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Abstract

We study the dynamics of risk-sharing cooperatives among heterogeneous agents. Based of their knowledge on their risk exposure and the performance of the cooperatives, agents choose whether or not to remain in the risk-sharing agreement. We highlight the key role of other-regarding preferences, both altruism and inequality aversion, in stabilizing less segregated (and smaller) cooperatives. Limited knowledge and learning of own risk exposure also contributes to reducing segregation. Our finding shed light on the mechanisms behind risk-sharing agreements between agents heterogeneous in their risk exposure.

Keywords: Agent-Based, cooperative, risk-sharing, learning, altruism, other-regarding preferences

1 Introduction

There is ample empirical evidence that agents who are heterogeneous in risk exposure often enter into informal risk-sharing agreements. Take for instance agrarian societies in developing countries, who face a high level of risk. Compounding this is the lack of formal insurance, which prompts individuals to employ various risk-coping strategies relying on informal arrangements with other individuals in their network (Morduch [1995]). Apart from agronomic tools aimed at reducing risk, there are two principal risk-coping strategies: either smoothing consumption over time (mostly through savings, lending, debts within the close network), or smoothing consumption across a population, via a group risk-sharing system (Alderman and Paxson [1992]). Access to money being limited in most agrarian villages in developing countries, and inflation being very high, this latter strategy of risk-sharing is very common. Here we examine repeated risk-sharing within informal cooperatives, among agents who are heterogeneous in their risk while performing the same activity. We focus one observable feature of risk-sharing, which is that less risky agents agree to share with more risky agents on a regular basis (DeWeerdt and Fafchamps [2011]).

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In this paper, we are interested in exploring a risk-sharing dynamics that would yield cooperatives mixing agents with different risk exposure. To do so, we build a model of risk-sharing cooperatives in which agents who are heterogeneous in terms of risk exposure share their income equally. What we are interested in observing is the dynamics of creation and destruction of the cooperatives and the degree of homogeneity in existing cooperatives at a moment in time (which we observe with a segregation index). The simulations help us identify (i) the obvious role of risk-aversion, (ii) the influence of other-regarding preferences, *via* altruism (Becker [1974]) or inequality aversion (Fehr and Schmidt [1999]), and (iii) the potential role of learning if it is assumed that agents do not know their risk ex-ante but discover it over time.

The main mechanisms behind our results are the following. First, because of risk-aversion, agents are ready to give up (expected) revenue to smooth their consumption. In our setting, this materializes in the fact that an agent with low-risk exposure may be ready to share income (equally) with a more exposed one, if she is risk-averse enough (as shown in Bourlès and Henriet [2012]). In that case, although she would stand to lose expected income (as she will more often transfer wealth than receive) she might agree to share risk to decrease income variation. Second, other-regarding preferences – the fact the agents care about the material well-being of others – make low-risk agents more willing to share risk with high-risk agents, as it increases their expected utility (see for example Foster and Rosenzweig [2001] on the effect of altruism on risk-sharing). The main contribution of our paper is to highlight how these mechanisms can interact with learning in a situation where agents are not perfectly informed about their risk exposure and learn it over time. Our results show that imperfect information reinforces the effect of risk-aversion and other-regarding preferences. Actually, imperfect information, by making agents less sure about their risk exposure, leads them to share income more easily. Then, once involved in a risk-sharing agreement (a cooperative), other-regarding preferences make them less inclined to leave, even though they are revealed as low-risk, because doing so would be harmful to the other agents in their cooperative.

Studying the dynamics and the stability of risk-sharing agreements goes back to Townsend [1994], who tests for the assumption of equal sharing of risk (or full insurance) in villages in India. He typically finds that risk-sharing is not perfect but that equal sharing provides a good benchmark to explain how individuals cope with uncertainty in village economies. Recent developments, moreover, suggest that full insurance might be rejected because risk-sharing occurs at a lower level than the village (i.e. communities or social network, see Fafchamps and Lund [2003] or Fafchamps and Gubert [2007]), or because of heterogeneity in risk-aversion (Chiappori et al. [2014]). The role of the social network in the formation of risk-sharing agreements has also been theoretically investigated by Bramoullé and Kranton [2007], who analyze the formation of risk-sharing agreements when connected agents share risk equally. We take this analysis further by adding heterogeneity in risk exposure and other-regarding preferences.

Since Arrow [1965], risk-aversion has been understood as the main motive for risk-sharing. Kimball [1988] confirms this mechanism by showing that higher risk-aversion increases the sustainability of equal sharing (by increasing the discount rate below which equal sharing can be achieved). More recently, Lazcó [2014] shows that – as soon as there is no aggregate risk – an increase in risk-aversion increases risk-sharing.

Part of the literature on risk-sharing agreements argues that the failure of full insurance can be explained by limited commitment. This means that lucky agents need realize long-term benefits from sharing with less lucky agents (see Ligon et al. [2002] or Dubois et al.

[2008]). Bloch et al. [2008] apply this framework to networks and study how the stability of informal insurance networks depends on the sharing rule and the punishment strategies. Here we study the evolution of informal risk-sharing cooperatives when transfers are driven both by risk-sharing perspectives and other-regarding preferences.

The importance of other-regarding preferences – and more precisely of altruism – in the economy of gift giving and transfers goes back to Arrow [1981] and has been reviewed by Mercier-Ythier [2006]. Moreover, altruism has been shown to be empirically relevant in explaining risk-sharing (see DeWeerdt and Fafchamps [2011]). The theoretical impact of altruism on risk-sharing has recently been studied by Alger and Weibull [2008] and Alger and Weibull [2010] in the case of pairs and by Bourlès et al. [2017] in the case of arbitrary networks. Alger and Weibull [2008] highlight the importance of altruism as a social norm that allows transfers to be enforced, whereas Bourlès et al. [2017] show that bilateral altruism can lead to a long chain of transfers under income shocks. We add to this analysis by considering agents heterogeneous in terms of risk exposure. We also attempt an alternative modeling of other-regarding preferences, analyzing how inequality aversion (a la Fehr and Schmidt [1999]) changes our results.

Few papers have tackled the effect of heterogeneity in risk exposure. From a theoretical point of view, Bourlès and Henriet [2012] analyze the incentive-compatible contract between two agents who can be heterogeneous in their probability distribution of wealth. They notably show that equal sharing of risk is then optimal if risk-aversion is high enough and heterogeneity is low enough. Empirically, DeWeerdt and Fafchamps [2011] confirm that transfers can occur between agents that are heterogeneous in terms of risk exposure, as chronic illness does not deter informal agreements. Our paper helps to explain this finding by other-regarding preferences but also by limited information of own risk exposure, which is subsequently learnt.

In our model, agents' learning about their profile is central and is based on observation of realizations of past income only. In general, learning is used when agents have limited ability to compute or limited information. In the first case, agents are not able to grasp the full complexity of a problem and need to make several attempts to identify the best response. This is related to learning models in game theory, which generally help to explain the gaps between theory and experimental results (Roth and Erev [1995],Camerer and Ho [1999]). It is also consistent with Agent-based Computational Economics (ACE), a more recent branch of economics (Kirman [2010], Rouchier [2013]). Agent-Based learning models are used in particular when agents have to learn about an evolving environment (social or physical) or when they are heterogeneous in type or characteristics, as in our case. For example, in Moulet and Rouchier [2008] agents learn over time, and through their interactions how to bargain with each other. Two classic types of learning are reinforcement learning (Brenner [2006]) and genetic algorithms (Vriend [2000]). The idea behind learning in this context is that agents are not optimizing their choices, either because they are limited in information or in computational ability (Simon [1955]), but that they choose and act on a very simple basis and evaluate ex-post the result of their actions, which they then classify so as to choose the "best" actions in the next steps. The process of learning generally converges to a dynamic equilibrium, which can be optimal (if this can be evaluated), but does not have to be.

Thus, to understand the dynamic evolution of cooperation of heterogeneous agents with limited knowledge and where no analytical solution can be found, we decided to produce an Agent-Based Model (programming in Netlogo). Very few ABM papers actually deal with risk learning from an individual point of view. Studies have looked at agents playing one-arm bandits and choosing risk dynamically, but without considering social interaction (Leloup

[2002]). An evolutionary setting for risk has shown that, in a context where agents can have different degrees of success, micro-analysis yields a deeper understanding of possible dynamics than a simple macro analysis of averages of risk (Roos and Nau [2010]). However, to the best of our knowledge, risk-sharing attitudes have not been modeled and studied with ABM.

The rest of the paper consists of four sections. Section 2 presents our model and its basic assumptions in terms of preferences, risk-sharing and information acquisition. In section 3, we describe our simulations and observation protocol for the model. In the fourth section we present the effect of learning and other-regarding preferences on the stability and segregation of risk-sharing cooperatives. Finally, we discuss our results and conclude in section 5.

2 A model of endogenously evolving cooperatives

We consider a community of $n \geq 2$ agents who live for a fixed number of periods T and at each period ($t = 1, ..., T$) face a risk of income loss (for example, farmers facing a risk of bad harvest). At each period, their income either equals y_+ with probability $(1 - p)$ or $y_- < y_+$ with probability p. Agents are heterogeneous with respect to their risk exposure. They can be low-risk, *i.e.* have a low probability (denoted $p = \underline{p}$) of bad harvest, or high-risk ($p = \overline{p} > \underline{p}$). We denote by π the proportion of low-risk agents in the community.

2.1 Agents' utility and learning

Agents can share this risk through cooperatives. A cooperative is here modeled as a risk-sharing agreement between $m \leq n$ agents who, at any period, agree to share income equally. Therefore, in a cooperative $\mathcal{C}$ with m members, the after-sharing income – called here consumption – at period t is:

$$c_{i,t} = \frac{\sum_{j \in \mathcal{C}} y_{j,t}}{m} \qquad \forall i \in \mathcal{C} \tag{1}$$

where $y_{j,t} \in \{y_-, y_+\}$ represents the income of agent j at time t.

We are interested here in understanding why low-risk agents may be willing to share risk in cooperatives with high-risk agents. Our agents have private preferences represented by an increasing and strictly concave utility function u (with $u' > 0$ and $u'' < 0$). Beyond these private preferences, we allow agents to have other-regarding preferences (ORP), *i.e.* to value the well-being of others. In this paper we investigate two forms of ORP: inequality aversion (IA) and altruism.

For altruism, following Becker [1974], Arrow [1981] or Bourlès et al. [2017] we assume that the social preferences of agent i write:

$$v(c_{i,t}, c_{-i,t}) = u(c_{i,t}) + \alpha \sum_{j \in \mathcal{F}_i} u(c_{j,t}) \tag{2}$$

where α denotes the coefficient of altruism and $\mathcal{F}_i$ is the set of friends of agent i. $\mathcal{F}_i$ defines the (exogenous) social network of agent i, and the sets $\{\mathcal{F}_i\}_{i=1}^n$ describe the entire network of our community. We focus here on the undirected network, meaning that if $j \in \mathcal{F}_i$, then $i \in \mathcal{F}_j$.

The overall shape of the network could be an important determinant of the dynamics and the stability of cooperatives, as discussed in the robustness check section. For the core of the paper, we assume that agents are embedded in a network exhibiting small world characteristics. Following Watts and Strogat [1998], we build the network starting from a regular graph (a ring of n agents each connected to her k nearest neighbors) and rewire it by deleting each link with probability q and replacing it by a link at random (if $q = 1$ we end up with a random graph).

In addition to altruism, we also analyze the effect of another type of other-regarding preferences: inequality aversion. Following Fehr and Schmidt [1999], we assume that an agent may suffer from creating inequality in utility when leaving a cooperative. In that case, social preferences on agent i write:

$$v(c_{i,t}, c_{-i,t}) = u(c_{i,t}) - \frac{\beta}{n-1}\sum_{j\neq i}\max\{u(c_{i,t}) - u(c_{j,t}), 0\} - \frac{\gamma}{n-1}\sum_{j\neq i}\max\{u(c_{j,t}) - u(c_{i,t}), 0\} \tag{3}$$

A key assumption of our model is the information that each agent has regarding her own risk exposure p_i. We assume that before the first period ($t = 1$), agents have no information on their type (low-risk, high-risk). They do, however, know the aggregate distribution of types in the community (*i.e.* π, the proportion of low-risk types) and the probability of loss of each type. They can therefore acquire information over time by observing the realizations of their past income. We build here a Bayesian learning model, that is a Bayesian updating of beliefs on risk-type. We denote by $\pi_{i,t}$ agent i's belief, at time t, about her probability of being low-risk. For all agents i, at time $t = 0$, $\pi_{i,0} = \pi$. At each following period, each agent computes a Bayesian update of her belief: if at time t she has experienced k losses among the t first periods, her belief about her probability of being low-risk type writes:

$$\pi_{i,t} = \frac{\underline{p}^k(1-\underline{p})^{t-k}}{\underline{p}^k(1-\underline{p})^{t-k} + \overline{p}^k(1-\overline{p})^{t-k}} \tag{4}$$

This gives a relationship between $\pi_{i,t}$ and $\pi_{i,t-1}$ depending on the realization of past income (risk) at time t for agent i: $y_{i,t}$.

- if $y_{i,t} = y_-$
$$\pi_{i,t} = \frac{\underline{p}\pi_{i,t-1}}{\underline{p}\pi_{i,t-1} + \overline{p}(1-\pi_{i,t-1})} \tag{5}$$

- if $y_{i,t} = y_+$
$$\pi_{i,t} = \frac{(1-\underline{p})\pi_{i,t-1}}{(1-\underline{p})\pi_{i,t-1} + (1-\overline{p})(1-\pi_{i,t-1})} \tag{6}$$

This belief about their own risk exposure is a key driver of agents' choice to stay in or leave their cooperative.

2.2 Staying in the cooperative of leaving

If already involved in a cooperative, at each period (after income sharing[1]), each agent has to choose whether to remain in this cooperative or to leave it. Bayesian learning makes it fairly

[1] We assume here that an agent cannot leave the cooperative between the realization of the risk and the sharing of income. In other words, agents commit to sharing when inside a cooperative. For a discussion on limited commitment, see Ligon et al. [2002] or Dubois et al. [2008].

easy to compute the expected utility for an agent of remaining alone:

$$E_{\pi_{i,t}}(u(y)) = \pi_{i,t}\left[\underline{p}u(y_-) + (1-\underline{p})u(y_+)\right] + (1-\pi_{i,t})\left[\overline{p}u(y_-) + (1-\overline{p})u(y_+)\right]. \quad (7)$$

However, due to potential changes in the composition of cooperatives, it is very difficult to form expectations on well-being inside cooperatives. We therefore assume that when deciding whether or not to leave her cooperative, an agent:

- uses her past experience to infer the value of staying, and more highly values the most recent experience (thus taking into account the dynamics of the cooperative)
- does not take into account the possibility of joining another cooperative after leaving.

Formally, in the absence of other-regarding preferences, an agent would leave her cooperative if

$$E_{\pi_t}(u(y)) \geq \overline{u(c_{i,t})} \quad (8)$$

where

$$\overline{u(c_{i,t})} = \sum_{s<=t} \delta^{(t-s)} u(c_{i,s})/\Delta \qquad \text{with } \Delta = \frac{1-\delta}{1-\delta^T} \quad (9)$$

$\overline{u(c_t)}$ therefore represents a weighted average of the utilities the agent has had inside the cooperative, giving more weight to the recent past (thereby taking into account the dynamics of the cooperative). According to equation (8), based on her belief and on the history of the cooperative, an agent will leave the cooperative if she is better off outside than inside the cooperative.

When other-regarding preferences are incorporated into the model, an agent considers the impact of her choice on others' well-being, and computes the utility the other members of the cooperative would have without her. Following the previous reasoning, an agent considers that without her, the cooperative would provide as utility:

$$\overline{u(c_{-i,t})} = \sum_{s<=t} \delta^{(t-s)} u\left(\frac{n.c_{i,s} - y_{i,s}}{n-1}\right)/\Delta \quad (10)$$

Note here that computing all the parameters needed for an agent to make her choice only requires her to keep tracking over time her own income and consumption inside the cooperative.

Then, an altruistic agent i leaves her cooperative if:

$$E_{\pi_t}(u(y)) + r.\alpha.\overline{u(c_{-i,t})} \geq \overline{u(c_{i,t})} + r.\alpha.\overline{u(c_{i,t})} \quad (11)$$

where r represents the number of friends agent i has in her cooperative. Agent i's decision to leave a cooperative will only impact the well-being of those of her friends involved in the same cooperative.

Similarly, an inequality-averse agent i leaves her cooperative if:

$$E_{\pi_t}(u(y)) - \beta.\max\left\{E_{\pi_t}(u(y)) - \overline{u(c_{-i,t})}, 0\right\} \geq \overline{u(c_{i,t})} \quad (12)$$

Once again, we assume here that the agent only considers the impact of her own choice on the system. The component of inequality aversion which accounts for the dis-utility of an agent who is disadvantaged compared to others ($-\gamma.\max\left\{\overline{u(c_{-i,t})} - E_{\pi_t}(u(y)), 0\right\}$) is always 0, because a necessary condition for i to leave is that $E_{\pi_t}(u(y)) \geq u(c_{-i,t})$.

2.3 Creating cooperatives

To assess the stability of risk-sharing cooperatives, we need isolated agents to be able to join new cooperatives. We however assume that an agent cannot "jump" from one cooperative to another, and that an isolated agent cannot join an existing cooperative. Therefore, the only way an isolated agent can share risk is to form a new cooperative with other isolated agents. We assume that only one (randomly selected) agent is able to create a new cooperative at each period. We actually allow the selected agent to build a cooperative with all the isolated agents in her network at level 2 (*i.e.* all agents who do not belong to a cooperative and with whom she has a direct link, as well as all their direct friends). For the model to remain tractable, we do not allow the selected agent to choose among these isolated agents, nor the other agents to choose whether or not to join the cooperative. We also consider that a cooperative is always created, since the selected agent is able to find in her network at level 2 at least one other isolated agent.[2]

The social network therefore plays two major roles in our setting. It defines those toward whom an agent is altruistic (equation (2)) and those with whom an agent can create a co-operative. Note here that the creation of a new cooperative does not involve the creation of new links in the network.

2.4 Observing the system: cooperative dynamics and segregation

Using this model, our aim is to study (i) how cooperatives work and evolve and (ii) which parameters drive low-risk agents to share risk with high-risk agents. As indicators for the first issue, we follow the size of cooperatives and the fraction of agents involved in a cooperative. To address the second issue, we build a segregation index inside cooperatives. We use an adaptation of the total segregation index based on the number of low-risk agents: n_j^l and high-risk agents: n_j^h in each cooperative j (an isolated agent will then be considered as a highly segregated cooperative). Denoting n^l (respectively n^h) the total number of low-risk (resp. high-risk) agents in the community, the total segregation index writes:

$$D = \frac{1}{2} \sum_{j \leq J} \left| \frac{n_j^l}{n^l} - \frac{n_j^h}{n^h} \right| \tag{13}$$

It equals 0 when the proportion of low- and high-risk agents in each cooperative is the same as in the whole society, and if no agent is isolated. It equals 1 when each cooperatives is completely segregated (no cohabitation in cooperatives) or if all agents are isolated. The

[2]Relaxing either this assumption or the fact that agents cannot jump from one cooperative to another would render the model extremely complicated. This would first call for additional assumptions on how agents offer and accept a creation or a change of cooperative, and on the identity of the agent in charge of the decision. Then, each decision would be conditional on others' acceptance, which would lead to possibly long computations to achieve convergence. For example, if one agent offers to create a cooperative, she chooses on the basis of the information on all other participants, and so do they. If one participant rejects the offer, the offer changes, and a new calculation should take place, conditional on who accepted. This then has to be repeated until convergence, if ever it happens. These concerns led us to choose the most classical evolutionary logic: any proposed cooperative is created, and all agents evaluate their satisfaction and decide to leave after one step. This simple setting moreover prevents learning from having both a direct impact on cooperatives' creation (through the mechanism of choice) and on cooperatives' evolution (through π_t in equations (8), (11) and (12)). Automatic creation allows us to disentangle these two effects of learning and to concentrate on cooperatives' evolution alone.

major bias of this index is that it includes isolated agents and does not directly indicate the composition of the cooperatives. To correct this bias, we use a modified index based on dividing the previous index into two parts. The first part computes the index on isolated agents (SI). SI only depends on the fraction of isolated agents and the composition of this fraction. Denoting $\mathcal{I}_l$ (and respectively $\mathcal{I}_h$) the isolated agents of low-risk type (resp. high-risk type) we have:

$$SI = \frac{1}{2}\sum_{i\in\mathcal{I}_l}\frac{1}{n^l} + \frac{1}{2}\sum_{i\in\mathcal{I}_h}\frac{1}{n^h} \tag{14}$$

SI is the part of D explained by the isolated agent. The second part of D comes from the composition of each cooperative and varies between 0, if there is no segregation in cooperatives, and $1 - SI$, if cooperatives are completely segregated. Denoting $\mathcal{C}$ the set of cooperatives we have:

$$0 \leq SC = \frac{1}{2}\sum_{j\in\mathcal{C}}\left|\frac{n_j^l}{n^l} - \frac{n_j^h}{n^h}\right| \leq 1 - SI \text{ and } D = SI + SC \tag{15}$$

By normalizing SC, we obtain a segregation index on cooperatives $D_{\mathcal{C}}$ that equals 0 when the proportion of low- and high-risk agents in each cooperative is the same as in the whole society, and equals 1 when cooperatives do not mix different risk types:

$$D_{\mathcal{C}} = \frac{SC}{1 - SI} \tag{16}$$

3 Simulation strategy

3.1 Description

As explained above, we analyze our model and the impact of various parameters using agent-based simulations. A typical run works as follow. At $t = 0$, n artificial agents are created and the network is built. A proportion π of the agents are given probability of failure $\underline{p}$, the rest are given probability $\overline{p}$. At each following time-step: (i) incomes are realized, beliefs are updated, and agents in cooperatives share their income equally, (ii) all agents choose whether to stay in the cooperative they belong to or to leave it (according to equations (8), (11) or (12)) and (iii) one isolated agent is selected up to create a cooperative with her isolated friends at level 1 and 2, if any. We run the model for T time steps. Note here that each step does not necessarily correspond to a real-word time period, but represents instead a theoretical framework for learning, as is common with this type of modeling.

3.2 Parameter values

For all our simulations, we consider: $n = 200$, $\pi = 0.5$, $\underline{p} = 0.1$, $\overline{p} = 0.3$, $y_- = 50$ and $y_+ = 100$. Under this setting, it takes about 50 steps for agents to know their type with a probability of 95%. Regarding the discounting of past values of consumption, we assume $\delta = 0.5$, *i.e.* a 6-step memory. The more distant past is discounted by more than 98%.

We assume that all agents are equally risk-averse[3] and have private (or material) preferences represented by a Constant Relative Risk Aversion (CRRA) utility function:

$$u(c) = \frac{c^{1-\rho} - 1}{1 - \rho} \tag{17}$$

with ρ the coefficient of relative risk-aversion ($-cu''(c)/u'(c) = \rho \ \forall c$).[4]

The network is assumed to be a small world (see Watts and Strogat [1998]) in which each agent has on average $k = 10$ friends. We use a rewiring probability $q = 0.10$.

We are interested here in analyzing the impact of learning, risk-aversion and other-regarding preferences. To understand the effects of limited knowledge of risk exposure and of learning, we study two polar cases. Either agents perfectly know their risk type from $t = 0$ or they only know $\pi = 0.5$ at that time and learn about their own exposure over time (see equations (4) to (6)). Regarding risk-aversion, we consider alternative values of ρ between 1 and 4 (see Kimball [1988], Chetty [2006] and Meyer and Meyer [2005]). For other-regarding preferences, we consider values of 0, 0.2 and 0.4 for the coefficient of altruism α (according to Hamilton's rule, two siblings should have a coefficient of altruism of 0.5, see Hamilton [1964a], Hamilton [1964b]); and values for advantageous inequality aversion β of 0, 0.4 and 0.8, in line with assumptions and observations in Fehr and Schmidt [1999].

3.3 Statistical methodology

Let us first provide a stability analysis of our model to define the number of time periods over which we study the evolution. We are looking for values of T above which the model is stable, in terms of number of cooperatives and degree of segregation. We are also able to define a degree of relative risk-aversion that is neither too low for the agents to be willing to share risk, nor too high for other parameters to influence the willingness of low-risk agents to group with high-risk agents (when risk-aversion is very high, low-risk agents agree to share risk with high-risk agents even in the absence of learning or other-regarding preferences).

After defining the number of periods and the coefficient of relative risk-aversion, we analyze the effect of our key parameters as follow. For each set of parameters, we run 1000 simulations and plot the resulting distribution of our indicators (chiefly mean cooperative size , fraction of agents in cooperatives and degree of segregation in the existing cooperatives). This allows us to analyze the effect of each parameter visually, using the notion of stochastic dominance.

To limit the path-dependence that might drive some of the results, we complement this analysis with deterministic histories of income (good/bad harvest). We study the effect of each parameter by comparing our indicators for 100 pre-defined histories (a history being an n by T matrix of y_- and y_+) and plot the difference using box plots, so as to determine to what extent the effect of a parameter is significant.

3.4 Stability analysis

3.4.1 General Dynamics of the Model

Let us first analyze the dynamics and the stability of our model.

[3] see. **?** for a discussion on heterogeneity in risk-aversion

[4] CRRA utility functions present the advantages of having already been used by Kimball [1988] in his seminal paper on cooperatives and of allowing for the estimation of the risk-aversion parameter (see for example Kimball [1988], Chetty [2006] or Meyer and Meyer [2005] who estimate ρ to be in the range $[1.1; 6]$).

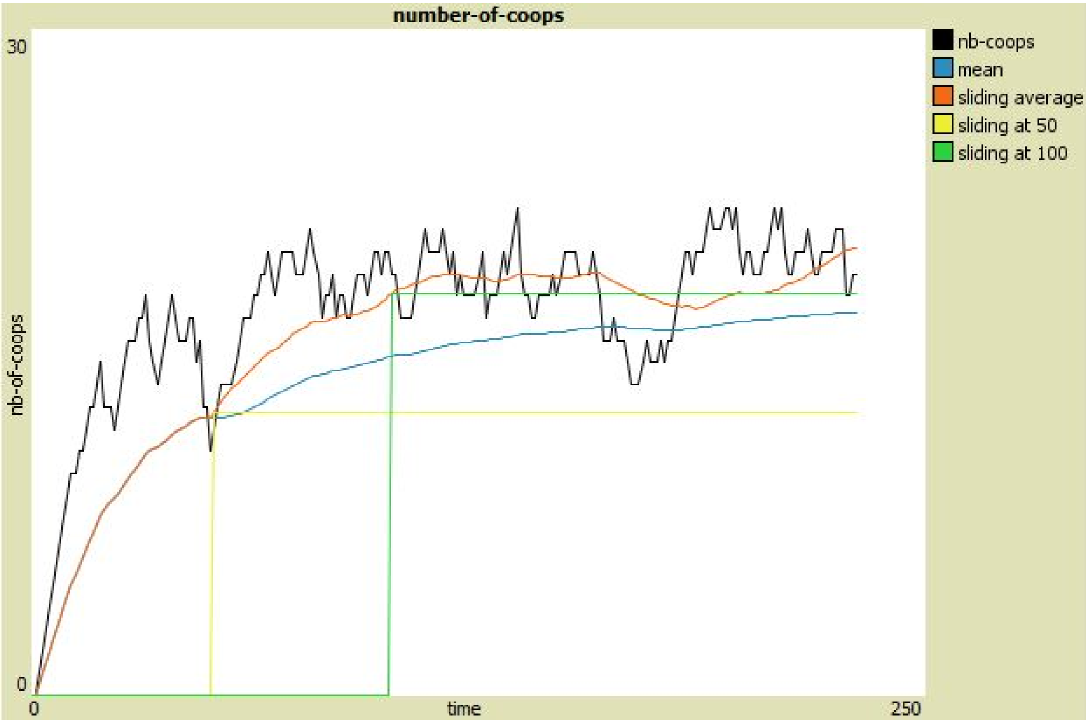

Figure 1: Illustration of the different regimes based on the number of cooperatives. The moving average is the mean of the indicator over the last 50 periods. We observe sharp convergence during the learning regime, a smoother readjustment during the convergence regime and then oscillations around the “stabilized level”. The vertical yellow and green lines indicate respectively the level reached at $t = 50$ and $t = 100$.

The first and simplest of the dynamics concerns learning. Our choice of parameters means that learning takes about 50 rounds (beyond which, agents have over 95% probability of knowing their type).

The system is however not stable once agents know their type. The learning regime is followed by a so-called “convergence” regime during which our indicators converge to the stabilized level (this is illustrated in Figure 1 using the dynamics of the number of cooperatives). The end of this convergence depends on the indicator, but it generally ends at around $t = 100$. Then, indicators oscillate around their stabilized level, in what we call the “stabilized” regime.

Based on these dynamics, we focus on three main dates for our analysis: $t = 50$, the end of the learning regime, $t = 100$, the end of the convergence regime, and $t = 250$, when stabilization is achieved. To smooth oscillations (in the last regime) and analyze the whole of the first two regimes, we look at mean values for our indicators for the previous 50 rounds at these 3 points in time.

3.4.2 Calibrating the level of risk-aversion

To highlight the effects of other-regarding preferences and learning, we seek to set an intermediate level of risk-aversion. As already pointed out, risk-aversion intuitively stabilizes cooperatives, increases the fraction of agents involved in cooperatives and overall helps to reduce segregation (see *e.g.* Kimball [1988] and Bourlès and Henriet [2012]). This is illustrated in section A.1. We therefore set (as a benchmark) a level of relative risk-aversion $\rho = 2.5$. Below this (e.g. at 1.5), the stabilizing effect of risk-aversion is too weak, cooperatives disappear quickly, few agents stay in them, and segregation is very high. Above this threshold (e.g. at 3.5) the stabilizing effect is too strong, leading to a large range of scenarios, from one in which the population is completely segregated to one in which cohabitation between different risk profiles is very easy. This would limit our ability to analyze the effect of other parameters on segregation.

4 Results and explanatory mechanisms

We now turn to our main results: the effects of other-regarding preferences and learning on the evolution of cooperatives and segregation (the effect of network shape is detailed in appendix A.2).

Our findings are:

- ORP decrease segregation and cooperative size. In the case of altruism, cooperatives are less stable and the fraction of agents in cooperatives also decreases. This unexpected instability comes from the fact that altruism also induces some high-risk agents to leave their cooperatives because of the negative effect they have on other members. This effect indeed disappears when we restrict ourselves to cases in which agents cannot leave a cooperative when they are benefiting from it.
- Limited knowledge of risk exposure has a large impact during the learning regime, which disappears gradually. It still reduces segregation during the convergence regime. When coefficients of inequality aversion or altruism are high this effect mainly comes from low-risk agents who stay in cooperatives (although they would have left if they had known their type) and are then "trapped" – even when they discover their type – because of their other-regarding preferences.

These effects are not only due to changes in individual behaviors but also depend on more macro mechanisms based on stocks and flows of agents, described in the next section.

4.1 The macro dynamics of the model

The macro dynamics of our model (an emerging phenomenon in ABM) is summarized in Figure 4.1. In ABM we define *ex-ante* the local rules for interactions and decisions of our agents and the scheduling of the model. The macro dynamics presented here is not directly implemented in our model but is the consequence at macro level of the local behavior of our agents. We chose *ex-post* to represent this macro dynamics as a stock and flow chart because we think this is the best key to understanding the results we observe. We can identify two relevant stocks:

1. The stock of isolated agents, characterized by its composition of low- and high-risk agents and the density of the network linking these agents in autarky.
2. The stock of agents in cooperatives, characterized by the number, the size, and the composition of cooperatives.

These two stocks are mathematically linked at every point in time by the following relation: $Stock.Autarky = Total.population - Stock.in.Coop$. Still, this relationship alone does not sufficiently clarify the dynamics, so we detail to understand well the dynamic, so we detail the flows between these two stocks.

There are two flows linking these stocks:

Flow A: One flow comes from the creation of cooperatives. It depletes the stock of isolated agents and increases the stock of agents in cooperatives. This flow is shaped by the number of isolated agents. As there is at most one cooperative created per round, it is the same size as this new cooperative. One agent is randomly picked to create a cooperative with her friends and the friends of her friends. Thus, the larger the stock of isolated agents, the lore likely the chosen agent is to find a lot of agents in her network to create her cooperative (arrow 1). This relationship between the size of the stock in autarky and flow A is very important for the general dynamics. A second factor influencing flow A is the density of the network connecting agents in autarky. For the same stock, a higher density leads the selected agent to gather more agents (arrow 7).

Flow B: The other, opposite flow corresponds to agents leaving cooperatives. For a given stock of agents in cooperatives, a larger flow implies (logical link) and is the consequence (causal link) of greater instability in cooperatives. The less (*resp.* the more) stable the cooperatives, the larger (*resp.* the smaller) this flow for a given stock (arrow 2). Thus, flow B is only driven by the micro level dynamics whereas flow A is essentially driven by the level and the nature of the stock of agents in autarky (*i.e.* by macro components).

From this structure we can infer the following:

- As the composition of flow B influences the composition of the stock of agents in autarky (dashed arrow 3), which in turn influences the composition of the new cooperative created (arrow 4), when the composition of flow B is stable, all these compositions become similar.
- When the stock of agents in cooperatives remains stable (as in the stabilized regime for example), a smaller stock increases cooperatives instability at the micro level. For the stock to be stable, flows A and B have to be equal. If there are few agents in cooperatives (and therefore a lot of agents in autarky), flow A is large, leading to a large flow B and therefore unstable cooperatives.

This macro structure already yields some intuitions about the mechanisms behind our indicators:

Size of cooperatives. The average size of cooperatives is influenced both by the size of the new cooperative (dashed arrow 6) and by the micro dynamics at cooperative level.

The fraction of agents in cooperatives. The fraction of agents in cooperatives only depends on the stock of agents in cooperatives, as it is the ratio of this stock to the total number of agents. Therefore, a stable low fraction means great instability in the cooperatives.

Segregation in cooperatives. At the macro level, the most important factor influencing segregation is the composition of the leaving flow, which impacts the composition of

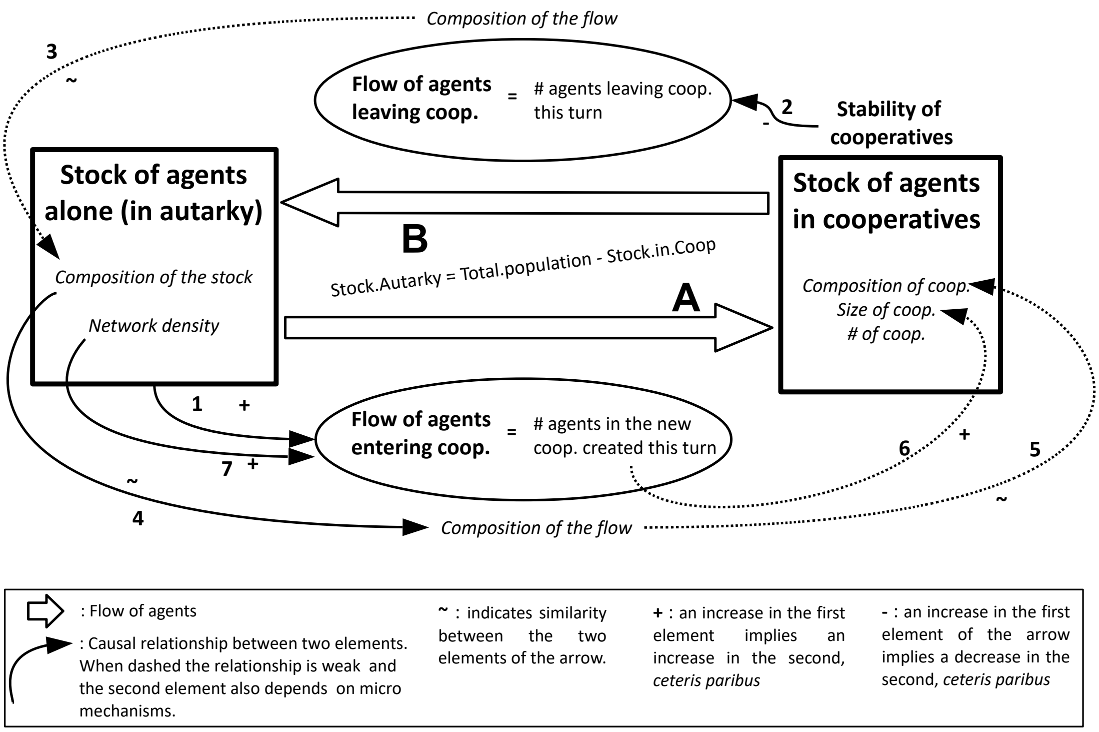

Figure 2: Scheme of the macro dynamics of the model

new cooperatives. If all the new cooperatives created are already highly segregated, segregation is likely to be large and only depends on internal cooperative mechanisms (dashed arrow 5). Segregation thus depends strongly on who leaves cooperatives, if the composition of this flow is stable enough.

We now turn to the micro dynamics at cooperative level (both creation and destruction), examining the relationship between these micro dynamics and the above effects, to explain the mechanism behind our results.

4.2 The baseline scenario

Let us first briefly describe the typical evolution of cooperatives with neither ORP nor learning. The effects of our various parameters can then be understood in terms of departures from this baseline scenario.

At the beginning, all agents are available to form new cooperatives, which are therefore quite big. Low-risk agents, however, quickly leave these initial cooperatives, whereas most high-risk agents stay. Most of the isolated agents are thus low-risk. They end up creating stable cooperatives among themselves. At this point, homogeneous cooperatives are very stable. As all agents in these cooperatives are of the same risk type, they have the same expected utility in isolation, and as soon as the expected utility of a cooperative is lower than this utility in isolation all the agents simultaneously leave the cooperative. Hence cooperatives' survival is extremely path-dependent, as is the composition of the leaving flow. This leads to high levels of segregation.

4.3 Other-regarding preferences

We now analyze the effect of other-regarding preferences: inequality aversion (IA, see equations (3) and (12)) and altruism (alt., see equations (2) and (11)).

The two models lead to different results due to the fact that high-risk altruistic agents internalize their negative effect on low-risk agents. If this effect is ignored, both ORPs reduce segregation and the mean size of cooperatives.

4.3.1 Inequality aversion

Let us first consider the effects of inequality aversion, see Figure 3.

On segregation (top right panel). IA reduces segregation. This effect lasts throughout the three regimes: learning ($t = 50$), convergence ($t = 100$) and stabilized ($t = 250$) and is non linear: a change from $\beta = 0$ to $\beta = 0.4$ has little impact, while a change from $\beta = 0.4$ to $\beta = 0.8$ has a major effect.

On the fraction in cooperatives (bottom right panel). IA has almost no effect on the fraction of agents involved in cooperatives in all three regimes. The only exception is for a high level of inequality aversion ($\beta = 0.8$) during the learning regime, where the fraction of agents in cooperatives slightly increases.

On the size of cooperatives (left panels). IA durably decreases the size of cooperatives. This effect appears during the learning regime and stabilizes during the convergence regime.

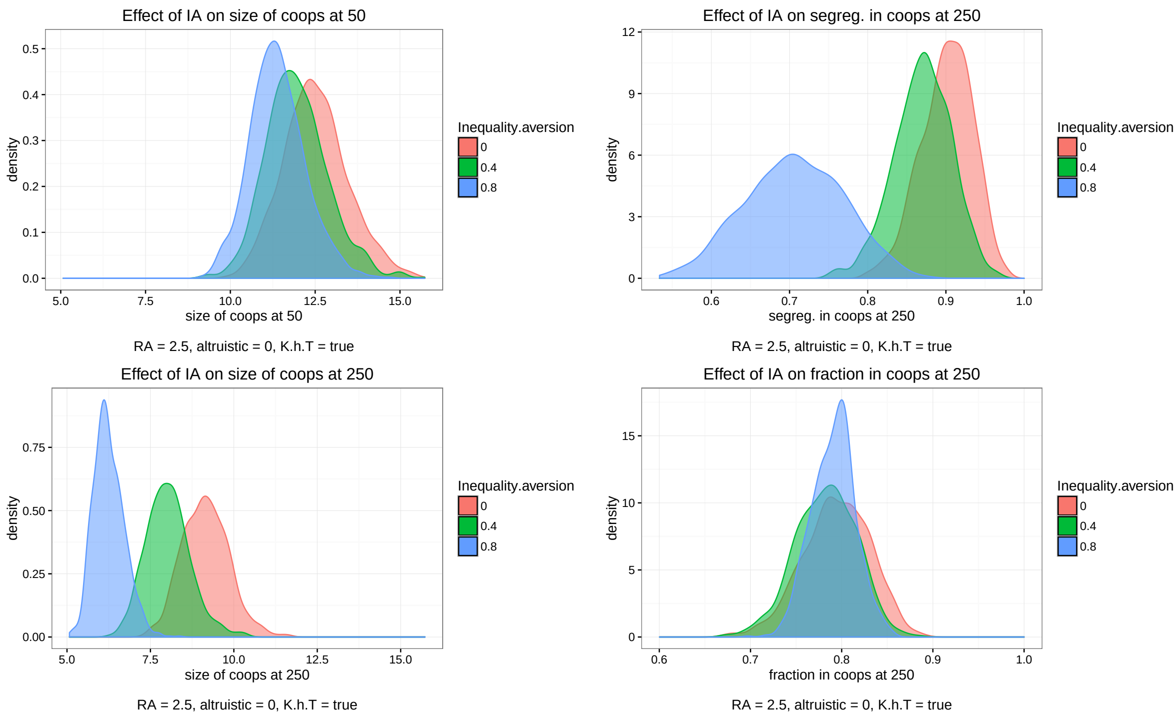

Figure 3: The effect of inequality aversion. The left panels represent the effect of IA on the size of cooperatives during the learning and stabilized regimes. The right panels represent the effect at $t = 250$ on the segregation index and the fraction of agents in cooperatives, respectively.

Inequality aversion thus durably decreases segregation (with a non linear effect) and engenders smaller cooperatives in the long term. The main mechanisms behind these results are the following:

- IA has a greater impact on small cooperatives. This is driven by two effects. First, the impact of an agent's realization of income on everyone's consumption is greater in a small cooperative. Second the impact of one agent leaving a large cooperative is smaller than the impact of her leaving a small cooperative. The stabilizing effect of IA is therefore higher in smaller cooperatives.
- Agents of the same risk type in the same cooperative can have different expected utilities depending on their individual realizations of past income (see equation 12). A very successful agent impacts more agents if she leaves, so that her incentive to stay is higher. The most successful agents are then "trapped" in the cooperative. Thus, contrary to what happens in the baseline scenario, all agents of the same type will not leave their cooperatives at the same time.

We can now describe a typical scenario behind the results.

As in the baseline scenario, large cooperatives of mixed composition are first created. The low-risk agents leave them quite quickly, changing the composition of the stock of isolated agents to almost 20% high-risk against 80% low-risk. Almost all newly created cooperatives thus reflect this in their composition, and the negative effect on consumption induced by this small fraction of high-risk agents is borne more easily by the low-risk agents, who stay in the cooperatives longer. They still leave but more slowly, and not all at the same time, as explained above. This ensures a mix which lasts longer and decreases segregation.

In terms of macro dynamics, agents now leave the cooperative individually (not in large groups as in the basic scenario) and thus do not greatly modify the composition of the stock of agents in autarky. This stabilizes the composition of newly created cooperatives. This self-reinforcing process at macro level leads to lower segregation.

Surprisingly the small leaving flow does not increase the fraction of agents in cooperatives, due to the lower density of the network of isolated agents (see section 4.1). As agents of the same type leave their cooperative at different times, they leave most of their friends behind and have less friends in autarky to create new cooperatives. Finally, as IA stabilizes small cooperatives, cooperatives are smaller on average.

4.3.2 Altruism

To observe the effect of altruism, see Figure 4.

On segregation (left panels). Altruism decreases segregation. This effect lasts throughout the three regimes, tends to intensify as time goes by and seems almost linear in α.

On the fraction in cooperatives (top right panel). Altruism durably decreases the fraction of agents in cooperatives.

On the size of cooperatives (bottom right panel) Altruism durably decreases the size of cooperatives.

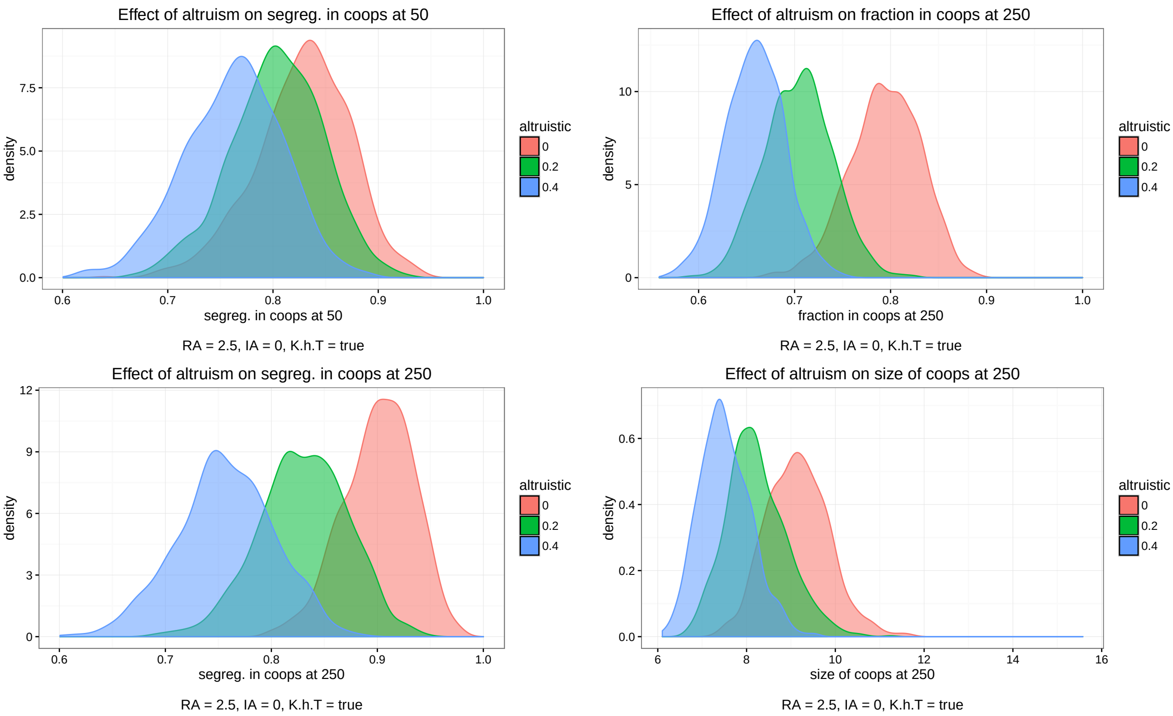

Figure 4: Effect of altruism. The left panels represent the impact of altruism on segregation at the end of the learning ($t = 50$) and the stabilized ($t = 250$) regimes. The right panels represent the effect on the fraction of agents in cooperatives (top-right panel), and the size of cooperatives (bottom-right panel) at $t = 250$ (the end of the stabilized regime).

Altruism thus durably decreases segregation at the cost of fewer people in cooperatives and smaller cooperatives.

The two mechanisms at work with IA also hold for altruism. The effect of altruism is stronger in small cooperatives and the decision of an agent to leave also depends on her own realizations of past income (not only on the cooperative's performance). In addition, a third mechanism means that altruism can lead agents who performed badly to leave their cooperatives so as to protect their friends. With altruism, utility has two parts (see equation 2): a material utility agents derive from their consumptions (which only depend on the results of their cooperatives), and a social utility derived from the utility of their friends. Whatever the risk profile of an agent, consecutive bad results lead to large material utility gains from the cooperative, but decreased social utility, as the utilities of other members of the cooperative decrease. If gains in material utility are lower than losses in social utility, the agent leaves the cooperative. This mechanism makes the model with altruism less stable than the model with IA or the baseline model. This also explains why altruism decreases the fraction of agents in cooperatives.

The typical scenario behind these results is the same as that for IA, except that the leaving and entering flows are larger. the compositional stability (around 20% of high-risk agents and 80% of low-risk agents) of these flows is self-sustaining. The cooperatives created, when not solely composed of low-risk agents, contain few high-risk agents. Low-risk agents leave little by little over time, which again makes cooperatives more mixed, less segregated. As the cooperatives get smaller and the stabilizing effect of altruism gets stronger, the remaining low-risk agents are "trapped" in the cooperatives. The eventual demise of the small cooperatives is due to the high volatility of their consumption and the departure of agents who perform badly, as explained previously.

4.3.3 Modified Altruism

We study a modified version of altruism where agents take into account the effect on their friends (i.e. social utility) only when it is positive. Equation (11) becomes:

$$E_{\pi_t}(u(y)) \geq \overline{u(c_{i,t})} + r.\alpha.\max\left\{\overline{u(c_{i,t})} - \overline{u(c_{-i,t})}, 0\right\} \tag{18}$$

It can be seen from Figure 5 illustrate that this modified version of altruism produces more stable cooperatives but also greater segregation. There is no longer the instability observed with normal altruism (as defined in the literature): the fraction of agents in cooperatives is similar to the level observed without ORP or with IA; and cooperatives are slightly larger than with normal altruism. Still, they remain smaller than without ORP (see right panels of Figure 5).

The effect on segregation is almost the same as with normal altruism during the learning regime (top left panel) but is lower during the stabilized regime (bottom left panel). The modified altruism leads to a less stable composition of the leaving flow and of the stock of isolated agents. The dynamics is thus closer to that observed without ORP, explaining this increase in the segregation index.

These results and the mechanisms behind them are further described in appendix B.1.

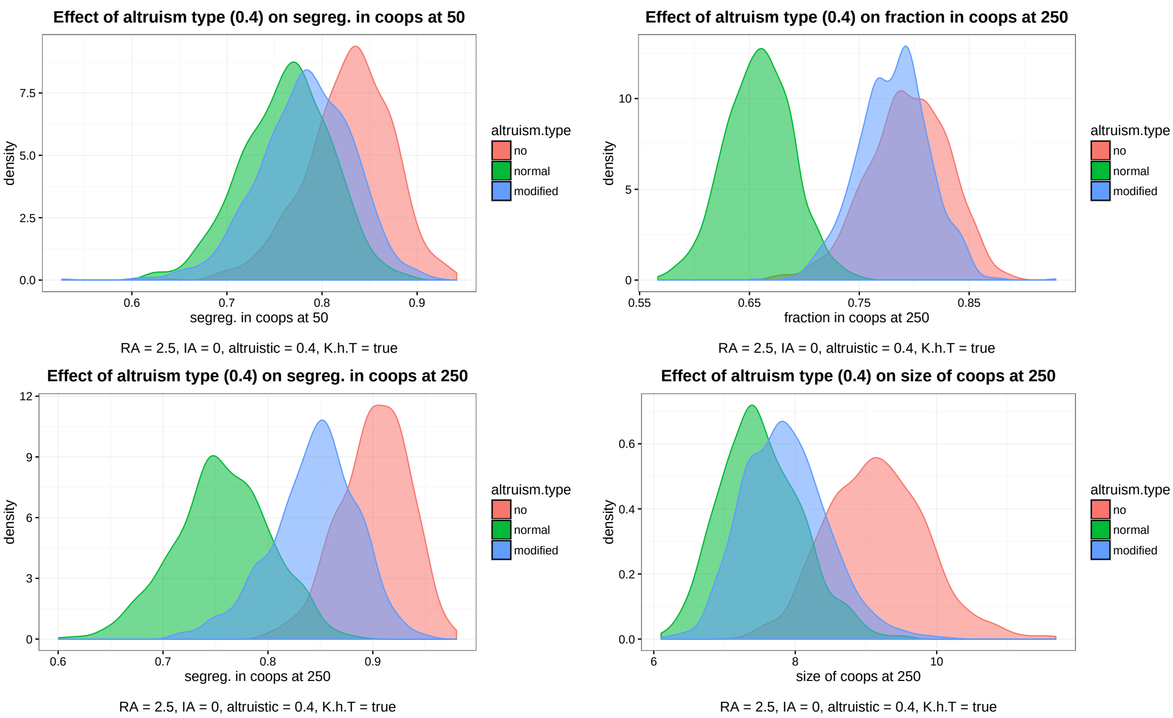

Figure 5: Effect of the modified version of altruism. The different colors distinguish no altruism ($\alpha = 0$), normal altruism (equation 11) and modified altruism (quation 18), both with $\alpha = 0.4$. The right panels represent the effect on the fraction of agents in cooperatives and on the size of cooperatives at $t = 250$. The left panels represent the effects during the learning and the stabilized regimes.

4.4 Information on risk types; Learning

We now analyze the effect of limited knowledge of risk type and Bayesian learning on segregation.

We correct for path dependence by considering the same histories, *i.e.* the same realizations of past income with and without learning. For each set of parameters we run 10 simulations for each of the 100 histories, a total of 1000 simulations. Let $I^s_{h,j}$ be the value of indicator I for the j^{th} simulation of history h (with $j \in \{1,..,10\}$ and $h \in \{1,..,100\}$) under set of parameters s. Call s and s' two identical sets except that there is learning in s' and no learning in s. We can now compute the effect of learning by computing for each h and j the difference $I^{s'}_{h,j} - I^s_{h,j}$. By looking at the statistical characteristics of these 1000 differences, we can infer the impact of learning. We also use $\frac{I^{s'}_{h,j} - I^s_{h,j}}{I^s_{h,j}}$ to look at the relative impact of learning.

We represent these results using box and whiskers plots (see Figures 6 and 7). Each box shows the median, the 25% and the 75% quantile. The inter-quantile range (IQR) is the height of the box, and the whiskers are the smallest (resp. the greatest) observation greater (resp. smaller) than or equal to the 25% quantile - 1.5 * IQR (resp. 75% quantile + 1.5 * IQR). Points are observations outside these limits.

Our main result therefore is that learning improves risk-sharing among heterogeneous agents during the learning and the convergence regime. This effect however disappears during the stabilized regime.

The mechanism behind these results is the following. During the learning regime, agents ignorant of their risk type make mistakes. Their expected utility in isolation is then computed based on their beliefs (see equation 7), making low-risk (resp. high-risk) agents compute a lower (resp. higher) expected utility than the real one. Low-risk agents will therefore stay longer in cooperatives with high-risk agents. This decreases segregation and increases cooperative size of cooperatives, at least during the learning regime.

In absolute terms (Figure 6), the effect of learning does not depend on the level of ORP. This could be taken to imply the absence of interaction between ORP and learning. However an analysis of the relative effects (see Figure 7) reveals (some) complementarity between ORP and learning. It shows that large coefficients of ORP strengthen the negative effect of learning on segregation during the learning regime (left panels), mainly when there is inequality aversion (top panels). This complementary effect comes from the major role played by inequality aversion in small cooperatives. Due to bad realizations of past income, some low-risk agents will learn more slowly than others and stay longer in their cooperatives. When they learn their type, they will realize that the cooperative results depend to a large extent on them, and will be reluctant to leave because of inequality aversion. Incomplete information on risk type thus decreases segregation, even more so when inequality aversion is high.

5 Conclusion

We study in this paper the motives that induce heterogeneous agents to share risk. In addition to the obvious impact of risk-aversion, we highlight the respective roles of other-regarding preferences and of limited knowledge of risk exposure. To explore the simultaneous learning of own risk type and cooperative performance, we build an agent-based model. Based on

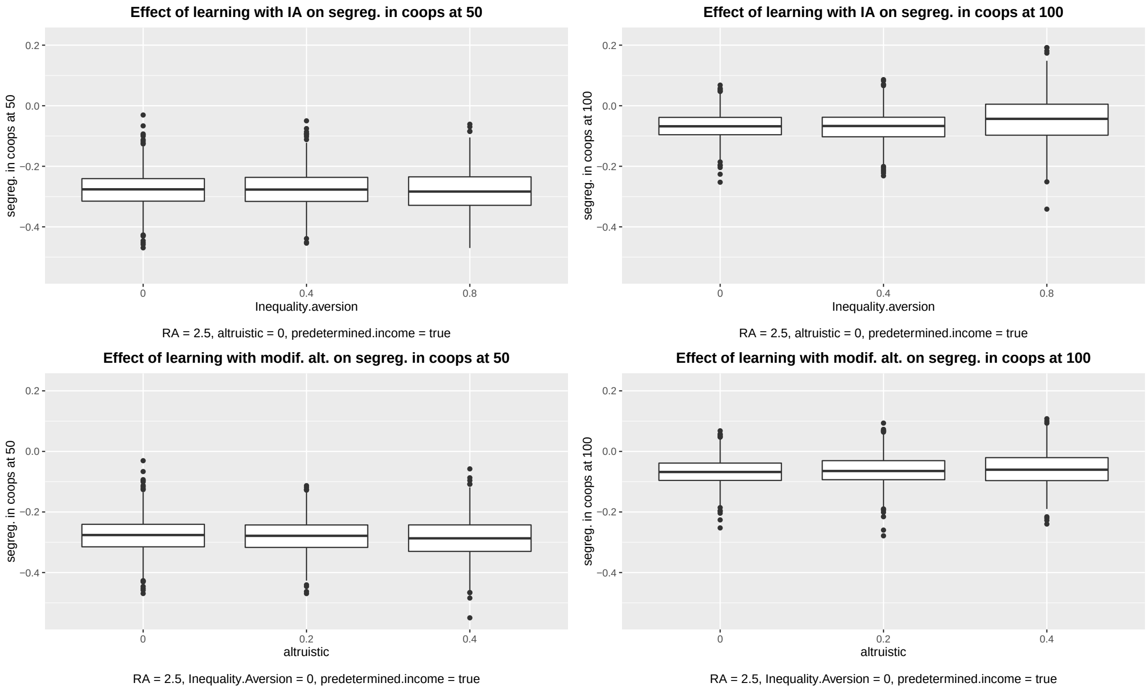

Figure 6: Effect of learning on segregation with ORP. The top panels illustrate the effect of learning on segregation, for various degrees of inequality aversion, during the learning regime (on the left) and the convergence regime (on the right). The bottom panels replicate this for modified altruism. All the results are presented in absolute terms.

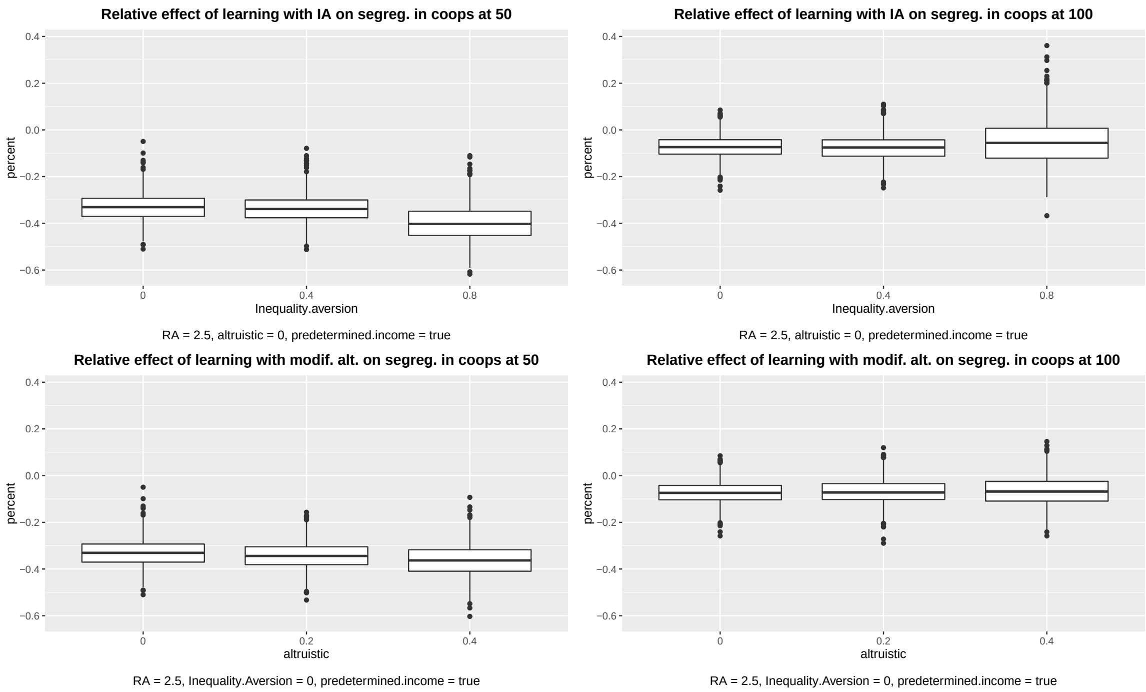

Figure 7: Relative effect of learning on segregation with ORP. The top panels illustrate the effect of learning on segregation, for various degrees of inequality aversion, during the learning regime (on the left) and the convergence regime (on the right). The bottom panels replicate this for modified altruism. All the results are presented in relative terms.

their beliefs and the risk-sharing offered in their cooperative, agents choose whether or not to leave it. This illustrates the evolving composition of risk-sharing cooperatives.

We show in this context that other-regarding preferences (inequality aversion and altruism) durably decrease segregation in cooperatives, *i.e.* they increase the willingness of low-risk agents to share risk with high-risk agents. Interestingly, this holds true even when agents are fully informed of their risk type. These other-regarding preferences, however, tend to lead to smaller cooperatives, as agents have a greater effect on each other in smaller cooperatives.

This effect is reinforced by learning, which also leads to more mixed cooperatives. Learning makes low-risk agents less sure about what they stand to gain in isolation, so that they stay longer in their cooperative. The two effects are moreover complementary: other-regarding preferences induce the last low-risk agents remaining to continue sharing with high-risk agents.

Interestingly, with the use of "normal" altruism (such that agents who disturb others by benefiting from the cooperation can decide to leave to increase utility of others) the stability of cooperatives greatly reduces.

These results suggest that more research is needed, notably regarding the interaction between risk-aversion, other-regarding preferences and learning. One way to enrich our model would be by making the creation process more sophisticated. We assume here that at each step one new cooperative is created, without any choice by the agents. Modeling another process would however call for more assumptions, in particular on the identity of the agent(s) who choose(s) to create the new cooperative or not, and the information she (they) use. Another interesting avenue of research would be to explore sharing rules other than equal sharing.

A Robustness checks

A.1 The effect of risk-aversion

The effect of risk-aversion is summarized in Figure 8.

On segregation (left panels). During the learning regime, RA decreases segregation. During the stabilized regime, the reverse effect is observed but is very small.

On the fraction in cooperatives (top right panel). RA increases the fraction of agents in cooperatives during the stabilized regime.

On the size of cooperatives (bottom right panel). RA decreases cooperative size during the stabilized regime. The reverse effect is observed during the learning regime.

RA greatly improves the stability of cooperatives. This has consequences that vary depending on the regime we study. Results are very path-dependent for high RA coefficient, stabilizing a large variety of scenarios from low segregation to complete segregation. The expected effect of RA, to promote a mixed risk profile, is only observed during the learning regime. Then the effect changes, because of the dynamics of the model.

- When the coefficient of relative risk-aversion equals 1.5, cooperatives are unstable. Low-risk agents quickly leave and the performance of the remaining homogeneous cooperatives is highly path-dependent (explaining high segregation and the small fraction of agents in cooperatives). Cooperatives become larger during the stabilized regime. The

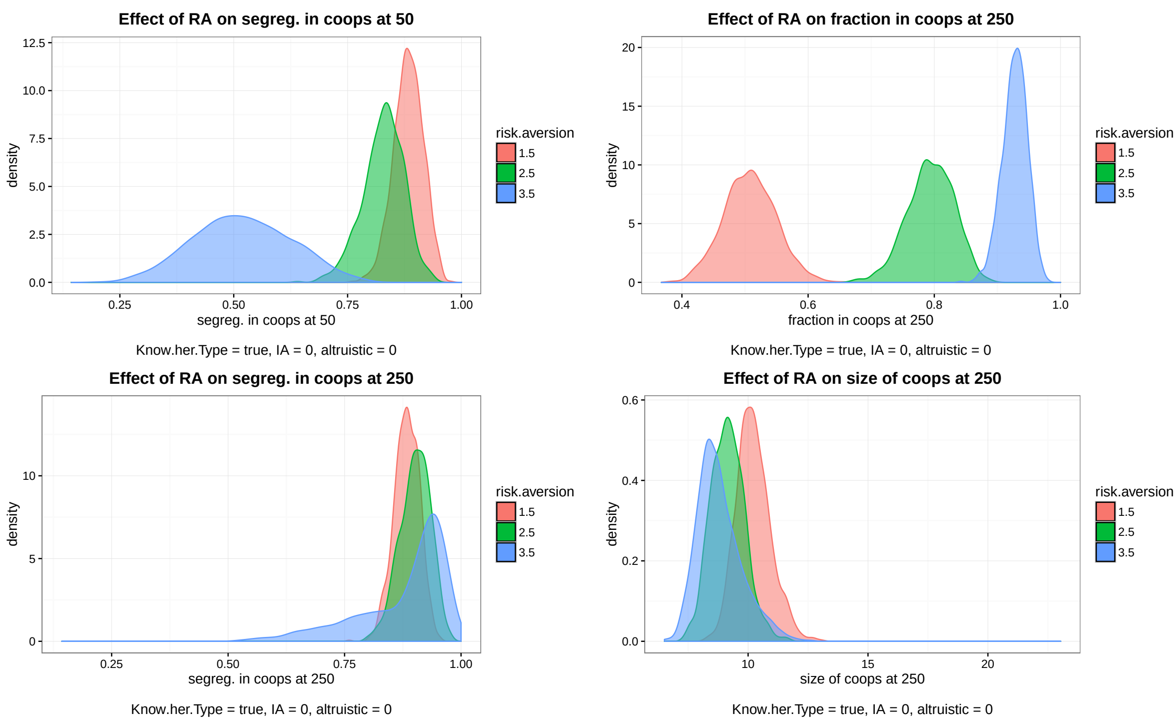

Figure 8: The effect of risk-aversion (RA) without learning or ORP. The left panels represent the evolution during the learning and stabilized regimes of the impact of RA on segregation. the right panels represent the effect of RA at step 250 on the fraction of agents in cooperatives (top panel) and on the cooperative size (bottom panel).

size and the homogeneity of the stock of isolated agents tend to create large and stable cooperatives.

- With a higher relative risk-aversion coefficient (2.5), the first cooperatives are more stable. Low-risk agents leave less quickly, so the segregation index decreases during the learning regime. Nevertheless, high coefficients of RA also stabilize homogeneous cooperatives, which is why in the long run (during the stabilized regime) the segregation index is higher for a coefficient of RA of 2.5.
- A coefficient of 3.5 is a special case, where the stabilized regime is highly path-dependent. RA can stabilize both situations in which every cooperative is completely segregated and situations in which cooperatives are mixed.

A.2 The shape of the social network

In this subsection, we analyze the impact of the social network. We study three shapes of network: small world with a mean number of friends of 10 (as in the core of the paper), random, with the same mean number of friends and complete, where everybody is linked to everybody. We focus on cases without ORP and with modified altruism. The shape of the network indeed impacts the choice both of those an agent can create a new cooperative with and of those she is altruistic toward. We abstract from learning, assuming that agents perfectly know their type from $t = 0$. Results are displayed in Figure 9.

On segregation (left panel). Segregation is maximal for the complete network. Without altruism, small world and random networks are equivalent. With altruism, small world networks lead to less segregated cooperatives.

On the size of cooperatives (right panel). Without altruism, the complete network generates two completely segregated cooperatives. With altruism, the complete network generates smaller cooperatives that are still a bit larger than with random networks. In both cases, the smallest cooperatives are generated by small world networks.

Results on the size of cooperatives are essentially driven by the size of the created cooperatives. With the complete network, all agents are linked. Every isolated agent therefore creates the largest possible cooperative at each round. With the small world network, friends of friends are more likely to be friends, and the selected agent will reach less agents than in the random network case, ending up with smaller cooperatives.

The results on segregation with modified altruism are driven by the stronger effect of altruism in smaller cooperatives. In the case of the complete network, everybody is altruistic towards everybody else, but cooperatives are too large for altruism to have an effect. Low-risk agents thus leave quickly and create large and completely segregated cooperatives. In the small world network, friends of friends are more likely to be friends and cooperatives are small. The effect of altruism on segregation is thus strongest in the small world network.

B Discussion

B.1 Modified Altruism

The following subsection describes results obtained with modified altruism and the mechanisms behind them, see Figure 5.

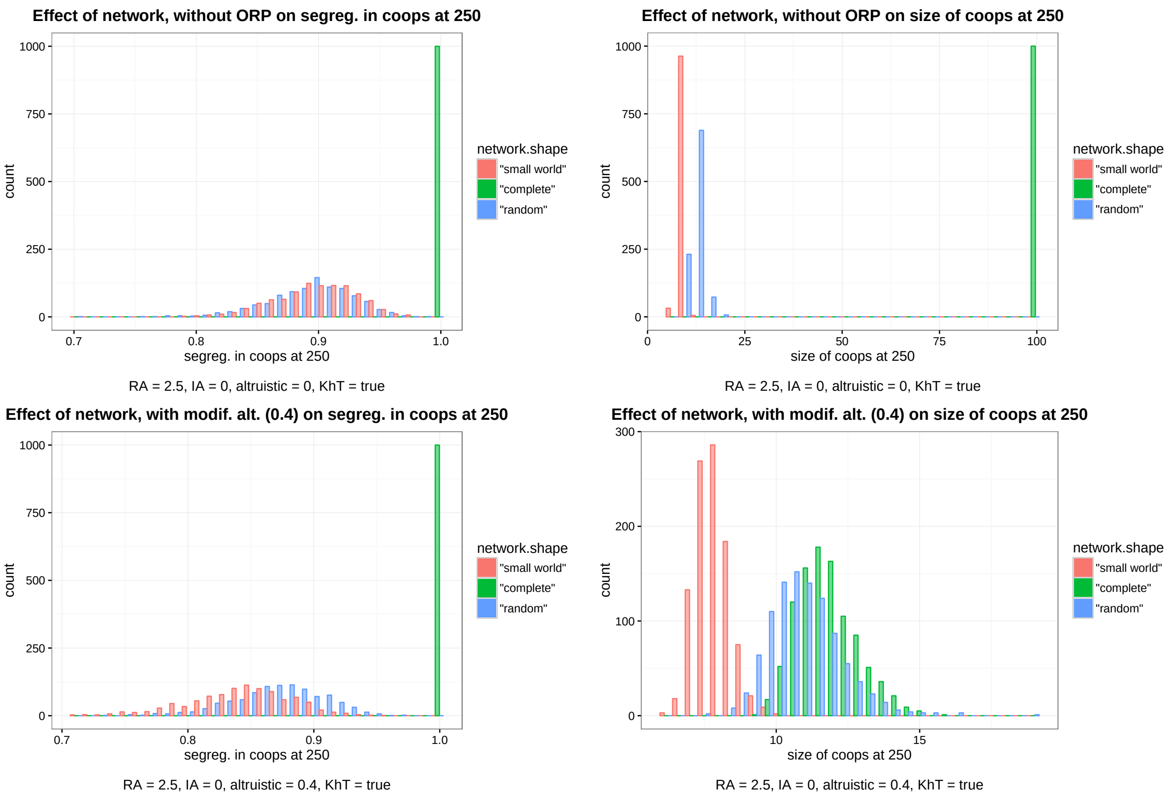

Figure 9: The effect of network shape. Each panel represents the distribution – via a histogram – of an indicator at $t = 250$ (the use of a histogram rather than density is necessitated by the homogeneity of results for the complete network). Left panels represent the effect on segregation, without (top) and with (bottom) modified altruism. Top panels represent the effect on the size of the cooperatives, without (top) and with (bottom) modified altruism.

On segregation (left panels). Modified altruism decreases segregation. The effect is however lower than with normal altruism after the learning regime.

On the fraction in cooperatives (top right panel). Modified altruism has no effect on the fraction of agents in cooperatives (contrary to normal altruism).

On cooperative size (bottom right panel). Modified altruism decreases the size of cooperatives, a little more than normal altruism.

Modified altruism creates more stable cooperatives but higher segregation than normal altruism. The results on the fraction of agents in cooperatives are explained by the fact that agents no longer leave a beneficial cooperative because of the negative effect they are having on their friends. This however decreases the stability of the composition of the leaving flow. This instability, as in the baseline scenario, leads to higher segregation index.

C Acknowledgment

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