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Bifurcations in business profitability: An agent-based simulation of homophily in self-financing groups☆

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ABSTRACT

Formal financial institutions inadequately distribute startup capital to business ventures of ethnic minorities, women, low-educated, and young people. Self-financing groups fill this gap because in these associations agents accumulate their savings into a fund that is later used to provide loans to the members. This study builds and simulates an agent-based model that compares the profitability of businesses started by members of self-financing groups against businesses financed by commercial loans. The results indicate that—besides the self-generation of debt capital—businesses of members of self-financing groups can have higher returns due to the consolidation of social capital and the competitive advantage created through a dual process of homophily. Higher quotas of savings boost profits, but only up to a threshold, after which a bifurcation pattern—typical of complexity dynamics—emerges. The practical and theoretical implications of the findings are discussed and future research lines are proposed.

1. Introduction

Small businesses have a cumulative economic impact on the economy due to their relevance for long-term economic growth, productivity and job creation—see Acs and Armington (2006) or Haltiwanger, Jarmin, Kulick, and Miranda (2016). In Sub-Saharan Africa for example, micro-enterprises employ an estimated 80% of the working population (Biekpe, 2004), while in Colombia small business represent 96% of the enterprises created annually (Santana, 2017).

Despite their remarkable relevance, Cheng (2015) and Berger and Udell (2006) note that the financing of small startups is limited by the informational opacity that hinders banks from assessing the profitability, survivability and financial credibility of small ventures. Moreover, ethnic minorities, women, low-educated and young people are disproportionately impacted by the difficulties in accessing financial resources for business startups, even in developed countries[1].

The limitations in business financing can be overcome through government grants and subsidized loans. Due to the high cost of these policies, disadvantaged groups also rely on emerging financing instruments such as loan guarantees, microcredits, crowd-funding, peer-to-peer lending and business angel investment (OECD, 2014). One additional financing option for entrepreneurs who want to start their own business is self-financing groups.

Self-financing groups are a form of community-based associations that act as small savings and loan cooperatives of individuals (Greaney, Kaboski, & Van Leemput, 2016). In a self-financing group, members agree to periodically provide an individual quota of savings with the aim of creating a collective pecuniary fund. The contribution is provided in group meetings during the life-cycle of a group. The fund of savings accumulated during the meetings is used for internal loan provision to the members.

Following Atlan (1991), self-financing groups can be conceptualized as a phenomenon of contextual complexity. Contextual complexity emerges from the communication among heterogeneous agents and the

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[1] Smallbone, Ram, Deakins, and Aldock (2003) for example found that ethnic minorities in the UK are less successful in accessing bank loans and thus have to appeal to informal sources of startup finance. Cheng (2015) further remarks that this form of lending discrimination is even more pronounced with women and entrepreneurs from minority groups, who face a higher rate of loan denial and have unequal access to commercial credit from formal financial institutions. In the context of entrepreneurial activities in Europe, the OECD policy brief on access to business startup finance for inclusive entrepreneurship (OECD, 2014) further highlights that low-educated and young people are more likely to mention financing problems as a major constraint on starting a business.

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interaction of their goals. This pattern is typical of self-financing groups, because in these associations heterogeneous members with bounded rationality actively interact with each other over time, pursuing both personal and group-level goals, before and after a startup venture.

Due to its versatility, agent-based modeling is a computational approach suitable to capture the contextual complexity of self-financing groups. Members of self-financing groups face budget constraints and can exhibit random behavior, limiting the applicability of the traditional paradigm of a representative, perfectly rational utility-maximizing agent (Farmer, Patelli, & Zovko, 2005). In an agent-based model of autonomous and non-homogeneous agents, as the one described in Macal and North (2010), rational effects are dominated by stochastic fluctuations, and emerging social and financial patterns arise from the interaction between the behavioral and strategic decisions of heterogeneous agents with bounded rationality (Ponta & Cincotti, 2018).

In the agent-based model herein, agents decide to join a self-financing group due to intra-household conflicts, homophily and lack of access to formal financial loans. The members of the group are selected by an autonomous agent, who optimizes a gender-composition criterion (i.e., a preference for women members). Default rates are a function of the individual behavior of agents and the interaction among agents. Homophily enables the creation of social capital among members, which is aggregated to the debt capital generated by the group to start up a business. The sequential simulation of the algorithms produces a complex system in which patterns emerge from the interaction of agents at the micro level (Pyka, Mueller, & Kudic, 2018).

The results of the computational experiments in this study indicate that—due to homophily and embedded relational dynamics—funding from self-financing groups can increase business profitability compared to businesses financed through external loans, but only up to a bifurcation threshold. Self-financing groups build social capital that is difficult to imitate, which contributes as an additional resource to the success of a businesses initiative. However, after a threshold in the savings quota, a bifurcation in profitability emerges as a consequence of household budget constraints, the mimicking default behavior of agents, and the high interest rates that self-financing groups tend to charge for internal loans.

The findings of this study fill the research gap left by studies that have been traditionally focused on formal financing of small businesses. The impact of providing formal credit to small and micro business has been largely studied by *inter alia* Tuyon, Mohammad, Junaidi, and Ali (2011), Shahriar, Schwarz, and Newman (2016), Newman, Schwarz, and Ahlstrom (2017), Evelyn and Osifo (2018) or Atmadja, Sharma, and Su (2018)—see also the review of Chen, Chang, and Bruton (2017). The conclusion of these studies is that formal financial institutions do not properly provide seeding to entrepreneurship, see for example Field, Pande, Papp, and Rigol (2013) or Nguimkeu (2014). By contrast, there has been limited research on the impact of financing small business through internal loans from self-financing groups, creating a research gap that this study fills.

This study also contributes to the field of agent based modeling and complexity in business by using homophily to extend the recent literature on strategic group formation. In strategic group formation, agents maximize their individual utility by deciding to join or leave a social group (Collins & Frydenlund, 2018). Under a resource-view approach, the maximization of utility in self-financing groups translates to acquiring more resources in the form of loans and/or social capital. This study argues that homophily plays an additional ancillary role in strategic group formation and can further promote business profitability up to a bifurcation point.

The rest of the study is organized as follows: Section 2 offers a conceptual overview of self-financing groups, agent-based modeling, social capital and homophily. Section 3 describes the agent-based model of self-financing businesses. Section 4 presents the results of simulating the model through computational experiments. Section 5 concludes and discusses the practical and theoretical implications of the findings. A replication package with `MatLab` codes and step-by-step instructions to reproduce the results is also provided in an online supplementary material[2].

2. Conceptual framework

2.1. Self-financing groups

Self-financing groups are community-based organizations formed by people related by affinities or a specific goal (Brody et al., 2015). The participants of a self-financing group join together to achieve individual and/or collective targets, which can be related to business startups, investment, consumption-smoothing, asset acquisition or economic empowerment. The members of the group achieve their objectives through the accumulation of savings, the provision of internal credit and the creation of an informal insurance fund.

The roots of self-financing groups can be traced back to two types of indigenous associations: rotating savings and credit associations (ROSCAs) and accumulating savings and credit associations (ASCRAs). In ROSCAs, there is no loan provision because the pooled fund of savings is distributed to the members in a rotating pattern. In ASCRAs, the savings are not instantly redistributed but are rather accumulated in order to make loans with a fixed maturity (Bouman, 1995).

Self-financing groups are promoted by formal banks, the government or non-governmental organizations, who develop their own group schemes based on the principles of ROSCAs and ASCRAs. According to le Polain, Sterck, and Nyssens (2018), the best-known facilitated self-financing models are the *village savings and loan association* initiated by CARE International, the *savings and internal lending communities* promoted by Catholic Relief Services and the *savings for changes* model promoted by Oxfam and Freedom from Hunger. In India, the National Bank for Agricultural and Rural Development (NABARD) steered the concept of self-help groups focused on the management of savings and credit (Pillai & Abraham, 2017).

Biggart (2001) relates the existence of self-financing groups to five situational circumstances: a communally-based social order, obligations that are held to be collective in nature, social and economic stability, social and economic isolation, and similarity between members. The research evidence has also discussed the importance of self-financing groups for capital accumulation (Alila, 1998), investment (Hospes, 1995), asset accumulation (Annan, Bundervoet, Seban, & Costigan, 2013), the promotion of income generating activities—Allen (2006), Ksoll, Lilleør, Lønborg, and Rasmussen (2016) or Flynn and Sumberg (2018)—and the generation of social capital (Ban, Gilligan, & Rieger, 2015).

Garikipati (2008) offers concrete examples about how self-financing groups can increase trust, which is the basis for social capital. For example, members of a self-financing group may help each other with childcare and livestock care without an explicit payment, or may help other members in finding waged work. Feigenberg, Field, Pande, Rigol, and Sarkar (2014) provide experimental evidence that shows that meetings of self-financing groups also aid to build social capital, measured by the number of times the members talk with each other about businesses.

2.2. Social capital and homophily

Loury (1977) define social capital as naturally occurring social relationships aimed at promoting valued skills. Bourdieu and Wacquant

[2] The MatLab replication package is freely available at: https://nl.mathworks.com/matlabcentral/fileexchange/73961-agent-based-model-of-nano-finance-groups

(1992) understand social capital as resources accruing from a durable network, institutionalized through mutuality of acquaintance and recognition. Cooke and Wills (1999) make an additional distinction between human capital and social capital: while both refer to acquired skills, qualifications and capabilities, in social capital assets are less capable of formal certification.

Nahapiet and Ghoshal (1998) propose three facets of social capital: structural, relational and cognitive. The structural dimension refers to the degree of connectivity (the network) between agents. The relational dimension—which is based on trust and trustworthiness (Fukuyama, 1995), identity and identification (Hakansson & Snehota, 1995)—is based on the nature and characteristics of relationships, which can be competitive or cooperative. The cognitive dimension is a shared cognitive system of representations among agents, which can improve interpersonal communication and enhance relationships between members within an organization (see Jiang & Liu, 2015, page 130).

Edwards and Foley (1997) raise two additional issues in the study of social capital: availability and equality. First, social capital is not equally available to all individuals, because geographic and social isolation limit the access to this resource. Second, not all social capital is created equal: the value of a specific source of social capital depends on the socioeconomic position of the individual within society. This inequality implies that agents will have heterogeneous levels of social capital depending on their socioeconomic and geographical characteristics (Hsung, Fu, & Lin, 2017).

Theoretically, the importance of social capital for businesses can be seen from a resource-view approach if social capital is conceptualized as a source of competitive advantage that adds value to a venture, as in Jiang and Liu (2015). For instance, Bourdieu (1986) interprets social capital as an aggregate of actual or potential resources, again linked by a durable network of relationships, mutual acquaintances and recognition. Lin (2001) likewise suggests that social capital consists of resources embedded in social networks accessed and used by agents.

The resource-view approach to social capital has led Batjargal (2003) to propose that heterogeneity in the structural, relational and resource-based aspects of social capital is reflected in various aspects of business performance. The agent-based model of this study is based on the premise of Batjargal (2003): self-financing groups build social capital that is difficult to imitate and thus contribute as an additional resource to the success of a business initiative. Through a process of homophily, embedded relations—that improve coordination and reduce organizational conflict—influence purchase and sale decisions of entrepreneurs.

McPherson, Smith-Lovin, and Cook (2001) define homophily as the principle that people tend to group with others who are like them. According to Collins and Frydenlund (2018), the factors that determine homophily include gender, religion, social class, education and other intrapersonal or behavioral characteristics. Granovetter (1985) and Jiang and Liu (2015) argue that intrapersonal and behavioral characteristics of members of a group create dense ties that support stronger reciprocity and greater trust. Social capital emerges from these dense ties, which minimize monitoring and transaction costs by reducing opportunistic behaviors (Uzzi, 1997).

2.3. Agent-based modeling

Agent-based modeling can be traced back to the developments of complexity theory and artificial intelligence—see Weisbuch (1991), Kauffman (1993), Order (1995), Langton (1997) or Macal and North (2010). Complexity analyzes patterns and structures that emerge from interactions (Kirman, 2010). Artificial intelligence, in turn, is a subfield of computer science aimed at building agents that exhibit aspects of intelligent behavior in terms of autonomy, social ability, reactivity and pro-activeness (Wooldridge & Jennings, 1995). Based on the interactions among intelligent agents, agent-based models produce insights that guide decision-making, help to solve complex problems and simulate real-life phenomena.

Hamill and Gilbert (2016) define an agent-based model as a computer program that creates an artificial world of heterogeneous agents and enables the investigation of their interactions. In this artificial world, agents react to other agents, pursue goals, communicate with other agents and move around within the environment (Wooldridge & Jennings, 1995).

According to Macal and North (2010), an agent-based model has three elements:

(i) A set of agents, with attributes and behaviors.
(ii) A set of agent relationships and methods of interaction, i.e. a topology of connectedness that defines how and with whom agents interact.
(iii) The environment. Besides interacting with other agents, agents can in some cases also affect their environment.

Following Lemos (2017), an agent $\mathcal{A}$ can be defined as a computer system that is situated in some environment and is capable of perceiving, deciding and performing actions in an autonomous way. Formally, let $E \in \mathbb{Z}^+$ be the set of possible environment states, and let $A \in \mathbb{Z}^+$ be the set of actions available to $\mathcal{A}$, then the sequence of environment states alternating with actions of $\mathcal{A}$ can be defined using the run of simulations $\mathcal{R}$, where $\mathcal{R}^A \subset \mathcal{R}$ is the subset of runs ending with an action, and $\mathcal{R}^E \subset \mathcal{R}$ the subset of runs ending with an environment state. Based on the definitions above, an agent will be a function that maps runs ending in environment states into actions: $\mathcal{A}: \mathcal{R}^E \mapsto A$ (see Wooldridge, 2009).

An agent-based topology defines how agents are connected to each other. Typical topologies are cellular automata (Wolfram, 2018), the Euclidean space, networks where nodes are the agents and the links are relationships (El-Sayed, Scarborough, Seemann, & Galea, 2012), spatial grids—based on a geographic information system (GIS)—and aspatial topologies where agents have no location because it is not relevant for the simulation at hand.

In some models, agents can also affect and modify their environment when the collective action of multiple agents causes changes in the environmental state in which agents operate, thereby generating the map $A \mapsto \mathcal{R}^E$. See *inter alia* Sengupta and Bennett (2003), who use a model of agents distributed in a geographical environment to simulate the ecological and economic impacts of agricultural policies.

Emerging patterns are also a characteristic of agent-based models. As Macal and North (2010) highlight, both the heterogeneity of agents and self-organization are features of agent-based simulation that allow the emergence of complexity patterns. This emergence differentiates agent-based models from other simulation techniques, such as discrete-event simulation and system dynamics.

3. Agent-based model of self-financing businesses

Small businesses play an important role in economic growth and socioeconomic development (Tuyon et al., 2011). Startup businesses normally confront a shortage of capital and limited access to loans from formal commercial banks and thus have to draw upon informal sources of startup finance, such as micro-credits provided by formal finance institutions or internal loans obtained from informal self-financing groups.

The agent-based model of this study aims to simulate the profitability of businesses financed by self-financing groups. The business profitability of the self-financing group is compared to the profitability of a counterfactual business financed with external loans from a formal financial institution.

In the agent-based simulation of self-financing groups (henceforth, ABS-SFG):

— The set of active agents are (i) women and men of the working population in an artificial community, and (ii) an autonomous agent

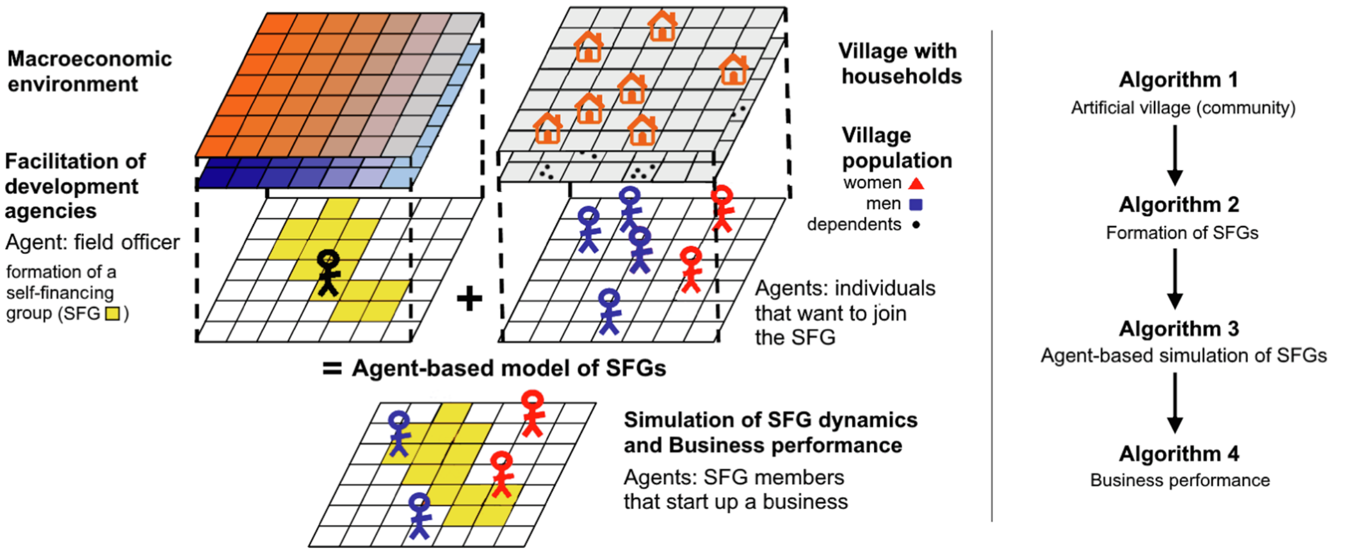

Fig. 1. Schematic representation of the agent-based model of self-financing groups (adapted from Rebaudo et al. (2011)). The figure illustrates the multilayered structure of the ABS-SFG model: SFG dynamics and business performance are the result of the interaction between external factors—the macroeconomic environment and the facilitation mechanisms of development agencies—plus the internal behavior of the individuals in the artificial community and the members of the self-financing group. The model is a sequence of four algorithms: Algorithm 1 randomly creates an artificial population inhabiting households in a village: working-age women, working-age men and household dependents (children and the elderly). Based on socioeconomic characteristics, homophily and intra-household conflict, some individuals of the working-age population want to join the SFG. In Algorithm 2, an agent hired by a development agency (the field officer) forms a SFG by choosing members from the individuals that want to be part of the SFG. Member selection is based on a gender rule (a preference for women). Algorithm 3 simulates the dynamics of the self-financing group: members allocate their savings into a common fund in each meeting and then take a joint loan from the accumulated fund. Social capital is created through homophily as the result of participating in the SFG. Algorithm 4 simulates the financial performance of a business started by the SFG members that do not fail to contribute with their savings. The performance of the business of the SFG is compared with the performance of a counterfactual business financed by a loan obtained from a formal financial institution.

in charge of creating the self-financing group. Passive agents are children and the elderly in the community, who do not make decisions but influence the behavior of active agents.

— The topology is defined in the Euclidean space $\mathbb{R}^n$, i.e. the set of all real n-tuples $\mathbb{R}^n = \{(p_1, \ldots, p_n)|p_j\}$ for a real number p_j in $j = 1, 2, \ldots, n$ (Abbena, Salamon, & Gray, 2017). The connectedness of the agent-based model in the Euclidean two-dimensional space $\mathbb{R}^2$ is calculated using (i) the Euclidean distance between households and (ii) the Euclidean distance between the intrinsic demographic characteristics of individuals.

— The environment is defined only by the interaction of agents with other agents. Agents cannot change their environment.

The computational ABS-SFG model is a multilayered simulation of four algorithms that run sequentially in two phases (Fig. 1). The agent-based simulation illustrated in Fig. 1 is a 'microverse' containing the dynamics and environment of self-financing groups, as in Guterman, Harmon, and Roiland (2015). The model creates an artificial world that emulates the behavior of the members of self-financing groups in a village, as in the second-order *simulacra* of Baudrillard (1994), who inspired the simulated reality of Wachowski and Wachowski (1999).

The four stages of the ABS-SFG model can be grouped into an initialization phase (Algorithms 1 and 2) and a running phase (Algorithms 3 and 4). In the first stage, the model starts simulating a community of agents in an artificial village (Algorithm 1). In the second stage, a self-financing group is formed by an agent that selects members from the individuals in the artificial village who want to be part of the group (Algorithm 2). In the third stage, heterogeneous agents in the self-financing group interact with each other to accumulate social and debt capital (Algorithm 3). In the last stage, an internal loan is provided to agents for the creation of a business venture and the profitability of a self-financing business is compared with the profitability of a counterfactual business of non-members financed by a loan from a formal financial institution (Algorithm 4).

Table 1 shows the submodels in the algorithms and lists the variables/traits included in each submodel. Table 1 also indicates which equations are used to calculate the traits in each submodel and further clarifies whether values are predetermined or produced by the model. The next subsections describe in detail the equations and submodels in each algorithm.

3.1. Algorithm 1: Artificial community

Box 1 shows the first algorithm of the simulation model. Based on the number of households (H), random numbers from probability distributions are used to create an artificial community of agents that have three demographic characteristics: age (a), gender (g), and the number of dependent individuals in the household (i.e. children and the elderly, δ_h).

The h-households in the village ($h = 1, 2, \ldots, H$) are populated with i-individuals based on the numerical values of a centered probability mass function generated from a discrete Poisson distribution:

$$i_h(\lambda_h) = \lambda_h + \exp^{-\lambda_h} \frac{\lambda_h^{i_h}}{i_h!}, \tag{1}$$

The stochastic function in Eq. (1) was chosen to populate the households following Jennings, Lloyd-Smith, and Ironmonger (1999) and Jennings and Lloyd-Smith (2015), who show that a Poisson process is suitable for modeling household size distribution. The number of productive individuals in the household (δ_h) is obtained from random numbers of a discrete uniform distribution (Eq. (2)), while the gender of

Table 1
Structure of the agent-based simulation of self-financing businesses (ABS-SFG)

Phase/algorithm		Variables/traits in each submodel	Equations
Initialization			
Algorithm 1: Generation of an artificial community			
	Households	° Family size	Centered Poisson distribution (Eq. (1))
		° Intra-household productive individuals	Uniform discrete distribution (Eq. (2))
		° Intra-household gender composition	Uniform discrete distribution (Eq. (3))
	Village (community)	• Number of households in the village	None (initialization parameter)
		° Age profile in the village	Mixture of uniform distributions (Eq. (4))
		° Income profile in the village	Log-normal distribution (Eq. (5))
Algorithm 2: Formation of a self-financing group (SFG)			
	Agents that want to join the SFG	° Probability of joining a SFG	Mixture of probabilities (Eq. (6))
		° Social bonds (homophily)	Sigmoid function (Eq. (7))
		° Geographical distance (homophily)	Sigmoid function (Eq. (8))
		° Intra-household conflicts	Sigmoid function (Eq. (9))
		° Lack of access to financial services	Sigmoid function (Eq. (10))
	Field officer (agent)	° Gender ratio of women in the SFG	Conditional function (Eq. (11))
Running phase			
Algorithm 3: SFG dynamics of savings accumulation and formation of social capital			
	Savings allocation across meetings	° Probability of not contributing with savings	Stochastic inequality (Eq. (12))
		° Group-level probability of default in savings	Hyperbolic tangent (Eq. (13))
		• Amount of savings quota of each member	None (simulation parameter)
		• Mimicking behavior	None (simulation parameter)
	Members of the SFG (agents)	° Idiosyncratic probability of default in savings	Mixture of probabilities (Eq. (14))
		° Income of SFG members	Sigmoid function (Eq. (15))
		° Age of SFG members	Sigmoid function (Eq. (16))
		• Gender risk of not contributing to the SFG	None (simulation parameter)
	Savings accumulation	° Savings accumulation in the common box	Accumulation of contributions (Eq. (17))
		° Adaptative rule in the case of default	Stochastic addition of savings (Eq. (18))
		• Threshold of SFG failure	None (simulation parameter)
	Social capital	° Social capital (function of homophily)	Homophily among members (Eq. (19))
		° Impact of participating in SFG	Scale factor (Eq. (20))
		° Age differences among members	Inverse Euclidean distance (Eq. (21))
		° Income differences among members	Inverse Euclidean distance (Eq. (22))
		° Household distance among members	Euclidean distance (Eq. (23))
Algorithm 4: Loan provision and business simulation			
	Loan allocation	° Probability of receiving a loan	Social capital and income (Eq. (24))
		• Risk aversion (ex ante)	None (simulation parameter)
		° Risk aversion (ex post)	Updated risk aversion (Eq. (25))
		° Amount of the loan allocated to borrowers	Fraction of total savings in the box (Eq. (26))
		° Effective interest rate charged to loans	Interest rate plus risk aversion (Eq. (27))
	Business performance	• Fraction of assets allocated to inventory	None (simulation parameter)
		• Impact of the macroeconomic environment	None (simulation parameter)
		° Total amount of debt (principal + interest)	Debt function (Eq. (28))
		° Inventory	Initial inventory (Eq. (29))
		° Retail sales	Income gained from sales (Eq. (30))
		° Cash flow	Income flow minus loan repayments (Eq. (31))
		° Utility (returns)	Returns minus random expenses (Eq. (32))
		° Average assets	Assets over the period (Eq. (33))
		° Returns on assets (ROA)	Returns divided by average assets (Eq. (34))
		° Market sales	Function of social capital (Eq. (35))

Notes on simulation values.
(•) Predetermined.
(°) Produced by the model.

each individual (g_i) is obtained from numerical values of a conditional uniform discrete distribution (Eq. (3)):

$$\delta_h \sim \mathcal{U}(1, u_\delta) \tag{2}$$

$$g_i | \delta_h \sim \mathcal{U}(1, u_{\delta,g}), \quad u_{\delta,g} = 2u_\delta. \tag{3}$$

The age of each i-individual (a_i) is produced from a mixture of discrete uniform distributions:

$$a_i \sim \mathcal{MU}(\alpha_a) = \sum_{j \in \mathcal{Z}^{1,2,3}} \mathcal{U}_{ij}(1, u_{age}) + \sum_{j \in \mathcal{Z}^{4,5}} \mathcal{U}_{ij}\left(1, \tfrac{1}{2}u_{age}\right). \tag{4}$$

The income (y_i) of the working population in the village is generated using random numbers from a log-normal distribution:

$$f(y_i|\mu_g, \sigma_g) = \frac{1}{y_i\sigma_g\sqrt{2\pi}}\exp^{\frac{(\ln y_i-\mu_g)^2}{2\sigma_g^2}}, \tag{5}$$

where $g \in \{w, \neq gw\}$ is a gender index for women (w) and men ($\neq gw$), under the assumption that men in the population have (on average) higher income than women ($\mu_{\neg w} > \mu_w$) and less dispersion around the average income ($\sigma_{\neg w} < \sigma_w$). The stochastic function for income was chosen as log-normal because although income follows a Pareto law in the upper tail, the distribution of the low-income population is normally described with a log-normal distribution; see for example Souma (2001) or Banerjee, Yakovenko, and Di Matteo (2006). The assumption about the difference of the distribution of income for women is based on evidence about the polarization of women's employment and income, which has been related to occupational segregation, discrimination, work-life balance, part-time work, career patterns across the life cycle and labor mobility—see Hakim (2016).

The first stage of the simulation produces a population matrix $\mathbf{P}_{\mathcal{A}_i}$ with the following agent's characteristics: household location (h) of agents, identification of individuals (i_h) in the population, gender (g_i), number of dependents in a household (δ_h), age of the agents (a_i) and income (y_i). See Box 1 below.

households in the village (ψ_i^h), the social connections among productive individuals (s_i), and intra-household conflicts (h_i^c):

$$\mathbb{P}_i(m) = \omega_{\mathbb{P}_i(m)}^2\mathbb{P}(f_i^a) + (1-\omega_{\mathbb{P}_i(m)})^2(\mathbb{P}(\psi_i^h) + \mathbb{P}(s_c) + \mathbb{P}(h_i^c)) \tag{6}$$

$$\mathbb{P}(f_i^a) = 1 - \frac{1}{1+\mathrm{e}^{1-y_{h,i}}} \tag{7}$$

$$\mathbb{P}(\psi_i^h) = \frac{1}{1+\mathrm{e}^{1-(\sum_i^N\sqrt{(h_i-h)^2})^{-1}}} \tag{8}$$

$$\mathbb{P}(s_i) = \frac{1}{1+\mathrm{e}^{1-i_{h,p}}} \tag{9}$$

$$\mathbb{P}(h_i^c) = \frac{1}{1+\mathrm{e}^{1-i_{h,\neg p}}} \tag{10}$$

In Eq. (6), $\omega_{\mathbb{P}_i(m)}$is the weight—the importance—that individuals assign to lack of formal financial access, $\mathbb{P}(f_i^a)$. Lack of financial access in Eq. (7) is based on the probabilistic transformation of the income of each individual in a household ($y_{h,i}$). Demirgüç-Kunt, Beck, and Honohan (2008) argue that cost-effective micro-financial services are not available to the extreme poor due to the imbalance between the fixed transactions costs of formal financial institutions and the small transactions and low demand of the extreme poor, which cannot be compensated with higher interest rates. Stiglitz and Weiss (1981) add that, in the presence of imperfect and costly information, the expected rate of return of banks increases less rapidly than the interest rate and, beyond a point, may actually decrease, thus generating a credit-rationing effect in formal banking. Hence, the low income of the agents in a village reduces the probability of having access to a formal loan from a financial institution.

Box 1. Algorithm 1: Artificial community

Data: $H, \lambda_h, u_\delta, u_{age}, \mu_g, \sigma_g$
Result: $\mathbf{P}_{\mathcal{A}_i} \ni \{h, i_h, \delta_h, g_i, a_i, y_i\}$
for $H \leftarrow h$ **do**
 $i_h(\lambda_h) = \lambda_h + \exp^{-\lambda_h}\frac{\lambda_h^{i_h}}{i_h!}$
 $\delta_h \sim \mathcal{U}(1, u_\delta)$
 for $i_h \leftarrow i$ **do**
  $g_i|\delta_h \sim \mathcal{U}(1, u_{\delta,g}), \quad u_{\delta,g} = 2u_\delta$
  $a_i = \sum_{j\in\mathcal{Z}^{1,2,3}}\mathcal{U}_{ij}(1, u_{age}) + \sum_{j\in\mathcal{Z}^{4,5}}\mathcal{U}_{ij}\left(1, \frac{1}{2}u_{age}\right)$
  $f(y_i|\mu_g, \sigma_g) = \frac{1}{y_i\sigma_g\sqrt{2\pi}}\exp\left(\frac{(\ln y_i-\mu_g)^2}{2\sigma_g^2}\right)$
 end
end

3.2. Algorithm 2: Formation of a self-financing group

In the second algorithm, an autonomous field agent $\mathcal{A}_f$ creates a self-financing group by selecting members from the subset of the individuals $P_{\mathcal{A}_i}$ of the population $\mathbf{P}_{\mathcal{A}_i}$ who want to join the group ($P_{\mathcal{A}_i} \subset \mathbf{P}_{\mathcal{A}_i}$). Due to the probabilistic nature of the agent's wish to join a SFG—and due to the optimization decision of the autonomous field agent when deciding on gender composition—the m-number of members of a self-financing group is not programmed in the model, but is rather one of the emerging patterns produced by the model.

Following the theory of strategic group formation (Collins & Frydenlund, 2018), agents join or leave a group in order to gather social and financial resources. Besides this utility maximizing behavior, homophily plays a role in the formation of self-financing groups. In the ABS-SFG model, the probability $\mathbb{P}_i(m)$ of i-agents wishing to join a self-financing group is a quadratic mixture of the probabilities related to their lack of financial access (f_i^a), the geographical proximity among

Homophily is implemented through the sigmoid functions (8) and (9), which transform to probabilities the geographical proximity of households (Eq. (8)), as well as the connections among productive individuals (Eq. (9)). Homophily plays a dual role in self-financing groups: during group formation and during the life-cycle of the group. During group formation, homophily interacts with the utility maximization behavior of agents who seek resource acquisition, because self-financing groups are generally formed by peers who share similar socioeconomic and demographic characteristics. During the life-cycle of the group, homophily consolidates social capital and reduces the risk aversion among agents.

In order to measure the probability of joining a group based on geographical homophily, the Euclidean distance between agent's households (d_h) is given by $\|d_i\| = (\sum_i^N \sqrt{(h_i - h)^2})^{-1}$, and this distance is converted to a probability measure through the sigmoid function of Eq. (8), which assigns more homophily to individuals living in households near the center of the village. The probability of joining a group due to social homophily in Eq. (9) is based on the probabilistic transformation of the number of productive individuals in a household ($i_{h,p}$). Households with a large number of productive individuals have more social connections with other productive agents, and thus have a higher probability of joining a self-financing group.

Finally, intra-household conflicts (Eq. (10)) are measured by the number of dependents in a household ($i_{h,\neg p}$), since a large number of dependent children and retired elderly can lead to higher intra-household conflicts among productive members in relation to investment decisions, and thus can increase the probability of agents joining self-financing groups. Conflictual interactions within a household has been put forward by Anderson and Baland (2002) as one of the main reasons to join self-financed groups when there are asymmetric preferences between men and women about investment in household goods.

The set of members that want to be part of the self-financing group ($P_{\mathcal{A}_i}$) is obtained with a rejection sampling algorithm in which the candidates are agents $\mathbf{P}_{\mathcal{A}_i}$ for which the mixture probability $\mathbb{P}_i(m)$ in Eq. (6) is higher than a random number $u_m \sim \mathcal{U}(0, 1)$, where $\mathcal{U}(\cdot)$ is a standard continuous uniform distribution.

The autonomous field agent $\mathcal{A}_f$ selects the $\mathbb{M}_{\mathcal{A}_i}$ members of the self-financing group from the set of individuals that want to be part of the group, $\mathbb{M}_{\mathcal{A}_i} \subset P_{\mathcal{A}_i}$ ($P_{\mathcal{A}_i} \subset \mathbf{P}_{\mathcal{A}_i}$). The autonomous field agent $\mathcal{A}_f$ that forms a group is commonly called 'field officer' by development agencies. Self-financing groups are promoted by development agencies that hire and pay an agent—the field officer—to create, train and supervise a group; see Allen and Panetta (2010).

The criterion of a field officer $\mathcal{A}_f$ for selecting the members $x_i \in \mathbb{M}_{\mathcal{A}_i}$, $i = 1, 2, \ldots, m$, is to have more women than men in the group. This positive gender discrimination is related to the fact that facilitating agencies—which pay and instruct the field officer $\mathcal{A}_f$—tend to target women because they consider women to make a higher contribution to family welfare, since women give priority to spending their earnings on their children (GGuha & Guptauha & Gupta, 2005). Rasmussen (2012) also attributes the gender focus of self-financing groups to women's economic resilience, since savings enable women to handle income shocks and confront unforeseen emergencies such as illness or loss of employment (Ghosh & Vinod, 2017).

Formally, when selecting the members $\{x_1, x_2, \ldots, x_m\} \in \mathbb{M}_{\mathcal{A}_i}$ from the potential set of candidates $P_{\mathcal{A}_i}$, an artificial agent $\mathcal{A}_f$ wants to achieve a gender ratio of women to men τ higher than $\tau_w \in (0,1]$,

$$S_{\mathcal{A}_f}(P_{\mathcal{A}_i}, \tau) = \begin{cases} x_1, x_2, \ldots, x_m & \text{if } \tau \geqslant \tau_w \\ \varnothing & \text{else} \end{cases} \tag{11}$$

Eq. (11) is computationally equivalent to a *while* loop. See the algorithm in Box 2 below.

Box 2. Algorithm 2: Formation of a self-financing group (group creation and members' selection)

Data: $\mathbf{P}_{\mathcal{A}_i} \ni \{h, i_h, g_i, \delta_h, a_i, y_i\}$
Result: $\mathbb{M}_{\mathcal{A}_i} \subset P_{\mathcal{A}_i} \subset \mathbf{P}_{\mathcal{A}_i}$
$\mathbb{P}_i(m) = \omega^2_{\mathbb{P}_i(m)} \mathbb{P}(f_i^a) + \left(1 - \omega_{\mathbb{P}_i(m)}\right)^2 \left(\mathbb{P}(\psi_i^h) + \mathbb{P}(s_i) + \mathbb{P}(h_i^c)\right)$
$\mathbb{P}(f_i^a) = 1 - \frac{1}{1+\mathrm{e}^{1-y_{h,i}}}$
$\mathbb{P}(\psi_i^h) = \frac{1}{1+\mathrm{e}^{1-(\sum_i^N \sqrt{(h_i-h)^2})^{-1}}}$
$\mathbb{P}(s_c) = \frac{1}{1+\mathrm{e}^{1-i_{h,p}}}$
$\mathbb{P}(h_i^c) = \frac{1}{1+\mathrm{e}^{1-i_{h,\neg p}}}$
$u_m \sim \mathcal{U}(0,1)$
if $\mathbb{P}_i(m) > u_m$ **then**
  $i_h \in P_{\mathcal{A}_i}$
else
  $i_h \notin P_{\mathcal{A}_i}$
end
while $\tau < \tau_w$ **do**
  $S_{\mathcal{A}_f}(P_{\mathcal{A}_i}, \tau)$
  if $\tau \geq \tau_w$ **then**
    $\{x_1, x_2, \ldots, x_m\} \ni \mathbb{M}_{\mathcal{A}_i}$
  else
    $\emptyset$
  end
end

3.3. Algorithm 3: Agent-based simulation of self-financing groups and formation of social capital

Algorithm 3 simulates the dynamics of savings accumulation as well as the formation of social capital among the members of a self-financing group. In the agent-based simulation, the emerging patterns of members' default and fund accumulation are the result of (*i*) the interactions among members and (*ii*) an adaptive rule—a rule that changes the rules—for savings accumulation, which is activated when a large number of members do not contribute with their savings to the group.

In a self-financing group, each $i = 1, 2, \ldots, m$-member contributes a ρ amount of savings to a common fund during the life-cycle of the group (Burlando & Canidio, 2017). This life-cycle is a round of meetings $1, 2, \ldots, t$ where the members get together to contribute their quota of savings to the common fund. In the ABS-SFG model, the number of meetings t is equal to the number of members m in a group, to account for the fact that larger groups need longer organizational periods.

The number of members of a group (m) is not predetermined but is rather an emergent parameter produced by the interactions of agents in the model. The m number of members of the simulated groups is similar to the number of members observed in real life: around 20 members. Bisrat, Kostas, & Feng (2012) notes that SFGs have this number of members because—although more members allow to accumulate a larger sum of money over a cycle—too many members involve a greater number of administrative problems, thus creating an incentive to keep the number of participants to around 20 members.

A member of a self-financed group enters a state of default *in savings* if the agent does not contribute his/her quota of savings during a meeting t. In the model, this default state is modeled as an inequality between the idiosyncratic probability of default $\mathbb{P}_i(d_s)$ and the group-level extrinsic probability of default $\mathbb{P}_e(d_s, t)$:

$$\mathbb{P}_i(d_s) > \mathbb{P}_e(d_s, t) + u, \quad u \sim \mathcal{U}(0, 1), \tag{12}$$

where u is a random component from a uniform distribution $\mathcal{U}(0, 1)$ that models the unexpected events that can increase the probability of default in savings.

The idiosyncratic probability of default $\mathbb{P}_i(d_s)$ is a convex combination of each member's intrinsic probability of default, related to age (a_i) and income (y_i), and weighted by gender (γ_g):

$$\mathbb{P}_i(d_s) = \gamma_g(\omega_{d_s}\mathbb{P}_{d_s}(a_i) + (1 - \omega_{d_s})\mathbb{P}_{d_s}(y_i)) \tag{13}$$

$$\mathbb{P}_{d_s}(a_i) = 1 - \frac{1}{1 + e^{1-(\sum_i^m \sqrt{(a_i - a)^2})^{-1}}} \tag{14}$$

$$\mathbb{P}_{d_s}(y_i) = 1 - \frac{1}{1 + e^{1-y_i}} \tag{15}$$

where $\gamma_g \in \mathbb{R}^{0,1}$ and $\omega_{d_s} \in \mathbb{R}^{0,1}$ are predetermined parameters, $\mathbb{P}_{d_s}(a_i)$ is the probability of default related to the age of an agent, and $\mathbb{P}_{d_s}(a_i)$ is the probability of default related to the income of an agent.

In Eq. (13), the parameter $\gamma_g \in \mathbb{R}^{0,1}$ measures higher female repayment rates when $\gamma_g \to 1$, as reported in, for example, Mayoux (2000) or Gonzales Martínez, Aguilera-Lizarazu, Rojas-Hosse, & Blanco (2019). The probability of default related to the age of an agent $\mathbb{P}_{d_s}(a_i)$ in Eq. (14) is calculated using the inverse Euclidean distance from the centroid of the age in the group. The parameter ω_{d_s} is the weight (the importance) of age for the probability of default in savings. $\mathbb{P}_{d_s}(y_i)$ is the probability of default related to the income of an agent. Individuals with low income, compared to the rest of the members, have a higher probability of entering a state of default in savings. Likewise, individuals in the tails of the age distribution (young and older members) have a higher probability of default, compared to other members. Gender is included as an interaction term, assuming that women are financially more reliable and thus have a lower probability of entering a default state compared to men—see Abbink, Irlenbusch, & Renner (2006) or D'espallier, Guérin, & Mersland (2011).

The extrinsic probability of default $\mathbb{P}_e(d_s, t)$ depends on group-level characteristics that arise from the interaction among members, the amount of savings contribution and the stage of meetings in the life-cycle of the group:

$$\begin{cases} \mathbb{P}_e(d_s, t) := \tanh z_e \equiv \frac{\sinh z_e}{\cosh z_e} = \frac{e^{z_e} - e^{-z_e}}{e^{z_e} + e^{-z_e}} \\ z_e = 1 - \beta(\rho + \sqrt{m} - t). \end{cases} \tag{16}$$

In Eq. (16), ρ is the individual amount of savings that each agent has to contribute to the common fund. Higher amounts imply a higher burden for the individuals and thus increase the probability of default. Parameter t is added to the default threshold z_e to reflect the fact that the probability of entering a default state increases over time. Conversely, $\sqrt{m}$ reduces the probability of default in larger groups, because peer pressure in such groups can act as a savings commitment device. For example, Kast, Meier, & Pomeranz (2012) conducted a randomized trial with microentrepreneurs in Chile and found that peers in savings groups provide a mutual service by regularly holding each other accountable for setting savings goals and regularly reminding each other of these goals.

Agents that enter into a state of default in a meeting $t - 1$ will also affect the behavior of other agents in the next meeting t, because non-defaulting agents that mimic the behavior of defaulting agents will fail to deliver their quota of savings. This mimicking behavior is modeled in Eq. (16) through a switching parameter $\beta \in \{\beta_d, \beta_{\neg d}\}$ that changes when agents enter a default state d in the group ($\beta_d > \beta_{\neg d}$). The predetermined parameter of mimicking behavior β increases the chances that the rest of the non-defaulting members will enter a default state when another member fails to deliver his/her quota of savings. Larger values of β imply that a defaulting agent can strongly interact and dramatically affect the behavior of the rest of the agents in a self-financing group.

The pattern of savings accumulation in the common fund (b) of the self-financed group is defined by,

$$b := \sum_{t=1}^{T} b_t = \sum_{t=1}^{m} (m - d_t)\rho \qquad \text{if} \quad \frac{d_t}{m} \leqslant \tau_d, \tag{17}$$

$$\sum_{t=1}^{m} (m - d_t)\rho(1 + u) \quad \text{if} \quad \frac{d_t}{m} > \tau_d, \tag{18}$$

It is common in agent-based models to introduce *adaptation*, where agents learn or adapt by changing their rules and behavior based on their experience and dynamic interactions (Smith & Conrey, 2007). In the case of a self-financing group, a high default rate in savings can dramatically reduce the fund accumulated for loans. Thus, to compensate for this reduction, an adaptive rule ('a rule that changes the rules') is introduced in the agent-based model (Eq. (18)): groups with a high default rate of savings ($\frac{d_t}{m} > \tau_d$) change the pattern of fund accumulation from a fixed scheme to a solidarity scheme, in which non-defaulting members provide an additional contribution—$\rho(1 + u)$, $u \sim \mathcal{U}(0, 1)$—beyond the quota (ρ) due at each meeting t, in order to stabilize the collective savings fund b_t over time. See the algorithm in Box 3.

Box 3. Algorithm 3: Agent-based simulation of self-financing groups and formation of social capital

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Data: $\mathbb{M}_{\mathcal{A}_i}, \rho$
Result: $k_m \ni \{k_l, k_s\}$
$\mathbb{P}_i(d_s) = \gamma_g\left(\omega_{d_s}\mathbb{P}_{d_s}(a_i) + (1-\omega_{d_s})\mathbb{P}_{d_s}(y_i)\right)$
$\mathbb{P}_{d_s}(a_i) = 1 - \frac{1}{1+\mathbb{e}^{1-(\sum_i^m \sqrt{(a_i-a)^2})^{-1}}}$
$\mathbb{P}_{d_s}(y_i) = 1 - \frac{1}{1+\mathbb{e}^{1-y_i}}$
for $meeting \leftarrow t$ **do**
    $u \sim \mathcal{U}(0,1)$
    $\beta \in \{\beta_d, \beta_{\neg d}\}$
    $\mathbb{P}_e(d_s, t) := \tanh z_e = \frac{\mathbb{e}^{z_e} - \mathbb{e}^{-z_e}}{\mathbb{e}^{z_e} + \mathbb{e}^{-z_e}}$
    $z_e = 1 - \beta\,(\rho + \sqrt{m} - t)$
    if $d_{\forall i}(t-1) = 1$ **then**
        if $\mathbb{P}_i(d_s) > \mathbb{P}_e(d_s,t) + u$ **then**
            $d_i(t) = 1$
        else
            $d_i(t) = 0$
        end
    else
        $\beta_{\neg d} < \beta_d$
        if $\mathbb{P}_i(d_s) > \mathbb{P}_e(d_s,t) + u$ **then**
            $d_i(t) = 1$
        else
            $d_i(t) = 0$
        end
    end
    if $\frac{d_t}{m} \le \tau_d$ **then**
        $\sum_{t=1}^{T} b_t = \sum_{t=1}^{m}(m - d_t)$
    else
        $\sum_{t=1}^{T} b_t = \sum_{t=1}^{m}(m - d_t)\rho(1+u)$
    end
end
$k_l \equiv \ell$
$k_s = \gamma_s\left(\|a_i\| + \|y_i\| + \|h_i\|\right)$
$\|a_i\| = \left(\sum_{i=1}^{m}(a_i - a)^2\right)^{-1/2}$
$\|y_i\| = \left(\sum_{i=1}^{m}(y_i - y)^2\right)^{-1/2}$
$\|h_i\| = \left(\sum_{i=1}^{m}(h_i - h)^2\right)^{1/2}$

The agent-based algorithm in Box 3 produces two outputs: debt capital (k_ℓ) and social capital (k_s). Debt capital is a fraction of the accumulated fund b and is discussed in Section 3.4. The formation of social capital, in turn, is the result of the homophily among the participants of a self-financing group.

The quantitative operationalization of social capital in the model is based on the multilevel ecometric approach of Raudenbush & Sampson (1999). This approach allows one to differentiate between individual and area-level sources of variation in social capital (Mackenbach et al., 2016). Formally, social capital is calculated as a function of the Euclidean distance between individuals in an artificial community, in terms of the homophily related to their age ($\|a_i\|$), income ($\|y_i\|$) and household location ($\|h_i\|$):

$$k_s = \gamma_s(\|a_i\| + \|y_i\| + \|h_i\|) \tag{19}$$

$$\gamma_s = 1 + \frac{d}{m} \tag{20}$$

$$\|a_i\| := \left(\sqrt{\sum\nolimits_{i=1}^{m} (a_i - a)^2}\right)^{-1} = \left(\sum_{i=1}^{m} (a_i - a)^2\right)^{-1/2} \tag{21}$$

$$\|y_i\| := \left(\sqrt{\sum\nolimits_{i=1}^{m} (y_i - y)^2}\right)^{-1} = \left(\sum_{i=1}^{m} (y_i - y)^2\right)^{-1/2} \tag{22}$$

$$\|h_i\| := \sqrt{\sum\nolimits_{i=1}^{m} (h_i - h)^2} = \left(\sum_{i=1}^{m} (h_i - h)^2\right)^{1/2}. \tag{23}$$

A multiplying gamma factor (γ_s) is included in the formula of social capital of Eq. (19) to account for the impact of being part of a self-financing group. The parameter γ_s accounts for the fact that non-default members of a self-financing group create additional bonds of trust, trustworthiness and reciprocity. These resources, according to Putnam (1993), promote their ability to undertake collective actions, such as starting a joint business venture.

In the case of agents that are not part of a self-financing group, their social capital is a function of their own homophily (i.e., $\gamma_s = 1$ for $\neq g\mathbb{M}_{\mathcal{A}}$), while in the case of non-defaulting members of a self-financing group $\gamma_s > 1$ because the ratio of defaulting members to the total members of a group is added to the scale parameter of social capital (Eq. (20)). This implies that in a group with a large number of defaulting members (d), stronger social bonds of trust will be created among the remaining non-defaulting members $m - d$.

In Eq. (21), less social cohesion is assigned to individuals that are not closer to the average age of the population (a), on the basis of studies of reduced social capital in young and elderly populations (Lauder, Mummery, & Sharkey, 2006). Lower social bonds are also allocated to individuals that have an income in the tails of the distribution (Eq. (22)), since income inequality has been found to be related to a reduction in social cohesion; see Khambule & Siswana (2017). Finally, less contextual social capital is assigned to individuals that live in households located in the village periphery (Eq. (23)). This last area-level allocation of social capital is based on the literature on neighborhood formation of social capital; see Butler & Robson (2001) and Forrest & Kearns (2001).

3.4. Algorithm 4: Loan allocation and business simulation

Box 4 shows the last stage of the simulation (Algorithm 4). In the last algorithm, agents start a joint business venture with the social capital and the debt capital obtained after being part of a self-financing group. It is assumed that the group members start a business together; this a direct result of homophily and tends to be common in low-income groups of women, as those served by self-financing groups. See, for example, the cases of informal businesses in Africa described in Spring (2009).

The probability of members receiving a loan (ℓ) from the self-financing group is conditional on the income (y_i) and social capital ($k_{s,i}$) of an i-individual:

$$\begin{cases} \mathbb{P}(\ell | y_i, k_s) := \tanh z_\ell \equiv \frac{\sinh z_\ell}{\cosh z_\ell} = \frac{e^{z_\ell} - e^{-z_\ell}}{e^{z_\ell} + e^{-z_\ell}} \\ z_\ell = \frac{2 + e(e^{-y_i} + e^{-k_{s,i}})}{(1 + e^{1-y_i})(1 + e^{1-k_{s,i}})}. \end{cases} \tag{24}$$

A member of the SFG will receive a loan if his/her probability of receiving a loan is higher than the ex-post risk aversion of the self-financing group (r_{post}):

$$\begin{aligned} \mathbb{P}(\ell | y_i, k_s) &> r_{post} \\ &> r - f(\omega_r; k_{s,(m-d)}) \end{aligned} \tag{25}$$

In Eq. (25), $r \in \mathbb{R}^{0,1}$ is the ex-ante risk aversion of the SFG. This is the risk aversion toward providing loans at the start of the group meetings. This risk is updated by non-defaulting members after being part of a SFG, on the basis of a Gompertz function of social capital ($k_{s,(m-d)}$),

$$f(\omega_r; k_{s,(m-d)}) = \omega_r e^{-\xi \omega_r e^{-\frac{\omega_r k_s}{\xi(m-d)}}}.$$

In the function $f(\omega_r; k_{s,(m-d)})$, ξ is the standard scientific notation $\xi_m \times 10^{\xi_n}$, for which a mantissa and an order of magnitude of $\xi_m = \xi_n = 1$ generate a smoothed curve saturated toward the asymptote ω_r (Laird, 1964); this is, the social capital of the non-defaulting agents $k_{s,(m-d)}$ reduces the ex-ante risk aversion of the SFG only up to an asymptotic ω_r-probability:

$$\lim_{k_{s,(m-d)} \to \infty^+} f(\omega_r; k_{s,(m-d)}) = \omega_r.$$

A value of 0.5 was chosen for the asymptotic risk-reduction probability ω_r (the hyperparameter $\omega_r = 0.5$), based on Laplace's uncertainty principle: if no additional information about the reliability of the potential borrowers is available, in the limit the SFG members assume that all possible events are equiprobable; see *inter alia* Gurov (2005).

The amount of the loan allocated to the borrowers (ℓ) is a fraction of the total savings in the common fund (b),

$$k_\ell := \ell = b(1 - r_{post}), \tag{26}$$

with an effective interest rate equal to the nominal interest rate plus the updated (ex-post) risk aversion of the self-financing group,

$$i_\ell = i + r_{post}. \tag{27}$$

Eqs. (25)–(27) capture the pattern of loan provision and bucketization of interest rates—as a function of risk aversion—that was observed empirically by Paravisini, Rappoport, & Ravina (2016) in peer-to-peer lending platforms. In the model, borrowers are jointly liable for the loan ℓ, as joint liability makes borrowers responsible for repaying each other's debt, which encourages risk sharing among the members who take a loan (Attanasio, Augsburg, & De Haas, 2016). As Chen et al. (2017) highlight, this type of group lending lowers operating costs due to diligence and monitoring, and therefore increases the likelihood of loan repayment by shifting the bulk of monitoring costs from lenders to groups.

The performance of the business created by the non-defaulting members of the SFG and the counterfactual business of non-members is calculated using the stochastic business model below:

$$\text{debt} = \ell(1 + i_\ell) \tag{28}$$

$$\text{inventory}_{(t=0)} = \ell(1 - \theta_\ell) \tag{29}$$

$$\text{sales}_t = m(\text{inventory}_t) \tag{30}$$

$$c_t = \text{sales}_t - q_t \tag{31}$$

$$\text{returns} = \sum_{t=1}^{\mathfrak{T}} c_t(1 - \epsilon_e) \tag{32}$$

$$\bar{a} = 2^{-1}\left(\ell + \text{inventory}_{(t=\mathfrak{T})} + \sum_{t=1}^{\mathfrak{T}} c_t\right) \tag{33}$$

$$ROA = (\bar{a}^{-1})\text{returns}. \tag{34}$$

In the model, the total debt capital of the business is the result of adding the amount of the loan borrowed by the SFG members plus the interest rate charged for the loan (Eq. (28)). At the start of the business (at time $t = 0$), a fraction (θ_ℓ) of the borrowed loan is set aside to buy retail inventory (Eq. (29)). The inventory reduction is a function of market sales (Eq. (30)),

$$m = (1 + e^{(-1+e^{-\eta^2})(-1+k_{s,(m-d)})})^{-\left(1+\frac{1}{\eta}\right)}, \tag{35}$$

which is boosted by the social capital of non-defaulting members ($k_{s,(m-d)}$) but can be lessened by the macroeconomic environment—the GDP growth—of a country (η).

Eq. (31) is a mathematical description of a simple cash flow in the business: income is obtained by sales at time t, minus the loan repayment quota q_t. The returns at the end of the period $\mathfrak{T}$ (Eq. (32)) are the sum of the cash flow minus random expenses related to unexpected events (ϵ_e). Returns on assets (ROA)—more precisely, returns on average assets—are obtained by dividing the business utility (Eq. (32)) by the average assets of the business (Eq. (33)). The formula of ROA in Eq. (34) is based on the business-success indicators suggested by the International Finance Corporation (2008) to evaluate micro, small and medium enterprises.

The simplified businesses model simulated in Eqs. (28)–(34) is motivated by Herranz, Krasa, & Villamil (2015), who found that risk-averse entrepreneurs run smaller, more highly leveraged firms, which default less because running a smaller firm with higher debt reduces the number of personal funds at risk in the firm. In the model, a simplified balance sheet is assumed where assets are an addition of the income derived from sales plus the inventory and fixed assets acquired with the loan. The liabilities of the business are only the loan repayments q_t. Fixed assets are assumed to depreciate to zero at the end of the life-cycle of the business, and thus the utility at the end of the period is computed as the aggregate income from sales minus the total expenses incurred in paying the capital and interest of the loan, along with the expenses caused by unexpected (random) events.

Social capital enters the business model through improvements in market allocation pushed forward by the social capital of the borrowers in Eq. (30). Following Batjargal (2003), the heterogeneity in the structural, relational, and resource-based aspects of social capital is reflected in various aspects of business performance because embedded relations influence the purchase and sale decisions of entrepreneurs. Also, as noted by Ling-Yee (2004), social capital helps to integrate the existing knowledge of members with the unique information from the market m. This in turn helps the group to update its knowledge, endow it with meaning, and translate it into organizational routines.

The counterfactual business simulation of non-members is also based on Eqs. (28)–(34). The ABS-SFG model (randomly) chooses agents from the population of the village who were not part of the self-financing group. The selected agents create a business under the same financial conditions of the business created by the members of the self-financing group, i.e. the same loan amount and interest rate. Using the same financial conditions in both the self-financing business and the business financed with formal loans allows us to isolate the financial effects from the effects on business performance caused by social capital.

4.1. Counterfactual experiment of business performance

Tables 4 and 5 and Fig. 2 show the results of a counterfactual experiment of business performance based on 1000 simulations of the ABS-SFG model ($s = 1, 2, ..., 1000; \mathcal{S} = 1 \times 10^3$). The experiment compares the returns on assets ($ROA_{\phi,s}$) of 1000 businesses created by non-defaulting members of 1000 self-financing groups against 1000 businesses created by non-members in 1000 artificial communities.

The experiment simulates the impact of annual loan interest rates equal to 10% to 70% on $ROA_{\phi,s}$ ($\phi \in \{.1, ..., \Phi = .7\}$, $\phi \equiv i$ in Eq. (27)) for different values of savings contribution ρ in self-financing groups. The large values of the interest rates are based on the fact that borrowers in self-financing groups typically pay interest rates of 5% to 10% a month, according to Rasmussen (2012). Table 2 shows the numerical values used to initialize the model. The main characteristics of the experiments are summarized in Table 3.

When annual interest rates are below 40%, the profitability of the businesses financed with loans from the self-financing groups is on average higher compared to the profitability of businesses financed with commercial loans (Table 4). When the savings quota is $\rho = 30MU$, for example, the average return of the businesses in the self-financing groups is 5.89%, while the average return of the businesses financed with commercial loans is -3.31%. The risk of the businesses financed with commercial loans is also higher, equal to 5.67%, compared to the average risk of the businesses of the self-financing groups (4.25%).

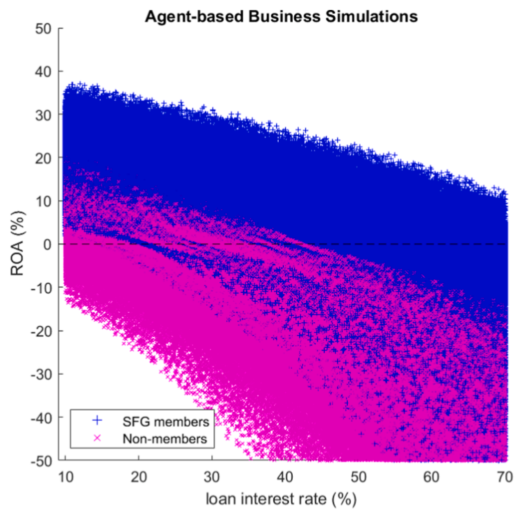
Box 4. Algorithm 4: Business simulation

Data: $k_m \ni \{k_\ell, k_s\}$, $\phi \equiv i$
Result: $ROA_{\phi,s}$
for $\mathcal{S} \leftarrow s$ **do**
$\quad \ell_s = b_s(1 - r_{s,post})$
$$m_s = \left(1 + e^{\left(-1+e^{-\eta^2}\right)\left(-1+k_{s,s,(m-d)}\right)}\right)^{-\left(1+\frac{1}{\eta}\right)}$$
$\quad$ **for** $\Phi \leftarrow \phi$ **do**
$\quad\quad i_{s,\ell} = \phi + r_{s,post}$
$\quad\quad \mathrm{debt}_s = \ell_s(1 + i_{s,\ell})$
$\quad\quad$ **for** $\mathfrak{T} \leftarrow \mathrm{t}$ **do**
$\quad\quad\quad \mathrm{inventory}_{s,(\mathrm{t}=0)} = \ell_s(1 - \theta_\ell)$
$\quad\quad\quad \mathrm{sales}_{s,t} = m_s\left(\mathrm{inventory}_{s,\mathrm{t}}\right)$
$\quad\quad\quad c_{s,t} = \mathrm{sales}_{s,\mathrm{t}} - q_{s,\mathrm{t}}$
$\quad\quad\quad \mathrm{returns}_s = \sum_{\mathrm{t}=1}^{\mathfrak{T}} c_{s,\mathrm{t}}(1 - \epsilon_e)$
$\quad\quad\quad \bar{a}_s = 2^{-1}\left(\ell_s + \mathrm{inventory}_{s,(\mathrm{t}=\mathfrak{T})} + \sum_{\mathrm{t}=1}^{\mathfrak{T}} c_{s,\mathrm{t}}\right)$
$\quad\quad$ **end**
$\quad\quad ROA_{\phi,s} = (\bar{a}_s^{-1})\mathrm{returns}_s$
$\quad$ **end**
end

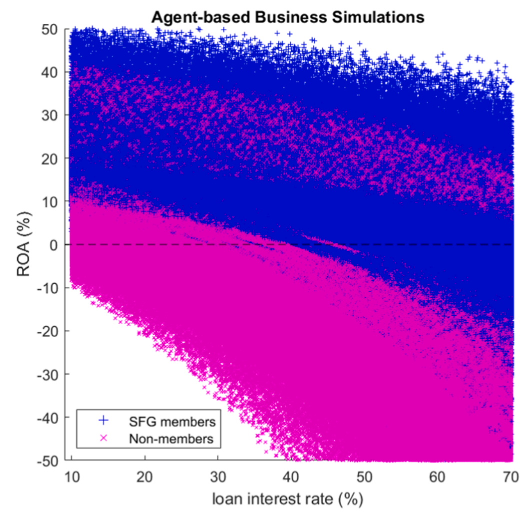
4. Results of computational experiments

This section runs $s = 1, 2, ..., \mathcal{S}$ simulations of the agent-based model of self-financing groups. The index s denotes running a single sequence of the whole model (the four algorithms described in Section 3), and hence $\mathcal{S}$ is the total number of simulations of the ABS-SFG model. For example, when $s = \mathcal{S} = 1$, only a single village, one self-financing group, and one business are simulated—for an illustration of this simulation see the Appendix A. If $\mathcal{S} = 1000$, then 1000 villages are randomly populated and 1000 different groups and businesses are generated in each village.

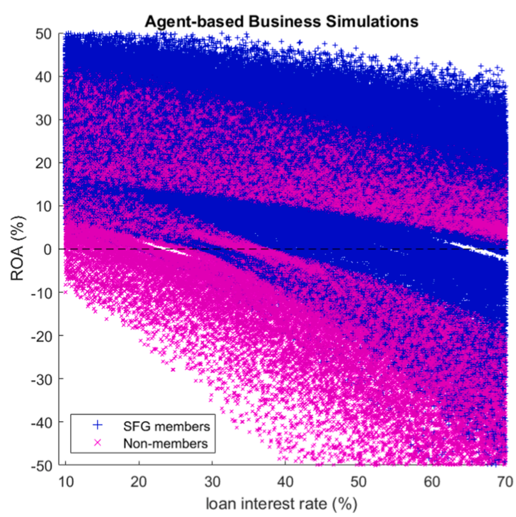
For annual interest rates between 40% and 70% and for savings contributions of $\rho = 30$ and $\rho = 40$, negative returns are observed both for the businesses financed with commercial loans and for the business financed with commercial loans from self-financing groups. The businesses in the self-financing groups have positive returns only for quotas of savings equal to $\rho = 50$ and $\rho = 60$ (Table 5). For a savings quota of $\rho = 40MU$ the average return of the businesses in the self-financing groups is -3.29%, while the average return of the businesses financed with commercial loans is -30.48%. If the savings quota rises to $\rho = 50MU$, the returns of the businesses in the self-financing groups increases on average to 4.82%. This last result is the consequence of



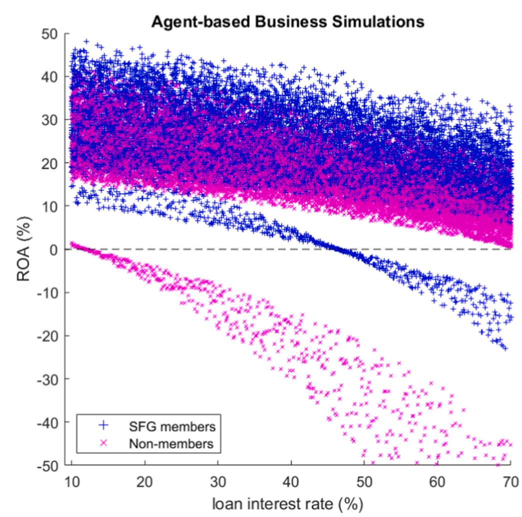
(a) Savings quota $\rho = 40$



(b) Savings quota $\rho = 50$



(c) Savings quota $\rho = 60$



(d) Savings quota $\rho = 70$

Fig. 2. Agent-based simulation of business performance. When $\rho < 60$, the performance of the businesses of the members of self-financing groups is higher compared to the performance of the businesses financed with commercial loans. After the bifurcation point ($\rho > 60$), in the lower bifurcation branch groups fail to generate enough financial capital—because many members fail to contribute to the common fund—and their businesses perform worse than those of non-members. In the upper bifurcation branch, members adapt to the high quota of savings and create additional social capital, boosting the performance of their business initiatives.

social capital in the self-financing group, which becomes important in the presence of costly debt capital.

Fig. 2 reveals an emergent pattern in the dynamics of the returns of businesses financed by self-financing groups: bifurcation. For values of the savings quota ρ equal to $40MU$ and $50MU$, the businesses of the members of self-financing groups tend to outperform the profitability of the businesses of the non-members (Figs. 2a and 2b). When the savings quota exceeds a threshold of $\rho = 60$ (Fig. 2c), however, business performance splits into two branches (Fig. 2d): in the lower bifurcation branch, the businesses of self-financing groups have average returns of -5.72% to 8.11%, while in the upper branch these businesses have returns of 20.32% to 27.47%. The risk, measured by the standard deviation of the returns, is also low in the lower branch of the simulated business of SFG members (Tables 4 and 5).

The bifurcation is caused by a quota of savings that exceeds a threshold of tolerance and creates nonlinear dynamics in the business profitability of self-financing groups. An extremely high quota of savings is a burden for agents with a restricted budget, which leads to savings default. Savings default is imitated due to the interaction of defaulting members with other group members, and as a consequence the group ends up having only a small fund available for loans. A lower amount of loans, in turn, leads to lower returns in the businesses created by the non-defaulting members, which generates the lower bifurcation branch in returns.

On the other hand, if members of the self-financing group manage to accommodate to the higher quota of savings and do not enter a default state, then the other members mimic their fulfilling behavior and hence at the end of the life-cycle of the group a larger fund is available for loans. The higher amount of loans, added to the social capital formed through homophily, boosts the profitability of the businesses created by self-financing groups, thereby generating an upper branch in the bifurcation pattern.

5. Conclusion

Atlan (1979, 1991) develops two complementary concepts of complexity: algorithmic complexity and contextual complexity. Algorithmic complexity is based on optimization, whereas contextual complexity is

Table 2
Numerical values used to initialize the ABS-SFG model.

Phase/algorithm	Numerical values	Notes on parameter values
Initialization		
Algorithm 1: Generation of an artificial community		
Family size	$\lambda_h = 2$	Parameter of a centered Poisson distribution.
Intra-household productive individuals and gender composition	$u_\delta = 3$	Upper parameter of a uniform integer discrete distribution. The lower parameter is always one because there is always one productive individual in a productive household
Number of households in the village	64	Number of households in a village
Age profile in the village	$u_{age} = 20$	Upper parameters of a mixture of discrete uniform distributions
Income profile in the village	$\mu_{\neg w} = 5.5$ $\mu_w = 5.8$ $\sigma_{\neg w} = 0.5$ $\sigma_w = 0.4$	First and second parameter of a log-normal distribution. Lower values of μ (compared to those of men) imply that the central tendency of the income distribution of women is lower than that of men. Higher values of σ imply that the income differences are more dispersed across individuals
Algorithm 2: Formation of a self-financing group (SFG)		
Overall probability of joining a SFG	$\omega_{\mathbb{P}_i(m)} = .55$	Weight (importance) of lack of access to financial services for the agents that want to be part of the SFG
Gender ratio of women in the SFG	$\tau_w = 0.7$	Minimum percentage of women in a group required by the field officer
Running phase		
Algorithm 3: SFG dynamics of savings accumulation and formation of social capital		
Mimicking behavior	$\beta = .007$	Larger values increase the probability that non-defaulting members will enter a default state when a member fails to deliver her/his quota of savings
Idiosyncratic probability of default in savings	$\omega_{d_s} = 0.5$	Weight (importance) of income and age in the probability of not contributing with savings
Gender risk of not contributing to the SFG	$\gamma_g = 0.7$	Women have less probability of failing to contribute their savings, compared to men
Threshold of SFG failure	$\tau_d = 0.2$	Maximum tolerance for the percentage of members failing to contribute their savings
Algorithm 4: Loan provision and business simulation		
Risk aversion (ex ante)	$\omega_r = 0.8$	Initial (ex ante) risk aversion of the group against allocating loans. This risk aversion is updated after the members experience being part of a SFG
Fraction of assets allocated to inventory	$\theta_\ell = 0.65$	Larger values imply that a higher proportion of the loan amount will be used to buy inventory for retail sales
Impact of the macroeconomic environment	$\eta = 0.05$	Impact of economic growth on market sales. Larger (smaller) values will increase (decrease) the business sales

Table 3
Main characteristics of the experiments.

Parameter	Values
Nominal interest rate ($\phi \equiv i$)	10% to 70%
Savings quota (ρ)	30, 40, 50, 60, 70

Table 4
Business simulation results: Loan interest rate in the range of 10% to 39.9%.

Savings quota	Business impact	ROA (%)	
		Members	Non-members
$\rho = 30$	Average returns	5.89	−3.31
	Risk	4.25	5.67
$\rho = 40$	Average returns	11.95	−3.17
	Risk	3.43	5.65
$\rho = 50$	Average returns	17.03	−0.18
	Risk	2.83	5.24
$\rho = 60$	Average returns	25.21	18.03
	Risk	2.10	2.92
$\rho = 70$	Average returns	[27.47, 8.11]	21.35
	Risk	(2.16, 2.82)	2.61

Note: When $\rho > 60$, a bifurcation pattern appears in returns.
ROA: returns on assets.
Average returns: average ROA in the 1000 simulations.
Risk: standard deviation of ROA in the 1000 simulations.

based on the communication among heterogeneous agents with conflicting goals (Vasconcelos & Ramirez, 2011). In this study, self-financing groups are considered a phenomenon of contextual complexity and an agent-based model is proposed to simulate how these groups form and create businesses in an artificial community.

The results allow us to conclude that the startup businesses of self-financing groups are more profitable and less risky compared to businesses financed with commercial loans, even with high interest rates, when social capital is properly consolidated. The consolidation of social capital is a consequence of the interaction among agents in the self-financing group. Social capital complements the debt capital in the fund available for loans, creating a competitive advantage that increases business profitability.

Higher quotas of savings in the group were found to boost profitability by raising the collective fund available for loans, but only up to a threshold, after which a bifurcation in returns appears. This bifurcation—typical in complexity dynamics (see Gao, Barzel, & Barabási, 2016)—is a branching process of the dynamical system in which the topological structure switches to different states due to a change in a bifurcation parameter (Crawford, 1991). In the ABS-SFG model, the bifurcation parameter is the quota of savings agreed among members of a self-financing group. The bifurcation implies that field officers—hired by development agencies for the task of managing a group—face a trade-off between two possible states when raising the savings quota of a self-financing group: while the bifurcation parameter is a potential source of profit, increasing the quota of savings exacerbates also the risk of group failure.

The emerging findings of the study indicate that self-financing groups create a competitive advantage for business, as a consequence of the social capital formed in the group through homophily. Social capital, according to Lin, Ho, & Peng (2016), constitutes an additional production factor that influences the competitive power and economic development of a venture, because social capital is based on network ties and thus it is a non-substitutable resource that cannot be acquired

Table 5
Business simulation results: Loan interest rate in the range of 40% to 70%.

Savings quota	Business impact	ROA (%)	
		Members	Non-members
$\rho = 30$	Average returns	-13.58	−30.76
	Risk	7.44	11.01
$\rho = 40$	Average returns	-3.29	−30.48
	Risk	5.65	10.95
$\rho = 50$	Average returns	4.82	−25.29
	Risk	4.42	10.03
$\rho = 60$	Average returns	16.66	5.25
	Risk	3.03	4.75
$\rho = 70$	Average returns	[20.32, −5.72]	10.84
	Risk	(2.67, 6.22)	3.90

Note: When $\rho > 60$, a bifurcation pattern appears in returns.
ROA: returns on assets.
Average returns: average ROA in the 10000 simulations.
Risk: standard deviation of ROA in the 10000 simulations.

through imperfect imitation[3].

The theoretical implication of the findings is that homophily plays a dual role in self-financing groups. Following a resource-view approach, group formation is based on the maximization of utility by acquiring more resources in the form of loans and/or social capital. In this study, we argue that homophily plays a complementary role to utility maximization during the formation of a group. Homophily among members consolidates social bonds and reduces risk aversion during the life-cycle of a group. Social bonds translate into stronger cohesion, trust and peer pressure among members, which reduces the chances of default and facilitates organizational strategies[4].

The study also has managerial implications for traditional competencies, networking and market appreciation[5]. First, in a business of a self-financing group, traditional managerial competencies—such as finance, accounting, marketing, personnel management technologies, organizational procedures and routines (Vasconcelos & Ramirez, 2011)—are necessary to manage internal issues, and coordinate, motivate and select priorities. Second, due to the networking nature of self-financing groups, additional managerial competencies are required to construct value co-production systems on the basis of the collaboration and arrangements between members. Finally, through contextual listening, businesses of self-financing groups are able to appreciate, evaluate, question, and understand the general trends that compose the transactional environment.

Future studies can explore the business impact of self-financing groups that include a component of human capital besides social capital, as well as the role of friendship in business performance and the potential competitive advantages of a transactive memory system in self-financing groups[6].

Self-financing groups improve human capital during the meetings of the group by providing members with training in entrepreneurial skills and financial literacy. Engström & McKelvie (2017), after analyzing a dataset of 739 micro-enterprises in Ecuador, find that the impact of this training leads to improved financial performance of micro-enterprises in the informal economy. More recently Tsai & Yang (2018) found that human capital, measured by education and experience, improves vendor profit.

In the case of friendship, Batjargal (2003) finds that friendship ties affect firm performance negatively, because friendship leaves little room for maneuvering and creates financial concessions that harm a business's revenues and profit margins. While self-financing groups often focus on individual ventures, a joint business creates a competitive advantage for group members due to the combined effect of debt capital and the social capital generated through a dual process of homophily. Business training—which improves human capital—further encourages the competitive advantage of joint businesses.

Development agencies who work with self-financing groups as a platform to provide communities with sustainable development programs—like entrepreneurship, agriculture, adaptation to climate change, health and sanitation, or programs of literacy, education, and women empowerment—can use the ABS-SFG model as a cost-effective virtual laboratory to perform artificial experiments. The impact of intervention programs and social policies can be evaluated ex ante through the artificial experiments in the virtual laboratories. Investigations about the impact of business interventions are a promising research avenue, since Gonzales Martínez (2019) finds that business training is not the most frequent intervention offered to self-financing groups by development agencies, but is in fact the most important program to encourage financial sustainability, particularly after a development agency leaves the community where a group operates[7].

As shown in this study, agent-based modeling offers fascinating opportunities to understand and explore phenomena through a set of flexible computational tools. The simulations of agent-based models inform decision-making and allow one to formulate theories, that can guide empirical research and the interpretation of experimental

[3] The findings on the importance of social capital are consistent with the empirical study of Bosma, van Praag, Thurik, & de Wit (2004), who find that investment in social capital enhances entrepreneurial performance of small businesses in terms of survival, profits, and generated employment. Torres, Marshall, & Sydnor (2018) show also that social capital increases revenues and is a key asset for the long-term resilience of small businesses.

[4] While Bosma et al. (2004) relate the impact of social capital on firm performance to productivity and signaling, this study argues instead that the impact of social capital on the performance of businesses in self-financing groups is related to the cohesion created by homophily, which reduces organizational conflict. Previous studies found that intra-organizational social capital has a significant impact on the performance of new ventures (Baum, Calabrese, & Silverman, 2000), because in business startups members are in unfamiliar roles and face new work relationships during a time of stretched resources. Nahapiet & Ghoshal (1998) further regard social capital as an organizational resource, and Stinchcombe (2000) propose that the performance of a new firm is significantly affected by the organizational conditions surrounding its founding. As Vasconcelos & Ramirez (2011) highlight, complexity, in this view, is a manageable dimension that can contribute to organizational learning.

[5] According to Vasconcelos & Ramirez (2011), management copes with complexity at three different levels: managerial competencies, networking and contextual listening.

[6] Self-financing groups can raise human and social capital through financial literacy. Engström & McKelvie (2017) argue that financial literacy addresses an individual's ability to internally assess the benefits and costs of an entrepreneurial opportunity. As Nguimkeu (2014) highlights, entrepreneurship requires not only financial capital but also human capital in the form of education, experience, and skills to develop ventures—see Radhakrishnan (2015)

[7] Gonzales Martínez (2019) provides large-sample empirical evidence of the importance of business for self-financing groups, based on machine-learning methods. Theoretically, self-financing groups can improve business performance because these groups are a vehicle for the formation of a transactive memory system, which consists of the knowledge stored in each individual's memory combined with a metamemory containing information regarding the different teammates' domains of expertise. Xu (2016)—building on Wegner (1987), Uzzi (1997), Nadler, Thompson, & Boven (2003), Borgatti & Cross (2003), and Argote, McEvily, & Reagans (2003)—indicates that strong relationships help the members of a group to develop transactive memory systems due to frequent interactions that facilitate reciprocal understandings of complex problems and consequently ease the transfer of complex information because of the norms of reciprocity and cooperation associated with social cohesion. As Xu (2016) concludes, this cognitive orientation influences how entrepreneurs develop a business plan, plan for a business operation, obtain funding to begin product/service development, and launch their startup.

evidence (Chávez-Juárez, 2017). In contrast to results estimated from observational data, the findings in agent-based models emerge from the interactions among heterogeneous agents in artificial worlds (Gilbert & Troitzsch, 2005); thus—as noted by Vermeulen & Pyka (2017) and Pyka et al. (2018)—agent-based modeling is a platform to experiment with complexity in a microverse of simulated realities.

Appendix A. Illustration of the dynamics of the ABS-SFG model with one single simulation

This appendix illustrates the dynamics of the ABS-SFG model by showing the results of running only one simulation. Fig. A1 shows the results of simulating one artificial community with $H = 64$ households. Each box represents a household. Blue squares in the households are productive men, red triangles are women, and black dots are the dependents in the household (children and non-working elderly populations). The parameter H calibrates the number of households in a community.

In some households there is only one woman or man and one dependent agent, while in other households there is more than one agent of the working population and also several dependents (Fig. A1). In the simulated community, there is a total of 364 individuals, 175 of which are men and 189 are women (the gender ratio is.93). In the village, 232 individuals are dependents agents and 132 are agents of the labor force.

Fig. A1 (left) also shows the distributions of age and income in the artificial village. The distribution of income is skewed—a common feature of income distributions—with a bulk of individuals in the average income and some individuals with high income in the right tail of the distribution. The income distribution of men is set higher compared to that of women, in order to simulate gender disparities in income commonly found in empirical studies. Fig. A1 (left) shows also that the average age in the population is 43 years, with some individuals having less than 20 years and others having close to 70 years. The age dependency ratio is 1.76 in the simulated community, reflecting the fact that the community has more dependents than workers.

The number of members of a self-financing group is an emergent parameter of the agent-based model. In a single simulation for $\rho = 40$ with a fixed seed (Fig. A2), a group of 18 members is created by an artificial field agent. In the group, 15 agents are women and 3 are men, indicating the preference of the field agent for women. The members of the group selected by the field agent yield a gender composition of the self-financing group equal to $\tau = 15/18 \approx 83\%$ of women.

In terms of group dynamics, Fig. A2b shows that in the fourth meeting a member of the group (a man) fails to contribute his quota of savings. Due to the mimicking behavior of agents, other members of the self-financing group also start to fail to contribute to the common fund by the middle of the life-cycle of the group (Fig. A2c). By the end of the life-cycle of the group—in the last meeting—only 9 members—7 women and 2 men—have not failed to contribute to the common fund of the self-financing group (Fig. A2d).

Table A1 and Fig. A3 show the impact of changing the amount of savings quota ρ that each member has to contribute to the self-financing group. When the members of the group contribute an individual quota of 30 monetary units (MUs), $\rho = 30MU$, there is no default since no member fails to contribute to the fund (Fig. A3a). For a quota of $\rho = 40MU$, half of the members in the group fail to contribute to the fund (Fig. A3b). When the quota is $\rho = 50MU$, 15 members fail to contribute to the fund (Fig. A3c) and and when the quota is $\rho = 60MU$ the individual savings contribution is too

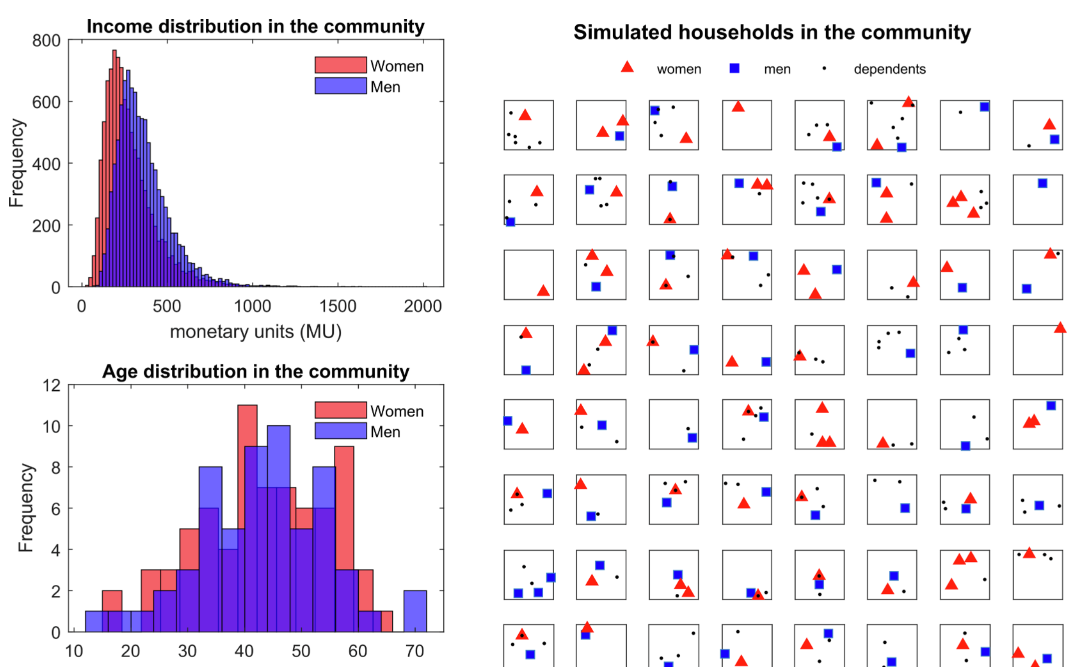
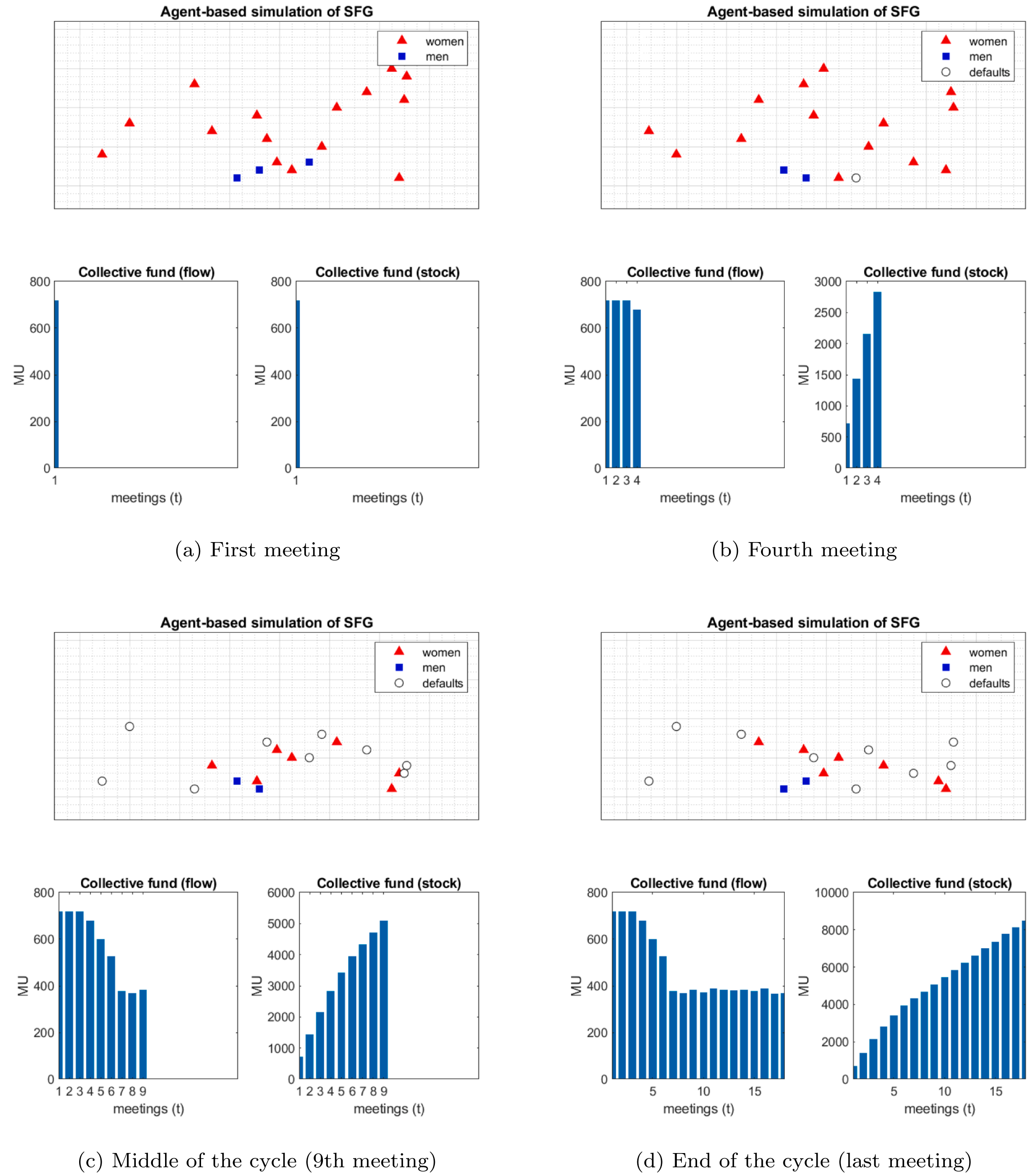


Fig. A1. Simulation of a community of $H = 64$ households. Each box represents a household. The households are inhabited by men (blue squares) women (red triangles) and children and non-working elderly populations (black dots). H can be modified to simulate smaller villages with few households or larger villages. Due to the random creation of villages, different simulations produce different household compositions. The high proportion of low-income individuals in the village and the gender disparities related to a higher income inequality for women can be seen in the left-skewed distributions of income in the village (Fig. A1 left). The distribution of age indicates a concentration of the population between 30 and 50 years, but with a high number of dependents compared to the labor force population, as shown in the demographic indicators below: Population: 364 individuals, Men in the community: 175, Women in the community: 189, Gender ratio: 0.93, Dependents in the community: 232, Labor force (productive population): 132, Income distribution of the agents in the community., Men income (median): 328.67 mu, Women income (median): 243.42 mu, Age distribution of the agents in the community., Average age of the productive pop: 43, Age dependency ratio: 1.76.



(a) First meeting
(b) Fourth meeting
(c) Middle of the cycle (9th meeting)
(d) End of the cycle (last meeting)

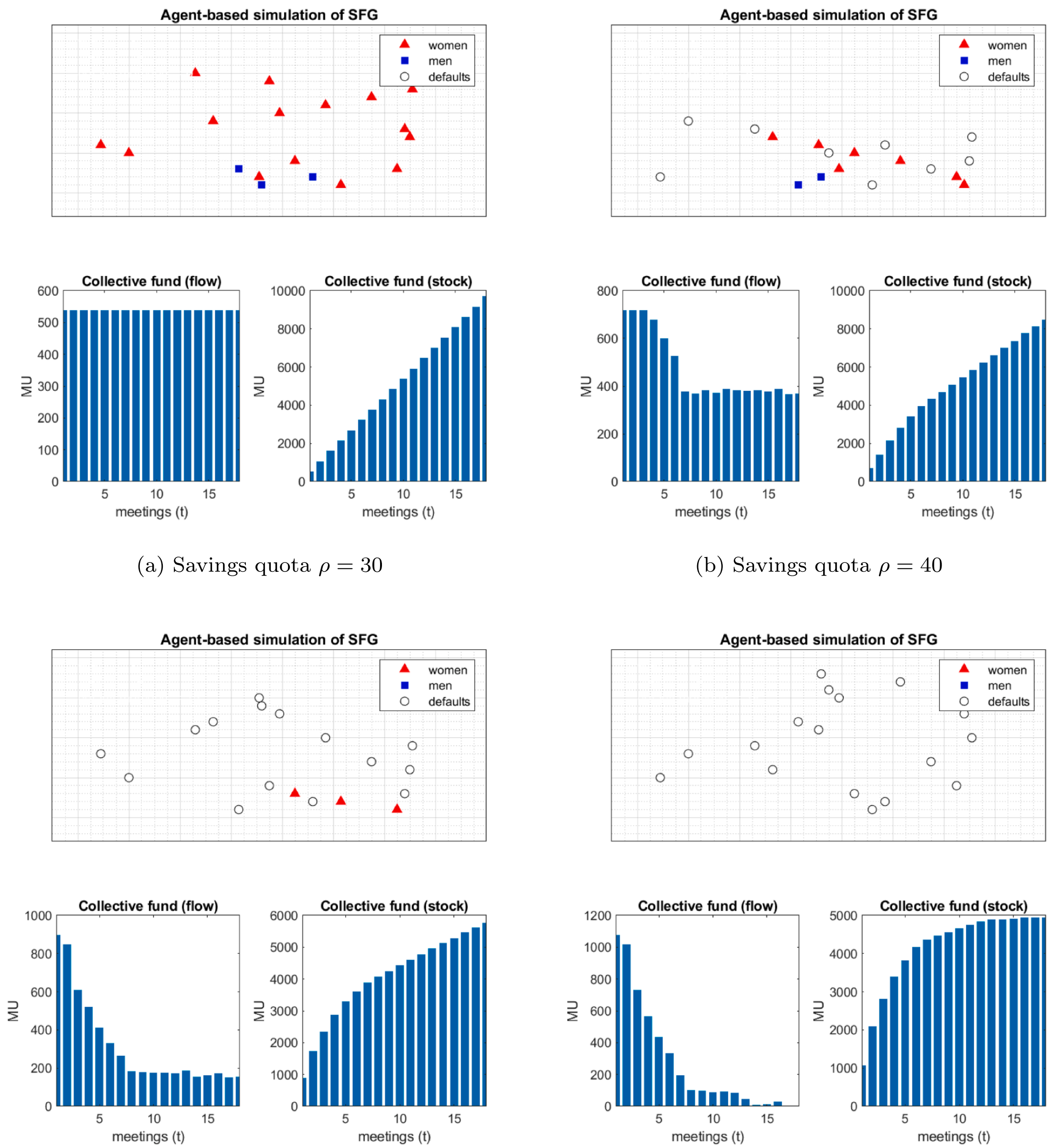
Fig. A2. Agent-based simulation: one single self-financed group, savings quota ρ = 40. All the members contribute their savings to the common fund in the first meeting of the group. A male agent fails to contribute from his savings in the fourth meeting, and due to the mimicking behavior of other agents, 9 of the 18 original members of the group end up failing to contribute their savings to the common fund of the self-financing group.

high and all of the members fail to contribute, leading to the failure of the group (Fig. A3d).

The simulations of the impact of ρ show that higher quotas of savings can increase the common loan fund, up to a point beyond which raising the quota starts to reduce the common fund. An extremely high quota of savings causes members to default, which eventually decreases the fund available for startup loans. The number of defaulting members is related both to the individual circumstances of each agent and also to the

Table A1
Results of the agent-based simulation on group dynamics.

	Savings quota			
	ρ = 30	ρ = 40	ρ = 50	ρ = 60
Total amount collected in the fund (MU)	9720	8520	5784	4961
Number of default members	0	9	15	18
Non-default members (end of the cycle)	18	9	3	0



(a) Savings quota $\rho = 30$

(b) Savings quota $\rho = 40$

(c) Savings quota $\rho = 50$

(d) Savings quota $\rho = 60$

Fig. A3. Agent-based simulation of a self-financing group with different values of savings quota (ρ). Low values of the individual savings contribution (ρ = 30) are not a burden for members of self-financing groups, but when the savings contribution increases to ρ = 60, members start to fail to contribute to the common fund, due to household budget constraints and the mimicking behavior of agents.

interaction among agents. At the individual level, an extremely high quota of savings creates a heavy burden for the members of the self-financing group, due to household budget constraints. At the group level, due to a mimicking behavior and the stochastic interaction among agents (Kirman, 2010), agents have fewer incentives to contribute to the common fund if they observe that other agents are failing to contribute to the fund.

Finally, Fig. A4 shows the social bonds of the agents before and after joining the self-financing group, for a quota of $\rho = 40MU$. Homophily—due to age, income, and household location—generates links among agents that increase the social capital in the group. The growth of social capital in the self-financing group is caused by the fact that during the life-cycle of the group, agents repeatedly meet with each other, strengthening their bonds. This is particularly true for those members that already had a tight social network before joining the group; for example, the female agents 16 and 15, and to a lesser extent the male member 7; see Fig. A4). Fig. A4 also reveals the inequality in social capital that the model aims to capture; i.e., agents have heterogeneous levels of social capital depending on their socioeconomic and geographical characteristics, as noted by Hsung et al. (2017).

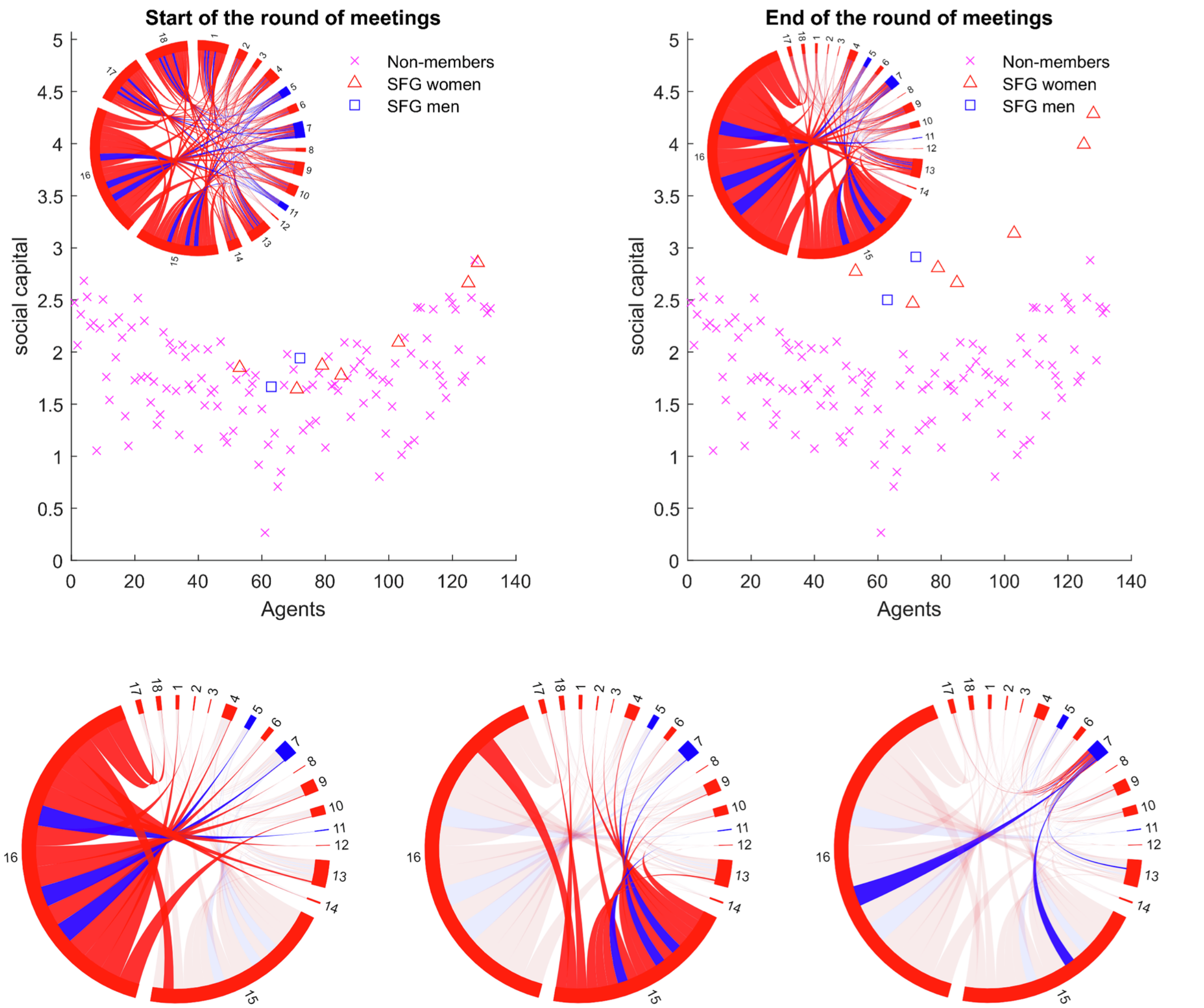


Fig. A4. Social capital in a self-financing group with a savings quota of $\rho = 40MU$. At the start of the life-cycle of the group, non-members and members of the self-financing group have similar social capital. At the end of the life-cycle of the group, non-defaulting members have higher social capital due to the strengthening of social bonds during the meetings. Female agents 16 and 15 have stronger social bonds with other members compared to other female and male agents (as agent 7). Thus, the heterogeneity in social bonds leads to inequality in social capital.

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