would not be running simulations to find out. For this baseline model at its relatively low level of complexity I can still make reasonable predictions and draw hypotheses as to what outcomes I can expect once the simulations are run. As this research agenda continues and the model becomes more complex, properties of the group will become impossible to predict in detail.

Acceptance rate and group wealth are directly related. For any rejection, while the individual’s wealth is not changed, both parties and the whole group will be poorer as compared to if the offer was accepted. For this reason, the group wealth will be the
highest where rejections are the lowest. Since punishments are automatic zero offers or rejections and rational agents do not punish, I expect both the group wealth and the acceptance rate to be the highest for the rational group, followed by the groups where only individual agents punish outperforming the groups where every agent punishes. Overpunishment will create a financial deficiency for groups where every member punishes. This phenomenon was already identified in Axelrod’s prisoner’s dilemma simulation tournament with the grim trigger strategy where the agent cooperates only until the other agent defects.\textsuperscript{1}. After that the grim trigger is tripped, and punishment (realized by defection) will occur in all future rounds regardless of the possible gains from mutual cooperation. \cite{16} This strategy did poorly because it punished defection and never forgave the loss of possible mutual gains. The grim trigger fell into the trap of overpunishment.

On the other hand, I expect the rational group to have less equality. The agents in the rational group will quickly figure out that their optimal $\hat{x}$ for each offer is around .5 and therefore will always offer 0 or 1. The offerers who keep 9 and offer 1 will in the next round be more likely to become the allocators again, creating an ever increasing wealth gap between the haves and have nots of the group. This gap should increase as the offerers are more likely to become offerers and keep offering 1 to the recipients.

To sum up the expectations:

- Acceptance rate and Wealth: Rational Group $>$ Realistic Group where Individuals Punish $>$ Realistic Group where the Whole Group Punishes

- Within group equality: Realistic Groups $>$ rational Group

\textsuperscript{1}In prisoner’s dilemma the agents’ options are to cooperate or defect; mutual cooperation yields the highest payoffs but both parties have an incentive to defect. Since it pays a premium to the agent that defects as long as the other cooperates, mutual defection is the Nash equilibrium and yields a low payoff to both parties.
Chapter 6

Findings

6.1 Group Harmony and Conflict (Acception Rates)

As expected rational agents’ acception rate (and mean expected offer) drops to .5 and settles around this point. (see Figure 6.1)

Figure 6.1: Acception rate for the group of rational agents
For groups where the agents have realistic acception functions and the individuals engage in punishing behavior, the results are more colorful (see Figure 6.2). Note that the scale of the charts are not the same, so at first glance they might seem misleading. In the later chart the high point of the Y axis is around .5, whereas .5 for the rational group’s chart was the mid-point.

Figure 6.2: Acception rate for groups where the individual punishes

Black, Red, Green: punishment for 3, 25, 150 encounters
Blue, Turq, Purple: punishment for 3, 25, 150 rounds.

Notice the distinct difference between the results where punishment is measured by encounters, versus where punishment is measured by rounds. Where punishment is measured by rounds, and agents hold grudges for a certain period of time, (regardless of whether they had an opportunity to get back at the social deviant) the level of punishment is substantially lower, and therefore total acception rate is higher. In
reality a mistreated agent will encounter the unfair allocator \( \frac{g}{n-1} \) times. \(^1\) So for our cases where a grudge is held for 3, 25, and 150 rounds, the mistreated agent will see to punish the social deviant .02, .17 times, and once\(^2\), on average.

Compare this with punishment administered for 3, 25, and 150 encounters. It is clear that acception rate is much lower, even if we compare the group where agents punish for 3 encounters to the group where agents hold grudges for 150 rounds. This is because punishment of any unacceptable offer will be exercised for three rounds, no matter how long the agents have to wait to meet again (as compared to punishment occurring once on average).

Inspecting the chart, the most visible phenomenon arises in the group where individuals punish for 25 rounds. Acception rate in this group quickly drops to about .30% and starts to climb back up at around round 5000, after which it dips again, but not as much as it did before. What is going on here? If you think about the processes at play within the group, many agents make at least one low offer, or find someone who finds even a reasonable high offer unacceptable. The offended agent will then punish the “deviant” for the following 25 encounters. The more discontent an agent creates around him/her self, the less people will play the game with her/him. Practically, this decreases the number of acceptions but does not eliminate them. During this time each agent has enough time to think about their socially unacceptable offers and can readjust their offer function to a relatively high \( \hat{x} \), where the cycle starts again. Averaging across the behavior of the 150 agents in the group and across 25 simulations these trends become less significant as time passes and as the individual agents make upward adjustments and dip again at different times, hence the (on average) smaller dip next time around.

Since I thought it would be interesting to see how this trend continues, I ran one

\(^1\)where \( g \) is the number of rounds the grudge is held and \( n \) is group size.
\(^2\)respectively
simulation for 50000 rounds and plotted the results (see Figure 6.3). Due to the lack of computing power and the analysis software’s (R’s) inability to deal with arrays much larger than I was feeding it, I was not able to run this simulation several times and average across the results, which is why you see much more scatter around the trend line in the graph. On this graph it becomes obvious that the trend of ever diminishing dips continues until they become impossible to observe by naked eye and completely disappear.

Figure 6.3: Further Exploration of Acceptance Rate

Acception rate for the group where the individual punishes for 25 encounters.
Single simulation run for 50000 times
For groups where agents have realistic acception functions but the whole group engages in the punishing of agents who make unacceptably low offers, the results are quite different (see Figure 6.4). Similarly to the groups where only the individuals punish, the groups where a grudge is measured by rounds do better versus groups that punish until they get back at the deviant agents. It is also important to point out that these groups, where punishment is measured by rounds, tend to do worse as compared to their counterparts where only the individual punishes. To some extent this makes sense. We can expect lower levels of group harmony for groups where everyone gets on everyone else's case versus those where individuals keep their grudges to themselves instead of telling everyone how bad other members of the group are.

Figure 6.4: Acception rate for groups where the group punishes

![Graph showing acception rate for groups where the group punishes.](image)

Black, Red, Green: punishment for 3, 25, 150 encounters  
Blue, Turq, Purple: punishment for 3, 25, 150 rounds.

For groups where the punishment is measured by encounters again, a wavy pattern emerges, most visible for the group where grudges are held for 150 rounds. The reason for the emergence of this wavy pattern is not much different from the explanation of
the waves for the groups where only the individual punishes. But the shapes are much different for a reason. If you look at the acceptance rate for the group where agents punish for 150 encounters, the acceptance rate actually hits 0. Due to the properties of random number generation and Gaussian laws with many cases, it becomes clear that each agent will either drop at least one low offer or meet someone who cannot be satisfied even with a relatively high offer. For the following rounds this agent will be excluded from all transactions until s/he meets everyone else in the group for 150 times. But during this long time this agent has to think about how much they offer the next time around, their expected offer adjusts back to high values. Every agent in the group goes through several waves of this unpleasant experience, and averaged across the whole group this phenomenon is the wavy pattern what we see on the graph. Note that similar but much more dampened trends are also present for groups where grudges are held for 3 and 25 encounters.\(^3\)

### 6.2 Group Wealth

We have already established that group wealth is a function of acceptance rate. Figures 6.5 and 6.6 show a clear positive relationship between group wealth and acceptance rate for all groups. Again the group that shows the best performance is the rational group, followed by the groups where individuals punish for a given number of rounds. Note the sharp break and slow drop off in the wealth line for the group where a grudge is held for 25 rounds (Figure 6.5 - green line). This is a direct function of the climb and second dip in acceptance rate already discussed above.

For the groups where every member punishes, overpunishment has a clear impact on the group members’ pocketbooks. It is interesting to note that in these cases the

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\(^3\)To verify this you might have to consult with additional charts presented in Appendix B.
wealth of the group is more a function of the length of punishment and not of whether it is measured by rounds or encounters. The two wealthiest groups are the ones that punish for three rounds and three encounters followed by the ones that punish for 25 rounds and 25 encounters and so on...

6.3 Group Equality

The measure of inequality in economics is the Gini index, with lower numbers representing more equal societies. (For an extended discussion of how the Gini index is measured, see Appendix C.) Though the Gini index is predominantly used to measure distribution of wealth within countries, I found no theoretical or mathematical objection to applying it to our groups of 150.

The rational group performed better than expected, presenting an ever increasing
equality outperforming most other groups. The only groups with higher equality are the ones where individuals punish and the level of punishment is relatively low (3 and 25, but not 150) and measured by rounds and not by encounters (see Figure 6.7). For groups where inequality was measured by encounters, the Gini index decreased at a much slower rate and increased for groups with high levels of punishment.

For groups where all members punish, the rational group outperformed all the other groups (see Figure 6.8). Also, similarly to group wealth, equality was more a function of the rate and not the mode of punishment. The groups where everyone punished for 3 rounds or encounters outperformed the groups where everyone punished for 25 rounds or encounters, etc.

Puzzled by the exceptionally good performance of the rational group, I decided to do some more post-hoc exploration (see results in Figure 6.9). Initially I suspected that this was due to group size. I suspected that as members of the rational group
Figure 6.7: Level of inequality (Gini index) for groups where the individual punishes

- Black: rational individuals
- Red, Green, Blue: punishment for 3, 25, 150 encounters
- Turq, Purple, Yellow: punishment for 3, 25, 150 encounters

Note: For better presentation first 200 rounds were not plotted

Figure 6.8: Level of inequality (Gini index) for groups where the group punishes

- Black: rational individuals
- Red, Green, Blue: punishment for 3, 25, 150 encounters
- Turq, Purple, Yellow: punishment for 3, 25, 150 encounters
figure out that the most logical offer is a low one, and as the receiving agents accept these low offers, group equality would decrease. Remember, the probability of having the powerful position, being the allocator in the transaction, is the function of the wealth difference of the two agents interacting. Since in the beginning all agents start with 0 dollars, group equality is perfect. This utopian state quickly erodes as some agents gain some money\textsuperscript{4}. It is logical to assume that in a group of 150, enough agents will meet others with similar wealth, and therefore inequalities will not emerge. This will be amplified by the fact that it takes rational agents some time to figure out that very low offers are also accepted. But when I decreased group size to 10, the results remained. In fact inequalities kept on decreasing until I fixed the probability of the more wealthy agent becoming the allocator, regardless of the magnitude of the difference in wealth. At .75 probability inequalities settled and stayed about the same and at .8 inequality started to increase. This verifies that inequalities could start to increase if large enough wealth gaps could develop in the first place, but in this model, this is not the case.

\textsuperscript{4}The Gini index is not efficient in measuring equality in the first rounds. Let us assume that we only have two agents. When one agent has $1 and another has $9 it will be seen as highly unequal. As wealth overall increases but the difference in wealth remains the same, for example when one agent has $100 and another $109, the distribution of wealth will be seen more equal. For this reason, and to make the graphs more presentable, I sometimes dropped the first two hundred observations from the charts
Figure 6.9: Level of inequality (Gini index) for groups with rational individuals

- **Black**: Powerful position decided by proportion of wealth
- **Red**: Same as above with small group - 10 agents in the group
- **Green**: Wealthier agents becomes allocator 80% of the time
- **Blue**: Wealthier agents becomes allocator 75% of the time
Chapter 7

Discussion of the Results

First, I will evaluate the results based on how the design needs to be improved, and what these baseline numbers mean and then discuss possible implications to political theory or empirical research.

The two main elements missing from this design are heterogeneous groups and error. Simulation studies in the past have suggested that heterogeneity of behavioral patterns can have a radical impact on the evolution of the group [12]. From a societal perspective it is clear that components of individual decision making varies from person to person. A recent study utilizing experimental game theory and fMRI technology concluded that the areas of the brain which are active during a decision vary across people and have a significant impact on the decision function of the person [20]. I would hypothesize that the results could be significantly different depending on how and to what extent heterogeneity of groups was achieved. We know from experimental studies, that context matters [21] [22]. Unfortunately building context into multi-agent models is no small task. Furthermore the generalizability of such models without the contextual element is always questionable, therefore researchers must strive to incorporate the contextual framework in the model and pay careful
attention to the validity and generalizability of the inferences they draw. Of course context goes beyond group composition. In this section I will cite other contextual elements that, if incorporated, might lead to radically different results.

Another possible improvement of the model once heterogeneity of groups is included would be some type of replication method for agents. It would be possible to give agents a life span and have them procreate with the more well-off agents having a higher chance of procreating. Results could then include the change of within-group distribution of certain behaviors. With such a model, the rule of fixed group size would also need to be reconsidered, and the comparability of groups with different sizes analyzed.

As far as evaluation of the results is concerned, it became increasingly clear that a distinction will need to be made between rejection and punishing behavior. With the current software it is not possible to separate the two behaviors. Also, in light of this problem, other designs of agent interaction should be considered that allow for clearer distinctions between the immediate rejection of an offer, a refusal to engage in social interaction, and long term grudge-holding and punishing behavior. Using ultimatum bargaining was extremely convenient since the large body of empirical research using this experimental design allowed for good agent designs. The downside of ultimatum bargaining is that rejection of interaction and socially unacceptable offers are not clearly separated from punishing behavior. The empirical researchers should start using designs that more clearly separate these behaviors.

To complicate the issue further, empirical research shows that people weigh costs and gains differently. Framing the same question in terms of gains and losses triggers different responses from people [23]. Currently, punishment in ultimatum bargaining is framed as forfeiting possible gains. While neo-classical microeconomic rationality is indifferent to the framing of losses and gains, we have sufficient empirical evidence
that if punishment would be framed in terms of enduring costs to the punisher, behavioral patterns would change significantly. This further complicates the design of agents. Though prospect theory does give us a quantifiable mechanism for distinguishing costs and gains, over-complication of simulation design can increase the chances of untraceable bugs, makes isolation of behavioral effects and interpreting results increasingly difficult.

Another obvious improvement to the model would be a varying amount in the divisible pot. It is unrealistic to claim that every social interaction has similar importance in people’s lives. It is unrealistic to claim that every economic transaction is the same. Take, for example, something as simple as every day purchases. When I buy batteries at a gas station, I know that I am being over-charged because I could get the same batteries in Wal-Mart for half the price. I still buy. Yet when I am purchasing a car, I would not consider buying from the dealer that sells it for twice as much and makes three times the profit versus other dealers. Similarly to the addition of a distinction between losses and loss of gains to the behavioral functions of realistic agents, the addition of considerations such as the weight of the transaction in an agent’s life would further complicate the behavioral functions.

The design of realistic behavioral functions is problematic. Take, for example, the conflicting results from the experiments which triggered this study. Third parties to a transaction are reluctant to punish deviant behavior, especially if the costs of the punishment are not also endured by themselves. If the costs of punishment are not deferred, these conclusions might not be valid and peoples’ decisions could be significantly different. Yet, people still care about what outside observers to their transactions think about their behavior.

These concerns could legitimately trigger conclusions that the world cannot be modeled with game theoretical models since these reduce the complexities of decisions
and ignore small but significant factors. While I believe this is a valid concern, I would still rather try to model the real world than to give up on research. Hopefully, through artificial intelligence technology and advances in evolutionary game theory and multi-agent modeling simulations, we can create more and more realistic environments. One day we might realistically replicate the real world within a computer.

Looking at the results of the simulation, I am going to conclude that the offer function also has flaws. While the function looked very reasonable on the drawing board, in practice any agent playing against a rational recipient would figure out that the best offer is 1 and not hover around trying to get away with a zero offer 50% of the time. One proposition to overcome this problem would be to decrease the standard deviation of the offer after every round. On the other hand, this change would lead to non-varying, deterministic offers after a certain amount of rounds depending on the standard deviation's pre-set value and the size of the decrease. With such a design early variation in behavior would not be comparable to late variation within a simulation. As was clear from the results, some patterns take several thousand rounds to emerge. With such an intervention these patterns might be altered before they can emerge.

Another possible way of dealing with the offerer function is to make it less incremental and more categorical. It would be possible to treat all six of the possible offers (0, 1, 2...5) as separate categories and assign probabilities to their occurrences, then develop a learning function using Bayesian updating that would modify the probabilities, based on the successes and failures of past offers. Though this approach might sound reasonable, its scalability is limited. Consider the possibility of not restricting offers to whole dollars. The number of possible offers jumps from six to 600. Also, with the possibility of varying allocatable pots as proposed above, I cannot see this categorical allocation approach working.
Lastly, we need information as to the cognitive mechanics of people’s angers and grudges. Do people generally forgive over time or do they hold a grudge until they get back at the person, until they get retribution? What determines the strength and length of social punishment? If answers to these questions are not clear cut (as I expect they will not be, I expect to see tremendous variation across people), what are the properties of the variation? What percent of people forgive over time? What are unforgivable offenses? To what extent the magnitude of the offense is a function of the level of grudge it triggers? These questions will have to be answered empirically and incorporated into the behavior functions of agents.

Agents within groups do not necessarily have to be homogeneous as to how long they hold a grudge or if they forgive over time. Further within group variation can be introduced into the model through these mechanisms.
Chapter 8

Conclusion

Though I forcefully warn against drawing definitive conclusions based on this preliminary model, I will go ahead and do it anyway for observations that were strongly consistent across all the simulations. It is obvious that high levels of punishment decreases the well being of the group. Fehr and Rockenbach presents evidence that “unfair” (high) levels of sanctions lead to decreased levels of cooperation within groups. The results of this simulation back up these findings and offer explanation for the reasons why this is the case in today’s societies [24].

These findings have clear policy implications. Government should be careful with punishment, and maybe we should encourage the development of a more forgiving society. It might be a stretch to claim that the results of this simulation definitively translate into the need to view the prison system as a rehabilitation tool and not a punishing institution, but the results surely make such suggestions.

It is clear that higher rates of punishment have a negative impact on the development of equality. Though most results show that equality is increasing, for groups with high levels of punishment this increase is significantly slower and at the highest levels of punishment might turn into a decrease. Equality statistics showed better re-
sults for groups where punishment was set to very, possibly unrealistically low levels. These results beg the question, why did punishment develop in the first place? Based on these findings it might be reasonable to formulate a hypothesis that punishment is a tool that evolved to reinforce the status quo.

The bottom line on equality statistics is that equality is increasing for most groups. Though ever since Marx wrote the Communist Manifesto, political circles have paid disproportionate attention to increases of the income gap and decreases of economic equality in society. Popular examples would be the ever increasing salaries of CEOs, professional athletes and popular culture stars [21]. On the other hand critics of Marxist theorists would claim that quality of life disproportionately increased for the working class compared to the owners of the means of production. Technology has brought entertainment, transportation and access to inconceivable information within reach of the majority of the world’s population. Empirical verification, especially on a global scale, measured in quality of life and not figures of currency, might verify that the gap between the rich and the poor is decreasing and not increasing. Further empirical research is needed to draw definitive conclusions.

And lastly the design that verified the hypothesis that equality is actually increasing and not decreasing was the one where the level of power agents have over the social process was fixed at high levels for wealthier agents. In all other cases this simulation used a wealth proportional allocation of the powerful allocator position between two agents. But how proportional this is in the real world requires additional empirical scrutiny. If I have twice the wealth compared to another person, do I on average have twice the power over our social and economical interaction? It is possible that as the income gap increases the power gap increases at higher or possibly lower rates. Answers to this question have to come from empirical evaluations of society.

The results of the study, at first, might sound discouraging. The findings will not
directly lead us to an understanding of why irrational behavior evolved. Based on this model rational behavior is what makes sense from an evolutionary perspective. But if this is the case, the question remains. Why are we not rational? I would be hesitant to draw conclusion based on this model.

For an evaluation of the merits of this study we have to return to its goals. The main goal of this research agenda was to create an evolutionary model that leads to insights as to why neo-classical rational behavior might not be rational from an evolutionary sense. While this study did not definitively answer the research question and conclude the research agenda, it led to insights on how to design a better model and its results served as a baseline for the analysis of future results. If we consider a pilot study in empirical research, working out unforeseen issues with the survey instrument or experimental design is the goal. Once we evaluate the results in light of these goals, the study is a sufficient fist step in a research agenda.

This study has raised several questions about how the world works, and hopefully given important guidance and pointed to a meaningful direction of empirical research. With future analysis of the behavioral trends laid out in the discussion and the conclusion, more realistic agents and better analysis of the evolution of behavioral traits will become possible.
Simulations were coded in Java. The program’s output was comma separated values that were sorted with Perl scripts, loaded into R and analyzed and plotted through R.

Most of the analysis was done on a Fujitsu P-2110 with 867 MHz Transmeta Crusoe CPU and 240MB of RAM. Additionally an e-machines laptop with an AMD 64 CPU was also used for running the simulations. After running the benchmarks it became obvious that on the Fujitsu alone the simulations would have to run for about 40 days non-stop to finish. The simulations produced around 15 GB of raw data. Individual processes like loading this raw data into R for analysis, and sorting and calculating the group averages and gini indexes often took several hours. R often informed me that the data array I was about to load was too large for its capacity.

Due to the lack of adequate computing power I often was not able to go into as much detail as I wanted to. I often wanted to run the simulation for longer than 10000 rounds, and it would have been nice to vary other variables more (like the extent of punishment). If I could go back to the beginning of this research I would not start it until I had adequate computing power to do it better, do it right and save me a ton of frustration, headache and compromises. (I would also have Andras, the programmer,
code this is something other than Java.)

Due to the insane amount of data that was created I will not make the simulation output available through the web. On the other hand this document, the simulation source code and binaries, and some of the pre-coded scripts used for sorting and analysis, along with the \LaTeX source code and charts of this document, will be made available at http://www.littvay.hu/thesis/ If you wish to receive a copy of the simulation output for replication purposes, I have it on CDs and can snail-mail you the data. With such requests please e-mail me at levi@bigred.unl.edu or contact me through my website at http://www.littvay.hu
Appendix B

Appendix B: Additional Charts

In addition to the charts presented in the body of the study, I have prepared additional charts that make it easier to compare groups across different properties. This appendix is devoted to the presentation of these charts.
Figure B.1: Acceptance rate for groups where punishment rate was set to 150

- Black: rational individuals
- Red/Green: individual punishes for 150 rounds/encounters
- Blue/Turq: group punishes for 150 rounds/encounters
Figure B.2: Acceptance rate for groups where punishment rate was set to 25

Black: rational individuals
Red/Green: individual punishes for 150 rounds/encounters
Blue/Turq: group punishes for 150 rounds/encounters
Figure B.3: Acceptance rate for groups where punishment rate was set to 3

Black: rational individuals
Red/Green: individual punishes for 150 rounds/encounters
Blue/Turq: group punishes for 150 rounds/encounters
Figure B.4: Wealth for groups where punishment rate was set to 150

- Black: rational individuals
- Red/Green: individual punishes for 150 rounds/encounters
- Blue/Turq: group punishes for 150 rounds/encounters
Figure B.5: Wealth for groups where punishment rate was set to 25

Black: rational individuals
Red/Green: individual punishes for 150 rounds/encounters
Blue/Turq: group punishes for 150 rounds/encounters
Figure B.6: Wealth for groups where punishment rate was set to 3

Black: rational individuals
Red/Green: individual punishes for 150 rounds/encounters
Blue/Turq: group punishes for 150 rounds/encounters
Figure B.7: Level of inequality for groups where punishment rate was set to 150

Black: rational individuals
Red/Green: individual punishes for 150 rounds/encounters
Blue/Turq: group punishes for 150 rounds/encounters
Figure B.8: Level of inequality for groups where punishment rate was set to 25

Black: rational individuals not plotted.
Red/Green: individual punishes for 150 rounds/encounters
Blue/Turq: group punishes for 150 rounds/encounters

Note: For better presentation first 200 rounds were not plotted
Figure B.9: Level of inequality for groups where punishment rate was set to 3

Black: rational individuals
Red/Green: individual punishes for 150 rounds/encounters
Blue/Turq: group punishes for 150 rounds/encounters
Note: For better presentation first 200 rounds were not plotted
Appendix C

Appendix C: The Gini Index

This appendix presents a conceptual description of what the Gini index is. Of course a calculus heavy mathematical explanation of how the Gini index is measured and calculated does exist, but for the purposes of this paper, it is unnecessary. The Gini index was calculated with R using the ineq package’s gini function. The ineq package was designed to calculate measures of inequality.

The Gini index is an index of equality within a group. How it is measured is best represented by a chart; throughout the description I will refer to the figure in the Appendix.

Imagine a perfectly equal society. Perfectly equal means that 20% of the population has 20% of the wealth, 50% of the population has 50% of the wealth, etc. This state is represented by the diagonal line above the blue areas. Now imagine a more realistic society that is less equal, where the poorest 25% of the population has 10% of the wealth, the lowest 50% of the population has about 20% of the group’s wealth and lowest 80% has about half of the wealth (the top 20% owning the other half). This state is represented by the line between the blue and the purple areas. The Gini index is the area between the perfectly equal and the actual state, the blue area.
Figure C.1: The Gini Index
Bibliography


