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REGULAR ARTICLE

Informal risk-sharing cooperatives: the effect of learning and other-regarding preferences

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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 preference (altruism and inequality aversion) in stabilizing less segregated (and smaller) cooperatives. Limited knowledge and learning of own risk exposure also contributes to reducing segregation, the two effects (of learning and other-regarding preferences) being complementary. Our findings 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

JEL Classification D82 · G22 · D83 · D64

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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 the population of which 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, or debts within ones 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 on one observable feature of risk-sharing, which is that less risky agents agree to share with riskier agents on a regular basis (DeWeerdt and Fafchamps 2011b).

In this paper, we are interested in exploring a risk-sharing dynamic 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 he is risk-averse enough (as shown in Bourlès and Henriet 2012). In that case, although he would stand to lose expected income (as he will more often transfer wealth than receive) he might agree to share risk to decrease income variation. Second, other-regarding preferences – the fact that the agents care about the 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.) Although this effect holds for both inequality aversion and altruism, our results shed light on a counter-intuitive effect of altruism (called “sacrificial” effect) that impedes the stability of cooperatives and can be linked to the literature on risk-sharing and altruism (Alger and Weibull 2010).

One of the main contributions 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 altruism. 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 2011b). The theoretical impact of altruism on risk-sharing has recently been studied by Alger and Weibull (2008, 2010) in the case of pairs and by Bourlès et al. (2017, 2018) 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 and Bourlès et al. (2018) discuss the impact of the network on the efficiency of risk-sharing. We add to this analysis by considering agents heterogeneous in terms of risk exposure. We also analyze an alternative modeling of other-regarding preferences by studying how inequality aversion (a la Fehr and Schmidt 1999) changes our results.

Our paper thus contributes to the literature on the motives for transfers by modeling both risk-sharing (or exchange) motives and altruistic motives (and, more broadly, other regarding preferences). This seems particularly relevant as a large empirical literature on these motives (see Fafchamps 2011; Arrondel and Masson 2006 for a survey) conclude that both are at work in explaining transfers in various contexts (village economies De Weerdt and Fafchamps 2011a, remittances Rapoport and Docquier 2006 or family transfers in developed economies Arrondel and Masson 2006). We also contribute to this literature by including asymmetric information and learning into the picture. Applied to the development context, our paper notably calls for frequent and long-term relationships to allow agents to learn about their exposure and the benefits of risk-sharing and it therefore echoes empirical results on micro-credit about the positive impact of long-term participation; see e.g. Islam (2011).

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 (2011b) confirm that transfers can occur between agents who are heterogeneous in terms of risk exposure, as chronic illness does not deter informal agreements. Our paper helps to explain this finding by altruism but also by limited information of own risk exposure.

In our model, agents' learning about their profiles 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 environment (social or physical) or when they are heterogeneous in type or characteristics, as in our case. 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. 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 (where agents discover by trial and evaluation of the best action) and belief learning (where agents discover the game they are playing at the same time); see Brenner (2006). Here we use belief learning: agents know the game but do not know who they are. They learn their type and thus complete their understanding of what they are supposed to do. In our case, the type of an agent is more precisely defined by his probability of success. Thus agents have to learn about probabilities and, consistent with the literature on asymmetric information, it seems natural to then rely on Bayesian learning.

Thus, to understand the dynamic evolution of cooperation of heterogeneous agents with limited knowledge we decided to produce an Agent-Based Model (programming in Netlogo). The addition of learning to already complex models such as those of Bourlès and Henriet (2012) – who only consider two selfish agents – or Bourlès et al. (2017) – who study altruism in networks with deterministic revenues – renders the analytic model untractable, especially when increasing the number of agents. Thus most of the papers dealing with risk-sharing under other-regarding preferences at least partly rely on simulations (Foster and Rosenzweig 2001; Bourlès et al. 2018). 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 to 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 Section 4, we present the effect of learning and altruism 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 $\mathscr{C}$ with m members, the after-sharing income – called here consumption – at period t is:

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

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 separately: altruism and inequality aversion (IA).

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

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

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

For 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, for social preferences on agent i write:

$$\begin{aligned} v(c_{i,t}, c_{-i,t}) &= u(c_{i,t}) - \frac{\beta}{m-1} \sum_{j \neq i} \max\{u(c_{i,t}) - u(c_{j,t}), 0\} \\ &\quad - \frac{\gamma}{m-1} \sum_{j \neq i} \max\{u(c_{j,t}) - u(c_{i,t}), 0\} \end{aligned} \tag{3}$$

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. In 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 his 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 Appendix F.2 we discuss the effect on the shape of the network by comparing our main results to those resulting from a random and a complete network.

A key assumption of our model is the information that each agent has regarding his 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 his 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

[1]Equation 2 can also be understood as the reduced form of a model in which agents care about others' social preferences (see Bourlès et al. 2017)

of his belief: if at time t he has experienced k losses among the t first periods, his belief about his 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' choices to stay in or leave their cooperative.

To understand the effect of learning on the composition and stability of cooperatives, we compare the outcome of our model with Bayesian learning mechanism to the outcome of a model in which agents know their type from $t = 0$. Another possibility would be to compare it with a model in which agents never learn. This would however come to consider homogeneous agents who all believe having the average probability of bad harvest, in which case – by the mutuality principle – larger cooperatives are better.

2.2 Staying in the cooperative or leaving

If already involved in a cooperative, at each period (after income sharing[2]) each agent has to choose whether to remain in this cooperative or to leave it. Bayesian learning makes it fairly easy to compute the expected utility for an agent of remaining alone:

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

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 his cooperative, an agent:

– uses his 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.

[2]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).

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

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

where

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

$\overline{u(c_t)}$ 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 Eq. 8, based on his belief and on the history of the cooperative, an agent will leave the cooperative if he is better off outside than inside.

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

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

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

Then, an altruistic agent i leaves his cooperative if:

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

where r represents the number of friends agent i has in his cooperative. Note that agent i's decision to leave a cooperative will only impact the well-being of those of his friends involved in the same cooperative, then the terms taking into account the utilities of agent i's friends outside his cooperative canceled out in the Eq. 11.

Similarly, an inequality averse agent i will leave his cooperative if:

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

Once again, we assume here that the agent only considers the impact of his 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 – notably for computational reasons – 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 his network at level 2 (i.e. all agents who do not belong to a cooperative and with whom he has a direct link, and those with whom these friends have a direct link)[3]. 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 his network at level 2 at least one other isolated agent[4].

The social network therefore plays two major roles in our setting. It defines those with whom an agent can create a cooperative and, in the case of altruism, those toward whom an agent is altruistic (2). Note here that, in the core of the paper, the creation of a new cooperative does not involve the creation of new links in the network. We discuss this assumption is Appendix F.2.

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. This index comes from the comparison between the composition (in terms of low- and high-risk agents) of each cooperative and the composition of the whole population. It takes different values:

– 0 if there is no segregation in cooperatives, that is, if the composition (fractions of low-and high-risk agents) of **all** cooperatives are exactly the same as the composition of the whole population. As soon as at least one of the cooperative has a different composition from the whole population the index is no longer equal to 0 and begins to increase.

[3]Note here that increasing the level of the network with whom the agent can create a cooperative will have a similar effect as densifying the network. This discussion is thus related to one on the shape of the network we expose in Appendix F.2

[4]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, he 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. We have also tested settings in which the selected agent had the choice to build the cooperative or not, based on his belief and the ones reported by the other potential members. Our results on the effect of other-regarding preferences were then qualitatively the same as the ones exposed here, whereas those on learning were more difficult to interpret as learning had then both a direct impact on cooperatives' creation (through the mechanism of choice) and on cooperatives' evolution (through π_t in Eqs. 8, 11 and 12). Automatic creation allows us to disentangle these two effects of learning and to concentrate on cooperatives' evolution alone.

- 1 if there is a complete segregation in cooperatives, that is, **none** of the existing cooperatives is mixing agents of different risk types. It is also equal to 1 if there is no cooperative, that is, if all agents are isolated.
- in between 0 and 1. The closer to 0 the less the cooperatives are segregated. Still, we cannot differentiate between cases where most of the cooperatives are perfectly non segregated with few cooperatives completely segregated and cases where all the cooperatives are barely segregated.

Our indicator adapts the standard demographic index of dissimilarity to our cooperatives case as presented in Appendix A.

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 $\underline{p}$, while 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 to which they belong or to leave it (according to Eqs. 8, 11 or 12) and (iii) one isolated agent is selected to create a cooperative with his isolated friends at level 1 and 2, if any. We run the model for T time steps. As it is usual in learning models in simulation (Rouchier 2003), the time step is not easy to interpret in terms of a real-world period. It can still be understood here as the time needed for agents to acquire more information on their risk-type. For example, in the case of agricultural cooperatives, it could correspond to a new harvest, which can be from two to four per year depending on the type of culture. Then, 50 time steps (the horizon to which most of our results would be presented, see below) can be seen as one or two decades. Still, our model is mostly theoretical and does not fit to a direct interpretation. It rather is designed to capture the impact of learning on the dynamics rather than learning itself. The assumption that agents do not know their type is also created following this theoretical aim.

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 time steps for agents to know their type with a probability of 95%. As we want to focus on the effect of learning, to be consistent with the possible interpretation of the time steps, most of our analysis will therefore consider the first 50 steps. 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[5] and have private (or material) preferences represented by a Constant Relative Risk Aversion (CRRA) utility function:

$$u(c) = \frac{c^{1-\rho} - 1}{1 - \rho} \tag{13}$$

with ρ the coefficient of relative risk-aversion ($-cu''(c)/u'(c) = \rho \; \forall c$)[6].

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 $q = 0.10$. Some extensions about the network shape can be found in the appendix, for simple types of networks.

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 Eqs. 4 to 6)[7]. Regarding risk-aversion, we consider alternative values of ρ between 1 and 4 (see Kimball 1988, Chetty 2006 and Meyer and Meyer 2005). For altruism, we consider values of 0, 0.2 and 0.4 α (according to Hamilton's rule, two siblings should have a coefficient of altruism of 0.5, see Hamilton 1964a, b); and values of advantageous inequality aversion β equal to 0, 0.4 and 0.8 in line with assumptions and observations in Fehr and Schmidt (1999).

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 Appendix F.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.

3.3 Statistical methodology

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 the average of our indicators (chiefly mean cooperative size, fraction of agents in cooperatives and degree

[5] See Chiappori et al. (2014) for a discussion on heterogeneity in risk-aversion.

[6] 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]).

[7] Note again that if agents would not learn their type in this case, they would behave as if they were homogeneous and would tend to stay in any cooperative to which they belong.

of segregation in the existing cooperatives) over $T = 50$ steps. This allows us to analyze the effect of each parameter visually, using the notion of stochastic dominance. As explained above, 50 steps allow us to capture the entire learning period. (See Appendix B for a more complete analysis of the dynamics of the model.)

Due to path-dependence, some of the results might be driven by differences in the draw of random histories. To limit this issue, we complement this analysis with deterministic histories of income (good/bad harvest). In this case, instead of drawing at each time step a realization of income for each agent, we draw (using the same probability distribution) the entire history before running the simulations (a history being an n by T matrix of y_- and y_+). We then study the effect of each parameter by comparing our indicators for 100 pre-defined histories and plot the difference using box plots, so as to determine to what extent the effect of a parameter is significant.

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 F.2.

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 Appendix C. These macro mechanisms are important to grasp completely how the model operates but not necessary to understand the results. In the rest of the section we will insist more on the micro dynamics at the cooperative level (both creation and destruction) to explain our results. In Appendix D we describe typical runs for the model with and without ORP. These typical scenarios expose the complete interactions between the macro and micro dynamics.

4.1 Other-regarding preferences

We first analyze the effect of Inequality Aversion (IA, see Eqs. 3 and 12) and Altruism (alt., see Eqs. 2 and 11) when agents know their type, and turn to the effect of learning in the next section. We start by presenting results on Inequality Aversion to highlight then the "sacrificial" effect of Altruism.

4.1.1 Inequality aversion

Figure 1 displays the effect of inequality aversion on the average index of segregation over 50 periods. It exhibits that inequality aversion leads to less segregated cooperatives. As expected, more inequality averse agents who realize being low-risk, are less likely to leave their cooperative. This effect sill appears to be non-linear and higher for high level of inequality aversion (this non-linearity is analyzed further in Appendix E).

If inequality aversion decreases the average level of segregation in cooperatives, it also leads to smaller cooperatives (see Fig. 2). This is likely to be driven mostly by two effects. First, the impact of one's realization on everyone's consumption is

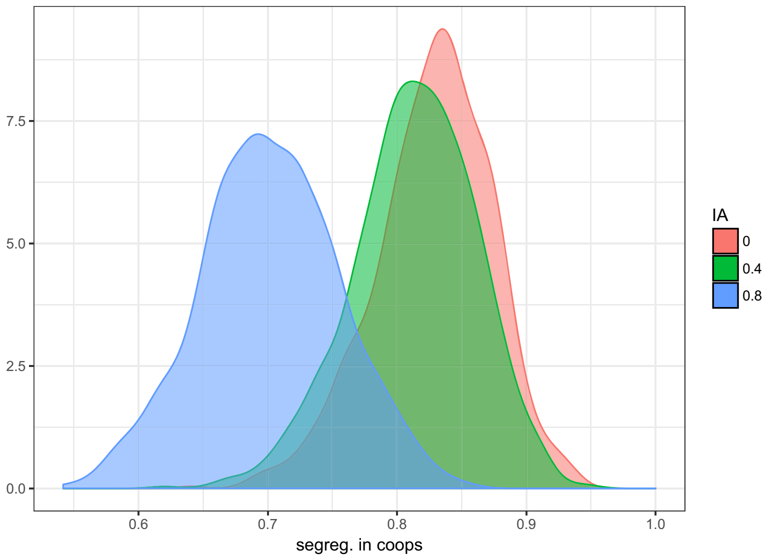


Fig. 1 The effect of inequality aversion ($\beta = 0, 0.4, 0.8$) on segregation when agents know their type and $\rho = 2.5$. (The distribution of the average index of segregation over the first 50 time steps for our 1000 simulations with $\beta = 0.8$ is represented in blue)

more important in a small cooperative. Then, the impact of one agent leaving a large cooperative is smaller than his impact of leaving a small cooperative. The stabilizing effect of IA is therefore higher in smaller cooperatives. Moreover, when computing the potential effect of their leaving on the other members of the cooperative (12), agents of the same risk type in a same cooperative make different choices depending on their individual realizations of past income (10). Very successful agents then anticipate a greater impact if they leave, so that their incentive to stay is higher. The most successful agents are then "trapped" in the cooperative. Still, Fig. 2 also exhibit that inequality aversion has barely no effect on the fraction of agents in cooperatives.

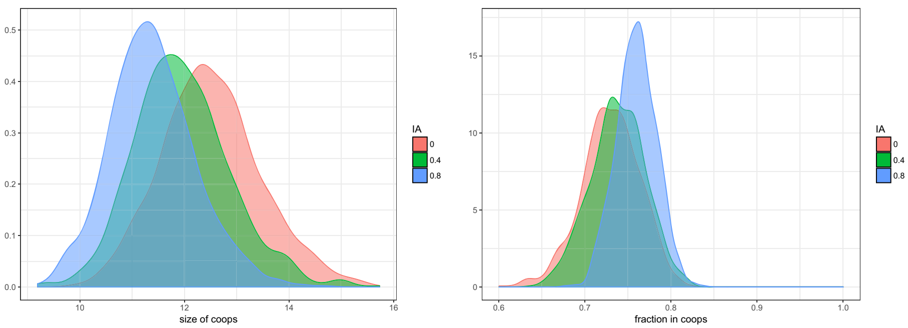


Fig. 2 The effect of inequality aversion ($\beta = 0, 0.4, 0.8$) on the size of cooperatives (left panel) and the fraction of agents in cooperatives (right panel) when agents know their type and $\rho = 2.5$

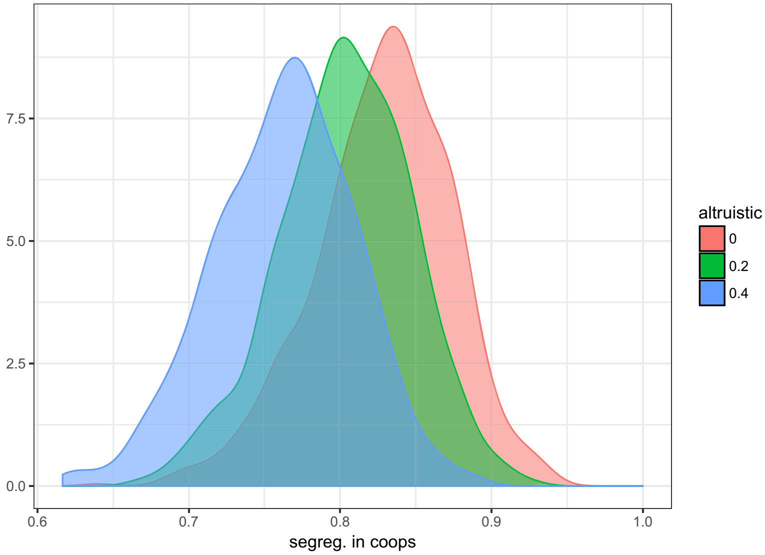
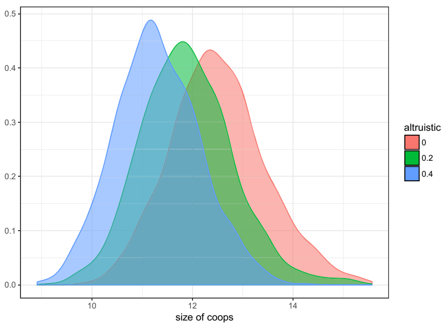


Fig. 3 The effect of altruism ($\alpha = 0, 0.2, 0.4$) on segregation when agents know their type and $\rho = 2.5$

To sum up, inequality aversion decreases segregation (with a nonlinear effect) but engenders smaller cooperatives. A typical run with IA is described in Appendix D.

4.1.2 Altruism

Now turn to the effects of altruism. If most of the mechanisms remain the same as for inequality aversion, leading to a decrease in segregation (Fig. 3) and in cooperative size (Fig. 4), our analysis also highlights a destabilizing effect of altruism through a decrease in the fraction of agents in a cooperative (Fig. 4).



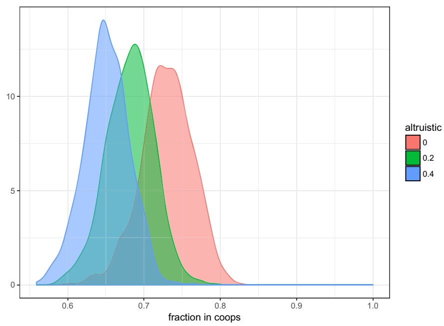


Fig. 4 The effect of altruism ($\alpha = 0, 0.2, 0.4$) on the size of cooperatives (left panel) and the fraction of agents in cooperatives (right panel) when agents know their type and $\rho = 2.5$

Figure 3 shows that altruism indeed decreases the average segregation in cooperative, and this effect seems linear in α. The two mechanisms at work with inequality aversion also hold for altruism: both types of ORP leads to less segregated but smaller cooperatives. Altruism has a stronger impact on small cooperatives and the decision of an agent to leave also depends on its own realizations (not only on the cooperative performances).

Still, contrary to inequality aversion, altruism also tends to decrease the stability of the cooperatives, ending up with fewer agents in cooperatives. This is due to the fact that high-risk altruistic agents internalize their negative effect on low-risk agents[8]. Altruism can indeed lead agents who performed badly to leave their cooperatives so as to protect their friends; we called it the "sacrificial" effect. With altruism, utility has two parts (see Eq. 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 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 without ORP or with inequality aversion.

A typical run with altruism is described in Appendix D.

4.2 Information on risk types; learning

We now analyze the effect of limited knowledge of risk type and Bayesian learning on segregation. We present here the case of inequality averse agents. Similar results are obtained for altruistic agents (see Barbet et al. 2017).

We correct for path dependence by considering the same histories, i.e. the same realizations of past income with and without learning (see Section 3.3). 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 Figs. 5 and 6). Each box shows the median, the 25% and the 75% quantile. The inter-quantile range (IQR)

[8]This destabilizing effect disappears when agents take into account the effect on their friends (i.e. social utility) only when it is positive (see Barbet et al. 2017).

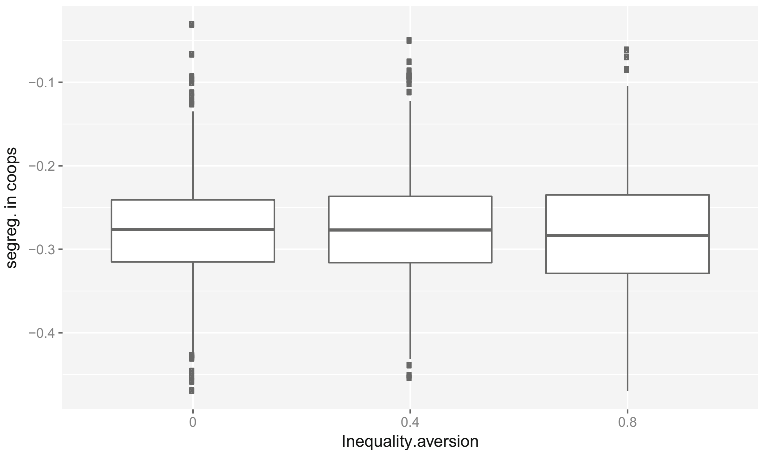


Fig. 5 The effect of learning on segregation with inequality aversion. The panels illustrate the effect of learning on segregation for various degrees of inequality aversion, averaging over the first 50 periods

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 phase. By construction, this effect then gradually disappears.

The mechanism behind these results is the following. While learning, agents ignorant of their risk type make mistakes. Their expected utility in isolation is then

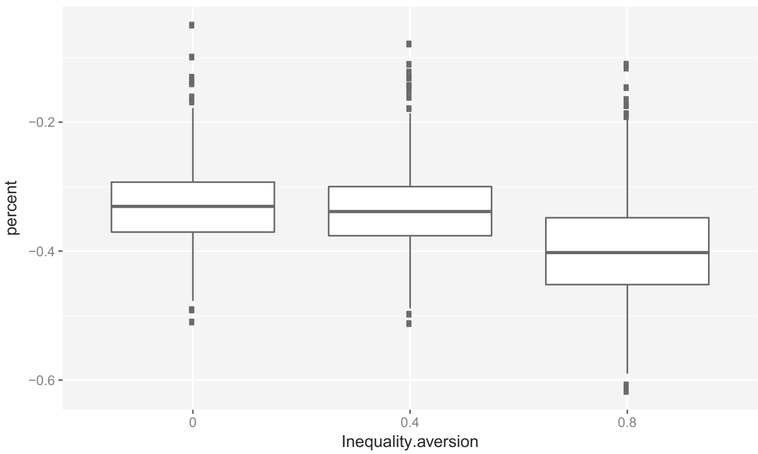


Fig. 6 Relative effect of learning on segregation with inequality aversion. The panels illustrate the effect of learning on segregation for various degrees of inequality aversion, averaging over the first 50 periods

computed based on their beliefs (see Eq. 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, at least during the learning phase.

In absolute terms (Fig. 5), the effect of learning does not depend on the level of inequality aversion. This could be taken to imply the absence of interaction between inequality aversion and learning. However, an analysis of the relative effects (see Fig. 6) reveals (some) complementarity between inequality aversion and learning. It shows that large coefficients of inequality aversion strengthen the negative effect of learning on segregation during the learning phase. 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 the 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 dynamics of risk-sharing cooperatives and the motives that induce heterogeneous agents to share risk. This modeling allows us to determine several dimensions impacting the functioning of cooperatives. In addition to the obvious impact of risk-aversion, we highlight the respective roles of other-regarding preferences (altruism and inequality aversion) and of initial 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 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 decrease segregation in cooperatives, i.e. increase the willingness of low-risk agents to share risk with high-risk agents. Other-regarding preferences, however, tend to lead to smaller cooperatives, as agents have a greater effect on each other.

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. Each agent's history has an impact on his belief about himself, and thus his future decisions. This path dependency, which applies to all, changes the global dynamics. The two effects are, moreover, complementary: other-regarding preferences induce the last low-risk agents remaining to continue sharing with high-risk agents.

Interestingly, under altruism (where high risks agents could leave the cooperative to increase utility of others) the stability of cooperatives greatly reduces. Only a modified version of altruism, in which agents don't self-sacrifice, can restore stability.

More modeling would be interesting to investigate deeper the theoretical interaction between risk-aversion, other-regarding preferences and learning in risk sharing agreements. One way to enrich our model would be by making the creation process more sophisticated in order to look at the impact of a more rational cooperatives' creation process. We assume here that, at each time 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 he (they) use(s). Another way would be to explore sharing rules other than equal sharing either by exogenous or endogenous variations.

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Compliance with Ethical Standards

Conflict of interests The authors declare that they have no conflict of interest.

Appendix A: Constructing a cooperative segregation index

In the core paper, we introduced a segregation index in cooperatives and detail its meaning. To obtain this index we have modified the standard demographic index of dissimilarity which compares the composition of each neighborhood to the composition of the whole population. It is equal to 1 if the segregation is complete, that is, if all neighborhoods are composed of only one type of individual. It is equal to 0 if there is no segregation, that is, the composition of all neighborhoods is equal to the composition of the whole population. To adapt this index to our model, instead of considering neighborhoods we consider the cooperatives and compare their compositions to the population composition. In our case, the standard demographic index of dissimilarity is:

$$D = \frac{1}{2} \sum_k \left| \frac{n_k^l}{n^l} - \frac{n_k^h}{n^h} \right| \tag{14}$$

with n_k^l and n_k^h denoting the number of low-risk and high-risk agents in cooperative k. An isolated agent is considered to be a cooperative composed of only one agent, that is, a highly segregated cooperative. n^l (respectively n^h) denotes the total number of low-risk (resp. high-risk) agents in the population. This index is equal to 0 when the proportions of low- and high-risk agents in each cooperative are the same as in the whole society, and if no agent is isolated. It is equal to 1 when each cooperative is completely segregated (no cohabitation in cooperatives) or if all agents are isolated.

This index includes isolated agents and does not directly give an indication of cooperatives' composition. To correct this bias, we use a modified index based on the decomposition of the previous one in 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 set of isolated agents with a low-risk type (resp. high-risk type) we have:

$$SI = \frac{1}{2}\sum_{i\in\mathcal{I}_l}\frac{1}{n^l} + \frac{1}{2}\sum_{i\in\mathcal{I}_h}\frac{1}{n^h} \tag{15}$$

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. We then have:

$$0 \leq SC = \frac{1}{2}\sum_{k\in\mathcal{K}}\left|\frac{n_k^l}{n^l} - \frac{n_k^h}{n^h}\right| \leq 1 - SI \text{ and } D = SI + SC \tag{16}$$

With $\mathcal{K}$ the set of cooperatives. By normalizing SC, we obtain a segregation index on cooperatives $D_{\mathcal{K}}$ 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:

$$D_{\mathcal{K}} = \frac{SC}{1 - SI} \tag{17}$$

By convention $D_{\mathcal{K}} = 1$ if there is no cooperative.

Appendix B: General dynamics of the model

The first and simplest of the dynamics concerns learning. Our choice of parameters means that learning takes about 50 time steps (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 Fig. 7 using the dynamics of the number of cooperatives). The end of this convergence depends on the indicator, but it generally ends around $t = 100$. Then, indicators oscillate around their stabilized level, in what we call the "stabilized" regime.

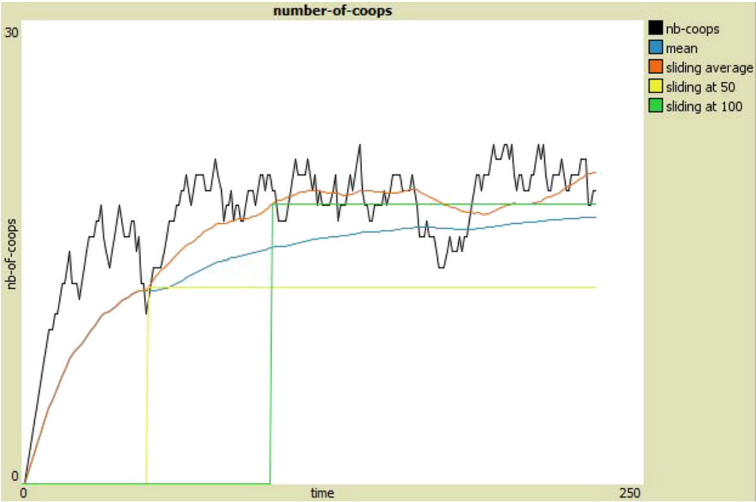

Fig. 7 Illustration of the different regimes based on the number of cooperatives. The moving average is the mean of the indicator over the last 50 periods. We observe sharp convergence during the learning regime, a smoother readjustment during the convergence regime and then oscillations around the "stabilized level". The vertical yellow and green lines indicate respectively the level reached at $t = 50$ and $t = 100$

Appendix C: The macro dynamics of the model

The macro dynamics of our model (an emerging phenomenon in ABM) is summarized in Fig. 8. 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 these 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 time step, it is the same size as this new cooperative. One agent is randomly picked to create a cooperative with his friends

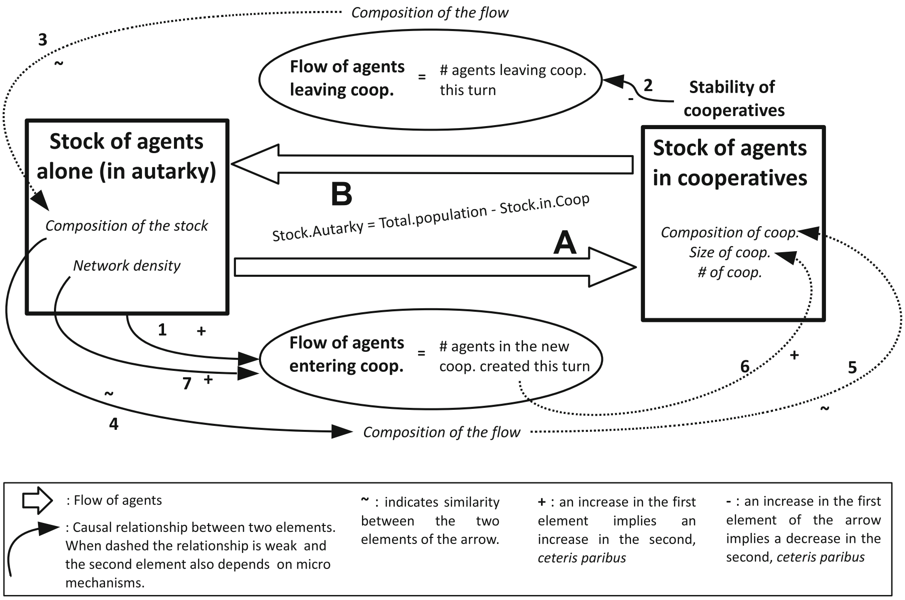

Fig. 8 Scheme of the macro dynamics of the model

and the friends of his friends. Thus, the larger the stock of isolated agents, the more likely the chosen agent is to find a lot of agents in his network to create his 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:

– 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). Then, 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 small fraction of agents in cooperatives implies a high instability of cooperatives at the micro level. Indeed, for the stock to be stable,

flows A and B have to be equal. Then, when there are few agents in cooperatives (and therefore a lot of agents in autarky), flow A is large and so flow B is large too, leading to the conclusion that cooperatives are unstable.

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 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.

Appendix D: Typical scenarios

In this section, we describe a typical run of the model, first without ORP then with altruism and with inequality aversion. These scenarios link macro and micro dynamics.

D.1 The baseline scenario: without ORP

Let us first describe the typical evolution of cooperatives with neither ORP nor learning. The effects of our various parameters can then be understood in terms of divergences 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 cooperative survival is extremely path-dependent, as is the composition of the leaving flow. This leads to high levels of segregation.

D.2 The scenario with altruism

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 25% high-risk against 75% 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. Moreover low-risk agents still leave but more slowly, and not all at the same time (as explained in the core paper, the most successful ones are "trapped" longer). 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 baseline 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 the macro level leads to lower segregation. At the same time due to the "sacrificial" effect, the leaving and entering flows are larger decreasing the overall fraction of agent in cooperative.

D.3 The scenario with inequality aversion

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 (for the same reasons exposed for altruism: most successful low-risk agents are "trapped" longer). 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 Appendix C). As agents of the same type leave their cooperatives at different times, they leave most of their friends behind and have fewer friends in autarky to create new cooperatives. Finally, as IA stabilizes small cooperatives, cooperatives are smaller on average.

Appendix E: The effect of inequality aversion on average segregation

To analyze further the non-linear effect of inequality aversion on segregation, Fig. 9 plots the average segregation index among1000 simulations, for various parameters of inequality aversion β.

This confirms the non-linear effect of inequality aversion on segregation, the (negative) impact being higher for high level of inequality aversion.

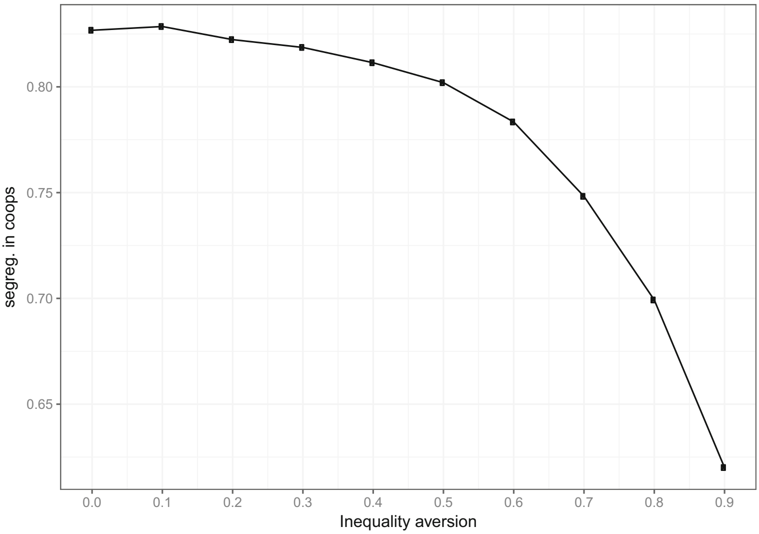

Fig. 9 The effect of inequality aversion on the average index of segregation when agents know their type and $\rho = 2.5$. (The average index of segregation over the 50 first time steps is averaged over 1000 simulations for each value of β))

Appendix F: Robustness checks

F.1 The effect of risk-aversion

The effect of risk-aversion is summarized in Fig. 10.

Risk aversion greatly improves the stability of cooperatives. Still, results are very path-dependent for high coefficient of (relative) risk-aversion, stabilizing a large variety of scenarios from low segregation to complete segregation.

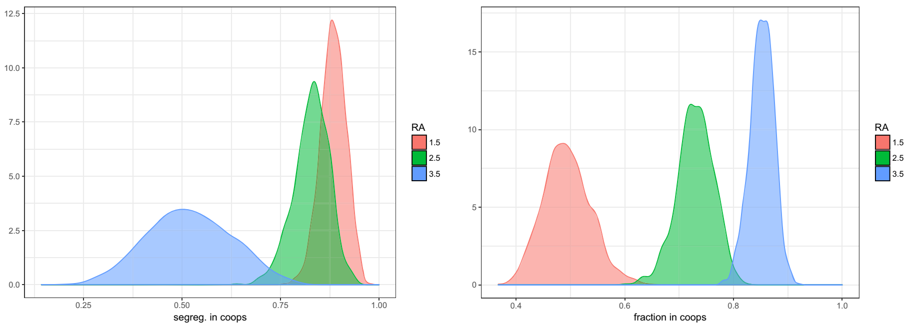

Fig. 10 The effect of risk-aversion (RA) without learning or ORP on the average level of segregation (left panel) and the average fraction of agents in cooperatives (right panel) over 50 steps

– 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).
– 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 phase. Nevertheless, high coefficients of RA also stabilize homogeneous cooperatives.
– A coefficient of 3.5 is a special case, where simulations are highly path-dependent. RA can stabilize both situations in which every cooperative is completely segregated and situations in which cooperatives are mixed.

F.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 inequality aversion. We abstract from learning, assuming that agents perfectly know their type from $t = 0$. Results are displayed in Figs. 11 and 12.

On segregation (Fig. 11). Segregation is maximal for the complete network. Without ORP, small world and random networks are equivalent. With inequality aversion, small world networks lead to less segregated cooperatives.

On the size of cooperatives (Fig. 12). Without ORP, the complete network tends to generate two completely segregated cooperatives. With inequality aversion, the complete network generates smaller cooperatives that are still 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

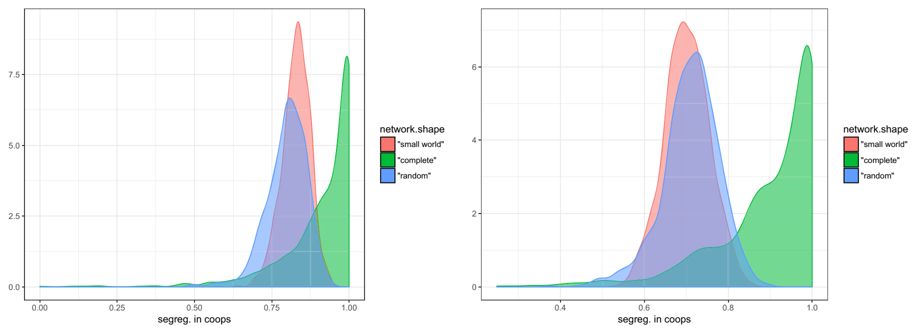

Fig. 11 The effect of network shape on the average segregation without ORP (left panel) and with inequality aversion ($\beta = 0.8$, right panel)

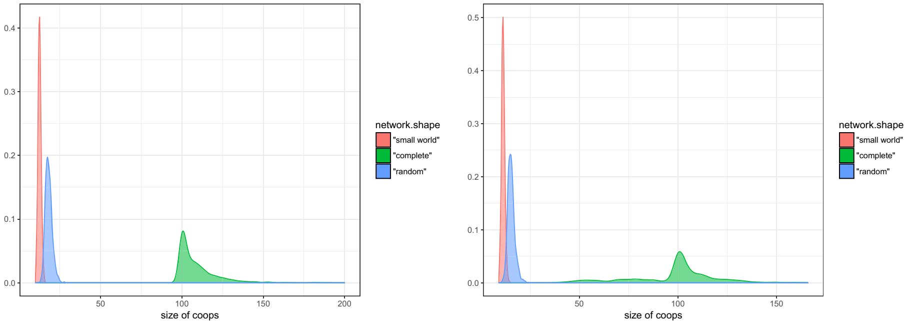

Fig. 12 The effect of network shape on the average size of cooperatives without ORP (left panel) and with inequality aversion ($\beta = 0.8$, right panel)

agent therefore creates the largest possible cooperative at each time step. 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 inequality aversion are driven by the stronger effect of inequality aversion in smaller cooperatives. In the case of the complete network, everybody is connected to everybody else, but cooperatives are too large for ORP 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 inequality aversion on segregation is thus slightly strongest in the small world network.

All these mechanisms also hold with altruism although there are larger effects on the size of the cooperative (due to the fact that, under altruism, the shape of the network also determines the agents toward whom one is altruistic).

We have also tested for endogenous evolving networks. The idea was that agents are able to drop some links to creates news ones inside their cooperatives. Each time step, with a certain probability, agents in cooperatives were able to do so. Counter intuitively this rewiring tends to increase segregation in cooperatives with altruism. Indeed the cooperatives are still more segregated than the network itself because in the network there is no correlation between my type and the type of my friends. The rewiring tends to create such a positive correlation: the composition of my friends will converge to the composition of my cooperative, which is segregated. Then the new cooperatives created will have more chance to be already segregated. Moreover, with sufficiently high probability of rewiring, the property of small world networks (high cliquishness and small average path) would no longer maintain and often the network splits.

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