Chapter 9
Trust, Growth, and Inequality: An Agent-Based Model

Shu-Heng Chen and Bin-Tzong Chie

Abstract An agent-based model of the investment game is proposed to study the complex dynamics between trust, growth, and inequality with different underlying technologies. It is found that agents in this economy, through learning to trust and to be trustworthy, are able to coordinate themselves well in networking, which hence facilitates wealth creation. The excessive smoothness in economic growth is, therefore, prevalent in all simulations, and the underlying technologies can only determine the speed of growth and network formation. While the advancement of technology can ameliorate the inequality of wealth distribution, it also lowers the social mobility of the agents.

Keywords Investment game • Network game • Cohesiveness hypothesis • Clique • State-dependent multiplier • Logit distribution • NetLogo

1 Motivation and Literature Review

Recent empirical studies show that social trust is an important determinant of social prosperity and economic growth (Zak and Knack 2001; Beugelsdijk et al. 2004; Berggren et al. 2008; Dearmona and Grier 2009; Algan and Cahuc 2010).[1] In this paper, we build an agent-based model of trust and growth dynamics upon the existing literature on the laboratory experiments of investment games. In this section, we shall first review the origin of the investment game experiments.

[1]For a brief survey, see (Chen et al. 2014).

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Trust and reciprocity have been studied in experimental economics since Berg et al. (1995) published a paper reporting the results of the now deemed prototypical investment game. In this two-stage game, the two players are endowed with $10 each. In stage 1 the first mover decides how much money to pass to an anonymous second mover. All money passed is tripled. In stage 2 the second mover decides how much to return to the first mover. In this original experiment, out of the 32 first movers, 30 sent a positive amount; only 2 sent 0. Out of the 28 second movers who received amounts greater than $1, 12 returned $0 or $1, and 12 returned more than the amounts their paired players sent them. So, the results clearly departed from the Nash equilibrium outcome that would be reached by the perfectly rational and selfish players. This experiment has been replicated many times since then, and the results are, from a qualitative point of view, quite robust. It is now widely accepted that trust and reciprocity are fundamental aspects of human social behavior.

The rest of the paper is organized as follows. Section 2 gives the main body of the paper, i.e., the agent-based modeling of the investment game. To do that, we first extend the original two-person one-role-playing model into a multi-person two-role-playing model (Sect. 2.1). We then introduce the essence of the model, i.e., the *network cohesiveness hypothesis* and, by that, we modify the original constant multiplier as a state-dependent multiplier. The second part of the model deals with agents' behavior (Sect. 2.2). In this model, the agents' decisions involve networking, portfolio, and kickbacks. Following a discrete stochastic choice model (Luce 1959; McFadden 1974, 1990), the agents base all these three aspects of decisions on trust. Section 3 shows the simulation results, and is followed by the conclusion (Sect. 4).

2 Network-Based Investment Game

The original version of the investment game has three essences: two persons, the role (either trustor or trustee) played by each person, and a fixed multiplier. In our extended version, we consider N persons, each taking a dual role, and a state-dependent multiplier.

2.1 The Model Sketch

The network-based investment game is a hybridization of the *repeated investment games* and the *network games*. It is outlined as follows. N agents engage in a repeated investment game with T repetitions (T rounds). In each round, each agent has to make a two-stage decision: *networking* and *investment*.

1. (*Partner Selection*) In the first stage, which is called the *network formation stage* or the *partner selection stage*, the subject i ($i = 1, 2, \ldots, N$), acting as a *trustor*, has to decide whom he would like to choose to be his *trustees*, say

j ($j \neq i$). Denote this decision by δ_{ij}.

$$\delta_{ij} = \begin{cases} 1, \text{ if } i \text{ chooses } j, \\ 0, \quad \text{otherwise.} \end{cases} \tag{9.1}$$

A link between i and j is said to be formed only if either $\delta_{ij} = 1$ or $\delta_{ji} = 1$; that is, all links are *undirected*.

2. Based on the first-stage decisions of all agents, a network topology is determined by a set of links, g,

$$g = \left\{ \overline{ij} : \delta_{ij} = 1 \text{ or } \delta_{ji} = 1,\ 1 \leq i < j \leq N \right\}. \tag{9.2}$$

The *neighbors* of agent i, denoted by N_i, are defined as follows:

$$N_i = \left\{ j : \delta_{ij} = 1 \text{ or } \delta_{ji} = 1,\ j = 1, 2, \ldots, N \text{ and } j \neq i \right\}. \tag{9.3}$$

3. In the second stage, a standard investment game is implemented on each pair connected by a link $\overline{ij}$. This will separate agent i's neighbors into two sets: the trustees of i (to whom agent i will send money, $\delta_{ij} = 1$), denoted as $N_{i,S}$ and $N_{i,R}$, respectively. Obviously, $N_i = N_{i,S} \cap N_{i,R}$, but $N_{i,S} \cap N_{i,R}$ may be nonempty.
4. (*Investment*) Then, constrained by his/her endowment or wealth, agent i has to make an investment decision on each link, $k_{i,j}$ ($j \in N_{i,S}$), where he or she plays the role of a trustor ($\delta_{ij} = 1$).

$$\sum_{j \in N_{i,S}} k_{i,j} \leq K_i, \tag{9.4}$$

and send the money. In the meantime, agent i's trustors js ($j \in N_{i,R}$) also make their investment decisions on i and send the money to him. As to the investment decision per se or the determination of $k_{i,j}$, they will be discussed in Sect. 2.2.
5. (*Social Cohesiveness Hypothesis*) The investment on each $k_{i,j}$ will then be associated with a multiplier $\tau_{i,j}$, which depends on the network topology. This leads to the major novelty and key contribution of the paper. The *multiplier*, basically, is related to productivity. The idea is to fully acknowledge the significance of the network size or the network scale effect on productivity. A similar idea has been found in many places in the economic literature, such as the knowledge externality or spillover in endogenous growth theory, the agglomeration effect in economic geography (Fujita and Krugman 2004), and so on.

In the investment game, all business relations are simply *dyadic*. The dyadic relation is not isolatedly placed; instead, it is embedded within a large network where many other dyadic relations co-exist. We first assume that the *cohesiveness* of this social embeddedness functions as an *infrastructure* which can be productivity-enhancing, and then use the size of the *clique* containing the specific dyadic relation as a measure of the size. A clique is a completely (fully) connected subnetwork of a given network. Let $g^*_{\overline{ij}}$ be the *clique* (the largest fully connected subnetwork) that $\overline{ij}$ or, equivalently, $\overline{ji}$ belongs to:

$$g^*_{\overline{ij}} = \left\{\left(i', j'\right) : \delta_{i'j'} + \delta_{j'i'} \neq 0, \text{ if } \delta_{uv} + \delta_{vu} \neq 0, \; u \in \{i, j\}, v \in \left\{i', j'\right\}\right\} \tag{9.5}$$

The *network cohesiveness* is then defined as the degree of $g^*_{\overline{ij}}$ and we denote it by $N_{\overline{ij}}$.

By Eq. (9.5), we are searching for the maximally fully connected subnetworks within which the business relationship between i and j is embedded. Intuitively. If the business between i and j is run within a well-connected society instead of a fragmentally isolated small group, then we expect a larger scale effect.

6. (*State-Dependent Multiplier*) Consequently, we assume that the multiplier $\tau_{i,j}$ is monotonically increasing in $N_{\overline{ij}}$. We now set the investment multiplier as a linear function of the cohesiveness of the social embeddedness of the partner relation (i, j), i.e.,

$$\tau_{i,j} = 1 + \alpha \left(\frac{N_{\overline{ij}}}{N}\right), \tag{9.6}$$

where α is a constant. Notice that when the cohesiveness comes to its maximum, i.e., $N_{\overline{ij}} = N$, $\tau_{i,j} = 1 + \alpha$. By setting $\alpha = 2$ and removing the scale effect characterized by $N_{\overline{ij}}/N$, we then have the usual setting of having a multiplier of three, frequently used in experimental economics. The production function and the total return received by the trustee is

$$y_{i,j} = \tau_{i,j} k_{i,j} \tag{9.7}$$

By Eq. (9.6), $\tau_{i,j} = \tau_{j,I}$; hence, $y_{j,i} = \tau_{j,i} k_{j,i}$.[2]

7. (*Kickbacks*) Then, as the usual second stage of the investment game, agent i has to make his/her decision on the share of the yield $y_{j,i}$ ($j \in N_{i,R}$) that he would like to return to his trustors j. We denote his/her own reserve by $y^i_{j,i}$ and hence his trustworthiness by $y^j_{j,i}$.

$$y^i_{j,i} + y^j_{j,i} = y_{j,i} \tag{9.8}$$

[2]This function (6) can be made more flexible to accommodate different hypotheses of network productivity; for the details, see (Chen et al. 2014).

In the meantime, he also receives money from his own trustees, $y^i_{i,j}(j \in N_{i,S})$. The details of the decision on kickbacks will be fully developed in Sect. 2.2.

8. This finishes one round of the network-based investment game. An end-result is the net income earned by agent i:

$$K_i\,(t+1) = K_i(t) + \sum_{j \in N_{i,S}} \left(y^i_{i,j}(t) - k_{i,j}(t) \right) + \sum_{j \in N_{i,R}} y^i_{j,i}(t). \tag{9.9}$$

9. We then go back to step (1). Each subject renews the network formation decisions, and they together form a (possibly) new network topology. The investment game, step (3) to (8), is then played within this renewed social network. It will be interesting to study what are the additional links that these subjects add or delete.
10. The cycle from step (1) to (8), as described in (9), will continue until T is achieved.

2.2 *Trust-Based Heuristics*

Section 2.1 provides a general description of the network-based investment game model. However, unlike most studies on the investment game, which involve human-subject experiments, this study is based on agent-based simulation. Hence, we need a separate section to address the behavioral aspects of the model. That is, we need to formulate the possible interesting behavior of artificial agents in this model, which, of course, can be further verified using the lab experiments. Based on the description in Sect. 2.1, there are three major behavioral aspects that need to be addressed, namely, decisions on *trustee selection* (Step 1), *investment and portfolios* (Step 4), and *kickbacks* (Step 7).

2.2.1 Trustee Selection

The initial question is how to characterize an appropriate set of alternatives for agents. We can make no restriction on the set of candidates, i.e., the agent can always consider every one in the society except himself $\{1, 2, \ldots, N\} \backslash \{i\}$; nonetheless, how many trustees can he choose at each run of the game? One obvious setting is as many as he wants. However, in considering all the transactions costs, such as communication, search and computation, it seems reasonable to assume that an incremental process exists for the upper limit of the number of trustees that an agent can choose. This upper limit is primarily restricted by the cost affordability of the agent. Here, without making these costs explicit, we indirectly assume that the affordability depends on the wealth of the agent, i.e., K_i. Hence, in a technical way, we assume that the additional number of trustees (links) is available if the wealth increases up to a certain threshold. For example, an agent's links may increase if he has positive growth of wealth, and vice versa.

$$l_{\max}(t) = \begin{cases} l_{\max}(t-1)+1, & \text{if } \dot{K}_i(t) > 0, \text{ unless } l_{\max}(t-1) = N-1 \\ l_{\max}(t-1)-1, & \text{if } \dot{K}_i(t) \leq 0, \text{ unless } l_{\max}(t-1) = l_{\min} \end{cases} \tag{9.10}$$

where

$$\dot{K}_i(t) = \ln \frac{K_i(t)}{K_i(t-1)} \tag{9.11}$$

Note that Eq. (9.10) serves only as a beginning for many possible variants, but the idea is essentially the same: each agent starts with a minimum number of links, say, $l_{\min} = 1$, and gradually increases the number of links associated with his good investment performance, and vice versa. One can certainly consider different measures of investment performance, but we shall leave this issue for further study. The rule (10) leaves two possibilities for the agent to change at each point in time: either adding one link (if he has not come to the maximum) or deleting one link (if he has not come to the minimum). For the former case, he will choose one from those who were not his trustees in the last period, i.e., the set $\mathbf{S} - N_{i,S}(t-1)$; for the latter case, he will choose one from his last-period trustees, i.e., the set $N_{i,S}(t-1)$. Let us assume that for both cases, his main concern for this one-step change is *performance-based* or *trust-based*. We call this the *trust-based selection mechanism*, which basically says that the agent tends to add the most trustworthy agent and delete the least trustworthy agent. To do so, let us define the *effective rate* of return of the investment from agent i to j, measured in terms of its kickbacks, as

$$\kappa_{i,j}(t-1) = \begin{cases} \frac{y^i_{i,j}(t-1)}{k_{i,j}(t-1)}, & \text{if } k_{i,j}(t-1) > 0 \\ 0, & \text{if } k_{i,j}(t-1) = 0. \end{cases} \tag{9.12}$$

Then the frequently used logit distribution can be used to substantiate the trust-based selection mechanism as follows.

$$\text{Prob}\left(j \middle| j \in (\mathbf{S} - N_{i,S}(t-1))\right) = \frac{\exp\left(\lambda_1 k_{j,i}(t-1)\right)}{\sum_{j \in \mathbf{S} - N_{i,S}(t-1)} \exp\left(\lambda_1 k_{j,i}(t-1)\right)} \tag{9.13}$$

$$\text{Prob}\left(j \middle| j \in N_{i,S}(t-1)\right) = 1 - \frac{\exp\left(\lambda_1 \kappa_{j,i}(t-1)\right)}{\sum_{j \in \mathbf{S} - N_{i,S}(t-1)} \exp\left(\lambda_1 \kappa_{j,i}(t-1)\right)} \tag{9.14}$$

Equation (9.13) above applies to the situation where agent i can add links, whereas Eq. (9.14) applies to the situation where agent i needs to delete a link. By Eq. (9.13), agent i tends to favor more those agents who have trusted in him and invested in him, i.e., $j \in N_{i,R}(t-1)(k_{j,i}(t-1) > 0)$, than those who did not $j \notin N_{i,R}(t-1)(k_{j,i}(t-1) = 0)$. By Eq. (9.14), agent i will most likely cut off the investment to the agent who offers him the least favorable return rate, i.e., the lowest κ.

2.2.2 Investment and Portfolios

Once the new set of trustees ($N_{i,S}(t)$) is formed, the trustor has to decide the investment portfolio applied to them, i.e., how to distribute the total wealth, $K_i(t)$ over $N_{i,S}(\mathrm{t}) \cup \{i\}$. We assume again that this decision will be *trust-based*. The idea is that agent i tends to invest a higher proportion of his wealth in those who look more promising or trustworthy, and less to the contrary. Technically, very similar to the decision on the trustee deletion (Eq. 9.14), let us assume that agent i will base his portfolio decision on the effective rate of return $\kappa_{i,j}(t-1)$. Those who reciprocated agent i handsomely in the previous period will be assigned a larger fund and vice versa. Then a trust-based portfolio manifested by the logit distribution is as follows:

$$w_{i,j}(t) = \frac{\exp\left(\lambda_2 \kappa_{i,j}\ (t-1)\right)}{\sum_{j \in N_{i,S}(t) \cup \{i\}} \exp\left(\lambda_2 \kappa_{i,j}\ (t-1)\right)}, \quad \forall j, j \in N_{i,S}(t) \cup \{i\} \tag{9.15}$$

where $w_{i,j}(t)$ is the proportion of the wealth to be invested in agent j; consequently,

$$k_{i,j}(t) = w_{i,j}(t) K_i(t). \tag{9.16}$$

Two remarks need to be made here. First, part of Eq. (9.15) is self-investment, i.e., $w_{i,i}(t)$.

$$w_{i,i}(t) = \frac{\exp\left(\lambda_2 \kappa_{i,i}\ (t-1)\right)}{\sum_{j \in N_{i,S}(t) \cup \{i\}} \exp\left(\lambda_2 \kappa_{i,j}\ (t-1)\right)} \tag{9.17}$$

Like the typical investment game, agent i can certainly hoard a proportion of the wealth for himself; however, based on the rule of the investment game, this capital will have no productivity and its effective rate of return is always 1, $\kappa_{i,i}(t) = 1$, $\forall t$. Therefore, by Eq. (9.15), hoarding becomes more favorable when an agent suffers general losses on his investment, namely, $\kappa_{i,j}(t-1) < 1$ for most j. Of course, when that happens, the social trustworthiness observed by agent i is lower and thus he may take a more cautionary step in external investment.

Second, for the new trustee ($j \notin N_{i,S}\ (t-1)$), $\kappa_{i,j}\ (t-1)$ is not available. We shall then assume that it is $\kappa_{i,0}$, which can be taken as a parameter of agent i's general trust in the case of *strangers*. The culture or the personality which tends to have little trust for strangers, being afraid that they will take all the money away, has a lower κ_0 or zero, and serves as the extreme. The culture or the personality which tends to be more friendly toward strangers has a relatively higher κ_0. The introduction of this parameter then leaves us room to examine how this initial trust may impact the later network formation.

2.2.3 Kickbacks

Finally, we consider the decision related to kickbacks. When investing in others, agent i also plays the role of a trustee and receives money from others $k_{j,i}(j \in N_{i,R})$. In the end, the total revenues generated by these investments are

$$Y_i(t) = \sum_{j \in N_{i,R}(t)} y_{j,i}(t) = \sum_{j \in N_{i,R}(t)} \tau_{j,i}(t) k_{j,i}(t) \tag{9.18}$$

Let us assume that the total fund available to be distributed over agent i himself and all of his trustors is simply this sum, $Y_i(t)$. That is, agent i will not make an additional contribution from his *private* wealth to this distribution.[3] Furthermore, we assume that the decision regarding kickbacks is also *trust-based*. We assume that agent i tends to reciprocate more to those who *seem* to have a higher degree of trust in him and less to those who *seem* to have less. This subjective judgement is determined by the received size of investment, $k_{j,i}(t)$.[4] Hence, a straightforward application of the logit model leads to the proportions of kickbacks allocated to each trustor of agent i.

$$\omega_{i,j}(t) = \frac{\exp\left(\lambda_3 k_{i,j}(t)\right)}{\sum_{j \in N_{i,R}(t) \cup \{i\}} \exp\left(\lambda_3 k_{i,j}(t)\right)}, \forall j,\ j \in N_{i,R}(t) \cup \{i\}, \tag{9.19}$$

where $\omega_{i,j}(t)$ is the proportion of $Y_i(t)$ that will be returned to agent j as kickbacks. Hence,

$$y^j_{j,i}(t) = \omega_{i,j}(t) Y_i(t). \tag{9.20}$$

[3]For either altruistic reasons or other strategic reasons, violations of this assumption are possible, but in this paper we shall refrain from the more thoughtful design.

[4]Here, we use the term "seeming" or "subjective", because agent i cannot have a direct observation of agent j's portfolio,

$$\left\{w_{j,l}(t)\right\}_{l \in N_{j,S}(t) \cup \{j\}},$$

to estimate his proportion in agent j's portfolio. For example, $k_{j,i}(t)$ can be large in absolute size, but relatively small in terms of its weight in the portfolio. In this case, agent j may not trust agent i as much as may be apparent.

Note that part of Eq. (9.19) is the reserve that agent i keeps for himself. In fact,

$$\omega_{i,i}(t) = \frac{\exp\left(\lambda_3 k_{i,i}(t)\right)}{\sum_{j \in N_{i,R}(t) \cup \{i\}} \exp\left(\lambda_3 k_{i,j}(t)\right)}. \tag{9.21}$$

By Eq. (9.16) and (9.17), the self-investment is

$$k_{i,i}(t) = w_{i,i}(t) K_i(t), \tag{9.22}$$

and the "retained earnings" are

$$\sum_{j \in N_{i,R}(t)} y^i_{j,i}(t) = \omega_{i,i}(t) Y_i(t). \tag{9.23}$$

Then the behavioral interpretation of Eq. (9.21) is that an agent who has a large hoarding size, kept as "retained earnings" for himself, tends to be more selfish. These people are, therefore, less social and less cooperative. The parameter which dictates this behavior is κ_0, as introduced in Sect. 2.2.2.

3 Simulation

The above agent-based model of the investment game is written using *NetLogo*, version 5.0.5, developed by one of our co-authors, Bin-Tzong Chie. The model code can be found at http://www.openabm.org/model/3915/.

3.1 Simulation Goals

To run the model, we first decide the main goal of our simulations, i.e., what we would like to know. In this paper, the simulation goal is as follows:

1. First, regarding *wealth creation*, we want to know whether agents are able to self-coordinate to fully explore the network productivity by attaining the largest possible clique and hence becoming the most productive economy. If such self-coordination is possible, how fast can it happen? If not, how far is it away from the ideal state? Specifically, we denote the full multiplier $1 + \alpha$ by τ^* and the realized τ time t by τ_t. Then the convergence behavior of τ_t toward τ^* becomes what interest us.
2. Second, we are interested in knowing the effect on wealth distribution when a society is becoming richer. Will the rich get richer and the poor get poorer during the development process?

Table 9.1 Tableau of control parameters

Parameter	Interpretation	Value
N	Number of agents	100
$K(0)$	Initial capital	1.00
α	Multiplier	0.2, 0.5, 0.8, 1.1
$l_{\min}$	Initial linkage number	1
λ_1	Trustee selection	0.04
λ_2	Portfolio	0.04
λ_3	Kickbacks	0.04
κ_0	Initial trust for strangers	2
T	Number of iterations	100

3.2 Parameter Settings

There are two kinds of parameters to be set before running the model: one is related to technology, i.e., α, and the other is related to behavior, i.e., the decision heuristics (stochastic choice). In this paper, we mainly focus on the former, and consider four different values of it, i.e., $\alpha = 0.2$, 0.5, 0.8, and 1.1. For the role of the behavioral parameters, such as κ_0 and λ, the interested reader is referred to (Chen et al. 2014). The parameter setting is summarized in Table 9.1. We run 30 trials for each set of parameters (mainly, different values of α), and the result presented below is based on the summary statistics of these 30 trials.

3.3 Simulation Results

Our simulation with a network of 100 agents shows:

1. The development of social capital depends on the involved technology. A higher α, as expected, leads to a well-connected society, rich in social capital (Fig. 9.1, left panel; also see Table 9.2, the row "Social Capital").
2. The development of social capital further helps the growth of wealth of individuals, and they are coupled together (Fig. 9.1, right panel; Table 9.2, the row "Physical Capital").
3. Wealth distribution measured by the Gini index declines with α. Figure 9.2 shows the shape of Lorenz curves with respect to different α (also shown in Table 9.2, the row "Gini Index"). The figures indicate that the richer the society is, the more equal the distribution is. Despite the more equal wealth distribution, the social status of agents, however, becomes less mobile in a richer society. To see this, we develop a rank statistic for each individual by first tracing his rank in terms of his physical and social capital throughout his life span. Figure 9.3 provides one example of an individual's rank over the time course. In fact, the plot of the time course of this chosen individual shows the high mobility of his social status:

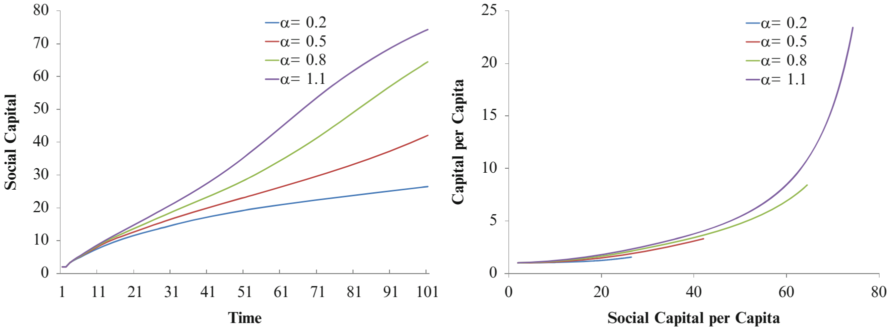

Fig. 9.1 Technology and the growth of social capital and physical capital. The *left panel* shows the growth of social capital under the different technology levels characterized by the parameter α, whereas the right panel shows the relationship between social capital per capita and physical capital per capita over time, with respect to different values of α. Physical capital is defined as the asset that the agent has, i.e., K_i; social capital is defined as the number of connections that the agent has, i.e., the cardinality of N_i or simply $\#(N_i)$

Table 9.2 Summary statistics

α	0.2	0.5	0.8	1.1
κ	91.49	96.98	102.26	104.25
	(1.34)	(1.41)	(0.81)	(0.38)
Physical capital (K)	1.55	3.3	8.27	23.56
	(0.01)	(0.07)	(0.37)	(2.02)
Maximum clique	3.82	4.42	5.26	5.83
	(0.08)	(0.17)	(0.34)	(0.45)
Gini index	0.34	0.32	0.19	0.11
	(0.01)	(0.01)	(0.01)	(0.01)
Social capital	27.71	43.56	65.37	75.52
	(0.67)	(1.34)	(1.40)	(0.91)
cc	0.33	0.48	0.66	0.75
	(0.01)	(0.02)	(0.01)	(0.01)
apl	1.74	1.58	1.36	1.25
	(0.01)	(0.01)	(0.01)	(0.01)

The summary statistics show the corresponding indicators of the termination period ($T = 100$), averaged over 30 runs and inside the parentheses are the respective standard deviations. If the indicator itself is a kind of average, then the average is taken over all 100 agents. Hence, from the top to the bottom, κ is the average gross return on investment (average taken over 100 agents); K, the average physical capital; maximum clique, the extent of the largest fully connected network; *Gini index*, an inequality measure defined as the area above the Lorenz curve but below the 45° line; *social capital*, the average number of connections; *cc*, the average cluster coefficient; *apl*, the average path length

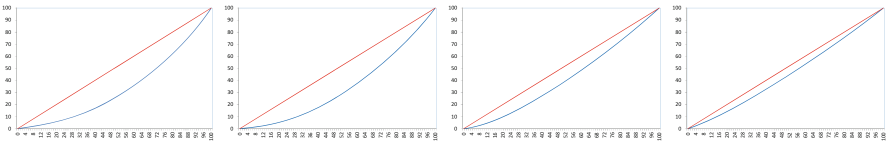

Fig. 9.2 Lorenz curve. From *left to right*, the four Lorenz curves correspond to the case of α being equal to 0.2 (*leftmost*), 0.5 (*middle left*), 0.8 (*middle right*), and 1.1 (*right most*)

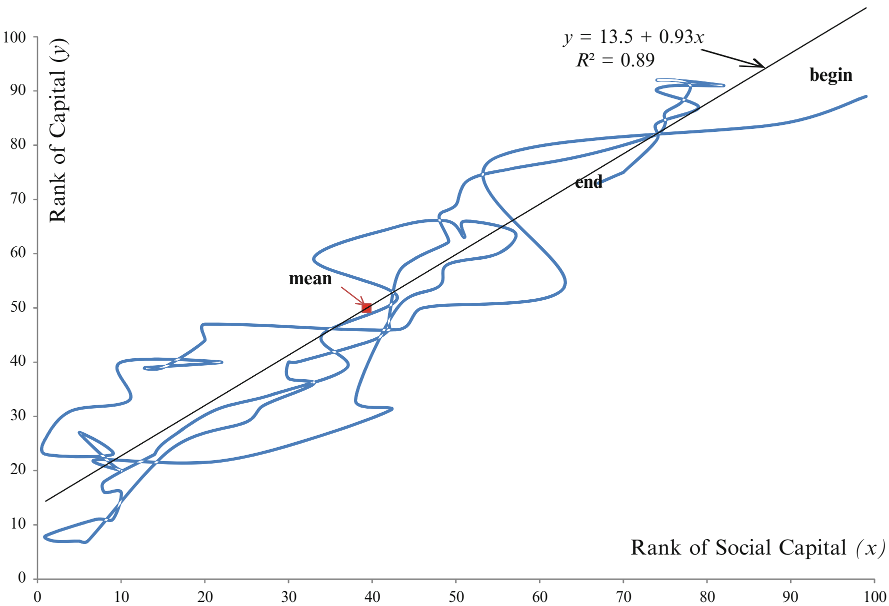

Fig. 9.3 Social mobility: a representative individual, the ranks of his capital and social capital over the entire time course

he was at the top, then slipped down to the bottom, then came back, but slipped down again to another bottom, and finally came back all the way to the top.

We then take the average of the ranks over each individual's life span. Figure 9.4 demonstrates the rank distribution of both social capital and physical capital under the different values of α. If the high-status agents remain high, and vice versa, then we may expect the distribution to be closer to a uniform distribution ranging from 1 to 100, but obviously this is not the case. The social status mobility is much higher as compared to the one represented by the uniform distribution. However, in the richest society ($\alpha = 1.1$), we start seeing that some richest agents can remain in that position permanently, a phenomenon which does not exist for the less rich society (a society with smaller value of α). In addition, the medium of the rank distribution begins to fall further below 50 when α becomes larger.

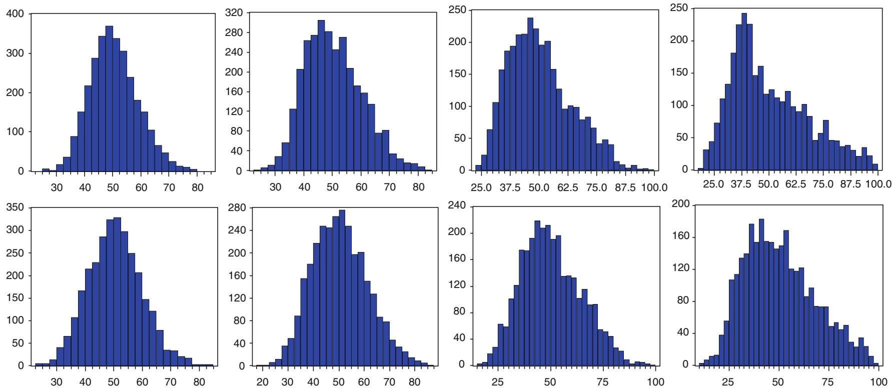

Fig. 9.4 Rank statistics: capital and social capital. The rank distribution of the capital (*upper panel*) and the rank distribution of the social capital (*lower panel*). From the left to the right is the distribution corresponding to α = 0.2, 0.5, 0.8, and 1.1, respectively

4. Although the clique size increases with α, possibly due to our rather conservative range of α, all societies have a rather primitive structure with only a small clique being formed (Table 9.2, the row "Maximum Clique"). However, the trend of both the cluster coefficient and the average path length is quite evident (Table 9.2, the rows "cc" and "apl"). Hence, a longer running time may be required before we see the formation of a large clique.
5. Finally, it is interesting to notice that the investment return is negative for most agents when α is relatively small. An average κ of less than 100 % indicates that agents did not even get their fair shares back (Table 9.2, the row "κ"). With this negative investment return, two questions arise. First, how could people generally get richer and richer? Second, why did they still invest? The answer to the first question is that they got rich by receiving investment from others through the productivity-related multiplier. The result show that even though the investment return can be negative, so long as people mutually trust each other and invest in each other, the agglomeration effect can dominate the deficiencies in kickbacks. Here, trust is built not only upon returns, but also upon the investment reciprocity. *This is essentially the unique feature of this network-based economy, showing how trust alone can beef up the economy*. Nonetheless, this strong, mutual investment is mainly a result of Eq. (9.10), which says that agents tend to find new partners (add links) as long as they are not financially constrained. Because of this *extroversive* personality, agents will always invest even though the received return is negative. Hence, in future work, some modifications and relaxations should be considered for the society with a mixture of extroversive and introversive agents. It would be also useful to conduct economic experiments to see whether there is any difference between extroversive and introversive people in their networking behavior.

4 Conclusions and Further Work

In this paper, we setup a baseline version of an agent-based model of multi-person investment games, which serves as the canonical theoretical model to provide a plausible trust mechanism in wealth creation and distribution. Under the chosen behavioral heuristics and parameters, we can generate a smooth growth pattern and the wealth distribution along the growth line. Altogether, they not only show how the underlying technology characterized by α can matter for the speed of the accumulation of both physical capital and social capital, but also show that they can impact wealth distribution, both in terms of the Gini index and social mobility. Despite its simplicity, this baseline model provides us with an avenue into more realistic explorations of the complex intertwining relationship between trust and growth.

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