Economy-driven Shaping of Social Networks and Emerging Class Behaviors

Philippe Caillou, Frédéric Dubut, Michèle Sebag

Economy-driven Shaping of Social Networks and Emerging Class Behaviors

Philippe Caillou, Frederic Dubut and Michele Sebag

LRI, Université Paris Sud, F-91405 Orsay France
caillou;dubut;sebag@lri.fr

1 Introduction

Agent-based Computational Economics (ACE) is a powerful framework for studying emergent complex systems resulting from the interactions of agents either mildly rational, or with incomplete information [1, 2, 3] or driven by the social network [4, 5, 6].

This paper focuses on the interrelationship between social networks and economic activities. Compared to the state of the art, the main originality is that the social network dynamically evolves based on the rational decisions of agents: a loan granting activity is enabled by the network and the agents continuously re-shape the network to optimize their utility. Three classes of agents (rational agents, free riders and "investors") are considered. The global welfare is investigated in relation with the agent diversity, examining the differential advantages/disadvantages of the agent classes depending on their distribution in the agent population. Lastly, the stability of e.g. the average interest rate is contrasted with the unstability of the network structure.

After describing the state of the art and the problem tackled in this paper (section 2), we present a loan granting game played by a society of rational agents with a long-term utility function, conditioned by and shaping their social network (section 3). Section 4 reports on the simulation results; the main contributions of the approach are discussed together with perspectives for further studies in section 5.

2 State of the Art and Goal of the Study

Introduced by Epstein and Axtell [7], Agent-based Computational Economics established two major results (the interested reader is referred to [2, 3] for a comprehensive presentation). Firstly, the lack of a centralized walrasian auctioneer does not prevent a society of 0th-intelligence agents from converging towards an economical equilibrium when agents interact and exchange in a decentralized manner; secondly, this result does not hold any longer if the agents can die or evolve.

Meanwhile, after the pioneering Milgram experiment [8] and many further studies (e.g., [9]), the structure of social networks is acknowledged a major factor of economics efficiency. A framework for analyzing social network economics was defined [10], and exploited through either analytical approaches, or various simulation-based extensions [4, 5, 6].

While both domains of ACE and social networks are clearly related, to our best knowledge little attention has been devoted to the interdependent evolution of social and economical activities, considering the social network as both a result and an enabling support of the economical activity. In such a unified perspective, the stress is put on the complex system emerging through the interaction of social and economical activities. Along this line, this paper investigates the complex system made of a population of agents engaged in a loan granting activity, where the activity is simultaneously conditioned by, and shaping, the social network. Basically, every agent is endowed with an individual utility function parameterized after its fixed preference toward immediate rewards; it accordingly decides between borrowing or lending money from/to its neighbors at every time step. While the network thus governs the instant rational optimization problem faced by the agents, agents can decide to create/delete links and thereby modify the network. This setting contrasts with former studies [10, 4, 5, 6] modelling the social network as the end of the socio-economic game, that is, where the network only supports the exchange of information and agents are assessed based on their position in the network.

Furthermore, agents will not reveal their preference − as opposed to e.g. [7] where the exchange price is based on the preferences of both agents. The fact that agents do not reveal their preference is relevant to the study of socio-economic games in two respects; firstly it is more realistic from a non-cooperative game perspective; secondly, the incompleteness of information might adversely affect the convergence of the game. Finally, the study examines the impact of the agent models and strategies on the global welfare in a long term perspective. This contrasts with e.g. [10] focussing on the immediate network efficiency, and discarding the long term impact of current decisions.

3 Overview

This section presents the agent model, the interaction setting and the observed variables of the system. Due to space limitations, the reader is referred to [11] for details.

3.1 Agent model

The agent utility function models the intertemporal choice of the consumer after the standard economic theory [12]. Formally, agent A_i maximizes the sum over all time steps of its weighted instant utilities. The utility weight at time t, set to p_i^t $(0 < p_i < 1)$, reflects the agent preference toward the present (parameter p_i). The instant utility reflects the current consumption level $C_{i,t}$, with a diminishing marginal utility modeled through parameter b_i $(0 < b_i < 1)$, standing for the fact that the agent satisfaction is sublinear with its consumption level [13]. Letting M_i denote the lifelength of agent A_i, it comes:

$$U_i = \sum_{t=0}^{M_i} (p_i^t C_{i,t}^{b_i}) \tag{1}$$

The instant neighborhood of agent A_i, noted $V_{i,t}$ involves all agents A_j such that link (i, j) belongs to the social network at time t. Additional agent parameters comprise:

- **Salary** R_i: A_i receives a fixed salary R_i at the beginning of each time step, and uses it to grant or pay back loans, to buy links, or for consumption.
- **Sociability factor** s_i $(0 < s_i < 1)$: A_i creates a new link (i, j) (where j is uniformly chosen) with a probability s_i at each time step; in case A_i is isolated, a new link is automatically created.
- **Strategy** S_i: The social network comes at a cost, i.e. every link (i, j) must be paid by agents A_i or A_j or both. Three social strategies (classes of agents) are defined:
  Optimizers accept to pay for a link iff it was profitable during the last five time steps (if the utility increase due to this link offsets the link cost). This strategy, referred to as rational strategy, deletes all links which are not sufficiently useful.
  Free Riders never pay for a link. While the free rider minimizes its social cost (the link cost), it does not optimize its neighborhood which might adversely affect its utility (see below).
  Investors always accept to pay for a link. On the one hand this

strategy gives the agent every means to optimize its economic activities, and possibly maintain beneficial relations with isolated agents; on the other hand, it suffers the cost of possibly many useless links.

Under mild assumptions [11], agent A_i can compute its threshold interest rate r_i (lower bound for grant activities and upper bound for loan activities). Note that this rate needs be updated after every elementary transaction as it depends on the agent current and expected capital.

3.2 Interaction protocol

Every agent lives a sequence of epochs, where each epoch involves four phases: i) salary and loans payback, ii) negotiation, iii) consumption, iv) social activity (link creation/deletion).

During the first phase, agent A_i receives its salary R_i, reimburses the money borrowed (plus interests) and is reimbursed for the money lended (plus interests). The negotiation phase involes a variable number of transactions. At each step, A_i determines the best possible borrowing and lending rate; it maintains its estimation $r_{i,j}$ of the interest rate for a transaction (borrow or grant) with every agent A_j in its neighborhood, and proposes the best possible transaction for one currency unit. Depending on whether the transaction is accepted, $r_{i,j}$ is updated (Alg. 1). Agent A_j accepts a borrow transaction if the proposed rate is lower than i) its limit rate r_j and ii) its last borrow rates during this negotiation phase (similar conditions hold for lend transactions).

The transactions proceed until no more transactions are realized.

```
BestRate r*=0;
foreach A_j ∈ V_i such that r_ij > r_i do
    Propose Loan(rate=r_ij);
    if accepted then
        if r_ij > r* then r* = r_ij;
        Increase(r_ij)
    else
        Decrease(r_ij)
    end
end
if r* > 0 then Lend one currency unit at rate r*
```

Algorithm 1: Lending transactions (borrowing transactions proceed likewise)

During the consumption phase, the agent computes its optimal fraction of consumption (see [11]) and scores the corresponding utility.

During the social phase, each agent decides whether it maintains its links depending on its strategy and whether the link has been profitable in the last five epochs. Link (i, j) is either maintained by agents A_i and/or A_j, or deleted. Independently, A_i creates a new link (i, j) with probability s_i (its sociability factor), where j is uniformly randomly selected. If A_i has no neighbor, a link (i, j) is automatically created.

After M_i epochs, agent A_i dies. It is then replaced by a new agent (reinitializing all agent parameters) *with same neighborhood*.

3.3 Fitness and Global Welfare

The socio-economical system will be assessed from the global welfare of the agents. As the agent utilities cannot be directly compared (parameters p_i and b_i depend on the agent), they are normalized w.r.t. the canonical consumer-only alternative strategy. Each A_i, would it have adopted the consumer-only strategy, would get utility The consumer-only agent, spending its whole salary in each time step, gets utility:

$$U_i^* = \sum_{t=0}^{M_i} (p_i^t R_i^{b_i}) = R_i^{b_i} \frac{1 - p_i^{M_i+1}}{1 - p_i}$$

Accordingly, the normalized fitness of A_i is defined as:

$$F_i = \left(\frac{U_i}{U_i^*} \right)^{\frac{1}{b_i}} - 1$$

Note that if A_i had spent a fixed fraction α, $0 \leq \alpha \leq 1$ of its salary in each time step (without engaging in any borrowing or lending transactions), it would score a normalized fitness $\alpha - 1$. In brief, agent A_i benefits from the social network iff its fitness F_i is positive.

The efficiency of the socio-economical system is thus measured from the average normalized fitness of the individuals, and its standard deviation. Further, each class (optimizers, free-riders and investors) will also be assessed from the average normalized fitness of the individuals belonging to this class.

4 Results

After the description of the experimental setting, this section reports on the impact of the network and agent dynamics on the global efficiency of the system.

4.1 Experimental settings

The socio-economical game is implemented and simulated within the Moduleco framework [14]. The initial structure of the social network is a ring, where each agent is connected to its two neighbors. Agents are initialized by independently drawing their parameters using Gaussian or uniform laws as follows.

- Time preference $p_i \sim \mathcal{N}(0.8, 0.075)$
- Utility factor $b_i \sim \mathcal{N}(0.5, 0.1)$,
- Sociability factor $s_i \sim \mathcal{N}(0.05, 0.05)$,
- Salary $R_i \sim \mathcal{N}(20, 5)$,
- Life expectancy $M_i \sim U(20, 100)$,

The link cost is set to .2 in the remainder of the paper. Complementary experiments with varying values of the link cost are reported in [11]. Experiments were conducted with a population size ranging from 25 to 100, with similar results. All reported results are averaged over 25 independent experiments conducted with 25 agents over 1000 epochs. The global (respectively, class) fitness is computed by averaging the normalized fitness of agents (resp. belonging to the class) that died before the 1000th. epoch.

4.2 Complete and costless information

The classical economic theory relies on the assumption of a complete and costless information, e.g. gathered and disseminated by the "walrasian auctioneer", enforcing the convergence of the interest rate toward the equilibrium rate. As formally shown in [11], the equilibrium rate can be analytically derived from the agent utility functions.

The first experiment, as a sanity check, thus considers the fully connected social network and compares the empirical interest rate toward the equilibrium rate. As expected, the average interest rate rapidly converges toward the equilibrium value τ ($\tau = .24$ in the experimental setting, Fig. 1). The standard deviation ($< .0025$ after 5 epochs in the fully connected case) is explained from the experimental noise, discrete loan amount and limited number of agents.

Interestingly, randomly removing edges in the social network only delays the convergence toward the equilibrium rate, although the standard deviation of the interest rate significantly increases for social networks with low density. Fig. 1 displays the standard deviation vs the percentage of edges in the social network after 20 epochs.

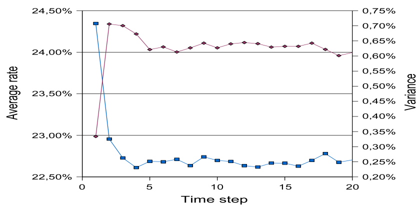


Fig. 1. Interest rate and standard deviation within a complete network

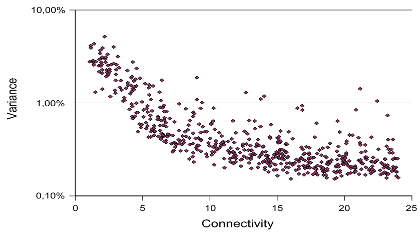


Fig. 2. Impact of the network connectivity on the standard deviation of interest rate after 20 epochs

4.3 Rational and Immortal Agents

The second experiment focuses on rational agents (optimizer strategy) with infinite lifelength. Despite the fact that the social network can evolve with the rational agent decisions, the empirical interest rate still converges toward the equilibrium rate. Still, the convergence is slower than in the previous case, and the standard deviation remains high after 1000 epochs (Fig. 3).

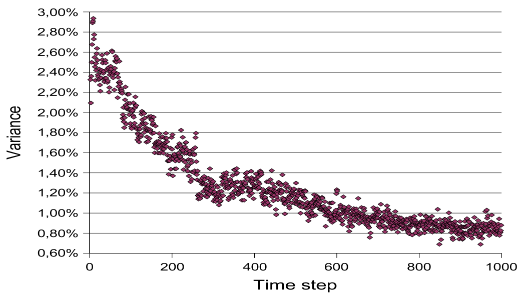


Fig. 3. Rational and Immortal Agents: Standard Deviation of the Interest Rate

Most surprisingly, while the interest rate reaches the equilibrium, it does so with a continuously changing social network; no edge in the network appears to last more than a few epochs, as agents endlessly optimize their neighborhood. Indeed, in either competitive or monopolistic situations, there always exists some profitable link creation or deletion. The canonical case of a 3-agent network, depicted in Fig. 4, involves three possible configurations (being reminded that a link is created automatically when an agent is isolated), all of which are unstable. In the n-agent case, instability is increased by cascading effects, the creation/deletion of a link leading to further link deletions or creations.

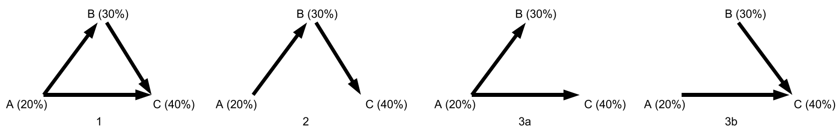


Fig. 4. 3-agent network configurations; arrows indicate the lender-borrower pair

1 In the triangle (clique) case, there are two possible situations:
   - If A can lend the desired amount to C with a rate higher than the B limit rate r_b, A is not interested in maintaining link AB, which will thus be deleted.
   - If the C limit rate r_c decreases (because of the loans contracted by C) and becomes lower than r_b, A will grant loans to B and C (with a rate lower than r_b). Therefore B will be unable to lend money to C, since C will refuse to borrow money with rate higher than r_b. Thus the BC link becomes useless and will be deleted.

2 In the line case, B borrows from A at rate $\tau_{AB} < r_B$. C borrows from B at rate $\tau_{BC} > r_B$. When A or C will create the link AC, it will be stable because A will accept to grant loans to C at a rate $\tau_{BC} - \epsilon$ which will be higher (and thus more profitable) than τ_{AB}. We are back to case 1.

3 In the star case (case 3a), agent A is the only one lending money. In this monopolistic situation, A will progressively increase the loan granting rate, until the BC link becomes profitable and thus stable when it will be created. We are back to case 1. Same analysis holds for case 3b (C will decrease its borrow rate).

4.4 Mixed Populations and Global Welfare

Let us consider the mixed population cases. Each possible distribution of the strategies (or classes) in the population is represented as a point in the 2D plane, where the x (resp. y) coordinate stands for the proportion of Free Riders (resp. Investors) in the population (Fig. 5). Point (x, y) is associated with the global population welfare or fitness. Considering the three pure strategies (optimizers only, (0,0); investors only (0,1); free-riders only (1,0)), the Optimizer strategy is by far the best one; this fact is explained as the free-rider-only population generates a sparse random network, while the investor-only population generates a clique (and pays the price for it).

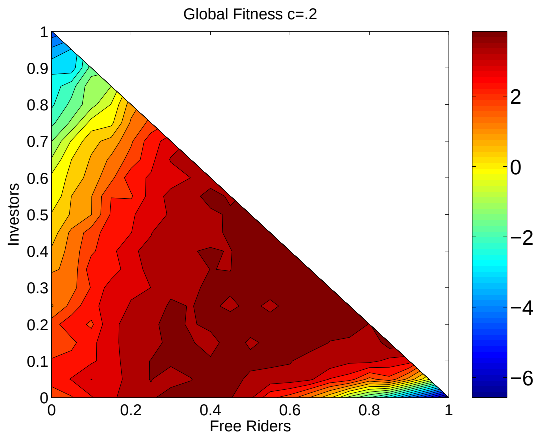


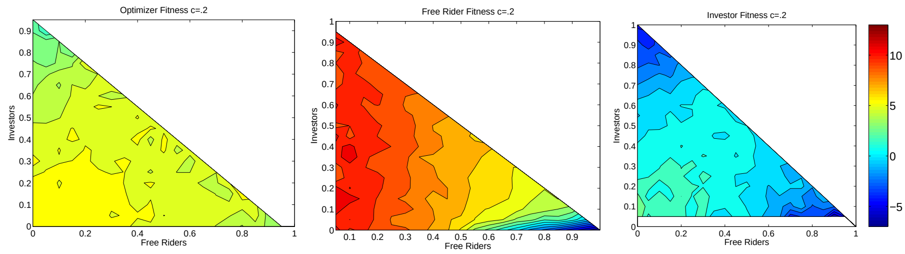
Fig. 5. Average Fitness vs Strategy Distribution in the Population. Point (x, y) correspond to the distribution of x% free-riders, y% investors and $1 - x - y$ % optimizers. Each fitness level differs by .5 from the neighbor fitness levels.

Most interestingly, in the case of mortal agents, mixed populations outperform optimizer-only populations; e.g. the uniform distribution (1/3 optimizers, 1/3 free-riders and 1/3 investors) gets an average fitness significantly higher than the optimizer-only population (complementary experiments show that this result also holds when the link cost is significantly higher or lower, see [11]). This fact is explained as the useless links paid for by investors, are actually very useful to quickly reorganize the network when an agent dies.

4.5 Class Behaviors

While agent diversity is beneficial on average, it remains to examine whether "class behaviors" appear in the population. Two issues will be specifically investigated. Firstly, do the average class fitness depend on its representativity, ie, its percentage of the population (intra-class effects); secondly, do the class representativity affect the average fitness of the other classes (inter-class effects).

The free-rider class does present a class behavior (Fig. 6): their fitness is excellent when they are a minority, and it decreases rapidly as the free-rider representativity increases. The investor class also displays

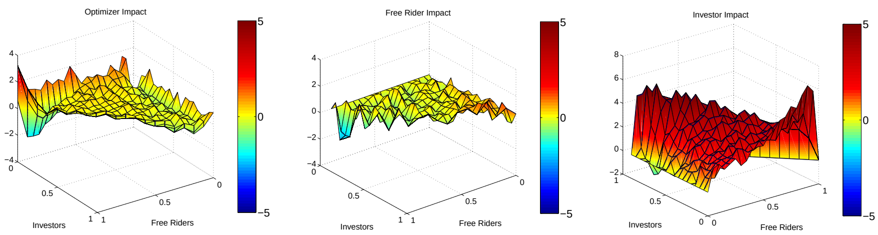


Optimizers Free riders Investors

Fig. 6. Strategy average fitness; each level represents an increase/decrease of 1 for the strategy average fitness

a class behavior: their fitness is good when the representativity of optimizers is sufficiently high, as the optimizers share the costs of the links. In summary, the average fitness of investors and free-riders depends on the class distribution; quite the opposite, the optimizer fitness does not.

We finally examine the impact on the global and class welfares, of the arrival of a new agent depending on its class (Fig. 7).



Optimizers Free riders Investors

Fig. 7. Adding a new agent: impacts on the fitness of the other classes

The arrival of an investor is globally beneficial to other classes. and even more so when there a few optimizers. Indeed, investors fund the infrastructure used by the other agents; their impact is greater when the network is poor (when there are few optimizers).

The arrival of a free rider has a negative impact on the rest of the economy, except when there are many investors. In this case, the free rider decreases the graph connectivity level (and cost) and allows a faster reorganization of the network.

Optimizers, which are not influenced by economic class structure, do not influence it either. Their impact is mostly neutral, though it might be positive in the extreme cases where there are no investors or no free riders.

5 Conclusion and Perspectives

The socio-economic game presented in this paper, based on autonomous and diversified agents, leads to two lessons. The first one concerns the fact that the convergence of economic macro-variables such as the interest rate is compatible with the unstability of the social network supporting the economic activities. Secondly, the benefits of the population diversity have been empirically demonstrated and interpreted in terms of the emerging class behaviors. While investors and free-riders display class behaviors (their fitness depends on the population structure, they have an impact on the welfare of the other classes), the optimizer class seems to be almost unaffected by the population structure, and exerts little influence in return.

Further research perspectives are concerned with the dynamics of the class structure, examining how the best fit agents can influence the distribution, preferences and strategies of the new-born agents.

6 Acknowledgments

We warmly thank D. Phan for making available his Moduleco Framework. This work was supported in part by the IST Programme of the European Community, under the PASCAL Network of Excellence, IST-2002-506778.

References

1. Axelrod, R.: Advancing the art of simulation in the social sciences. Advances in Complex Systems **7**(1) (2004) 77–92
2. Tesfatsion, L.: Agent-based computational economics: Growing economies from the bottom up. Artificial Life **8**(1) (2002) 55–82
3. Tesfatsion, L.S.: A constructive approach to economic theory. In Judd, K.L., Tesfatsion, L.S., eds.: Handbook of Computational Economics. Volume 2 Agent-Based Computational Economics of Handbooks in Economic Series. North-Holland (2006)
4. Bala, V., Goyal, S.: A noncooperative model of network formation. Japanese Journal for Management Information Systems **12**(3) (2003)

5. M. Slikker, A.v.d.N.: Network formation models with costs for establishing links. Review of Economic Design **5**(3) (2000) 333–362
6. Carayol, N., Roux, P.: Behavioral foundations and equilibrium notions for social network formation processes. Advances in Complex Systems **7**(1) (2004) 77–92
7. Epstein, J., Axtell, R.: Growing Artificial Societies. Social Science From the Bottom Up. The MIT Press (1996)
8. Milgram, S.: The small-world problem. Psychology today **2** (1967) 60–67
9. Watts, D., Strogatz, S.: Collective dynamics of 'small-world' networks. Nature **393** (1998) 440–442
10. Jackson, M., Wolinsky, A.: A strategic model of social and economic networks. Journal of Economic Theory **71** (1996) 44–74
11. Caillou, P., Dubut, F., Sebag, M.: Loans in social networks: when sub-optimality increases global welfare. Technical report, LRI (2007) http://www.lri.fr/ caillou/CaillouAliceTech.pdf.
12. Fisher, I.: The Theory of Interest. Macmillan (1930)
13. Menger, C.: Principles of Economics. Dingwall and BF Hoselitz (1871)
14. Phan, D.: From agent-based computational economics towards cognitive economics. In Bourgine P., N.J., ed.: Cognitive Economics. Handbook of Computational Economics. Springer Verlag (2004)