Selfish Altruism

How sharing may be economically rational on a network

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This paper presents a network model in which individuals receive a resource endowment every period, and the links in the network represent connections between people who exchange part of their resource endowment with one another. After running multiple simulations of the model, the results provide initial evidence that the maximum possible payoff for a player in a network occurs when she allocates an intermediate fraction of her resource endowment to her neighbors. This conclusion may justify why individuals share resources with one another, without needing to compromise the classical economic assumption that actors make decisions in their own self-interest. An empirical study is also designed that could test the model's conclusions in reality.

1 Introduction

Classical economic theory does not naturally lend itself to justifications or explanations of altruism. Rational actors make decisions to maximize their own utility, solely acting in their own self-interest. Behavioral economists have been most critical of the foundational assumption in economics of full awareness and rationality, and have put forth significant amounts of evidence to undermine this assumption. The troubling part of this criticism is that many important conclusions in classical economics assume perfectly rational agents. If this seemingly simple assumption is invalidated, then that calls into question many of the conclusions of economic theory.

Some of the most well-known experiments conducted to demonstrate the limits of individuals' rationality are the Ultimatum Game, and its derivative, the Dictator Game. Both games consist of two participants, where one player is the "proposer" and the other player is the "acceptor". The proposer is given a sum of money and told to offer the acceptor some fraction of the sum. In the Ultimatum Game, if the acceptor refuses the division, then neither person gets any money. In the Dictator Game, the acceptor has a passive role, and does not have the option to reject the allocation. Although the optimal strategy for rational economic agents in both games is for the proposer to keep the maximum amount possible for herself and for the acceptor to accept any allocation, researchers consistently observe in the Ultimatum Game that proposers usually divide the sum more equitably and that acceptors reject low allocations (Stanton, 2006). These results do not match the game-theoretic equilibrium, but at least the acceptor has some leverage over the proposer. The acceptor may in fact be acting optimally if the game is played multiple times, and the proposer rationally adjusts her offer based on the acceptor's behavior pattern. The dictator game is more puzzling, because the only possible explanation for why the proposer offers anything more than the minimum to the acceptor is that the proposer's utility function is a broader social utility function, in which concepts such as fairness and reputation may be important to the proposer (Stanton, 2006).

The most important mystery that needs to be resolved is to understand what drives people to behave in a way that seems to contradict classical economics. The existing economic research most relevant to the current topic has to do with the economics of gift-exchange and favor-exchange. Although similar, the main conclusion that researchers have found in the former case is that agents mainly reciprocate gift-giving for obligatory purposes, with ever-larger gifts creating greater pressure to give in return (Landa, 1994). Favor-exchange differs in that the amount of time between the initial favor and when the recipient reciprocates can be much larger. Further, Neilson (1999) points out that unlike gifts, for which the giver chooses the value and the moment to give the gift, favors occur by chance. The possibility of doing a favor for the recipient only occurs when the recipient needs some help, and the giver merely has a binary decision of whether to complete the favor or not. This makes favor-exchange much more volatile, and can allow socially-inefficient favors to be performed (Neilson, 1999).

This research relates to the current paper's topic, but it fails to address the ordinary behavior of economic agents; that is, how people allocate their endowments on a regular basis and not solely when they owe other people favors or have received gifts from others. The existing literature does not take into account individuals' positions in a network, but network papers have not delved deeply into these kinds of actions. Galeotti, Goyal, Jackson, Vega-Redondo, and Yariv (2009) survey the work that has been done on games on networks. They find that despite the growing number of insights and wide applications, the focus of research has remained on how the actions of individuals in a network affect the actions of her neighbors, but the actions are not being performed on an individual's neighbors. That is, even the action-focused models are effectively variations of learning or opinion models such as the DeGroot (1974) opinion-formation model. For example, Conley and Udry (2005) present a network model in which individuals witness the actions of their neighbors, and then adjust their own actions based on the outcomes around them. These network participants are pineapple farmers whose decisions are influenced by their neighbors, but the actions of their neighbors do not affect their own payoffs directly.

The closest existing work to the current topic was done by Sinatra, Iranzo, Gómez-Gardeñes, Floría, Latora, and Moreno (2009). They examine the outcome of the Ultimatum Game on a network, and find from an analysis of their model that fairness and altruism can emerge on a network if the network has natural selection, which means that agents adjust their strategies after seeing the payoffs of the strategies of other agents in the network, and social penalties for low offers. Although these results are interesting, they do not translate well to modeling how individuals allocate their time and energy among their contacts. For example, if person A offers person B some fraction of her wealth, if person B disapproves of the small amount that person A is offering, that does not affect whether person A gets her own allocation. Further, introducing constructs such as social punishment and strategy mimicry prevents the researchers from being able to conclude that by purely acting in one's self-interest, altruism will emerge on a network.

This paper aims to address the lack of truly action-influenced network models. It presents a model to see whether economic agents, who are altruistic, such as the participants in the Dictator Game studies mentioned above, are also behaving rationally when the problem is presented on a network over multiple time periods rather than in an isolated laboratory environment. Action-influenced networks as opposed to opinion-influenced networks provide a more comprehensive and realistic simulation of how people interact in the real world, because they account for the fact that an individual's neighbors' actions influence not only an individual's opinions but also her payoff.

2 Model

This model aims to replicate how a network grows and contracts based on each individual's generosity. The nodes are the people in the network and the links represent exchange relationships between people in the network. That is, if a link exists between two players, then they are exchanging some fraction of their respective resource endowments. The initial network structure is a random network, with each node roughly assigned a number of connections inversely proportional to the square root of the number of nodes in the network. This ensures that as the initial network becomes larger, the number of people to whom each player is connected does not decrease as quickly as in a strictly inverse relationship while also ensuring that players are not too well connected initially. This seems to be a reasonable assumption because people tend to only know well a small proportion of the total people in a full network (such as the student body of a university).

In this model each player has an endowment every period, which represents her total wealth, time, and other resources that she can choose to spend partly on herself and partly on others. This concept tries to capture the broad idea that people spend part of their resources on others, such as meeting up for meals, helping each other with projects, or helping a friend pay a down payment on a house. Every person in the model is assigned a generosity index, α, where $\alpha \in [0,1]$. The higher one's generosity index, the more she allocates to the people with whom she is connected. It is assumed that this generosity index does not change, and that it is not dependent on wealth. This is a reasonable assumption, because the generosity index is a component of a person's personality, and not a result of one's wealth. For example, there are wealthy people who actively donate to charities as well as wealthy people who prefer to spend most of their income on themselves. Likewise, some poor people give back what little wealth they have to the community, while others only care about using their meager wealth to sustain themselves. Every person's payoff every period is a combination of the fraction of her endowment which she keeps for herself and the sum of the portions of her neighbors' endowments which they give her each period.

Each variation of the model will build upon the previous version, adding complexity to the model, and at each step the performance of the model will be tested in a simulation. The tests will use a normally distributed α, implying that most people are somewhat generous with their resources, a few are completely "altruistic", and a few do not share much at all. This seems to fit with the existing empirical data, because Rege and Telle (2004) find from their public good experiment that even without the pressure of social approval the distribution of one's allocation to the group endowment follows a similar normal distribution. Granted, the model in this paper is not dealing with a public good, but the Rege and Telle (2004) results probably reflect the distribution of people's mindsets when deciding how much to give to others. Each model will also be tested with a uniform distribution of the generosity index to accentuate the effect that one's social allocation has on one's final payoff.

The sequence of actions in each version of the model is the same. First, every node is assigned a generosity index, and links are formed using a binomial distribution where the probability that any two nodes will be linked is inversely proportional to the square root of the number of nodes in the network. Once this initial setup is complete, the following actions repeat until each node's degree stabilizes. A node receives payoffs from each of her neighbors according to their generosity indices and degrees. Then, a node looks at her payoffs from each neighbor and severs the link between them if the payoff from her neighbor is below the decision threshold specified in each version of the model. Lastly, from one's existing remaining neighbors, each node determines whether a neighbor's payoff was above the threshold, in which case the node creates a link between that neighbor and another one of the node's contacts who has not been previously linked to the generous neighbor.

2.1 Basic Model

In the basic model each person is given a normalized resource endowment every period equal to 1. It is further assumed that every person consumes her payoff each period, so no accumulation occurs between periods. The last assumption is that given a person's social allocation of her resource endowment as determined by her generosity index, this fraction of endowment is equally distributed among a person's connections. Each of these assumptions will be relaxed in later versions of the model. Thus, a player *i*'s payoff, π_i, each period in this model is:

$$\pi_i = \begin{cases} 1 - \alpha_i + \sum_{j=1}^{d_i} \frac{\alpha_j}{d_j} & if\ d_i > 0, \\ 1 & otherwise \end{cases}$$

In this equation, d_i represents the degree of person *i*, or the number of people to whom person *i* is connected. The ratio $\frac{\alpha_j}{d_j}$ represents the benefit that person *i* gets from her link with person *j*. From this equation, a member of this network only benefits from having connections with other people if the quantity $\sum_{j=1}^{d_i} \frac{\alpha_j}{d_j} - \alpha_i$ is greater than 0. This would imply that the person gets a net benefit from participating in the network. Although a person strictly benefits from having more links because she then receives more fractions of resource endowments while her total social allocation remains constant, there is an inherent tradeoff because as a person gains more links, her own allocations to each neighbor are diluted.

Thus, there is a natural threshold for an agent to determine whether her neighbors are worth being connected to – on average, an agent needs to be receiving $\frac{\alpha_i}{d_i}$ from each neighbor to break even. This ratio will be referred to in the paper as the decision threshold. Any neighbor that provides sufficiently less than this threshold will be cut off from the agent. A node will tolerate someone who provides slightly less than the threshold because the node still receives some allocation from that neighbor. Any neighbor who provides sufficiently more than this threshold will be linked with another one of the agent's neighbors to whom the generous neighbor was not previously connected, if possible. An agent will not create links if the benefit from a neighbor is only slightly more than the threshold, because creating this additional link will inherently dilute the agent's benefit from the generous neighbor. This way an equilibrium will arise, as links will be formed until players are too diluted to be contributing sufficiently to another player's payoff and then the excess links will be severed. This model is realistic because it captures the idea that a person will not want to help out someone who does not offer her a similar level of benefits in return.

2.2 Weighted Allocation Model

Although the even distribution of an individual's social allocation among her neighbors is a good starting point for the model, a more realistic distribution would weight neighbors based on their closeness to the individual. To proxy for closeness, it is assumed that neighbors of an agent who share more common neighbors with the agent are closer to the agent, and so the agent will weight these closer neighbors more heavily when distributing her social allocation. This modification of the model makes sense because people tend to have more common acquaintances with their closer friends, and people spend more of their time and energy on their closer friends. Further, since a person cuts off a link with a neighbor who contributes significantly less than the person's threshold, this weighting mechanism reflects the fact that people care more about preserving a link with their closer friends, so they will give their closer friends more of their social allocation to keep themselves above their friends' decision thresholds. Also, this modification to the model fits in with the mechanism by which nodes gain links. In a nebulous sense, a person who receives a significant social allocation from a neighbor will think more highly of that neighbor, and so by forming the additional link, the generous neighbor and the receiver will be considered closer acquaintances by the metric of common neighbors. Thus, a player *i*'s payoff, π_i, each period in this model is:

$$\pi_i = \begin{cases} 1 - \alpha_i + \sum_{j=1}^{d_i} \alpha_j \left[\frac{1 + t_{ij}}{\sum_{k=1}^{d_j} (1 + t_{kj})} \right] & if\ d_i > 0, \\ 1 & otherwise \end{cases}$$

Player *i*'s payoff in this equation is very similar to her payoff in the basic model, except that instead of receiving a social allocation from neighbor *j* inversely proportional to neighbor *j*'s degree, player *i*'s social allocation from neighbor *j* is proportional to the number of triads in which both person *i* and her neighbor *j* are present, t_{ij}, as a fraction of the total number of triads in which neighbor *j* is present.

2.3 Accumulated Wealth Model

This modification of the model relaxes the assumption that people consume their total payoff every period. Everyone still receives a resource endowment of 1 every period, but they also save their payoff from the previous period, so their wealth accumulates, and this allows the social allocation of wealthier people to increase. The compounding effect will increase the payoff of people with net social benefits and decrease the payoff of those with net social costs. For example, someone who does not have any connections will simply be increasing her wealth over time linearly, while connected individuals with social benefits will experience their wealth increasing exponentially. Now the payoff equation for person *i* is influenced by person *i*'s payoff in the previous period, *t-1*. Given a payoff in the previous period of $\pi_{i,t-1}$, a $\pi_{i,0}$ of 1 for all players, and a person *i*'s payoff in the current period, $\pi_{i,t}$ can be expressed as:

$$\pi_{i,t} = \begin{cases} (1+\pi_{i,t-1})(1-\alpha_i) + \displaystyle\sum_{j=1}^{d_i}(1+\pi_{j,t-1})\alpha_j \left[\frac{1+t_{ij}}{\sum_{k=1}^{d_j}(1+t_{kj})}\right] & if\ d_i > 0, \\ 1+\pi_{i,t-1} & otherwise \end{cases}$$

The decision threshold for person *i* now becomes $\frac{\alpha_i}{d_i}(1+\pi_{i,t-1})$ instead of $\frac{\alpha_i}{d_i}$. Intuitively, wealthier individuals will demand more from their neighbors.

2.4 Distributed Initial Wealth Model

The final variation of the action-influence model relaxes the assumption that everyone starts with the same initial resource endowment in order to try to capture the idea that people do not all have the same amount of resources if one were to take a cross-section of the population. This model extends the 2.3 model, having the payoff in period *t* be influenced by period *t-1*, but the agents do not also receive an additional constant amount every period. Although strict payoff aggregation does not exist in this model, rather than interpret agents as consuming their entire payoff each period, we can think of an actor's payoff each period as her flow of payoffs. That is, a player's periodic payoff is her rate of wealth accumulation. For the *n* agents in the network, each agent has a $\pi_{i,0} \in [.5, 1.5]$, $\pi_{i,0} \sim N(1, .16)$, with the normal probability distribution truncated at .5 and 1.5. This initial wealth distribution roughly follows the data from the US Census Bureau (2004) which shows that a small percentage of people have very high income levels, a small percentage have very low income levels, and most people have middle levels of income. By centering the normal probability distribution at 1, the aggregate wealth in the network should be close to the aggregate wealth in the network in which everyone's resource endowment starts at 1. An advantage of the current version of the model could be that it examines a player's social payoff regardless of the wealth of her initial neighbors. The payoff equation for player *i* can be expressed as:

$$\pi_{i,t} = \begin{cases} \pi_{i,t-1}(1-\alpha_i) + \sum_{j=1}^{d_i} \pi_{j,t-1}\alpha_j \left[\frac{1+t_{ij}}{\sum_{k=1}^{d_j}(1+t_{kj})}\right] & if\ d_i > 0, \\ \pi_{i,t-1} & otherwise \end{cases}$$

The decision threshold for person *i* now becomes $\frac{\alpha_i}{d_i}\pi_{i,t-1}$ instead of $\frac{\alpha_i}{d_i}(1+\pi_{i,t-1})$.

3 Results

Instead of solving the models mathematically, simulations were run using a computer program into which the actions and rules of the models were coded. The simulations iterated through the steps of actions until the degree of each node stabilized. Using a normally distributed generosity index and a uniformly distributed generosity index, each model was run ten times with a network size of one hundred nodes. The starting degree distribution, ending degree distribution, generosity index distribution, and final payoffs were recorded for each iteration. Then scatterplots were constructed from these data. Only the scatterplots from the normally distributed generosity indices are included because very little difference was observed when the generosity indices were distributed uniformly. Also, each version of the model was run using a scale-free network as the starting point as well, but in this type of network all links consistently were broken, leaving a completely disconnected network. This result makes sense given the rules of the model, since the hubs of the scale-free network would be providing very small allocations to each of their neighbors, who would then sever their ties to the hub. If everyone severs their ties to the hubs, then the network quickly disintegrates. This result is not troubling because social networks are not scale-free. Also, in the final model with normally distributed initial wealth, final payoff had no relationship with the initial distribution of resource endowments.

3.1 Effect of the Generosity Index on Payoff

After running the simulations for each version of the model, the payoffs of each player were plotted against the players' generosity indices. These plots are presented in Figure 1 in the appendix. Although the payoffs do not have similar values at a given generosity index, several common trends can be observed if one focuses on the range of payoffs at each generosity index. Since the distribution of links and generosity indices at the beginning of the model is an inherently stochastic process, the payoffs at each generosity index reflect the possible payoffs for a player with a given social allocation.

For each variation of the model, the lower bound of payoffs decreases as the generosity index increases, while the upper bound of payoffs increases up until an intermediate generosity index and then starts decreasing. The variance of payoffs is increasing as the generosity index increases to an intermediate value, and then the variance starts decreasing as the generosity index increases further, except for the 2.2 version of the model, in which the variance continues to increase. The noticeable straight line in the first three versions of the model reflects that isolated nodes in the network will be receiving the same, constant payoff each period. The varying starting resource endowment in model 2.4 masks the constant payoff of isolated nodes, but the first three versions of the model clearly demonstrate that a player in this network can only end up with a better payoff in the network than her initial resource endowment if she donates an intermediate portion of her resource endowment.

3.2 Effect of the Generosity Index on Network Structure

Figure 2 in the appendix presents a plot of the degree of each player once equilibrium is reached in the model against the generosity index of the player. As in the previously discussed figure, rather than look at averages, the most illuminating conclusions are derived if one looks at the range of degree at a given generosity index. In equilibrium, as a player's generosity index increases, the upper bound of her degree increases. This makes sense intuitively, since only players with a lot of neighbors who donate a significant amount of their resource endowment will be able to satisfy their neighbors' decision thresholds. Interestingly, the equilibrium in each of the models contains isolated players at all values of the generosity index. Individuals with low generosity indices may become isolated because their social allocation does not satisfy their neighbors' decision threshold, so their neighbors sever the tie between them. Conversely, an individual with a high generosity index may become isolated because her own decision threshold is very high due to her generosity index, so her neighbors do not satisfy her decision threshold, so she cuts her neighbors off. Unlike the low generosity index individuals who are at the mercy of their neighbors, high generosity index individuals can tolerate neighbors who provide them with a smaller amount if the degree of the high generosity index individuals becomes high enough to lower their decision threshold. Figure 3, which displays histograms for the generosity indices of isolated nodes in the equilibrium state for models 2.2 and 2.3, confirms this prediction because the highest frequency of values for the generosity index for isolated individuals occurs at the extreme ends of the generosity index.

Figures 6 and 7 demonstrate that the equilibrium network structure depends not only on the distribution of generosity indices, but also on the initial network arrangement. Under this model, the random network in Figure 6 forms a closely knit cluster and a large number of isolated nodes in equilibrium. The scale-free network, depicted in Figure 7, results in a network consisting of fully isolated nodes after running the model simulation.

3.3 Effect of the Decision Threshold on Payoff

The results in Figure 4 show that as the model becomes richer, the inverse relationship between the equilibrium decision threshold of a player and her payoff becomes more obvious. Low decision thresholds are beneficial because they allow a player to form a greater number of links, so the number of people who give her a portion of their social allocation increases. In this model, a low decision threshold is achieved by some combination of a low generosity index and a high degree. The surest method of obtaining a low decision threshold is to have a low generosity index, but as shown above, the individuals in the model with the highest degree are those who have higher social allocation. With this tradeoff, the optimum balance may be reached at intermediate levels of social allocation, which explains why the highest possible payoffs in Figure 1 occur at intermediate values of the generosity index.

An important thing to note is that the plotted data points exclude the isolated nodes because they have a degree of zero, so their threshold decision would not be a defined number. This is not a problem because isolated nodes are not interacting with other players, so they have no need for a decision threshold value. For models 2.1 and 2.2, the isolated nodes only receive the fixed, normalized endowment of 1, because their equilibrium payoff is independent of their past decisions and payoffs. In models 2.3 and 2.4, the payoff of the isolated nodes depends on their actions from previous periods. Section 3.2 explained that isolated nodes are most likely to be individuals with very high or very low generosity indices. As discussed above, the reason for the individuals' isolation differs depending on which extreme of the generosity index they are located. An individual who has a very small social allocation will quickly get cut off from her neighbors, but since her payoffs depend on her payoffs from previous periods, she may amass sufficient social allocations from her neighbors before she is cut off, so her equilibrium payoff may be higher than her initial resource endowment. Alternatively, an individual with a high social allocation will end up giving away a greater portion of her initial resource endowment than the amount she receives from her neighbors before she cuts off her ties with her neighbors, leaving her with a lower equilibrium payoff than her initial resource endowment. Figure 5, which plots the equilibrium payoffs of isolated individuals against their generosity indices for models 2.3 and 2.4, confirms the above explanation because there is a clear negative relationship between generosity index and equilibrium payoff for isolated nodes.

4 Interpretation

Despite having made significant improvements with added layers of complexity, the current model does not yield conclusive results in the simulation as to whether utility-maximizing agents in a network may act in their own self-interest by exhibiting altruistic behavior. The most advanced variation of the model currently has two possible conclusions. If an agent wants to try to obtain the greatest possible equilibrium payoff, she should allocate an intermediate percentage of her resource endowment to her connections. This result is exciting because it can provide a possible reason for why individuals in the Dictator Game may offer the "acceptor" an intermediate amount of the endowment. Rather than interpret this phenomenon as being caused by an unidentified social utility function, perhaps people are conditioned by their experience in their network to give their connections an intermediate fraction of their resource endowment to maximize their payoff, so they behave similarly in the laboratory setting. Although this result is compelling, an alternate conclusion from the model is that if an agent wants to obtain the greatest possible equilibrium payoff with certainty, then she will allocate a very small fraction of her resource endowment to her neighbors. Thus, the strategy that an actor chooses may be related to her level of risk-aversion.

To help clarify which conclusion is more representative of reality, the model should be modified to more accurately reflect reality. There are several adjustments that should be made to the model to allow it to better capture real-life social dynamics. First, the initial distribution of links should be such that individuals of similar initial resource endowments are more likely to be linked to one another. This would reflect the basic idea that an individual tends to have friends and coworkers who have a similar level of education and wealth as her. For models 2.1 to 2.3, all of the individuals have the same initial resource endowment, so this modification is unnecessary in those cases; however, model 2.4 would be much more realistic with this added detail.

The second adjustment to the model that would increase its realism is for links to also form and become severed organically. By randomly changing a small portion of links each period, the model would capture the idea that people sometime form relationships with other people by chance meetings, and this would allow isolated nodes to potentially reenter the network. Further, a small number of links may be severed each period to reflect arbitrary disputes that people may have, which prevent them from collaborating together in the future.

Also, despite the generosity index being an inherent facet of an individual's personality, allowing the generosity index to change as a function of an individual's payoff may lend itself to a more dynamic model in which people with low payoffs may increase their social allocation to try to increase their number of connections in order to increase the amount of benefit that they are getting from others in the network.

In terms of the initial network structure, a random network is probably not the most realistic arrangement, despite being the easiest to construct. A more accurate structure would be clusters of individuals, which would represent friend or coworker groups, connected to one another by a few links which would serve as bridges between the clusters. Modeling this style of network on a large scale was not feasible for the current project, but future work should consider running the model simulation on this kind of network.

5 Empirical Verification

Because of the nebulous quality of the concept of resource endowment, no comprehensive research has been conducted to gauge how individuals divide their time and wealth between themselves and their neighbors. One potential way to verify whether this model accurately reflects reality would be to conduct a study at small high schools with class sizes of about a hundred students. At the beginning of the study, researchers would survey all of the students from about ten high schools, asking students to rank their acquaintances from a list, ordered from closest friend to most infrequent acquaintance. This would provide a rough estimate of how individuals weight the social allocation of their resource endowment. The proxy for how students allocate their resources would be the amount of time that they spend with each of their acquaintances – if students spend less time with other students then they presumably have a lower generosity index, and vice versa. Of course this is not a perfect measure of resource allocation, but it serves as a reasonable approximation.

The main limitation of this study would be ethical concerns, because the way that the amount of time a student spends with her acquaintances could be measured by placing a small device on the student, or implanting a small diode, which would sense when another person with this kind of device was within a certain radius of the student. The other student's unique ID number could be recorded, and by this system, each person's device would record how much time she spent over a certain time frame with each acquaintance. Then, ideally over a period of several years, researchers would periodically ask the students to update their list of ordered acquaintances, and see whether the students' ordered lists corresponded to the amount of time that they spent with each person. A student's payoff would be measured by the total amount of time that other students spent with that student. By conducting this study, researchers could start to determine whether people weight the social allocation of their resource endowment according to how close they are to their acquaintances, and also whether the people who allocate more of their time to others have the greatest payoff from other people in the network.

6 Conclusion

The current model may not have established conclusive evidence that altruistic behavior optimizes a rational agent's payoff, but it shows the possibility of the idea. Network analysis is still a budding field of research, and academics have not yet fully brought together the implications of social networks with the theories of classical economics. The field of economics has traditionally been divided into two subfields – microeconomics and macroeconomics. The beauty of network analysis is that it demonstrates how the decisions of individuals affect the overall outcome of the network. Applied to economics, networks may help bridge the divide between the two subfields, and explain some of the seemingly irrational choices that people make. The model presented in this paper attempts to quantify the well-known fact that the most successful people in the world are the best communicators and collaborators. Following the terminology of this paper's model, these successful people have an intermediate generosity index, providing others with their time and resources, but generating a net benefit for themselves. Rational, selfish individuals should be willing to share their resources with others if this allows them to receive a net benefit from their participation in the network.

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Appendix

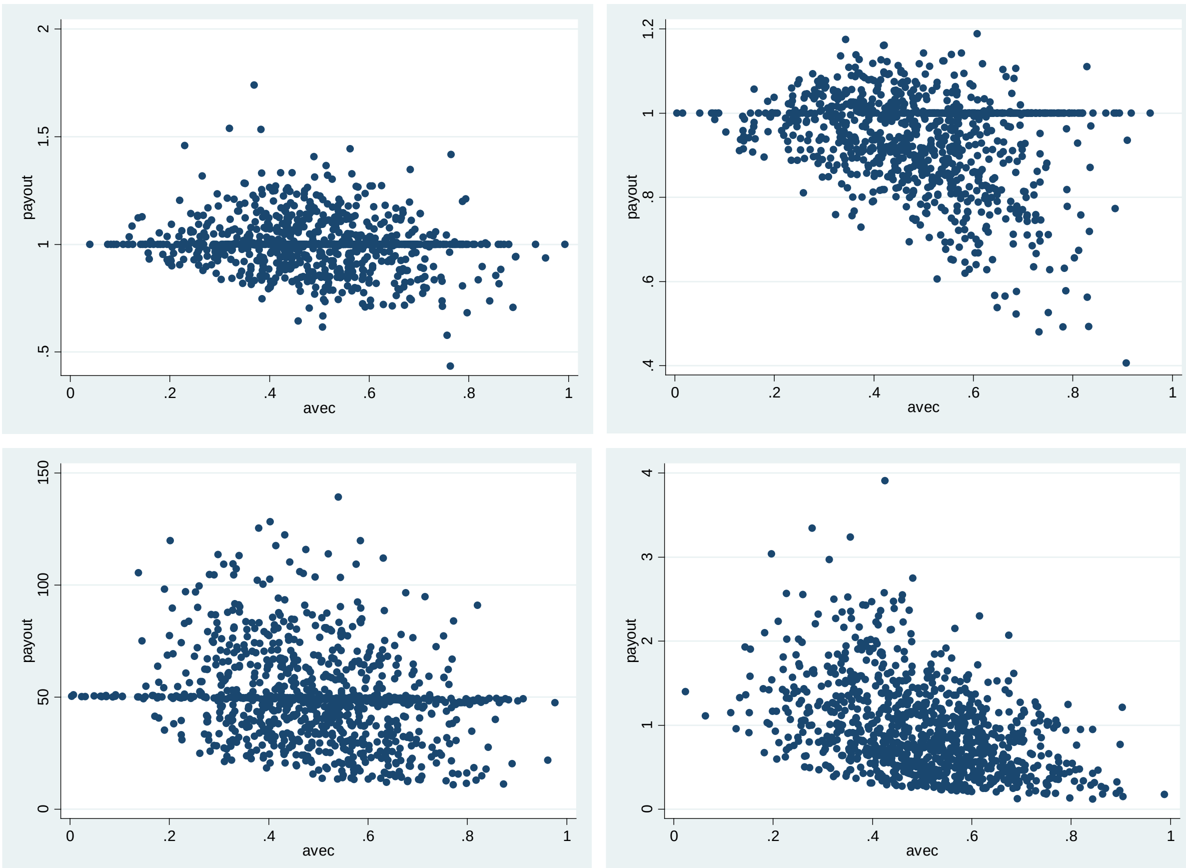

Figure 1 : Plots the payoff of a player in the network as a function of her generosity index; each box represents one of models 2.1 – 2.4, from left to right and top to bottom

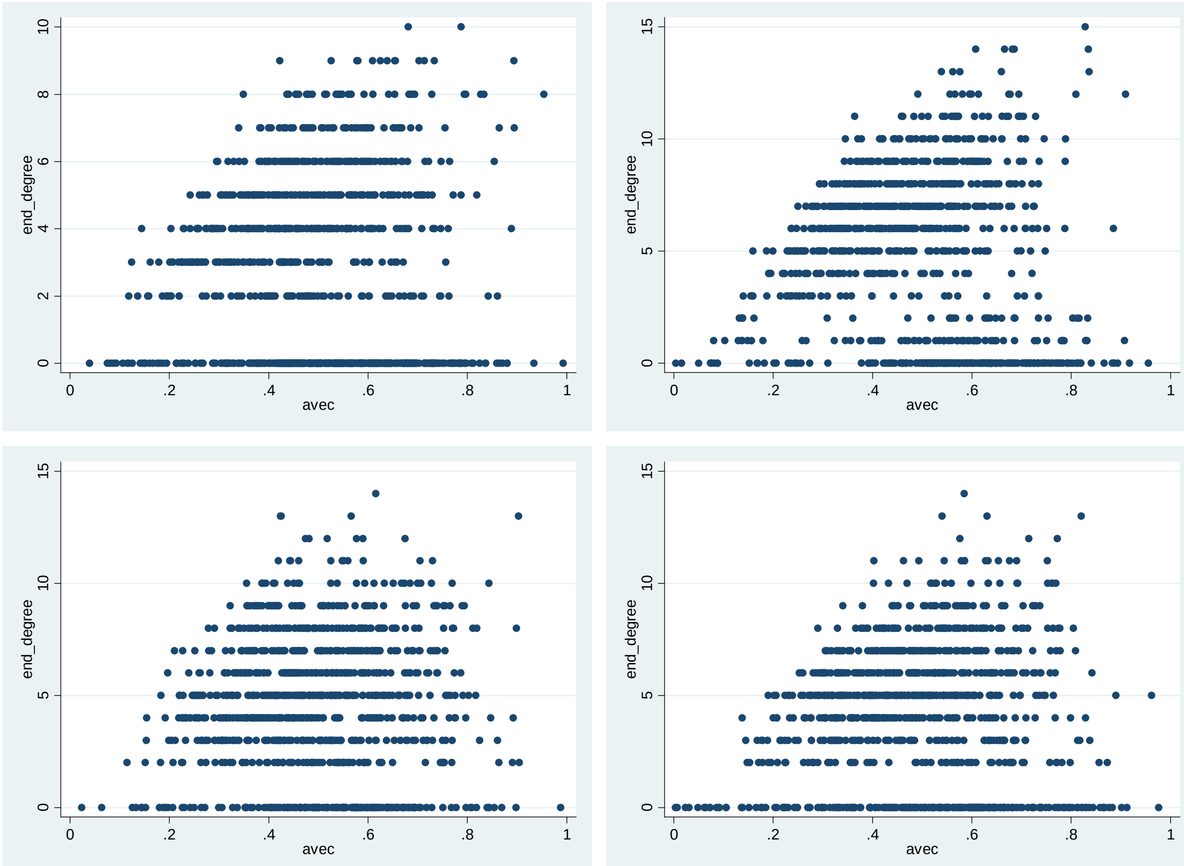

Figure 2 : Plots the final degree of a player in the network as a function of her generosity index; each box represents one of models 2.1 – 2.4, from left to right and top to bottom

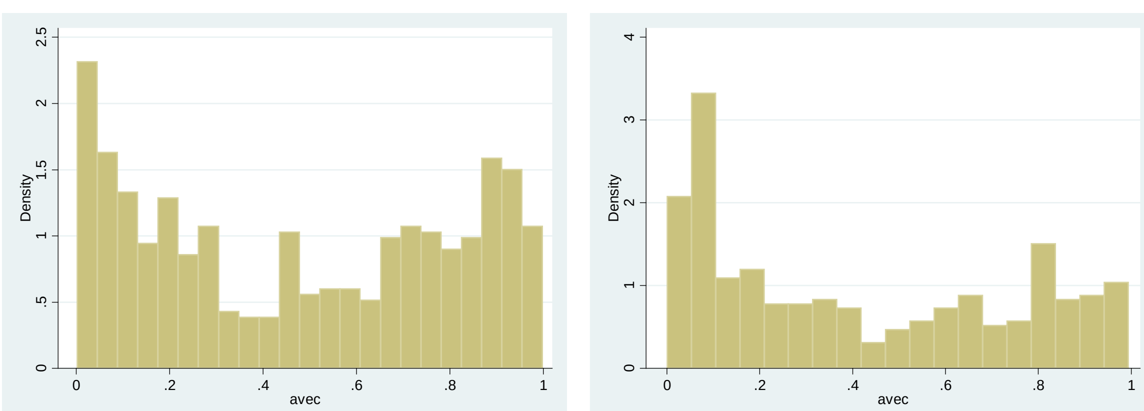

Figure 3 : Histograms of the generosity indices for models 2.2 and 2.3 for the isolated nodes in equilibrium

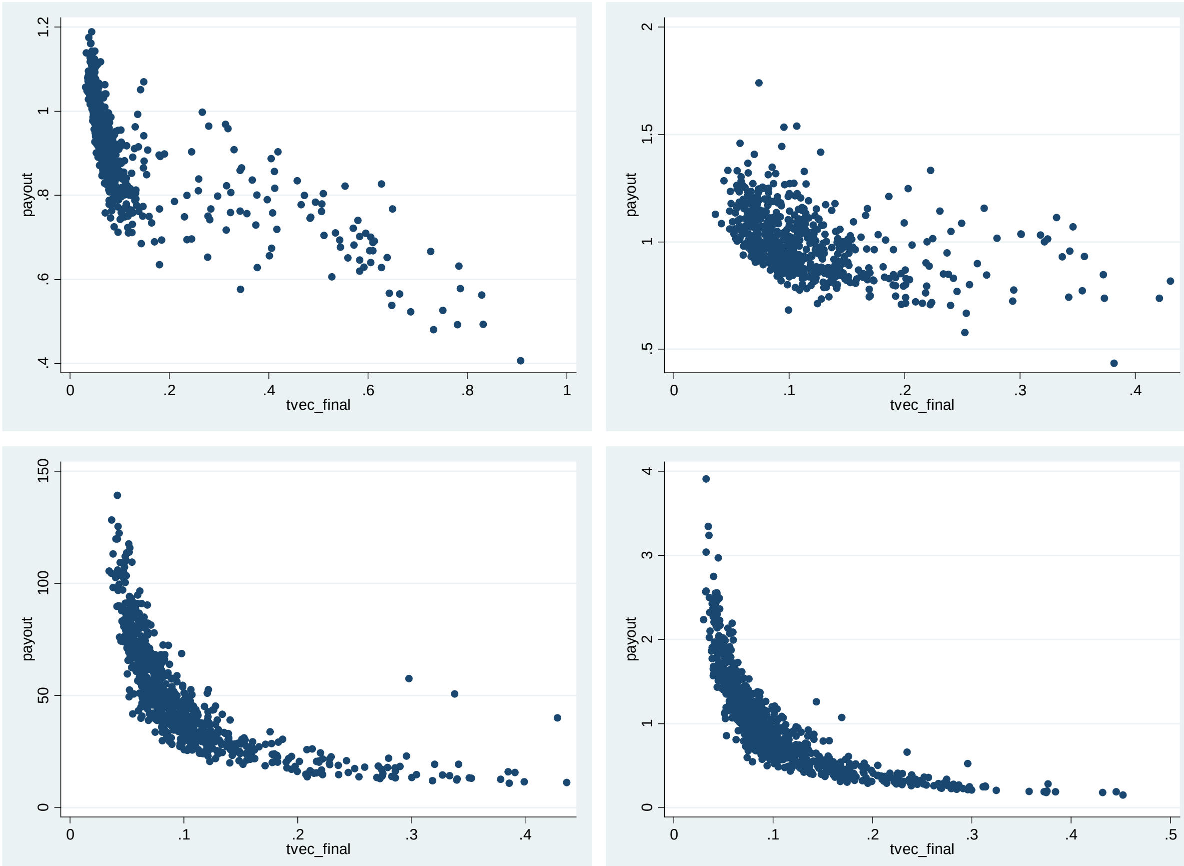

Figure 4 : Plots the payoff of a player in the network as a function of her final decision threshold, excluding players who have a final degree of zero; each box represents one of models 2.1 – 2.4, from left to right and top to bottom

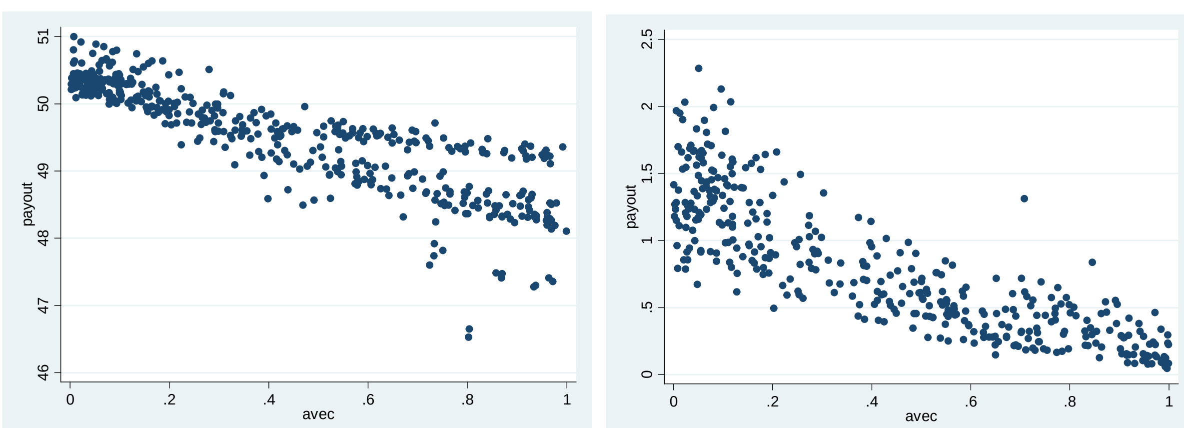

Figure 5 : Plots the payoff of a player in the network as a function of her generosity index, only including players with a final degree of zero; each box represents one of models 2.3 – 2.4, from left to right

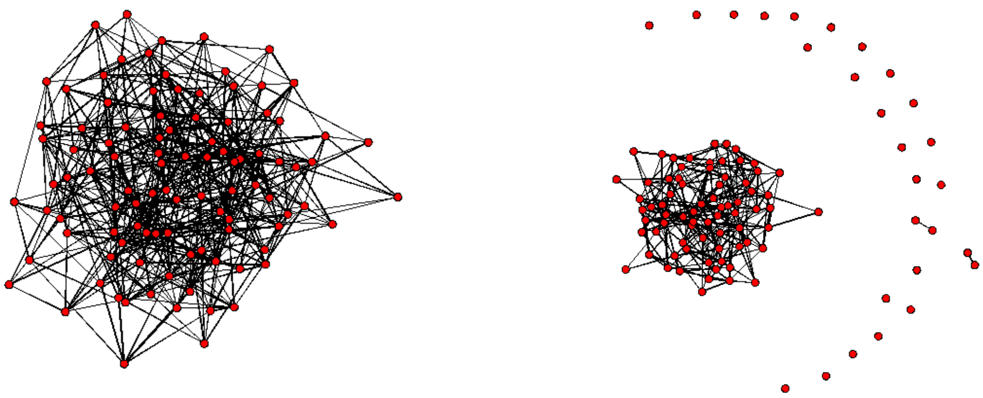

Figure 6 : The left image is a sample initial random network in the model, and the right image is a sample of the equilibrium network after the model acts on the random network

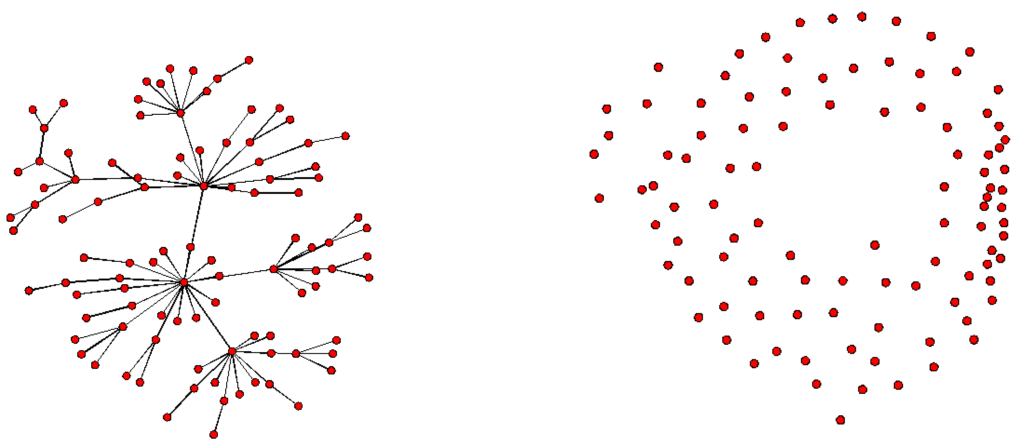

Figure 7 : The left image is a sample initial scale-free network in the model, and the right image is a sample of the equilibrium network after the model acts on the scale-free network