Dynamics of effort allocation and evolution of trust: an agent-based model

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Abstract

Trust is a dynamic and complex phenomenon and understanding the factors which affect its formation, evolution and disappearance is a critical research issue. It has been shown that trust plays a key role in how human and social capital develop, how economies grow and how societies progress. In this paper, we present an agent-based model of the relations between a dynamic effort allocation system, an evolving trust framework and a reputation module to study how changes in micro-level rent-seeking traits and decisions can shape the emergence of trust across the simulated environment. According to our results, variations in trust are correlated more with the returns to being productive, rather than rent-seeking. In line with previous studies, our model shows that higher than average levels of risk-taking by agents lead to further trust and gains during an interaction, though taken to an extreme, both trust and gain can decline as a result of reckless decisions. We also report on the formation of trust clusters in our model as an emergent phenomenon.

1. Introduction

Research on the role of trust in economies and its relationships to trade and institutions has flourished in recent years. Early work included Janet Landa's studies of ethnic trading networks (1981; 1994) and Avner Greif's (1989; 1993) research on Maghribi traders in medieval times. Francis Fukuyama (1995) brought the academic discussion on the relationship between trust and economic development to a wider audience with his book *Trust: The Social Virtues and the Creation of Prosperity* (insightfully reviewed by Quddus *et al.* 2000).

As Labonne and Chase (2010) observed, it is now well established that higher levels of trust in a society are associated with higher economic growth rates (Knack and Keefer 1997; Zak and Knack 2001), higher quality and less corrupt institutions (Porta *et al.* 1997; Uslaner, 2002) and better public goods (Ostrom 2000; Ostrom and Walker 2003).

Using data from the Philippines for example, Labonne and Chase (2010) showed that lowering transaction costs by making connections easier, in this case through road building, led to an increase in generalized trust. They also highlighted the frequently overlooked endogeneity of trust: It is not simply that high trust environments lead to growth, but that growth itself can make possible investments in public goods such as roads, which themselves lower transaction costs even further, thereby fostering a further increase in trust.

Research into trust now encompasses a wide variety of fields, including, for example, the role of trust in international relations (Kydd 2005), in the international climate regime (Vogler 2010), in energy policy (Kydd 2010), in shaping institutions (Wang & Gordon 2011), in informal borrowing networks (Karlan *et al.* 2009), in humanitarian logistics (Tatham and Kovács 2010), in human development (Özcan and Bjørnskov 2011), in the relationship between culture and development (Breuer and McDermott 2012), and in experimental economics (Johnson and Mislin 2011).

In this paper, we focus on one particular aspect of the role of trust in economic exchange, namely the relations between trust and rent-seeking, which to our knowledge has not been studied so far. More specifically, we want to investigate how rent-seeking behaviors of individuals and their mutual trust at the micro-level can result in different rates of economic growth – as, for example, when they come together for a particular project to produce a common product. Rent-seeking behavior during such collaborative projects may include effort allocated to activities such as lobbying and bribing which, while they are likely to increase the resource allocation returns for the rent-seeker himself, are considered a waste of resources and an unproductive allocation when each contract is considered or the economy is considered as a whole (Krueger 1974; Tollison 1982; Murphy, Shleifer and Vishny 1993).

To model the rent-seeking decisions and behaviors of the individuals, here, each agent's trust toward the counterparty to an interaction is coupled with the economic theory of effort allocation whereby economic agents can allocate their resources either to productive or to unproductive activities (e.g. Bhagwati 1982; Baumol 1990). This theory has been widely used to analyze social behaviors especially in the field of rent-seeking and economic conflicts (Hausken 2005). The dynamics of model in which agents can allocate effort between different options, as discussed later in the paper, depend not only on each of the players individually and the sum of their individual decisions and actions, but are also associated with complex mutual strategic decisions of individuals about their trust and rent-seeking decisions. We have therefore employed an agent-based computational model to study this complex phenomenon.

Trust has been studied extensively in computational models (Sabater and Sierra 2005), including multi-agent systems (Ramchurn *et al.* 2004). More recently, models of trust have also featured in the agent-based modeling literature including by Will (2010) and an important exercise in replicating a previously published model of trust, cooperation and market formation in the U.S. and Japan (Macy & Sato 2002, 2008; Will & Hegselmann 2008a, 2008b; Will 2009).

Considering the literature discussed above, the main contribution of this study is the development of an agent-based model which is capable of linking individual rent-seeking decisions and risk attitudes and micro-level interaction outcomes with both micro- and macro-level social (trust) and economic (gain) concepts through a dynamic social network and a reputation module. The model is introduced in the next section, followed by analyses of how changes in micro-motives can result in the emergence of new forms of macro-behavior.

2. The Model

The model is presented using the updated version of the ODD protocol (Grimm, *et al* 2010) where first the model's building blocks are introduced in the overview section, followed by its design concepts and details. The ODD protocol has been used to facilitate possible replications or extensions. In some parts the order of titles recommended by the protocol has been changed to match the model conditions. The model was implemented using NetLogo 4.1 (Wilensky 1999).

2.1. Purpose

The purpose of this model is to investigate how directly unproductive activities such a bribing and lobbying might impact an economy by affecting the trust between the parties engaged in a contract. We proceeded by exploring the dynamics of effort allocation to productive and unproductive activities and the evolution of trust and reputation in an agent-based model where the terms of a contract could be violated by dishonest agents through rent-seeking activities.

2.2. Entities, state variables and scales

The model has three main components including players, links, and the reputation module. The model starts with *N* initial players, where $N > 3$. Each player has two main characteristics including its effort allocation and risk-taking attitude (*RTA*). Effort allocation is represented as a dynamic-size bit vector where, for each bit, if it is 1, the agent will be allocating all his effort to productive purposes and so is called honest (H), and otherwise it presents rent-seeking behavior and acts dishonestly (D) in interactions through misallocation of effort to unproductive conduct. The number of bits in the vector is equal to the number of neighbors each agent has, since each bit represents a link to one neighbor. The risk-taking level is a normally distributed random variable between 0 and 1 which represents the agent's attitude in trust formation.

Links are the core of the model. During the linking process, agents connect to the agent closest to them which is not already one of their connected neighbors. When there is a link between two agents, it means that they can engage in one interaction per tick called a "contract". A contract is implemented using two separate weighted directed links in NetLogo, but for simplicity, in the model description we use the term "Link" to refer to both of them.

Each contract has a value called *Income* which shows the total amount of utility that can be gained from that contract. When two agents are involved in a contract they gain a share of that *Income,* which is accumulated every tick in a variable called *Wealth*.

The amount of *Income* for any contract is a function of the *MutualTrust* between two agents; when agents trust each other more, they are more likely to have contracts with higher possible incomes, whereas if the trust degrades, the income will decrease as well. This is implemented using a logistic function as Equation 1 where *MutualTrust* is the sum of agents' *Trust* of each other. As *Trust* is between 0 and 1 and *MutualTrust* is between 0 and 2, $\alpha = 7$ so that Income is between 0 and 1.

$$Income = 1 / (1 + \exp(\alpha (1 - MutualTrust))) \qquad (1)$$

While *Income* is a function of *Trust*, *Trust* is represented as a dynamic value which is affected by the contract outcome as well. If both sides of the contract are honest, or if they cannot recognize each others' dishonesty, *Trust* increases. Change in the *Trust* value is a function of *RTA*. Agents with higher *RTAs* increase their *Trust* more when they think they are in a fair contract and decrease their *Trust* less when the other agent violates the contract terms.

If the *Trust* value for a contract decreases and reaches zero, the *Trust* link is broken and the agent can tag the other agent as a violator. When agent A tags agent B, A will not create a link to agent B for period of time dependent on its *RTA* as it puts Agent B on its blacklist. Also A sends a message to its social network to decrease their *Trust* in B. The decrease is a function of each neighbor's personal *RTA* and also its trust of A. Agents downgrade their trust of a violator more if they are advised to do so by an agent they trust more and/or they have lower *RTA*.

2.3. Process overview and scheduling

The smallest unit of time is a "tick" where all main procedures are called once. Since only one generation of agents is used in our model, ticks are not associated with agents' life-cycles.

All the agents start with having a fully random effort allocation pattern as they engage in their first interaction with their *Trust* equal to their *RTA*. During each interaction the possible income from that contract is divided among the two engaged agents based on a simple game theory model called an Income Distribution Table (IDT). In Table 1, H represents an honest attitude in the contract and D stands for a dishonest rent-seeker. Each cell shows the agents' shares from the total possible income.

Table 1: Income Distribution Table (IDT) format for honest (H) and dishonest (D) agents

		Player 2	
		H	**D**
Player 1	**H**	(HH1, HH2)	(HD1, HD2)
	D	(DH1, DH2)	(DD1, DD2)

For simplicity, in the majority of simulations we have considered that whenever both agents are honest, the income is divided equally between them, so HH1 and HH2 are equal to 0.5. In the other three cases, dishonest behavior in the form of violating the contract means that at least one agent is allocating effort to unproductive behavior, and so, following the rent-seeking literature, since some resources are wasted, we assume that the total gain will be less than the maximum income. So HD1 + HD2, DH1 + DH2 and DD1 + DD2 are all less than 1. Using the same logic, we usually expect DD1 + DD2 to be less than both HD1 + HD2 and DH1 + DH2. Also since being dishonest provides agents with an opportunity to have a higher share of the total income, HD1 is smaller than HD2 and DH1 is greater than DH2. Two sample IDTs are shown below. Each link between any two agents has its own IDT whose values can be produced randomly when the model initiates or can be made similar for all links.

Table 2: Two sample Income Distribution Tables

		Player 2	
		H	**D**
Player 1	**H**	(0.5, 0.5)	(0.2, 0.7)
	D	(0.6, 0.1)	(0.4, 0.3)

		Player 2	
		H	**D**
Player 1	**H**	(0.5, 0.5)	(0.1, 0.8)
	D	(0.8, 0.1)	(0.2, 0.4)

As can be seen in the tables above, not only have we allowed the DH and HD combinations to have asymmetric outputs, but the same feature is considered for HH and DD contracts. To implement that, we ensured that the contract *Income* is divided between the agents in correct order since NetLogo randomly calls the agents during the simulation.

When the contracts are concluded, each agent records all the gains separately for each link and also adds their gains to their wealth. In the next step of the function (but within the same time tick), they compare their outcome with the previous ones to find out if their current strategy has performed better and should be recorded for later optimization. The comparison is a cyclical procedure as shown in the pseudo code below in Box 1.

Here *cycle* is a counter for the iterations of the optimization process and *max-cycle* shows the length of each complete optimization round. If *cycle* is less than max-*cycle*, it is increased by 1 and the current value of *gain* for each link is added to the value of *store* for that link. These iterations continue until *cycle* reaches *max-cycle*. Then if the accumulated amount in each link's *store* is higher than its previous *max-store*, *store* is recorded as *max-store* and the current behavior type, H or D, is stored as the best type. Finally, *store* and *cycle* are both initiated to start a new round.

In the simulation, if an agent changes its type, from H to D or *vice versa*, both *store* and *cycle* are reset to ensure that their values always are associated with one specific type. Changes in value of *max-cycle* have been studied in the sensitivity analysis and are discussed in the next section. Also to avoid having an elephant memory embedded in the agents, we have added a factor to the algorithm, β, which is responsible for degrading the *max-store* value over time. As β is between 0 and 1, it guarantees that agents do not lock in one particular value for max-store. This provides better dynamics in the model by resembling a process which enables the agents to forget this value.

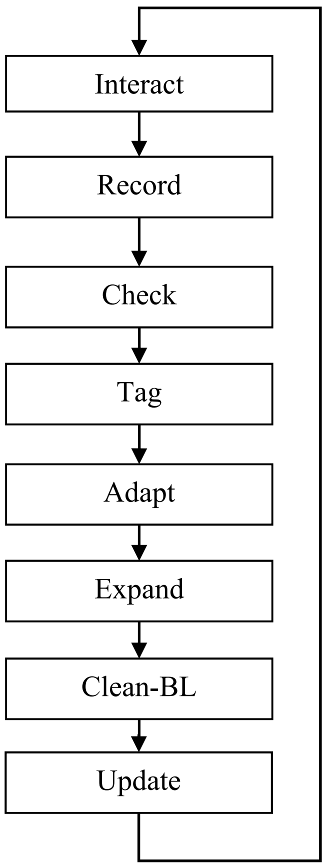
Box 1: Pseudo-code for recording the type with the highest return

```
Ask agents
[
   Ask my-links
   [
      ifelse cycle is equal to max-cycle
      [
         if value of store is higher than maximum store so far
         [
            set max-store to store
            record the current strategy as the best strategy
         ]
         set store 0 and set cycle 0
      ]
      otherwise
      [
         Set cycle cycle + 1 and set store store + gain
         Set max-store max-store – max-store × β
      ]
   ]
]
```

During the *Check* procedure, two main functions are performed. Firstly, for each link, agents monitor each others' type, trying to investigate if the other agent has behaved dishonestly. If the other side of the link has been dishonest and the caller can recognize it based on its associated probability, the Agent decreases its trust to the other agent, otherwise it increases it. Agents decrease their trust based on (1 – *RTA*) which implies that the higher their risk-taking the lower their trust decline if they discover dishonesty during a contract and increase their trust considering *RTA* so more risk-loving agents raise their trust more after experiencing a fair contract.

In the second part of *Check*, the links with *Trust* equal to or less than zero are broken and the violator agent is added to each agent's blacklist. The agent also invites its connected agents to decrease their trust of the violator based on their own (1 – *RTA*). The proportion of the decrease is simply calculated by multiplying their *MutualTrust* and the neighbor's *RTA*, then the amount is deducted from the current value of *Trust*.

Four different genetic operators are implemented in the code. Mutation guarantees that the agent changes its type over time (between Honest and Dishonest), looking for a type with higher return. The other three are all crossovers providing adaptation, learning and optimization. For crossovers, each agent takes into account the links' best-performing type, the best type among its links and also the best performing type of its connected agents. The rates at which agents adapt to any of these three are provided as inputs on the model interface. Finally each agent attempts to expand its social network to increase its income and wealth. During this step, agents select an agent which they are not already linked to and also is not on their blacklist. The new link can also be recommended by other agents whom the caller has a high trust of. As mentioned previously, blacklisting may not be permanent. In that case, the probability of a violator being removed from the blacklist is associated with an agent's *RTA* as it takes longer for agents with lower risk preferences to delete an entry from their list. The blacklist removal is a first-in first-out process.



Procedure	Condition	Probability (out of 1)
Interaction	N/A	1
Record	Cycle	1
Check	Recognition	Avg. 0.25
Tag	Link Break	(0.01 to 0.05)
Genetic Operator	Activation	Defined Input Rates
Expand	Avg. Trust > RTA	0.0005
Clean-BL	BL size > 0	RTA / 1000
Update	N/A	1

Fig 1: Model Processes, their conditions and probabilities

2.4. Design concepts

Considering the model's specifications and features, some of the main design concepts are introduced in this section.

2.4.1. Basic principles

While the model is based on the theory of effort allocation to incorporate an economic system, it takes a dynamic game theoretical approach to implement the micro-level interaction based on strategic decisions. The model also is enriched with a social network which not only serves as the infrastructure for agent-to-agent interactions, but since strategies can diffuse through the network, it can also be considered to be an adaptation framework. Finally, the tagging system is embedded as an attempt to extend the agent's individual-level perception and decisions to the meso-level.

2.4.2. Emergence

Trust and *Income* both emerge from individual level interactions, since any decisions made by agents are not only affected by their individual features such as their *RTAs*, but also their social networks.

2.4.3. Adaptation

Beyond merely considering personal experiences, the agents also adapt their decisions by taking into account their social network. The adaptation to the experiences of other agents can be direct, for instance when the agent receives suggestions from others through the reputation system, or indirect as the strategy recommendation can transfer to not-directly-connected agents via intermediate nodes.

2.4.4. Objectives

The main objective of the agents is to increase their *Gain* from each contract, which is their share from the maximum *Income*. This is subject to a trade-off as allocating all the effort to productive activities increases the *MutualTrust* but has a medium return in terms of personal *Gain*. On the other hand unproductive efforts lead to higher returns, especially if the counterparty to the contract is honest and productive, but is likely to decrease the *MutualTrust* and so the maximum *Income*.

2.4.5. Learning

As mentioned previously, learning is implemented using four genetic operators and their associated occurrence probabilities including mutation, link-level crossover, agent-level crossover and network-level crossover.

2.4.6. Sensing

The agents sense the other agent's *type*, if their recognition probability condition is satisfied but they cannot identify its best *type*, *Gain*, *Wealth* or even the recognition strength. In other words, A may know whether B is honest or not, but A has no way of knowing how wealthy B really is. Agents can also sense some variables from their social network, such as the highest gaining *type* without discovering to whom that *type* belongs.

2.4.7. Interaction and Stochasticity

The details about the interaction procedure in the form of contracts were given in the first section and the sources of stochasticity in the model are presented in Table 2.

2.4.8. Observation

The main observed variables include the trends of honest and dishonest behavior, the proportion of agents selecting each of the best types, the mean trust in the model, number of links, blacklists' sizes, broken and created links, agents' *Wealth* and links' *Gains*.

2.5. Sensitivity Analysis and Initialization

In order to decide on the initial conditions, we performed a sensitivity analysis (SA) over the main variables in the model. Table 3 shows the variables and their tested values.

Table 3: Tested values in sensitivity analysis experiment

Variable	**Range**	**Variable**	**Range**
Mutation Rate	0.001, 0.002, 0.005	*Individual Crossover Rate*	0.001, 0.002, 0,005
Agent Crossover Rate	0.001, 0.002, 0.005	*Network Crossover Rate*	0.001, 0.002, 0,005
Initial Links	2, 5, 10	*Initial Population*	25, 50
Initial Type	1, Random	*Max-Cycle*	20, 50, 100
Blacklist Removal Rate	0.001, 0.0005	*Link Creation Rate*	0.002, 0.0005, 0.0010

The above set of initial conditions results in more than 17,496 simulations which are run for 5000 ticks under five different random seeds (1 to 5). Figure 2 shows the distribution for mean *Trust* for a sample set of 8748 simulations under random seed = 1, covering all the combinations except for the initial *type*.

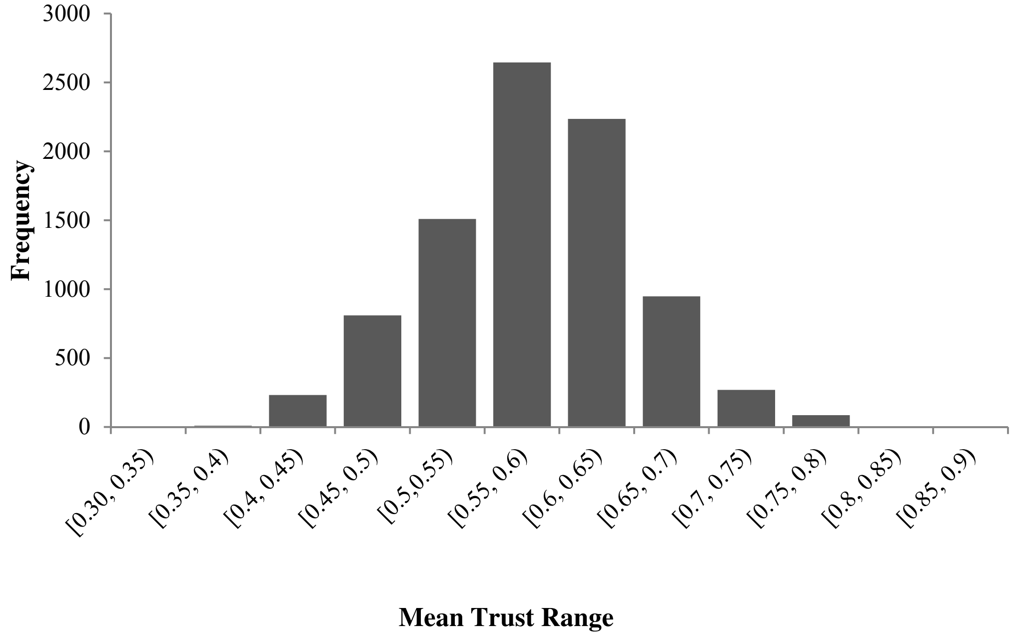


Fig 2: Distribution of mean *Trust* over the sensitivity analysis experiments

According to the full SA results, while increases in the population only slightly affect the final *Trust* outputs (-0.0012% per each extra agent), it can have impacts on the trends due to changes in the model dynamics. The impacts are clearer when changes in the population are accompanied by higher levels of run-time connectivity, which can lead to higher *Trust* among the agents. The initial number of links is not important in the long-run. Based on these observations we decided to run the model with 50 initial agents with three initial contracts.

Changing the *max-cycle* does not affect the outputs significantly even at the 90% confidence level although models with higher *max-cycles* produce outputs with lower variance as they experience less variation in their best type. It should be noted that as any change in the link's bit pattern resets the *cycle*, the *max-cycle* must be selected in a way that continuous *cycle* initializations are avoided. For that reason we have valued *max-cycle* at 50.

Based on the SA outputs, an increase in the rate of all four genetic operators will to some extent decrease the trust, but the impacts are not limited to the mean values. High mutation rates prevent agents from learning and adapting and increase the amount of noise in the outputs. The SA shows that the proportional values of genetic operators' probabilities are more important than their absolute values. If the mutation rate is proportionally higher than the crossover rates, it makes them ineffective and if crossovers are very frequent in relation to mutation, agents will be locked in one specific type of behavior, unable to adapt to changes in the other agents.

Finally, considering different combinations in the SA, the mutation rate is set to 0.001. Then the link-level crossover probability is 0.004 and for agent-level and network-level crossover probabilities it is 0.002. It means that on average, between every two mutations, the agents have eight opportunities to adapt. It also is a sensible choice considering the *max-cycle,* because on average, between every two operations, at least two full *cycles* are possible.

The final decision is about how frequently new links are created and how long agents keep a violator on their blacklist. As for the genetic operators, these two are associated as well. According to the SA outputs, if the link creation rate is set to 0.001, the number of created links is almost equal to the number of broken links. As a result, this value keeps the number of links almost constant in the model. Considering this decision, the blacklist removal rate is set to 0.0002, so each violator is blocked for almost five new connections on average. The final selected initial conditions are presented in Table 4.

Table 4:Initial conditions for the model

Variable	**Range**	**Variable**	**Range**
Mutation Rate	0.001	*Individual Crossover Rate*	0.004
Agent Crossover Rate	0.002	*Network Crossover Rate*	0.002
Initial Links	5	*Initial Population*	50
Initial Type	Random	*Max-Cycle*	50
Blacklist Removal Rate	0.002	*Link Creation Rate*	0.001

Each simulation is run for 50,000 ticks under 30 different random seeds to provide enough data for statistical analyses. The main monitored variables include: 1) Average *Trust* of all links and the distribution for all individual links. Since the number of links in the model can be different and it is hard to compare this value with a specific objective, we have divided the value by $m (m - 1)$, which is the total possible *Trust* in a model with m agents and two links connecting each two; 2) Links with Honest and Dishonest *types* as a proportion of all the links; 3) Average *Gain* of all links and the distribution of gain over the links and time; 4) Sum of all agents' *Gain* and *Wealth*; 5) Run-time created and broken links (i.e. excluding links created when the model is initialized); 6) Number of mutations and crossovers for each type per agent for the total model. We also have recorded specific variables in particular cases, for instance the distribution of *Wealth* based on *RTA*.

3. Results

Before presenting the results on how the IDT, *RTA* and different reputation module values can affect the model outputs, we illustrate how a single-run model evolves over time. Figure 3 shows a sample output for a run with 200,000 ticks based on the IDT presented in Table 5.

Table 5: Sample run – 200,000 ticks

		Player 2	
		H	**D**
Player 1	**H**	(0.5, 0.5)	(0.1, 0.8)
	D	(0.8, 0.1)	(0.4, 0.4)
Seed: 32			

As can be seen, while overall *Trust* increases in the simulation, there were significant variations in its level, as the moving average clearly shows in the lower part of the figure. The mean value for *Trust* is 0.043, the standard deviation is 0.0076 and skewness is equal to -0.47 representing the increasing trend.

The source of these variations can be partly traced to the proportion of agents who are honest or dishonest at any point of time. Figure 4 shows the trend for the proportion of agents who select each type over the simulation. The presence of different cycle lengths in the dataset shows that it is not directly produced by a single factor, but rather it has emerged from the model complexity.

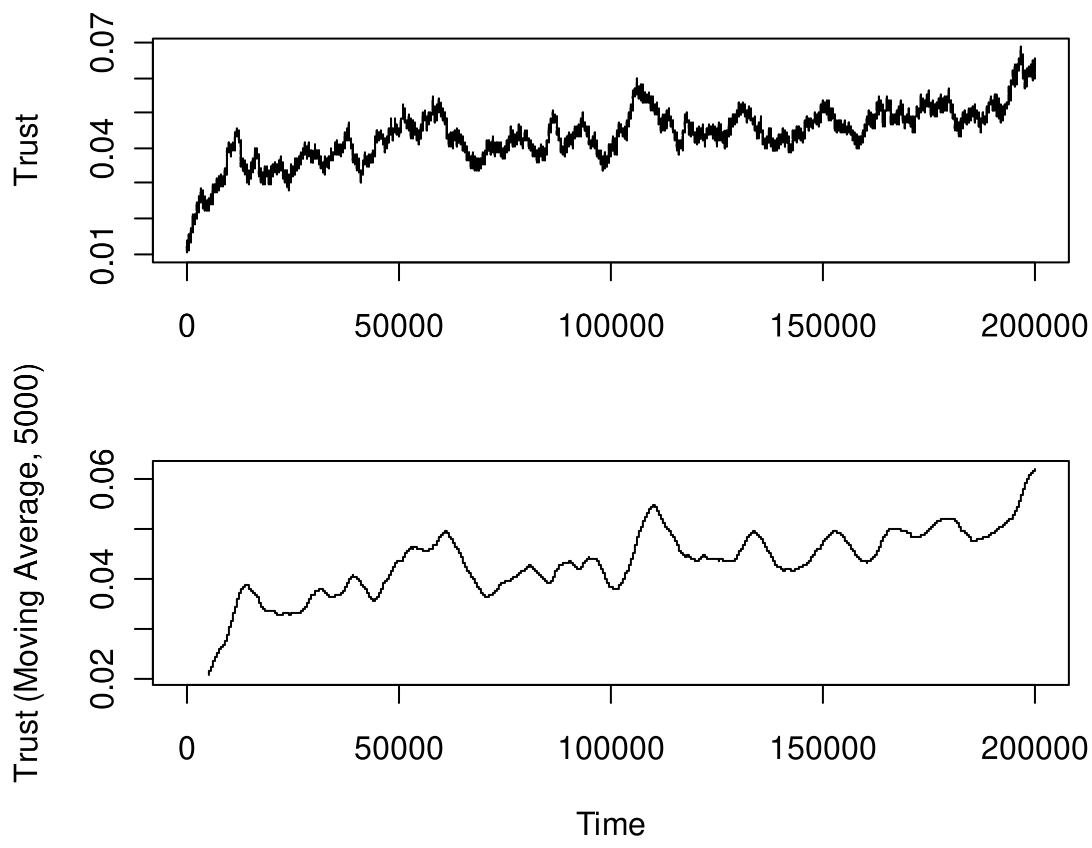


Fig 3: Trust trend for a sample simulation. Model produced data (top) and its 5000-moving average (bottom)

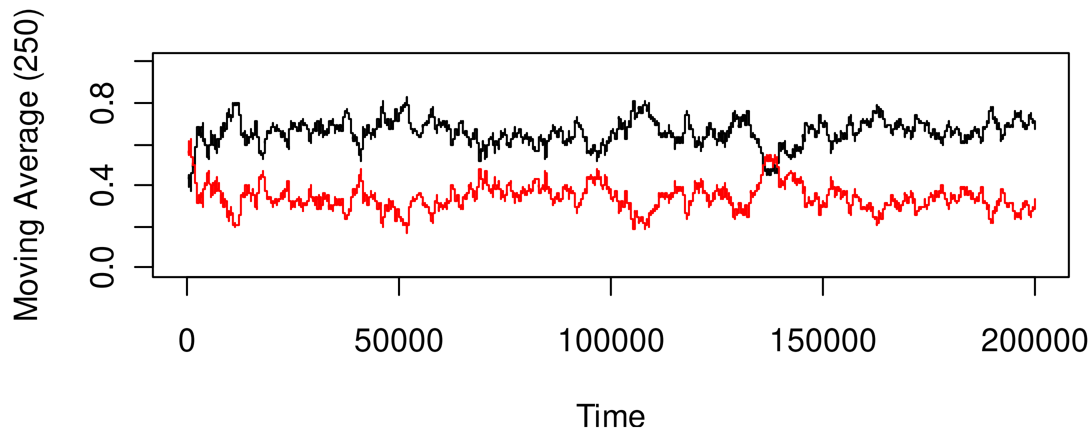


Fig 4: The proportion of agents with honest (black) and dishonest (red) type in the sample model (250-Moving average)

The important issue in the above figures is that while *Trust* is rising in the model, the *type* trends do not converge to a specific value but their cyclical behavior continues indefinitely. This can be due to an increase in the average amount of *Trust* per link in trust clusters which are introduced later in this section.

Changing the Income Distribution Tables (IDTs)

One of the main factors affecting agents' decisions is how the contract income is divided between two agents. This is a complex topic since not only it is associated with each agent's own type, but it is affected by how the counterparty to the contract responds. Firstly, we ran a set of experiments based on Table 6. As can be seen in the table, we keep all the values fixed except for HH1 and HH2 which can be one of the numbers from (0 to 0.5 by 0.1) combined with a value from a similar array, resulting in 36 different combinations for (HH1, HH2).

Table 6: IDT for studying the impacts changes in HH1 and HH2 on trust in the model

		Player 2	
		H	**D**
Player 1	**H**	((0, 0.1, 0.2, 0.3, 0.4, 0.5), (0, 0.1, 0.2, 0.3, 0.4, 0.5))	(0.2,0.7)
	D	(0.7, 0.2)	(0.4, 0.4)
Seeds 1:30			

According to the regression results for *Trust* against the possible values of HH1 and HH2, increases in the values of both variables encourage the agents to raise their trust at 1% significance level, HH1 (0.0085, t = 4.47) and HH2 (0.0077, t = 4.053), although R^2 is only 0.17, highlighting the missing contributions by other possible factors. We also test for some non-linear relations and the coefficients are not statistically significant.

Running new experiments based on Table 7, we investigated how different combinations in HD1, HD2, DH1 and DH2 may affect the *Trust* distribution in the model. The simulation leads to 256 different runs but only 90 of them are valid since sum of HD1 and HD2, or DH1 and DH2 is more than one in the rest of cases.

Table 7: IDT for studying the impacts of changes in HD and DH on trust in the model

		Player 2	
		H	**D**
Player 1	**H**	(0.5, 0.5)	((0, 0.1, 0.3, 0,5), (0.5, 0.7, 0.9, 1))
	D	((0.5, 0.7, 0.9,1), (0, 0.1, 0.3, 0,5))	(0.3, 0.3)
Seeds 1:30			

The Ordinary Least Squares (OLS) regression results presented in Table 8 show that while the *Gain* of the honest agent impacts the results, the coefficients for the dishonest behavior are not significant. The upper mid-range R^2 in the results below is primarily due to the complexities embedded in the model through different feedback loops which decrease model sensitivity to the inputs.

Table 8: Model output for IDT presented in Table 7

SUMMARY OUTPUT				
Dependent variable: *Trust*				
Regression Statistics				
R Square	0.715606			
Adjusted R Square	0.702223			
Standard Error	4.518956			
Observations	90			
	Coefficients	***Standard Error***	***t Stat***	***P-value***
Intercept	0.019546	3.484033	13.7451	2.6E-23
DH1	-0.00172	3.023191	-1.3906	0.167977
DH2	0.011115	3.374906	8.0685	4.12E-12
HD1	0.011192	3.371578	8.1330	3.06E-12
HD2	-0.00133	3.248934	-1.0026	0.318899

We finally ran a comprehensive simulation based on the IDT presented in Table 9 which covers all the eight *type* variables.

Table 9: IDT for studying the impacts of changes in all the IDT values

		Player 2	
		H	**D**
Player 1	**H**	((0.4, 0.5), (0.4, 0.5))	((0, 0.1, 0.3), (0.5, 0.7, 0.9))
	D	((0.5, 0.7, 0.9), (0.1, 0.3, 0,5))	((0, 0.1, 0.2, 0.4) , (0, 0.1, 0.2, 0.4))
Seeds 1:30			

The results for a linear OLS model are presented in Table 10. We have also tested for possible non-linearity in the model but the produced coefficients are either non-significant.

Table 10: Model output for *Trust* against the IDT values presented in Table 9

SUMMARY OUTPUT

Dependent variable: *Trust*

Regression Statistics

R Square	0.510643			
Adjusted R Square	0.509402			
Standard Error	24.15425			
Observations	3164			
	Coefficients	***Standard Error***	***t Stat***	***P-value***
Intercept	0.0295	6.3508	11.3882	1.79E-29
DD1	-0.0057	2.9340	-4.7818	1.82E-06
DD2	-0.005	2.8015	-4.3704	1.28E-05
DH1	-0.0408	2.8350	-35.2597	6.7E-230
DH2	0.0029	3.8015	1.9168	0.055349
HD1	0.0023	3.5272	1.6499	0.099047
HD2	-0.0429	3.2598	-32.3004	5.3E-198
HH1	0.0633	8.5882	18.0626	1.77E-69
HH2	0.0659	8.5882	18.8034	7.56E-75

According to the results, two coefficients for DH2 and HD1, are significant at 95% level while the other six at 99%. Based on the estimated coefficients, the main factor which can increase trust in this model is ensuring that agents gain the maximum share of income in the HH interactions since the positive impacts of a HH type on trust is more 10 times higher than the negative effects from a DD type.

On the other side, agents decrease their trust more when they are honest and their partner is not, compared to the situation when they are both dishonest. Using stepwise selection and all-subset regression (*stepAIC*[1] and *leaps*[2] functions in R (R Development Team, 2011), we tried to discover any better possible combination of the explanatory variables with higher levels of

[1] It calculates the Akaike information criterion for measuring the goodness of fit.
Source: http://stat.ethz.ch/R-manual/R-devel/library/MASS/html/stepAIC.html

[2] According to the documentation, *leaps* "performs an exhaustive search for the best subsets of the variables in *x* for predicting *y* in linear regression, using an efficient branch-and-bound algorithm."
Source: http://cran.r-project.org/web/packages/leaps/leaps.pdf

R^2 or statistical significance, but according to the results, the regression outcome presented in Table 10 is the best possible arrangement.

Changing the *RTA*

In order to create communities with low or high levels of *RTA*, we applied a Gamma distribution with the values presented in the Figure 5. In each case, first the distribution is produced and then its output is divided by the maximum value to provide us with numbers between 0 and 1.

We also used two other distributions, one with a uniformly distributed *RTA* between 0 and 1, and the second one using a normal distribution, *N* (0.5. 0.15). In the normal distribution if the function produces values less than 0 or higher than 1, it is valued at 0.5. The applied IDT for the experiment is presented in Table 10.

Table 11: IDT for studying the impacts of changes in *RTA*

		Player 2	
		H	**D**
Player 1	**H**	(0.5, 0.5)	(0.1, 0.8)
	D	(0.8, 0.1)	(0.3, 0.3)
Seed: 1:30			

First of all, as we expect, in models with higher risk-taking population, more links are preserved as less links are broken during the simulation. In the three modes with low risk-taking, on average, around 30,000 links are cut, leading the model to end with 1.4 links per agent, while in the three risk-loving models, on average around 600 links connect the agents together at the end, around 10 times higher than the previous case.

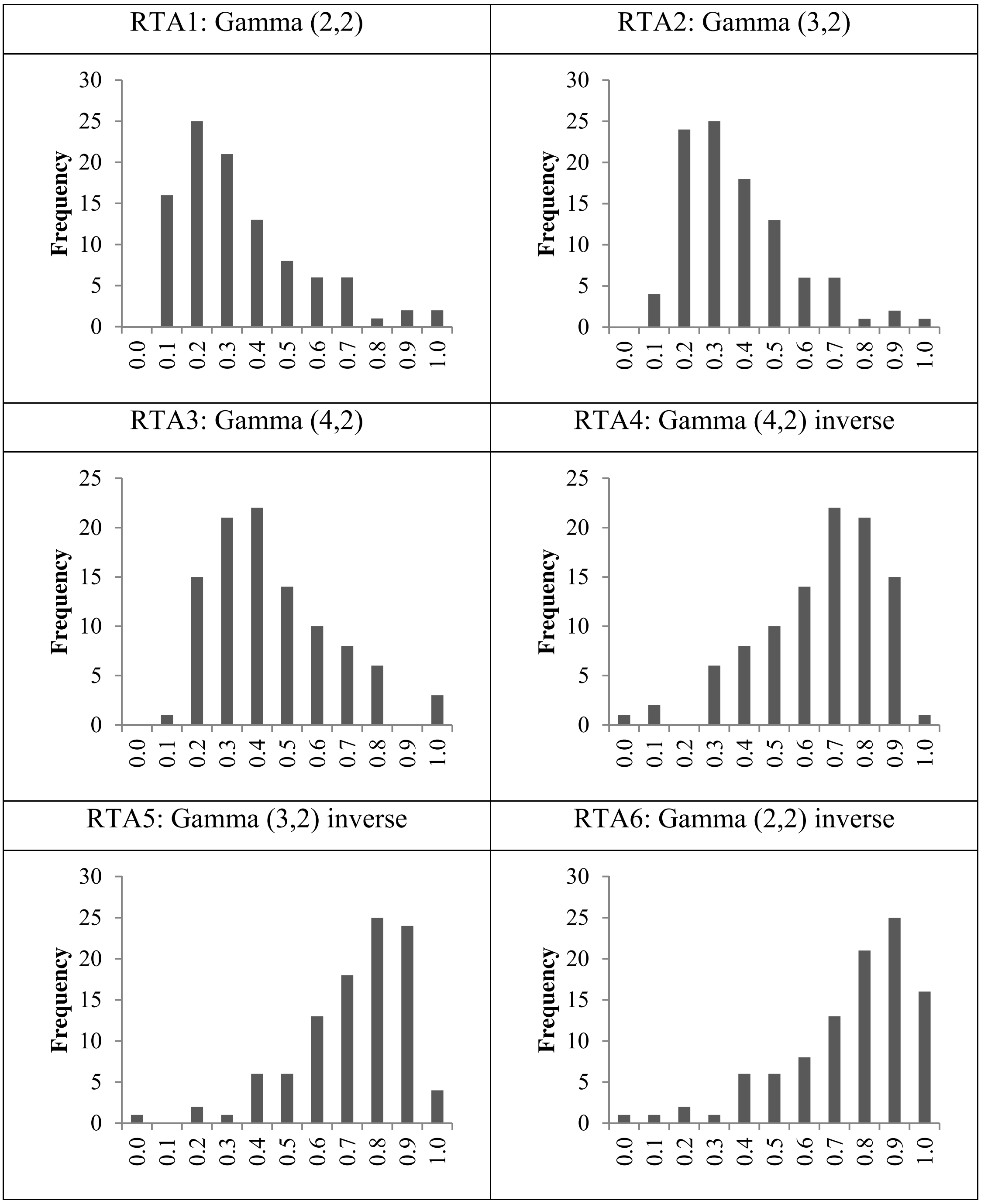


Fig 5: Sample Gamma distributions used for the *RTA* experiment

In the results presented in Figure 6, while increases in *RTA* lead to higher levels of *Gain* in the environment, the effects are not constant. Extremely high levels of *RTA*, for instance in the *RTA*6 from Figure 5, can actually decrease the level of *Gain,* which can be due to the fact that extremely risk-loving agents engage in many sub-efficient contacts as they do not break their links with the violators.

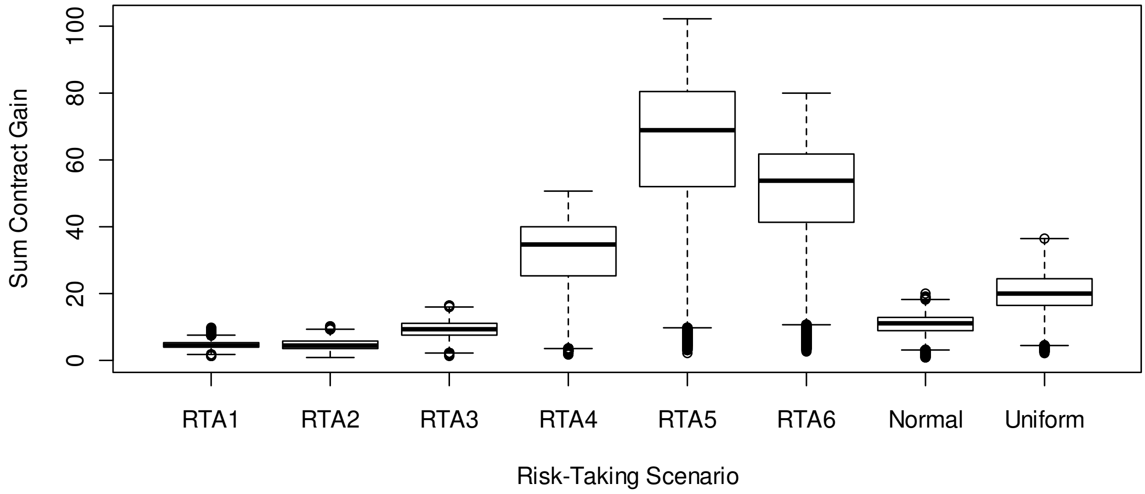


Fig 6: Changes in the contract *Gain* based on different risk scenarios

The Reputation Factor

The third part of results reports how changes in the reputation module affect the model outputs. In this section we designed four experiments based on the IDT in Table 12.

Table 12: IDT for studying the impacts of changes in *RTA*

		Player 2	
		H	**D**
Player 1	**H**	(0.5, 0.5)	(0.1, 0.8)
	D	(0.8, 0.1)	(0.4, 0.4)
Seed: 1:30			

In the first scenario (Sc-01) the reputation module is deactivated, in SC-02 when agent A breaks its link with a violator B, A's neighbors (the set {C}) decrease their trust in B as a function of their trust in A and their individual *RTAs*. In Sc-03 the same approach is taken, but members of C ask their own neighbors to do the same thing, so two layers of neighbors are affected. Sc-04 has a more effective reputation framework as agents only consider their *RTA* in decreasing the trust so they deduct higher values from their trust in B. Finally in Sc-05, neighbors not only decrease their trust, they also break their link with the violator. The changes in the distribution of *Trust* for these five scenarios are presented in Figure 7.

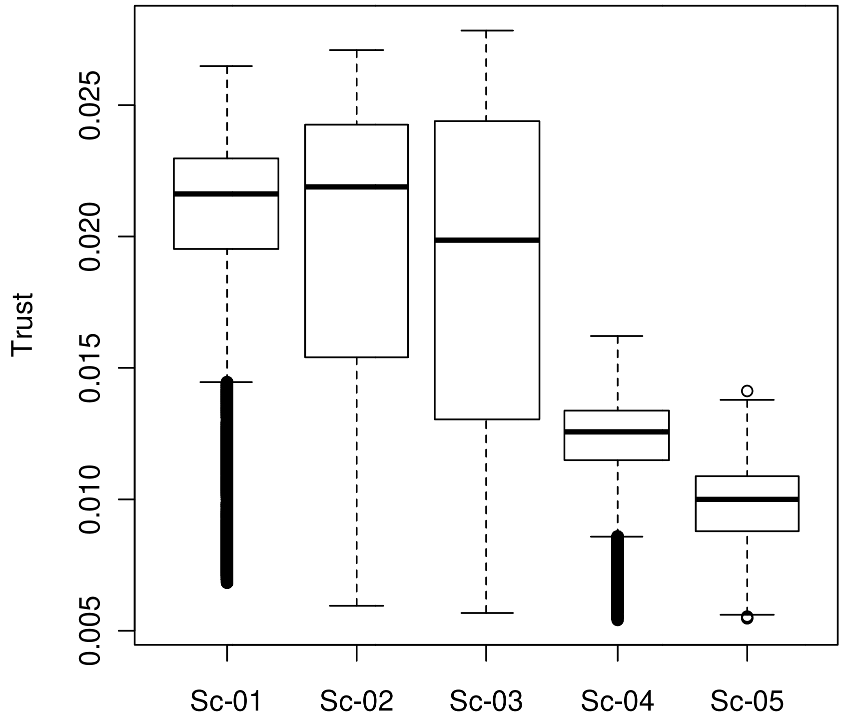


Fig 7: Changes in trust over different reputation scenarios (30 runs per scenario)

According to the results, the reputation module initially increases *Trust* variance without affecting the average *Trust* in the model and even increasing it in specific cases. But extreme levels of reputation as introduced in scenarios 4 and 5 can decrease the *Trust* in the model by more than 50%. The average link *Gain* follows the same order.

Emerging Trust Cluster

One of the model outputs that emerges from the interactions at the micro-level among the agents is the formation of what we call *trust clusters*. As can be seen in Figures 8 and 9, four sample environment snapshots for simulations with 50 and 100 agents are presented.

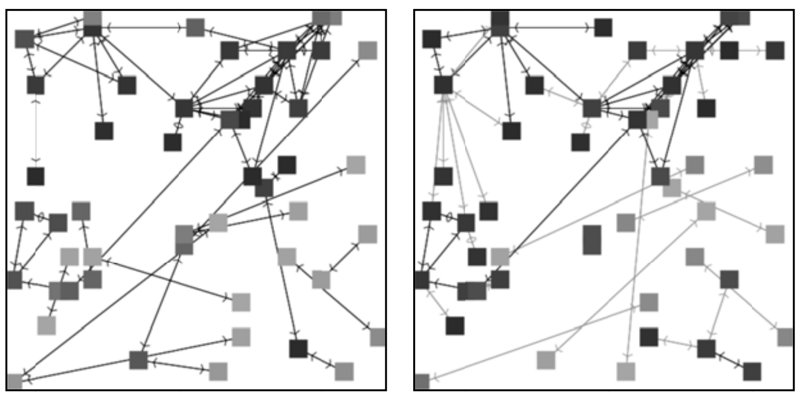


Fig 8: Model snapshots presenting trust clusters. Population: 50. Darker boxes represent agents with higher average links' *Trust*

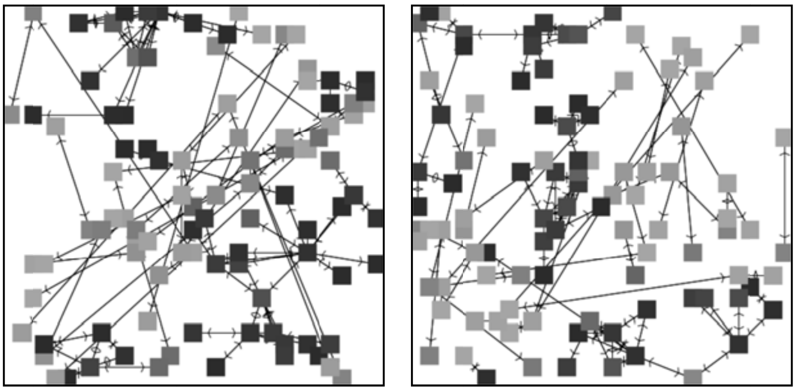


Fig 9: Model snapshots presenting trust clusters. Population: 100. Darker boxes represent agents with higher average links' *Trust*

Our primary investigations show that in a considerable number of simulations the model environment is divided into a few parts, each containing agents with very high or very low average link *Trust*. The low-trust clusters usually have lower link density among their agents with also longer links while the high-trust ones incorporate many short links.

To verify the existence of this phenomenon mathematically, we applied the Girvan-Newman algorithm which detects the possible clusters in a network by calculating the "betweenness" of the edges and provides a hierarchal structure (a dendrogram) which presents possible clusters in the network (Girvan and Newman, 2002). For this purpose, the *betweenness()* function from the SNA package[3] and the *edge.betweenness()* and *cluster()* functions from igraph package[4] in R (R Development Core Team 2011) are used through a loop to recognize the network structure. After identifying the clusters, we take into account the average trust between them by testing a hypothesis for equal trust means and also considering F-statistics in the Analysis of Variance (ANOVA) to compare variations between the resulted clusters and within them.

Two sample outputs are combined and presented in Table 13. As can be seen, in an analysis performed over 6 clusters each with at least 10 agents (100 in total), the between groups variations, on average, are almost three times higher than within group variations, indicating substantial differences among the clusters, a fact which is also confirmed with value of F-Statistics. As the coefficients show, at least 3 out of these clusters have a mean value which is significantly different from a randomly selected cluster (Cluster 1 in this case). The mean of trust in the last cluster is almost 50% higher than the first one.

[3] http://cran.r-project.org/web/packages/sna/sna.pdf
[4] http://igraph.sourceforge.net/

Table 13: Sample results for trust clustering detection in the model

ANOVA Summary	**Mean Square**			
Between Groups	0.2539	**F Stat**	2.9879	
Within Groups	0.0849	**F Critical**	2.311	
	Average	*Coefficient*	*t Stat*	*Count*
Cluster 1	0.5439	-	-	21
Cluster 2	0.8297	0.285827	-0.0170	18
Cluster 3	0.5422	-0.00168	1.4571	15
Cluster 4	0.6708	0.126939	1.7629	24
Cluster 5	0.7299	0.185991	2.3581	12
Cluster 6	0.8080	0.264143	3.0522	10

To achieve a more robust result, the model was run under 5 different random seeds, the clusters are identified under each seed value, and a pool of clusters is generated containing 500 agents distributed among 60 clusters. Then one cluster is selected randomly as the reference and all the others are compared to that one. According to the results, at least 30 clusters show statically significant differences when their mean is compared to the reference which has the average trust of 0.57. To ensure that this difference is not driven with the mean value of the reference, we manually give new mean values to the reference ranging between 0 and 1, as presented in Table 14. As can be seen, with variations across the range, the differences in trust across the clusters are consistent. Removing the clusters with smaller number of agents results in the same findings.

Table 14: Difference in trust when the clusters are compared to different levels of trust mean value in the reference cluster

Mean trust of the reference	0	0.2	0.4	0.5	0.6	0.8	1
Number of difference clusters	37	18	10	20	36	53	57

Conclusions

This study investigated how trust, as an emergent phenomenon, is associated with the micro-level decisions made by individuals. We presented an agent-based model that is able to capture some of the complexities involved in the formation and evolution of trust in an environment where agents can be productive or rent-seeking. This was by achieved by embedding different levels of adaptation, modeling feedback loops, applying a game theoretic interaction framework and taking an asymmetric approach toward information sharing and transfer.

The results suggest that in an environment with the features we have considered, the returns to being honest and productive in a contract play the most critical role in encouraging agents to avoid rent-seeking behavior such as lobbying and bribing. In other words, providing a fair and efficient business environment can motivate agents to avoid allocating effort to unproductive activities to increase their gain. The results also show that the trust decreases that result from an honest agent encountering a dishonest agent are greater than the positive impacts that an honest individual can have on a dishonest one. In other words, the negative impacts of rent-seeking behavior on the economic output through the trust link can be higher than the direct waste of resources which are allocated to unproductive activities, since the net impact of an interaction between an honest and a dishonest agent is more likely to encourage the honest one to allocate further effort to rent-seeking. As we also presented in the findings, this may even be amplified through clusters of rent-seeking which form across the network.

We also discussed the fact that while higher levels of risk-taking can lead to more productive allocation and *Gain* in contracts, the relationship is non-linear, so risk-loving agents may engage in any kind of interaction without being cautious about the inefficiencies. This behavior, as in real life, can result in reductions in both their *Trust* and their *Gain* and has been verified empirically by studies such as by Roth (2009) who concludes that a curvilinear relationship exists between trust and economic growth.

This model can be extended by calibrating its mechanisms against real-world trends of trust across communities with different cultural and business environments and by trying to discover specific simulation setups which can reproduce the evolution of trust in actual economic networks such as supply chains and manufacturing networks.

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