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Evolving informal risk-sharing cooperatives and other-regarding preferences

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Abstract

In this paper we present a model of formation and destruction of informal cooperatives in a population of agents who perform a risky activity and who are heterogeneous in terms of success in their actions. Although some agents have high-risk and others low-risk, our model displays a dynamics with cooperatives in which agents share equally their income with a certain stability. We are interested in studying at the same time the existence of cooperatives, their ability to integrate a large proportion of agents and the degree of segregation of these cooperatives. Three factors can explain the existence, stability and lack of segregation. First, we show that the classical explanation in economics holds within the framework of our model: when agents are risk averse, high success agents can share with low success agents so that to stabilize the value of their income - the higher the risk aversion, the more stable the cooperatives and the lower the segregation. Learning can explain in a small proportion the existence of cooperatives: we designed agents so that they have to learn whether they are high or low-risk, and while they are learning, they tend to create cooperatives that can last. Eventually we worked on the integration of other-regarding preferences in the model, with two different definitions. As expected, the influence of other-regarding preferences is to increase stability and decrease segregation, and the two models of rationality react differently to the type of network in which the agents are immersed. This paper, mainly exploratory, presents our model and shows the influence of the definition of network as well as all other factors presented before. In that sense, although we have mainly done a rough exploration of its relevant parameters for the moment, it exposes different insights that can be gained by its study.

Keywords: Agent-based, risk-sharing, other-regarding preferences, learning, segregation

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1 Introduction

In this paper we present a model with which we want to study repeated risk-sharing among agents who are heterogeneous in terms of risk. More precisely, we would like to know why less risky agents would accept to share risk with more risky ones. To do so, we model risk-sharing through cooperatives in which agents share risk equally, in a population which is homogeneous in risk aversion, but heterogeneous in risk.[1] We are more precisely interested in how cooperatives evolve (that is how they are created and destroyed) and to what extend people with different risk exposures accept to share (equally) risk between each other. In our model, a cooperative can be seen as a coalition which is formed by one agent who proposes others to join, and from which agents[2] can choose to leave individually. The dynamics of formation and destruction of the cooperative is not highly dynamical or complex, since all decisions of agents are coordinated as once every step.

In this paper, we try to analyze three ways of explaining how and why people with different risk exposures share risk. We use Agent-Based modeling to establish their credibility and limits. The first explanation of this behavior is rather usual in economics: agents can have a negative attitude towards risk and, when given the choice, prefer a secure income to a stochastic one. It is then said that these agents are risk-averse and it has been shown that this attitude towards risk can explain the existence of pooling in a group. Another point can be their lack of knowledge: it is not obvious that individuals know their own risks precisely when they perform an activity, and it seems logical that they should know others' risks even less clearly. In that case, could imperfect rationality be the explanation for the fact that some lucky people are ready to share with unlucky ones on a regular basis? Eventually it is possible to imagine that individuals are not just selfish (and that others' income are also of interest to them) or that participating to a community is as important as having a high income. There is no positive model concerning what is called in economics "other-regarding preferences", where others' are considered in an agent's utility, so we propose and test two different models of rationality and see if (and why) they increase the stability of sharing behaviors.

We present the main results showing that our three different modelling features can explain, with more or less strength, an increase of stability of our cooperatives. This paper is rather exploratory in the sense that it mainly shows how our platform can be re-used to test more specifically the influence of network or the definition of other-regarding preferences. It also helped us to stabilize some of the observation indicators.

The paper is built in four parts. The first part motivates our research and gives some elements on informal cooperatives, equal sharing, their link to risk aversion, and other-regarding preferences. In a second part we present the assumptions we used to build the model and give the equations on which it is based, as well as the simulation and observation protocol for running the model. In a third part we present the dynamics of the model, depending on parameters that are presented previously. We eventually discuss our results and conclude in the last part.

[1] Even though statistically rejected, equal sharing of wealth have been shown to be a relatively good benchmark by Townsend [1994].

[2] The meaning we give to the notion of "agents" is closer to economist approach than multi-agent modeling, in that they deal only with little information about their own utility and the belief they have on the utility of others, without actually having notion of collective action.

2 Attitude towards risk, learning, and other-regarding preferences

The questions of the functioning and the stability of risk-sharing agreements have been relatively well documented in economic literature during the last decade. This literature starts from empirical studies in village economies analyzing to what extend villagers share risk. Testing the empirical relevance of equal sharing of wealth in India, Townsend [1994] found that even though equal sharing is statistically rejected, it is a surprisingly good benchmark. Moreover, Fafchamps and Lund [2003] argue, using data from Filipino, that this finding may be due to the fact that risk-sharing takes place at a lower level than the entire village (i.e. across communities). Based on this result, Genicot and Ray [2007] propose a model describing how such communities form. More precisely, they analyze the stability of cooperatives (or coalitions) under limited commitment, that is when transfers are not enforceable (and therefore occur only if the agents have a long term interest to do so). Bloch et al. [2008] add a network component to the model and analyze the stable transfer schemes depending on punishment strategies.

The literature on risk-sharing also points out the important role played by risk aversion. This question goes back to Arrow [1965] in which efficiency gains from risk-sharing increase with risk and with aversion towards risk. This is confirmed in a model with two homogeneous agents by Kimball [1988] that states that the higher risk aversion, the higher the discount rate below which an equal sharing agreement is sustainable. However, considering limited commitment, Fafchamps [1999] argues that this might no more be the case as an increase in risk aversion might make an agent leave the agreement. Still Lazcó [2012] shows that as soon as there is no aggregate risk, an increase in risk aversion increases risk-sharing.

We differ from this literature by adding heterogeneity across agents, imperfect information and altruistic preferences. Few papers on risk-sharing model heterogeneous agents. One exception is Genicot [2006] who analyzes sharing agreement between agents that are heterogeneous with respect to their level of wealth. She finds that most of the time, more inequality increases the likelihood of equal sharing of risk. As we focus here on risk heterogeneity, a closer paper is Bourlès and Henriet [2012] that analyzes the optimal risk-sharing agreement between two agents who differ about their risk exposure. This paper shows that equal sharing is optimal if risk aversion is high and heterogeneity is low. Regarding the formation of cooperative or coalition, Moizeau et al. [2011] show that, under perfect information and selfish preferences, agents form groups with those who have pretty close risk exposure. We analyze here to what extend imperfect information and altruistic preferences can decrease this "homophily" (that we measure with a segregation index). Indeed, altruism (in particular in the case of kinship ties) has been shown to be key in risk-sharing agreement in both empirical (Fafchamps and Gubert [2007]) and theoretical (Alger and Weibull [2010]) literature.

2.1 Learning about one's own risk

One element that is rarely addressed in the classical economic literature on risk-sharing is the one of information. It is always assumed that agents know well their own probability of success and that they also have access to the probabilities of success of the other agents or, at least, the expected income they will get from their belonging to the cooperative.

Learning in agent-based model is a central concept, and is even the main justification for using such a modelling techniques (Brenner [2006]). Indeed it is a very specific characteristics to have autonomous agents, each of them getting different information and hence creating their own representations of their environment. In economics, the most usual learning is made on actions - it is called reinforcement learning in a generic way, and has been made very popular in the form of the Roth-Erev algorithm (Roth and Erev [1995]). Agents learn to choose the action which brings them the highest profit among all the possible actions belonging to a fixed set. Information that is used is only personal past actions, but one can expect some kind of optimization at the population level, where everyone converges towards Nash strategy. Another usual reinforcement learning is genetic algorithm, where the set of possible actions evolves in time (see for example Vriend [2000])

On top of the learning on action, agents can also learn about the characteristics of the environment, which is called "belief learning". For example, an agent can learn which other agent he should interact with and construct a map of good and bad partners (Rouchier et al. [2001]). He can also learn to link context to relevant actions, with classifier systems (Moulet and Rouchier [2008]). One integration of belief learning that is very well known is the one of Camerer and Ho, EWA (Camerer and Ho [1999]), which mixes reinforcement and fictitious play, so that to create a representation of the best actions which is not just linked to one's own past actions.

Here we use a learning about the belief of the agent, what he believes to be his risk exposure. The issue we want to address is the impact of informational blindness on the stability of cooperatives, that is how would cooperatives evolve if agents only knew that there is heterogeneity of risks among them but do not know which level of risk they themselves undergo. We also add a noise in the transmission of information among agents and test its impact on our dynamics.

2.2 Other-regarding preferences

The term other-regarding preferences is rather generic, since it represents any situation where agents are biased in their individual choice because of the presence of others.[3] It does not mean just positive attitudes towards others, but any attitude that transforms decision process in presence of others: aversion to inequality, for example, can make agents avoid situation where they earn more than others, but also where others earn more than they do. These preferences are so strong that in some cases individuals are ready to lose money so that to punish those who deviated from a behaviour they consider as acceptable (Fehr and Schmidt [1999]).

Empirical evidence are often taken in village economy (Townsend [1994]). Concerning risk-sharing issues, people pay more attention to family members or friends (Fafchamps and Lund [2003]) than other villagers or even other members of a community. Compassion - usually translated into patience or willingness to accept to loose some money for the sake of sharing - has a huge impact on participation to cooperatives.

[3]It should be noticed that in our model, preferences are not clearly defined here. They are only summarized by the "objective" function

To the best of our knowledge, almost none has proposed positive representation of other-regarding preferences, by integrating them in the decision process of an agent based models. Janssen and Ahn propose an interesting, but complex, model for integrating relation to inequality in a learning model in a context of public good provision games (Janssen and Ahn [2006]), taking inspiration in the equation proposed by Fehr and Schmidt (Fehr and Schmidt [1999]). In this paper we propose two different ways to represent the sensitivity of agents to the presence of others in their choices.

2.3 Assumptions for the model

We want to test three dimensions of agents' rationality that can have an impact on risk-sharing among agents who are **heterogeneous in their probability of success**: the **risk aversion** of agents, an **incomplete information** and when they have other-regarding preferences (here designated as **compassion** and **friendship**). In our model, the size of the network certainly has an impact and will also be tested.

Heterogeneity and similarities of agents. The basis of our questioning is the heterogeneity of agents in terms of risk. We divide the population in two levels of risk: high and low. We represent this risk as a probability of losing some fixed amount of money for each agent, those probabilities being uncorrelated in the group. For other parameters, such as the level of risk aversion or the size of the network they belong to, agents are homogeneous. When drawn, the network is made following the same algorithm for all agents but each of them of course has a different network.

Leaving a cooperative. At each step, an agent who belongs to a cooperative calculates if he wants to stay in the cooperative or not. If not, he becomes a lonely agent.

Sharing. Within a cooperative, agents use the equal sharing rule (meaning that the aggregate wealth in the cooperative is equally shared among its members), which is the most documented in the literature.

Building a cooperative. At each step, an agent who does not belong to a cooperative can choose to build one. Before deciding, he gathers information about the risk of agents who belong to his network, going to level two (friends and friends of friends), and who are lonely, i.e. not part of a cooperative. He roughly evaluates the risk, as will be seen in the description of model algorithms, and decides if he wants to belong to the cooperative he could be creating. If the cooperative is created, agents who have been contacted have no choice but to accept to share the income at this time-step. They can decide to leave the cooperative at the following step.

Aversion to risk. To represent the attitude of the agents toward risk, we choose to use a CRRA (for Constant Relative Risk Aversion) utility function. This means that this attitude is summarized by a parameter, the relative risk aversion. Such a formulation has two main advantages. First, it is consistent with the evidence of decreasing absolute risk aversion (namely, the richer an agent, the lower his risk aversion). Second, most of the papers estimating aversion towards risk, estimate the coefficient of relative risk aversion (see for example Chetty [2006] or Meyer and Meyer [2005]). Based on this utility function, agents can choose among the options they face: either to stay in a cooperative or leave; either to create a cooperative or not.

Agents do not know their type. Agents use Bayesian learning to know which type they belong to (they assign a probability to each existing type). Therefore they use their past performance only to estimate their level of risk. The algorithm is such that the more difference there is between success probabilities (of high-risk and low-risk types), the easiest it is for agents to identify their type. For example if the difference in probabilities of success between both types is 0.20, it takes an agent 85 steps to know his own type with a strength of 95%; whereas if the difference between probabilities is 0.70, it takes him 5 time-steps.

Agents do not know others' type. At each step, agents have to evaluate the income they get by staying in a cooperative. Since they have no information about others' types, they evaluate the cooperative performance using ex-post results, i.e. the income they got from belonging to the cooperative. Learning algorithms classically include forgetting, and it is particularly relevant in our context, since the cooperatives evolve a lot and expected consumption is not stable: with our forgetting rate, agents put value mainly on the most recent information and give almost no weight to events older than 6 time-steps.

Agents like others. We use two ways to model the fact that agents are not just driven by income and reduction of risk, but that they also have a sense of belonging to a group. One aspect is the responsibility agents feel towards the others. When deciding if he wants to leave a cooperative, an agent sees if his gain in utility would be significant compared to the loss others would incur from his departure. This issue can make a low-risk agent stay because his presence raises the average income of his cooperative (we will refer to such a mechanism as "compassion"). Another aspect is an individual pleasure that agents have when belonging to the same cooperatives as members of their network. This pleasure is directly integrated in the utility function (friendship). Both attitudes are modeled with the use of a parameter that can take a range of values.

3 Model

The model is described in several steps. We define the "basic" model as the choice process of agents who are defined just by their risk-type and their attitude towards risk (that varies with the value of risk aversion).

3.1 Basic economic model

Agents are producers who work and see the success of their activity after their work is over. They can have two types of result: success or failure, which makes them gain two different values: $y \in \{y_+; y_-\}$. Each agent is characterized by his **probability of failure**, which determines the history of his income. We assume that agents are heterogeneous in this probability of failure and more precisely that it can either be low (noted $\underline{p}$) or high ($\overline{p}$). In our setting, half of the agents will be of low-risk type, the other half being of high-risk type.

When an agent belongs to a cooperative, he shares his gain equally with others: all participating agents put their income in a common pool, and the value is redistributed equally to all. This constitutes what is called the consumption, c, which is a characteristic, at a given time-step, of the cooperative. If a cooperative is made of agents $\{a_1, ...a_n\}$ with income $\{y_1, ...y_n\}$,

$$c = \frac{\sum_j y_j}{n} \tag{1}$$

Agents are also defined by their **behavior towards risk**, which can push them to prefer to be in the cooperative even if it decreases their expected consumption. To represent this behavior we use a classical utility function, which has already been used to describe the behaviors of populations in farmers' societies Kimball [1988]: CRRA (for Constant Relative Risk Aversion). It is based on a parameter ρ that describes the relative risk aversion. Based on previous works (Kimball [1988], Chetty [2006] or Meyer and Meyer [2005]) we allow ρ to vary in $[1.1; 6]$. For an agent of consumption c, the utility is:

$$u(c) = \frac{c^{1-\rho} - 1}{1 - \rho} \tag{2}$$

The shape of $u(\cdot)$ then represents agents' behavior towards risk and the index of concavity: $-u^{''}(\cdot)/u^{'}(\cdot)$ is called index of absolute risk aversion. Agents are said risk averse if this index is positive, which means that they are averse to a mean preserving spread of consumption (in other words they always prefer $\mathbb{E}(\widetilde{x})$ to $\widetilde{x}$, where $\widetilde{x}$ is a random variable). The main property of the CRRA class chosen here is to exhibit a constant index of relative risk aversion: $-cu^{''}(c)/u^{'}(c) = \rho \ \forall c$, which is notably consistent with the observation that the index of absolute risk aversion is (in real life) generally decreasing with revenue. It turns out that the higher ρ, the more the agents are ready to sacrifice (expected) consumption to reduce risk (i.e. variance in consumption).

When belonging to a cooperative with high-risk agents, agents with low risk (i.e. a low probability of failure) will not get as high an expected consumption as if they were alone, but they will get a more stable consumption since the risk is shared among the members of the cooperative. In our context of equal sharing, a low value of ρ pushes agents with low risk to stay out of a cooperative, and a high value of ρ makes them prefer to be in the cooperative.

3.2 Bayesian learning

Our agents have cognitive limitations: they do not know their own risk (i.e. their own probability of failure) and have to learn it along the time, building **beliefs**. They know that there exists two different probabilities of failure, high ($\overline{p}$) and low ($\underline{p}$), and that each group of agents represents half of the population. At each time-step t, they have beliefs (subjective probabilities) of belonging to each category: π_t of being low-risk (that is of having a probability of failure of type $\underline{p}$) and $(1-\pi_t)$ of being high-risk (that is of having a probability of failure of type $\overline{p}$). They initially believe that they have probability of 50% to be of each category (they know the real distribution of the population). Each agent then updates his belief in time following a Bayesian learning: at time t, if he has experienced k losses among the t first periods, his belief on his probability of being of low-risk type writes:

$$\pi_t = \frac{\underline{p}^k(1-\underline{p})^{t-k}}{\underline{p}^k(1-\underline{p})^{t-k} + \overline{p}^k(1-\overline{p})^{t-k}} \tag{3}$$

Therefore, at time t, the belief of agent i that he belongs to the low-risk type is such that $\pi_0 = 0.5$ and the update depends on the achievement of the previous period:

- if $y_i(t) = y_-$

$$\pi_t = \frac{\underline{p}\pi_{t-1}}{\underline{p}\pi_{t-1} + \overline{p}(1-\pi_{t-1})} \tag{4}$$

- if $y_i(t) = y_+$

$$\pi_t = \frac{(1-\underline{p})\pi_{t-1}}{(1-\underline{p})\pi_{t-1} + (1-\overline{p})(1-\pi_{t-1})} \tag{5}$$

The interest of this learning is that agents keep track of the quality of their belief, which is expressed as a **probability of belonging to one group or another**. Depending on the difference between $\overline{p}$ and $\underline{p}$, the time to learn is different, i.e: if $\overline{p} - \underline{p} = 0.20$, it takes an agent 85 steps to know his type with a strength of 95% whereas if $\overline{p} - \underline{p} = 0.70$ it takes him 5 steps.

3.3 Staying or leaving

A cooperative applies equal sharing, which means that, at each period t, the consumption of each belonging agent corresponds to the average income of the cooperative. Formally, in a cooperative made of agents $\{a_1, ...a_n\}$ with income $\{y_1(t), ...y_n(t)\}$, the consumption of every agent is:

$$c(t) = \frac{\sum_{j=1}^{n} y_j(t)}{n} \tag{6}$$

is the **consumption** of each agent belonging to the cooperative.

In the basic model, an agent stays in the cooperative he belongs to if:

$$E_{\pi_t}(u(y)) - \overline{u(c)} \leq 0 \tag{7}$$

that is if, based on his belief and on the history of the cooperative, he his better off outside than inside the cooperative.

More precisely:

$$\overline{u(c)} = \frac{\sum_{t<=T} \delta^{(T-t)} u(c(t))}{Z} \tag{8}$$

with

$$Z = \frac{1-\delta}{1-\delta^T} \tag{9}$$

meaning that our agent computes a weighted average of the utility levels he had inside the cooperative, putting more weight to the near past (this allows to take into account the dynamic of the cooperative).

And:

$$E_{\pi_t}(u(y)) = \pi_t u^+ + (1-\pi_t)u^- \tag{10}$$

where u^+ (resp. u^-) is the expected utility of low- (resp. high-) risk agents:

$$u^+ = \underline{p}u(y_-) + (1-\underline{p})u(y_+) \tag{11}$$

$$u^- = \overline{p}u(y_-) + (1-\overline{p})u(y_+) \tag{12}$$

Therefore, $E_{\pi_t}(u(y))$ represents the utility the agent expects alone, according to his belief π_t on his probability of being low-risk.

3.4 Compassion, friendship

We include altruism ("other-regarding preferences") through two mechanisms: compassion and friendship, which are translated in the algorithm thanks to parameters *comp* and f that are constant over the simulation and the same for all agents.

Compassion makes the agent matter for his marginal impact on common welfare: he is more reluctant to leave if it is bad for the $(n-1)$ other agents belonging to the cooperative. He stays if:

$$E_{\pi_t}(u(y)) - \overline{u(c)} \leq comp. \left(u(\bar{c}) - u\left(\frac{n\bar{c} - E_{\pi_t}(y)}{n-1} \right) \right) \tag{13}$$

where $\bar{c} = \sum_{t<=T} \delta^{(T-t)} c(t)/Z$ represents his "estimation" of individual consumption in the cooperative (based on past levels of consumption, with forgetting) and $E_{\pi_t}(y) = \pi_t[\underline{p}y_- + (1-\underline{p})y_+] + (1-\pi_t)[\overline{p}y_- + (1-\overline{p})y_+]$ represents the expected individual income according to his belief π_t. These two terms enable the agent to calculate the individual utility of others in the cooperative if he stays compared to their individual utility if he goes; if the gain he adds to others by staying is high enough (using factor *comp*) compared to his own interest of leaving the cooperative (on the left hand side), he will stay.

The utility of agents is directly transformed by friendship, and the more friends are present in the cooperative, the higher the agent gets from being part of it. He stays if:

$$E_{\pi_t}(u(y)) - (1 + rf)\overline{u(c)} \leq 0 \tag{14}$$

where r is the share of friends in the cooperative. Under this formulation, the agent takes into account directly the utility of his friends in the cooperative (recall that they all have the same level of consumption in the cooperative).

3.5 Building a cooperative

At start, there is no cooperative. At each step, one agent who does not belong to a cooperative is randomly chosen to test if he wants to create a cooperative. For this he contacts all single agents belonging to his network at level 2 (all agents who do not belong to a cooperative and with whom he has a direct link (friends) and all their direct friends). This is the pool of people who will be included in the cooperative if it is created. The agents answer their own belief on their probability to be of low-risk type. The building agent trusts his direct friends (that is $\forall j \in r_1$) at a level of 90% (with probability 0.1 he assigns them the average probability in the population: 0.5) and the friends of his friends (that is $\forall l \in r_2$) at $(90\%)^2$. The agent who wants to form a cooperative then aggregates the information so that to create one virtual agent with whom he decides to create the cooperative or not. First, he calculates the probability of this virtual agent g being in the low- risk group: $\widehat{\pi}_t$.

$$\widehat{\pi}_t = \frac{\sum_{j \in r_1} (0.9 * \pi_{t,j} + 0.1 * 0.5) + \sum_{l \in r_2} (0.81 * \pi_{t,l} + 0.19 * 0.5)}{card(r_1) + card(r_2)} \tag{15}$$

The agent building the cooperative then infers the risk of the group seen as one agent g at the next step as:

$$p_g = \widehat{\pi}_t \underline{p} + (1 - \widehat{\pi}_t)\overline{p} \tag{16}$$

He already knows his own risk at the next step:

$$p_i = \pi_t \underline{p} + (1 - \pi_t)\overline{p} \tag{17}$$

and the expected utility when associating with the fictitious agent g is then:

$$\begin{aligned} E_{p_g}(u(c)) &= p_i p_g u(y_-) + (1 - p_i) p_g u\left(\frac{y_+ + y_-}{2}\right) \\ &\quad + p_i(1 - p_g) u\left(\frac{y_+ + y_-}{2}\right) + (1 - p_i)(1 - p_g) u(y_+) \end{aligned} \tag{18}$$

which has to be higher than his own expected utility ($E_{\pi_t}(u(y))$) for the cooperative to be created.

One can note several elements about this model. First, the agent has a pessimistic view of the association, since he aggregates all agents' income in a way that overestimates risk. Moreover, there is no link creation associated to the building of cooperative. Even if agents belong to the same cooperative and share their income, they do not get linked and our network is thus exogenous and stable. All agents can belong to one cooperative only since they are not chosen to built one or to participate if they are already in a cooperative. The cooperative cannot increase in size either - nobody gets in after it has been created, and it can only loose agents.

4 Simulations

4.1 A typical run

At time 0:

- N (usually, 200) artificial agents are created;
- Half of the agents are given probability of failure $\overline{p}$ and other half $\underline{p}$;
- Network is created (we only use random network in this paper)

Afterwards:

- All agents check if they want to stay in the cooperative they belong to;
- One lonely agent (that is an agent who does not belong to a cooperative) is chosen to check if he wants to create a cooperative;
- We run for 50 steps

4.2 Parameters

The values of the parameters used in the simulations are given in Table 1 below.

Parameters	**Values**
Number of agents	200
$\{\overline{p}; \underline{p}\}$	$\{0.90; 0.70\}$
Risk aversion (ρ)	1.1, 1.2, ... 3.9, 4
Knowledge of own risk	no, yes
Compassion (*comp*)	0, 1, 2,... 5
Friendship (f)	0, 0.05, 0.1, 0.2
Network density	5, 10, 15
Information trust	0.9, 1
Valuation of the past (δ)	0.5 (6 steps memory)

Table 1: Parameter values

4.3 Observed indicators

- Number of cooperatives formed over the simulation
- Number of cooperatives that exist on average at each step
- Number of agents who belong to a cooperative
- Segregation index characterizing the mix of agents of high-risk and low-risk type in each of the J cooperatives. Calling n^l (resp. n^h) the number of low-risk (resp. high-risk) agents in the population and n^l_j (resp. n^h_j) those in the cooperative j, the segregation index writes:

$$D = \frac{1}{2} \sum_{j \leq J} \left| \frac{n^l_j}{n^l} - \frac{n^h_j}{n^h} \right| \tag{19}$$

- Revised segregation index that we built after running preliminary simulations. This index is the same as the one described above but each lonely agent is also considered as part of a cooperative (containing only one agent). We kept both indexes as explained in the result section.

5 Results

All results that are shown in figures are given for each value of risk aversion and as an average result for 30 simulations, each simulation running for 50 steps.

5.1 Impact of risk aversion

As can be expected, the value of risk aversion has a huge impact in our system. When risk aversion increases, the number of cooperatives that are created increases and then decreases, and at the same time the number of cooperatives existing in the system on average increases up until risk aversion is around 2.5 and then is stable (see Figure 1). It means that up until a certain level of risk aversion, more and more cooperatives get created when risk aversion increases. When risk aversion is higher than 2.5, the created cooperatives last and hence there are less and less available agents to create cooperatives along the simulation. At the end, less cooperatives are created because there is no one to create them. At the same time, the higher risk aversion the more stable the cooperatives: their average lifetime increases almost linearly with risk aversion, from around 9 time-steps when risk aversion is 1.1 to 20 when risk aversion equals 4.

[Figure 1 about here.]

We have used two different segregation measures in our model (see Figure 2). The first one is supposed to be used to compare situations where a constant population is used. However, as we saw before, our model does not involve a constant number of agents in cooperatives. When risk aversion is low, few agents are in cooperatives, and when watching in details, they are mostly high-risk agents (since low risk agents tend to leave fast from cooperatives and do not create that many). Hence the basic segregation index is low because the population of "agents belonging to cooperatives" is low with respect to the entire population. When risk aversion increases, and the population is mostly involved in cooperatives, then the basic segregation index decreases. On the other hand, the revised segregation index ("segregation 2" on figures) incorporates free agents as extremely segregated cooperatives (of segregation 1) and that's why this index is much higher than the basic one, but is decreasing in risk aversion.

Combining both in the analysis shows the influence of risk aversion on our model again. In some settings (low risk aversion) cooperatives are not segregated with basic segregation index (using the population of agents belonging to cooperatives only, who are mainly high-risk agents) but low-risk agents do not share much because they stay alone. In other settings (when risk aversion is higher than 2.5), most agents are integrated in cooperatives and then, an increase in risk aversion makes cooperatives more and more mixed. This value of 2.5 for risk aversion in the basic model corresponds to a size of population within cooperatives that reaches about 120 agents. We note that for all cases that are given later, this value of 120 agents is always the one where our indicators change.

[Figure 2 about here.]

In that sense, the size of network has a direct impact on the number of cooperatives that are created, although rather limited since it just changes this value of 2.5. The larger the number of friends in the network, the quicker many agents are involved in a cooperative, since at each run, the agent who creates the cooperative can reach more agents. Hence, the value of 120 is reached for slightly lower values of risk aversion, and as a consequence the tendency to decrease of all indicators which have a concave curve (total number of cooperatives and basic segregation) takes place for lower values of risk aversion, as can be seen in Figures 3. The average number of cooperatives decreases once this turning point is attained for networks of size 10 and 15, which is not true for size 5, but over all, the dynamics is the same. Segregation also has different values when size of network varies, but is similarly impacted by the value of risk aversion: the larger the network the smaller segregation.

[Figure 3 about here.]

The probability of success, that are set in the basic simulation to $\overline{p} = 0.9$ and $\underline{p} = 0.7$ does not have much an impact in terms of qualitative result (as long as the difference between the two are the same). After a change in $\overline{p}$ and $\underline{p}$, the shape of the curves remain similar, even though the turning point (when basic segregation is at its maximum or the number of cooperatives reaches its peek) changes. For example, when $\overline{p} = 0.8$ and $\underline{p} = 0.6$ this peek is for risk aversion close to 2. The dynamics is similar.

5.2 Impact of information

We test the system in three different situations regarding the access of information for agents: in the first case they follow the mechanism that is described above (they learn and received information with noise from their neighbors - WLNI = With Learning and Noise Information), in the second case they know their type but there is noise in the transmission of information (NLNI - No Leaning Noise Information), and in the third case they know their type and get the right information from their neighbors (NLPI - No Learning Perfect Information). For most of our indicators, there is no difference after 50 steps. The results that are synthesized in Figure 4 show that there is no difference among these cases for the average number at each time-step indicators. The mean lifetime of cooperatives is also similar. The total number of cooperative that are created in the simulation is different when risk aversion is low. Observing simulation runs, one can explain the difference by the dynamics of the first steps, during which more cooperatives get formed when agents have no information about their type: low-risk agents build cooperatives although they have no interest to do so, as the case without learning shows. There is also a small difference in segregation for high value of risk aversion, which is also due to the first steps where low-risk share more and hence the number of agents who are included in a cooperative is higher. The more simulation goes, the less low-risk agents form cooperatives and the more segregation increases. It is important to note that the noise in communication has no impact on all the indicators we are interested in. This was tested with various values of noise and this result holds when the noise increases.

[Figure 4 about here.]

5.3 Impact of compassion

We studied the impact of compassion: for this we ran simulations for 50 steps, with 5 friends per agent, varying compassion from 1 to 5. On figures, one can see that there is a similarity for compassion 0 and 1, and that when the value increases to 5 there is a qualitative difference in the dynamics. The number of cooperatives (Figure 5) is higher on average with compassion 1 than 0, but the curve is pretty similar, showing an increase and almost a stabilization when risk aversion increases, as seen before. When compassion is equal to 5, the number of cooperatives at each step is higher for low risk aversion than high risk aversion. But what has to be noticed is that the number of cooperatives in the population at each step is equal to the total number of cooperatives created, which means that almost all cooperative that is created stays until the end of the simulation. lifetime also increases when compassion goes from 0 to 1, and hence the number of cooperatives that are created in total decreases with compassion. We indeed stabilize cooperatives by adding compassion in our model. In parallel, at least 160 agents are on average in a cooperative when compassion is 5, whereas the value increases for compassion 0 from 40 to 140 when risk aversion increases. With compassion 1, there is no qualitative change compared to 0 (lifetime and number of agents belonging to cooperatives is similarly related to risk aversion) but all indicators indicate a stabilization of cooperatives.

[Figure 5 about here.]

Segregation also shows that compassion allows cooperatives to be stable and mixed even for low values of risk aversion. The curve of basic segregation when compassion is 5 (Figure 6) is very different from the others. Many agents are in cooperative and this is why the mix of population is more clearly linked to risk aversion. Above the already witnessed turning point (risk aversion 2.5), compassion 5 shows that it creates cooperatives that are much more mixed than other compassions. This is rather logical in our setting, since the interest for others does not depend on their success, and the desire for sharing that compassion creates is so strong that any cooperative survives. Interestingly, there is almost no difference in segregation when compassion is 0 and 1, which confirms the fact that a small level of compassion does not change the dynamics qualitatively.

[Figure 6 about here.]

5.4 Impact of friendship

When friendship is higher than 0, its influence is very strong. When increasing its value, it increases this tendency, without changing the impact qualitatively. The number of cooperatives is very low as soon as risk aversion is above 1.5 and these cooperatives are very stable. This can be seen as the number of cooperatives and the number of cooperatives created in total are very close (Figure 7). Their mean lifetime are also very long as soon as risk aversion is higher than 1.5. With friendship, the segregation is lower than in any other situation we have built before (Figure 8). This is due to the fact that agents do not leave the cooperatives at all, contrary to all other cases. Even with compassion, cooperatives are stable but lose some of their members who are mainly low-risk agents. The other sign is that the number of agents in cooperatives and the number of low-risk agents in cooperatives reach almost the maximum, for any value of risk aversion. Hence, as there is no possibility to create cooperatives anymore, their number is low.

The impact of the size of network is very strong in this setting, since it determines the size of cooperatives, and hence the number that are created. When risk aversion is higher than 1.5 and agents have 5 friends this value is 20, but it drops to 12 when they have 10 friends and to 8 when they have 15 friends. However, there is no such difference in segregation, which stays lower than in any other setting, between 0.2 and 0.3 for almost any value of risk aversion.

[Figure 7 about here.]

[Figure 8 about here.]

6 Conclusions

In this paper, our aim was to explore a rather generic framework in which agents who are heterogeneous in success in an action can create cooperatives to share and reduce their risk in time. In economics, the only usual explanation for the possibility to perform risk-sharing is risk aversion: by sharing, agents expect to be helped on the days they would need it. One author who says that redistribution is also existing because individuals have to follow social norms or are interested in the consumption of others on top of their own, could put this element forward quite recently. The point is that up until now, the inclusion of other-regarding preferences in utility-based models has not been so general, and there is no largely accepted robust model to represent this tendency. Our model enabled us to test several representations of this type of preferences, especially because they both gave very different types of results. We could assess the dynamics of the model thanks to the cross analysis of several indicators, a work which was most of the time necessary, even with indicators that could seem redundant (like our two versions of segregation).

As expected, risk aversion has a strong impact on the system. Learning effect is not so clear when running the simulation for 50 steps. The variation of some of our parameters, like the probability of success, does not change the dynamics much. Surprisingly, the density of the network only has a small impact on stability and segregation. Compassion has a strong impact on the stability of cooperative, but not so strong on the reduction of segregation. Only when it gets high, it can almost neutralize the influence of risk aversion by increasing a lot the stability and mixing of our population. Friendship stabilizes our cooperatives and reduces segregation even more, although it is not true for very low values of risk aversion.

One critic has been done several times already to this model by economists who do not use agent-based. The building of cooperatives has been criticized because it is a one-way autocratic process. The agent who decides on building the cooperative gives no chance of refusal to the ones who come in the cooperative. If one considers the building as a one time-step process, this critic is very logic. However, since we consider that the judgement of a cooperative is made ex-post by agents, and that they can leave after just one time-step, one can consider that the process is just in two steps: agents who have been chosen to belong to the cooperative participate in one step and can decide if they want to stay. The alternative would be to have all agents decide if they accept to be in the cooperative. But in the case when one agent does not accept, all agents have to recalculate their own decision; and each time an agent decides to drop out, all agents calculate again. This process implies endless calculation, which we transform in learning in our model. We do not think this choice is so illogical within the agent-based framework.

These results are preliminary, since we need to perform a better statistical analysis, but also to decide if we want to simplify the model (like keeping learning or not, keeping the two-step network for the creation of cooperatives, etc...) so that to make it maybe easier to compare to analytic results. For this we might have to check more precisely the dynamics of the model for the first steps with and without learning more precisely. Another step would be to integrate heterogeneity not only in the probability of success, but also in risk-aversion, compassion and friendship, which have been proven to be idiosynchratic and have a massive impact on reciprocity or participation to common good Anh et al. [2003].

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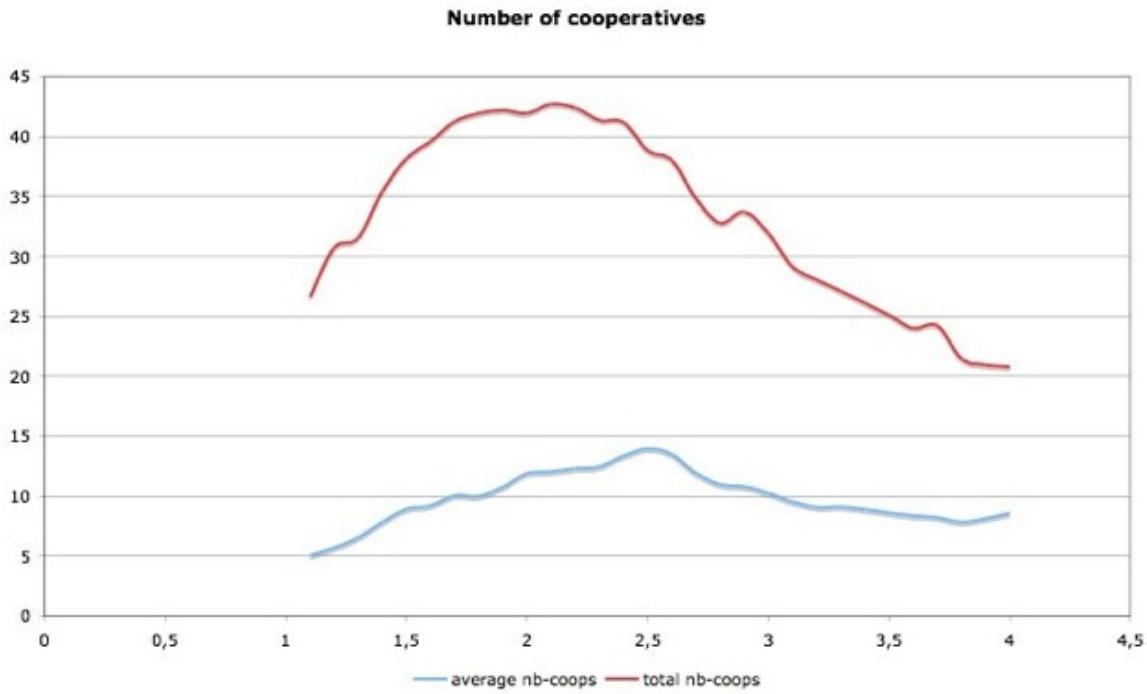

Figure 1: The impact of risk aversion in the basic model: the number of cooperatives on average at one step and the number of cooperatives that are created for the case when agents have 5 friends in their network and there is no compassion nor friendship.

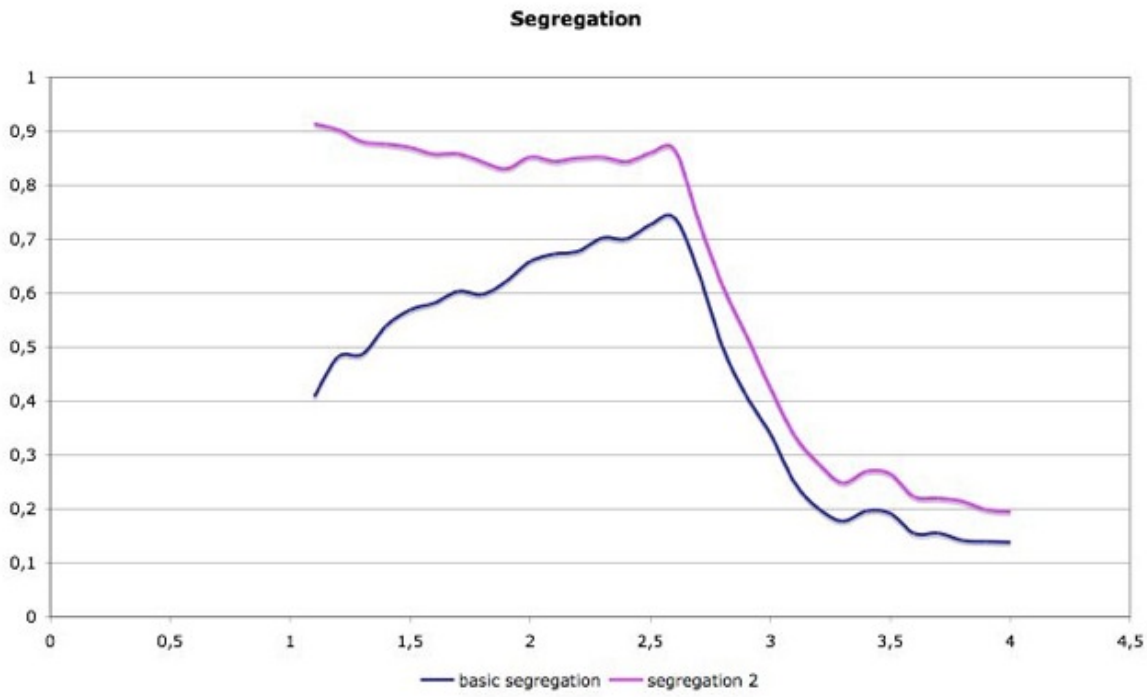

Figure 2: The impact of risk aversion in the basic model: basic segregation and segregation2 for the case when agents have 5 friends in their network and there is no compassion nor friendship.

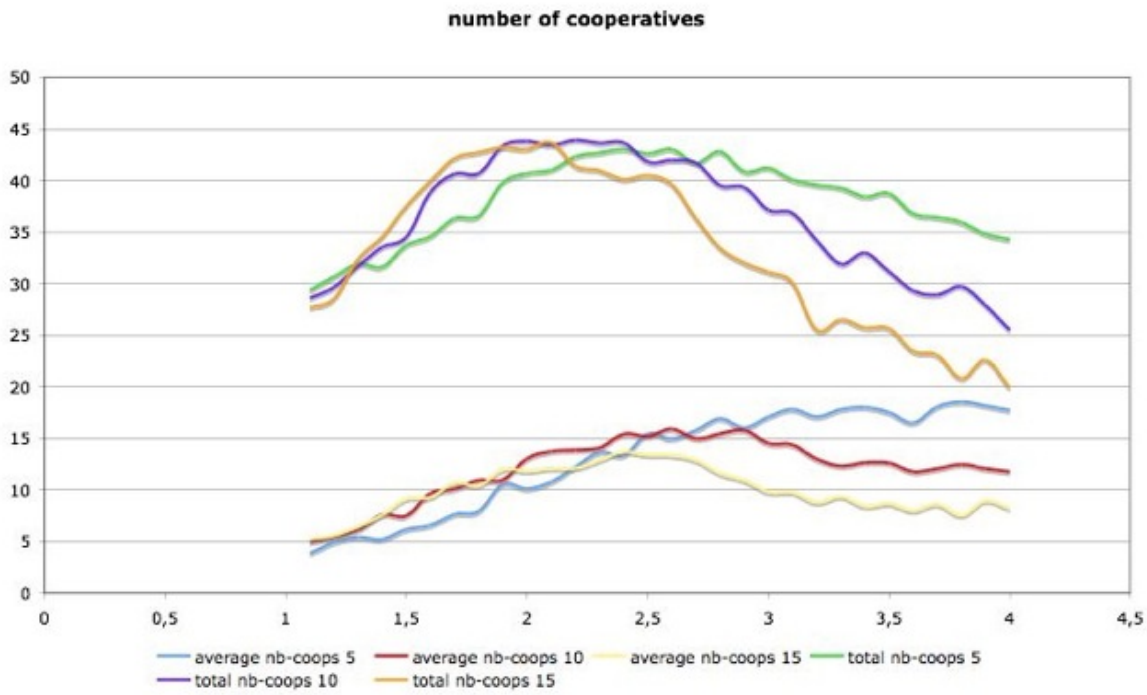

Figure 3: Number of cooperatives on average and created in total depending on risk aversion with different size of network (5, 10, 15). The size of network does impact on the number of cooperatives but there is no qualitative difference among the dynamics.

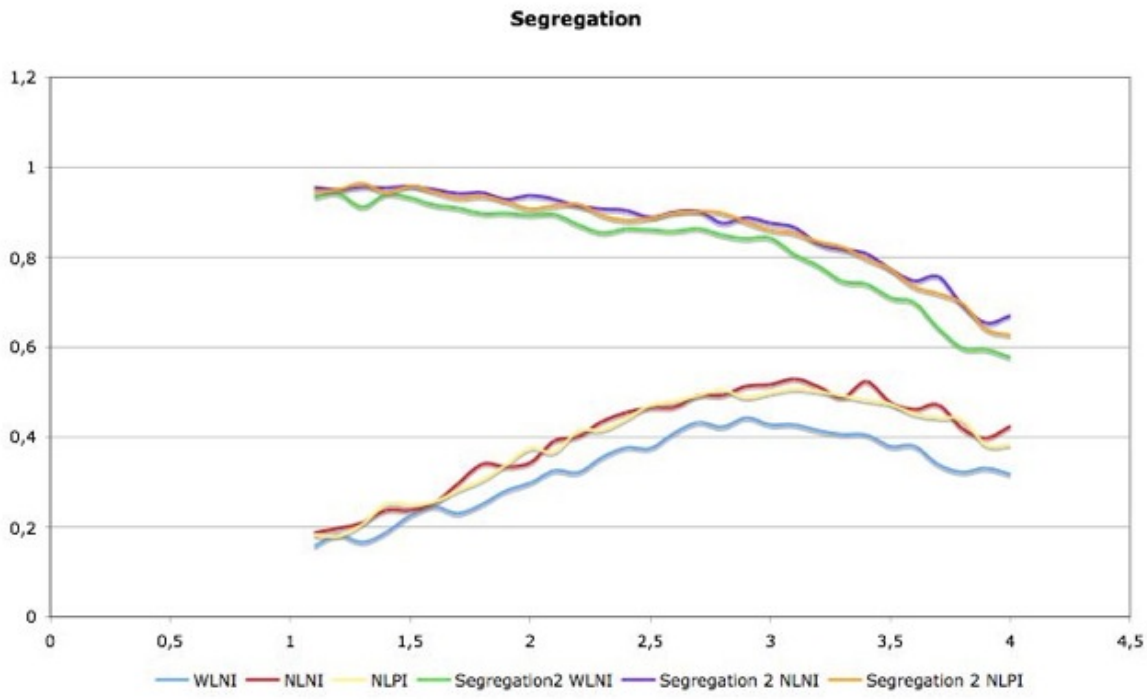

Figure 4: Segregation for situations where agents learn their type, know their type, and know everyone's type with certainty. This knowledge has a very small impact on the sharing behavior of agents - this is due to the fact that they learn pretty quickly their actual risk.

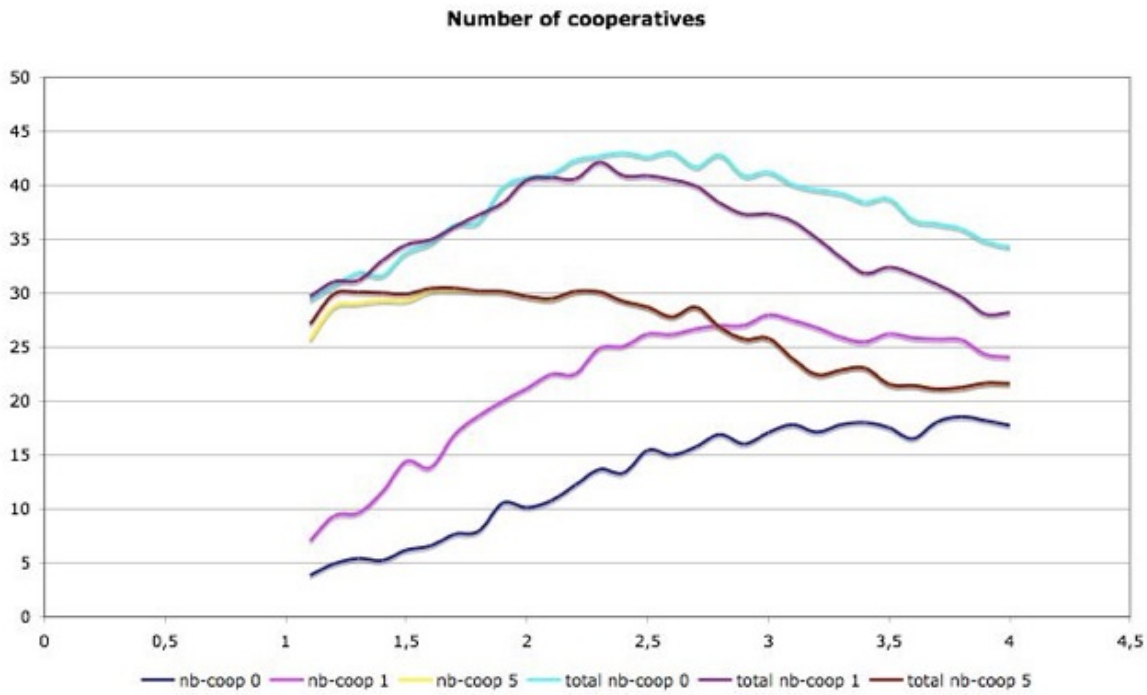

Figure 5: The number of cooperatives that are created and those that exist in the population at each step, for network with 5 friends and different values of compassion. When compassion increases, cooperatives are more stable, and especially when compassion is 5, the value of risk aversion has less impact on stability.

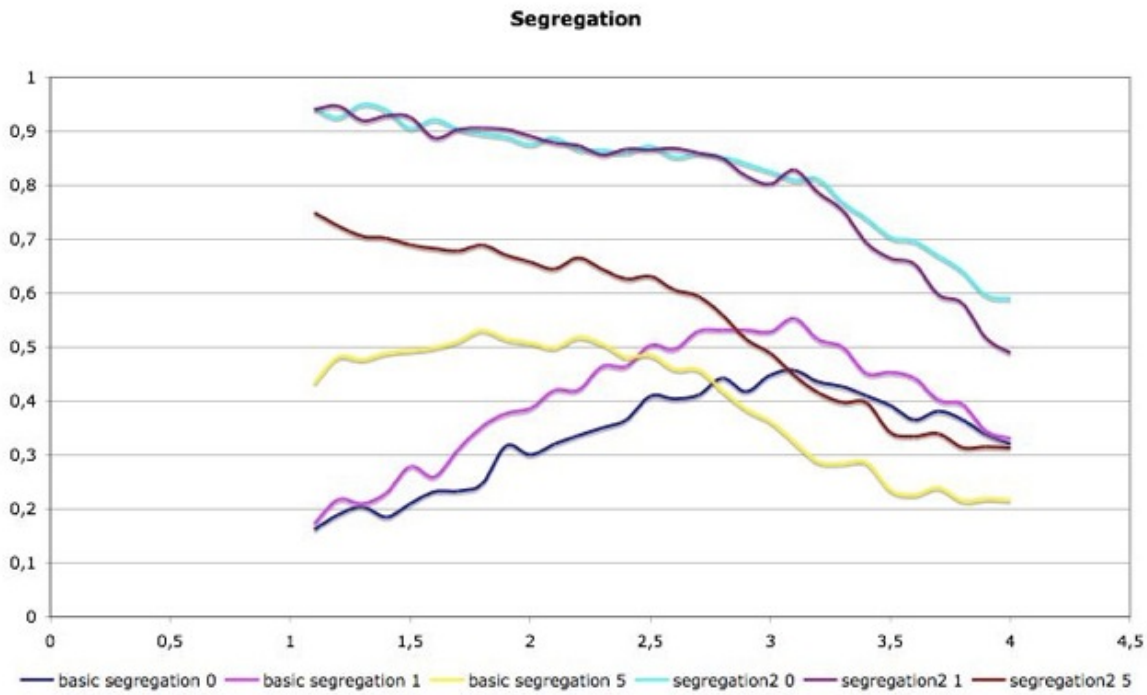

Figure 6: Basic segregation and segregation2 for network with 5 friends and different values of compassion. Compassion reduces segregation.

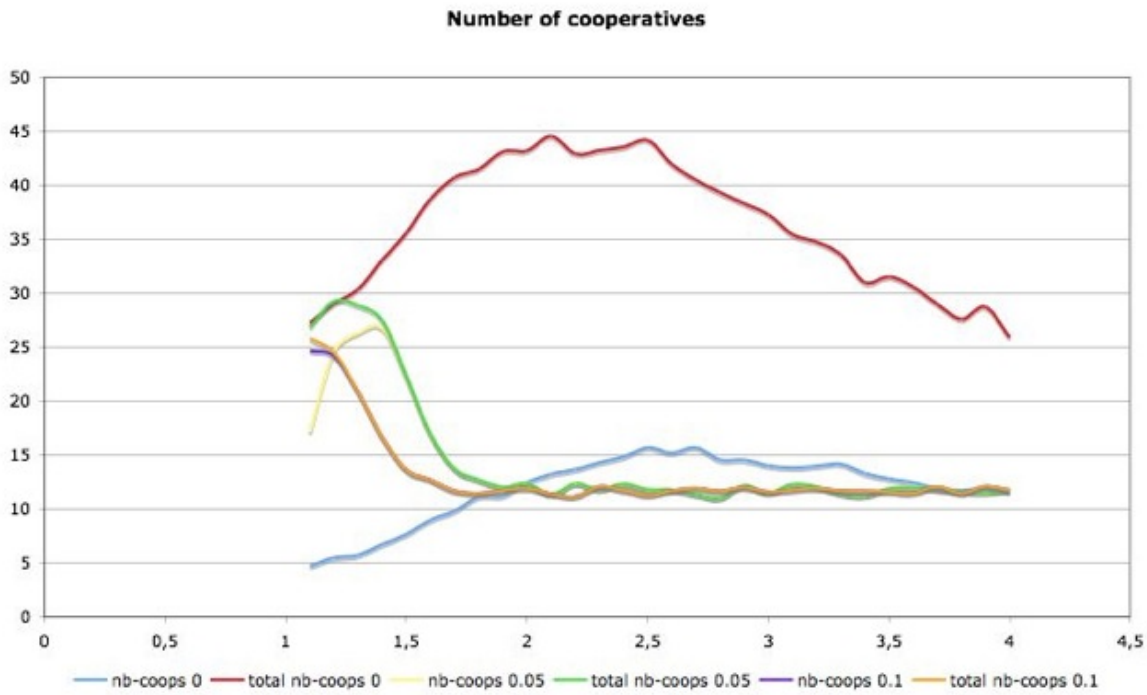

Figure 7: The number of cooperatives that are created and those that exist in the population at each step, for network with 5 friends and different values of friendship. As soon as friendship is positive, the number of cooperatives created and staying are almost the same and are equivalent for all values of risk aversion above a certain threshold.

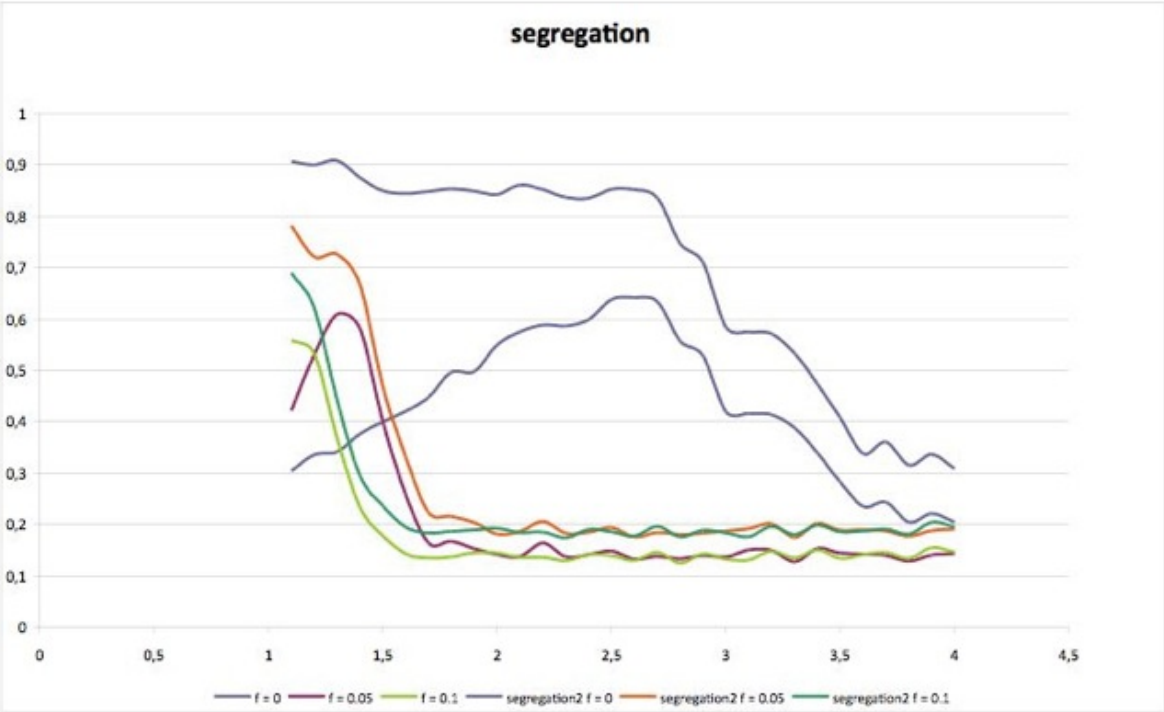

Figure 8: Basic segregation and segregation2 for network with 5 friends and different values of friendship. Friendship reduces segregation except for very low values of risk aversion.