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Solidarity in collaboration networks when everyone competes for the strongest partner: a stochastic actor-based simulation model

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ABSTRACT

This article examines the emergence of solidarity from interactions between professionals competing for collaboration. Research on multiplex collaboration networks has shown that economic exchange can elicit solidarity when mediated by trust but did not consider the effect of competition. To fill this gap, we built an agent-based model that simulates the evolution of a multiplex network of collaboration, trust, and support expectations. Simulations show that while resource heterogeneity is key for collaboration, competition for attractive collaboration partners penalizes low-resource professionals, who are less connected and highly segregated. Heterogeneous resource distribution can trigger segregation because of preferential selection of resourceful peers and reciprocity. Interestingly, we also found that low-resource professionals can reduce their marginalization by building in-group mutual support expectations.

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1. Introduction

Examining the emergence of solidarity when economic agents have competitive incentives to collaborate is relevant to understand the complex interplay of economic and social factors in socio-economic exchanges (see Coleman, 1990; Granovetter, 2017). Moreover, studying the conditions that make the development of solidarity possible between economic agents whose collaboration is neither institutionally nor organizationally enforced is relevant to understand how solidarity that goes beyond mere economic collaboration can emerge from the tension between cooperation and competition.

Following Lindenberg (1998), understanding the development of solidarity requires to consider the formation of the behavioral correlates of solidarity, such as expectations of receiving support from others (see also Komter, 2001; Lindenberg, Fetchenhauer, Flache, & Buunk, 2006). To which extent in a given situation economic agents expect social support from each other can be considered as a key prerequisite for solidary behavior. Therefore, in this article we studied the emergence of ties of mutual support expectations in an economic context.

Previous research has shown that independent professionals collaborating for business-related purposes can develop expectations of receiving support from each other (Bianchi, Casnici, & Squazzoni, 2018) provided that the structure of their collaborations makes learning about each other's trustworthiness possible in risky business-related situations (Molm, Schaefer, & Collett, 2009).

However, this mechanism can be sensitive to the level of competition characterizing business contexts. Considering that collaboration is often motivated by one's desire to access resources controlled by others (Coleman, 1990), professionals might strive to collaborate with the most

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attractive partners, who control a higher level of resources (e.g., certain skills or contacts). Given that these resources are often unequally distributed either in a group or an organization (Blau, 1977; Bourgeois & Friedkin, 2001; Yamaguchi, 1996), it can be expected that centralized collaboration networks emerge (Cook & Emerson, 1978; Cook, Emerson, Gillmore, & Yamagishi, 1983; Emerson, 1972; Schaefer, 2007), which could eventually affect the development of trust. On the one hand, centralization of collaboration relations among resourceful individuals could suppress expectations of support between agents with unequal resource levels. On the other hand, theoretical modeling work has suggested that professionals with lower resource levels could be more prone to expect and seek support because of their higher level of "neediness" compared to resourceful professionals (Flache & Hegselmann, 1999a, 1999b).

In this study, we examined the effect of these counterbalancing social forces on the formation of mutual support expectations between professionals who have unequal resources and compete for resourceful collaboration partners. To do so, we used a stochastic actor-oriented model for multiplex network dynamics (Snijders, 1996, 2017; Snijders, Lomi, & Torló, 2013) as an agent-based model (Macy & Flache, 2009; Bianchi & Squazzoni, 2015; see also Snijders & Steglich, 2015; Stadtfeld, 2018; Stadtfeld, Takács, & Vörös, 2019). This permitted us to simulate the evolution of a multiplex network of collaboration, trust and expectations of support, while controlling various factors and manipulating relevant parameters to generate new theoretical hypotheses about the conditions under which socio-economic exchanges can be expected to give rise to solidarity. By manipulating resource distribution and agents' neediness for support, we explored artificial scenarios in which the counterbalancing forces of preferential selection of resourceful partners and emergence of support driven by collaboration, trust and reciprocity could be thoroughly examined.

The rest of the article is organized as follows. Section 2 presents our research background. Section 3 illustrates the model, while Section 4 presents model specification and simulation design. Finally, Section 5 shows simulation results, while Section 6 discusses implications and limitations of our study.

2. Research background

Although the effect of social network structures on economic behavior has been studied extensively in sociology (see Granovetter, 2017), examining the opposite direction, i.e., how economic exchange relationships between individuals can generate solidarity, has attracted less attention (Bianchi et al., 2018; Kuwabara, 2011; Lawler, Thye, & Yoon, 2008; Molm, Collett, & Schaefer, 2007). However, this is key not only to understand the interplay of social and economic exchange but also to examine important network and organizational processes, as structural interaction constraints, organizational settings and incentives can influence the interplay of economic and social motivations, thereby magnifying or inhibiting collaboration.

Experimental research in social psychology has studied the link between economic exchange and solidarity, by focusing mainly on the 'sentiments' of solidarity developing between exchange partners (Homans, 1950; see also Fararo & Doreian, 1998). On the one hand, some studies have found that successful economic exchanges in equal-power networks tend to promote coordination of common interests and elicit shared positive emotions, with partners conferring expressive value to their relationship (Lawler, 2001; Lawler et al., 2008; see also Thye, Yoon, & Lawler, 2002). On the other hand, studies on unequal-power networks have found that this link depends on the generation of trust between partners. In turn, trust is affected by the presence of agreements protecting partners from mutually exploiting each other. These agreements would not allow partners to learn each other's trustworthiness, which would prevent partners to develop trust relationships and eventually hinder the emergence of solidarity (Molm et al., 2007; Molm, Takahashi, & Peterson, 2000; Molm, 2003; see also, 2010).

Further research suggested a more context-specific view of the link between economic exchange, trust, and solidarity. Barrera (2007) has shown that subjects who are engaged in repeated economic exchanges can develop trust in each other, provided that none of them has a structural advantage over the other. A positive effect of economic exchange on trust was also found by Molm et al. (2009), who reported results of exchange interactions with loose "non-binding" agreements, which allowed partners to effectively prove their trustworthiness to each other. However, the success of these exchanges was often undermined by opportunistic behavior, thereby generating a "fragile" form of trust. In a similar vein, Kuwabara (2011) found that the effect of economic exchange on trust and solidarity depended on partners' perception of risk-taking, conflict and expressive value.

Nevertheless, social psychological research has provided evidence of a link between trust and sentiments of solidarity (Molm et al., 2007). This suggests that a key condition for solidarity to develop from an economic exchange is that partners can learn about each other's trustworthiness in risky exchanges (Kuwabara, 2011; Molm et al., 2009).

While experimental research has mainly studied sentiment, other scholars have focused more on behavioral aspects of solidarity (Homans, 1950; Hechter, 1987; Lindenberg, 1998; see also Fararo & Doreian, 1998). In particular, Lindenberg (1998) has identified the following five patterns of 'solidary behavior' that define the level of solidarity observable in a social group: cooperation in social dilemmas, fairness in resource sharing, support (i.e., provision of costly help) to others in need, avoiding breach temptations, and considerateness in mishap situations (see also Lindenberg et al., 2006). By focusing on support as an instance of 'solidary behavior', Bianchi et al. (2018) tested the hypothesis that solidarity can emerge within economic exchanges via trust by empirically observing a network of independent professionals sharing a coworking space. They measured economic exchanges among subjects as professional collaboration networks. Subjects were found to engage in frequent informal professional collaborations with each other to outsource some tasks to other professionals in order to manage scheduling and quality in risky and volatile markets. These collaborations consisted of informal, loosely-binding agreements. They were similar to risky economic exchanges where trust could emerge once partners eventually resisted their temptation to exploit cheating opportunities. By analyzing the subjects' multiplex relationships of collaboration, trust, and support, the study found no evidence of a direct association of collaboration and support. Instead, it was found that subjects disproportionately expected to receive support from those professionals whom they trusted, which in turn was associated to previous successful collaborations. In sum, expected solidary behavior from economic exchange partners was mediated by the generation of trust.

It is worth noting that professional collaborations have been extensively studied by empirical research in a variety of contexts (e.g. Andersen, 2013). Studies on corporate management (e.g. Mizruchi, 2004; Westphal & Milton, 2000), scientific research (e.g. Moody, 2004; Newman, 2001), and creative production (e.g. Uzzi & Spiro, 2005) suggested that resource heterogeneity is one of the main drivers of collaboration, by enabling functional complementarity. Moreover, studies on multiplex networks have shown that heterophily in collaboration networks often co-occurs with similarity on certain attributes of individuals (e.g., Casciaro & Lobo, 2008; see also Blau, 1974).

However, to the best of our knowledge, the effect of heterogeneity either on professional collaboration and other co-occurring relationships, such as trust or social support, has been less studied. It is reasonable to expect that resource heterogeneity – e.g., interpersonal differences in advanced skills or competencies – could induce professionals to compete for collaboration with partners controlling these resources (Blau, 1964, 1977; Coleman, 1990). This would possibly cause the emergence of centralized collaboration network structures with more resourceful professionals occupying the most central positions (Bourgeois & Friedkin, 2001; Cook & Emerson, 1978; Cook et al., 1983; Emerson, 1972; Patton & Willer, 1990; Schaefer, 2007).

While network centrality has been shown to yield positive effects on individual performance (e.g., Baldwin, Bedell, & Johnson, 1997; Brass, 1981), more recent research has pointed to the possible detrimental effects of resource centralization on team performance (Mora-Cantallops & Sicilia, 2019). Given that successful economic exchange can breed trust and support expectations, it can be expected that centralization in collaboration networks could concentrate on emergent solidarity among more resourceful professionals (see also Molm, 1994).

Here, it is important to note that simulation studies have suggested that resource heterogeneity could also positively affect the emergence of social support networks as long as resourceful agents are sufficiently altruistic to seek out those partners who could benefit the most from receiving support. In a theoretical work, Flache and Hegselmann (1999a) have shown that individuals with heterogeneous resources and partially altruistic preferences can develop efficient support exchange networks because their different endowments are inversely related to differences in "*neediness*" – i.e., the need for social support. Being less capable of providing social support, low-resource agents are more needy than high-resource ones. This would cause an efficient exchange of support within the network to develop.

However, assuming that professionals in business contexts do not primarily aim to exchange support out of altruistic preferences, but compete with each other for collaboration partners with specific skills, resource heterogeneity could have a double-edged effect on the formation of social support expectations. On the one hand, it can be expected that everyone would seek to establish collaboration relationships with resourceful partners, thereby causing the emergence of a centralized collaboration network. This would in turn lead trust to cluster between core partners in the collaboration network with the same partners who would disproportionately expect support from each other rather than from less trusted professionals. On the other hand, low-resource professionals would be constrained in the peripheral regions of the collaboration network (see, e.g., Flache & Hegselmann, 1999b). This would limit their opportunities to form trust ties and expectations of support.

In order to test the theoretical consistency of our expectations, we formulated two propositions, as follows.

Proposition 1a Competition for high-resource partners in a collaboration network with unequal resource distribution generates a support expectation network with lower connectivity compared to a situation in which there is no competition.

Proposition 1b Competition for high-resource partners in a collaboration network with unequal resource distribution generates a support expectation network with segregation between high-resource and low-resource agents.

However, considering that an unequal resource distribution implies a negative correlation between resources and neediness, it is also possible that the negative effect of competition could be counterbalanced. This will happen when low-resource agents who are excluded from exchanges with resourceful agents eventually turn to each other to establish mutual support relations.

This led us to formulate the following proposition:

Proposition 2 Heterogeneous neediness negatively correlated with resources compensates for the exclusion of low-resource agents otherwise generated by competition and unequal resource distribution.

3. The model

In order to test that our propositions follow consistently from a set of fundamental behavioral assumptions, we developed an agent-based model (ABM) which reproduced previous findings about expectations of social support from collaboration relationships via trust (Bianchi et al., 2018). We then manipulated the level of agents' resources and neediness in idealized simulation scenarios.

Following Flache and Stark (2009), our ABM was based on a stochastic actor-oriented model (SAOM) for multiplex network dynamics (Snijders, 1996, 2017; Snijders et al., 2013). This allowed us to model tie formation, maintenance, and disruption by considering the complex interdependencies between agent preferences for partners' attributes (e.g., collaboration ties with high-resource nodes) and endogenous structural processes (e.g., a tendency to reciprocate trust ties). Note that SAOMs are a combination of theoretical and statistical models (Snijders & Steglich, 2015) and are mainly used for statistical modeling of longitudinal network panel data and their co-evolution with node attributes. This is to assess the effect of certain network local configurations or nodes' attributes on the evolution of empirically observed networks. Parameters of the model can be interpreted as representing agents' preferences for certain local configurations in their own personal networks. Parameter estimates and standard errors are computed by artificially generating a stochastic distribution of networks. This is achieved by a stochastic simulation algorithm, which derives the expected evolution of network ties from theoretically specified assumptions about agent preferences and a decision-making mechanism. Computer simulations of the algorithm can then be performed to generate macro-level artificial network configurations. Note that we followed the application of SAOMs as ABMs suggested by Snijders and Steglich (2015) only partially as we did not fit the model to any specific empirical data. Indeed, our model was theoretical, while referring to an idealtypic empirical situation (Boero & Squazzoni, 2005).

At each iteration of the simulation algorithm, an agent i was randomly drawn from a population of size n and had to decide whether to change one of its outgoing ties or not. To do so, i first calculated the utility that would be obtained given each possible tie change, according to an *objective function*:

$$f_i(x) = \sum_k \beta_k s_{ik}(x), \tag{1}$$

where $\sum_k s_{ik}$ was a set of graph statistics calculated on i's personal network. Note that these statistics represented local configurations of agents' personal networks toward which they could have positive or negative preferences of various magnitude, according to values of parameter coefficients, β_k, e.g., a preference for reciprocated trust relations above unilateral trust.

Secondly, i selected one of the n possible subsequent states – including no change – through a multinomial random experiment, in which each possible state had the following probability:

$$p(\text{change in } x_{ij}) = \frac{\exp(f_i(\text{network after change in } x_{ij}))}{\sum_h \exp(f_i(\text{network after change in } x_{ih}))}. \tag{2}$$

Following Snijders et al. (2013), we included a multiplex network X with three layers: *Collaboration* ($X^{(C)}$), *Trust* ($X^{(T)}$) and *Support expectations* ($X^{(S)}$). Algorithm 1 shows the main steps of the model algorithm. At each iteration, randomly selected agent i could decide to change the state of one randomly selected network layer. Each network layer was selected with fixed equal probability $\lambda = \frac{1}{3}$.

Algorithm 1 Pseudocode of the simulation algorithm

Input: Time t, number of iterations m, network X with nodes $\in \{1, 2, 3, \ldots, n\}$ and layers $X^{(C)}$, $X^{(T)}$, $X^{(S)}$, change probability of network layers $\lambda^{(C)}$, $\lambda^{(T)}$, $\lambda^{(S)}$.

Initialize $t = 0$
while $t < m$ **do**
    Randomly select one node i
    Randomly select one network layer $X^{(r)}$
    $t \leftarrow t + 1$
    for all nodes $j \neq i$ **do**

    Set utility after change $h_{ij} \leftarrow f_i(X^{(r)})$ if $X_{ij}^{(r)}$ is changed
  end for
  $h_{ii} \leftarrow f_i(X^{(r)})$
  Select one node j with probability $\pi(j) = \frac{\exp(h_j)}{\sum_k \exp(h_k)}$
  if $j \neq i$ **then**
    if $X_{ij}^{(r)} = 0$ **then**
      $X_{ij}^{(r)} \leftarrow 1$
    else
      $X_{ij}^{(r)} \leftarrow 0$
    end if
  end if
end while

In order to consider these mechanisms with realistic network dynamics, we parameterized the model both with within-network (i.e., agent preferences for local configurations) and cross-network processes (i.e., multiplexity) for each of the three network layers, i.e., *Collaboration, Trust*, and *Support expectations*. This means that agents considered three different objective functions.

3.1. *Collaboration*

We modeled *Collaboration* as a directed network $X^{(C)}$ where $x_{ij}^{(C)} = 1$ if i sent a request of collaboration to j and 0 otherwise. If $x_{ij}^{(C)} = 1$ and $x_{ji}^{(C)} = 1$, i.e., a request of collaboration was reciprocated within a dyad, we assumed that i and j had a collaboration tie. Here, we followed Ferligoj, Kronegger, Mali, Snijders, and Doreian (2015) in modeling $X^{(C)}$ as a directed network.

The objective function for $X^{(C)}$ was as follows:

$$f_i^{(C)}(x) = \beta_0^{(C)} \sum_j x_{ij}^{(C)} + \beta_1^{(C)} \sum_j x_{ij}^{(C)} x_{ji}^{(C)} + \beta_2^{(C)} \sum_j x_{ij}^{(C)} R_j + \beta_3^{(C)} \sum_j x_{ij}^{(T)} x_{ij}^{(C)} \tag{3}$$

The first term of the sum ($\sum_j x_{ij}^{(C)}$, *outdegree*) represented agents' baseline tendency of requesting collaboration to other agents. The second term ($\sum_j x_{ij}^{(C)} x_{ji}^{(C)}$, *reciprocity*) represented agents' tendency of accepting collaboration requests. The third term ($\sum_j x_{ij}^{(C)} R_j$, *resource popularity*) represented agents' tendency to requesting collaboration to agents based on the receiver's level of resources, R_j. Finally, the last term represented agents' tendency of collaborating with agents with whom they already had a trust tie ($\sum_j x_{ij}^{(T)} x_{ij}^{(C)}$, *association with Trust*).

3.2. *Trust*

We modeled *Trust* as a directed network $X^{(T)}$ where $x_{ij} = 1$ if i trusts j and 0 otherwise. For $X^{(T)}$, we assumed the following objective function:

$$f_i^{(T)}(x) = \beta_{0,0}^{(T)} \sum_j x_{ij}^{(T)} + \beta_{0,1}^{(T)} (\sum_j x_{ij}^{(T)})^2 + \beta_1^{(T)} \sum_j x_{ij}^{(T)} x_{ji}^{(T)} + \beta_2^{(T)} \sum_j \sum_h x_{ij}^{(T)} x_{ih}^{(T)} x_{jh}^{(T)} + \beta_3^{(T)} \sum_j x_{ij}^{(C)} x_{ij}^{(T)}. \tag{4}$$

The first term of the sum ($\sum_j x_{ij}^{(T)}$, *outdegree*) represented agents' baseline tendency to trust others, while the second term ($(\sum_j x_{ij}^{(T)})^2$, *outdegree slope*) modeled the utility change of an additional trust tie change when the outdegree increased. The third term ($\sum_j x_{ij}^{(T)} x_{ji}^{(T)}$, *reciprocity*) represented agents' tendency to reciprocate trust, while the fourth term ($\sum_j \sum_h x_{ij}^{(T)} x_{ih}^{(T)} x_{jh}^{(T)}$, *transitive triplets*) represented the tendency of i to trust j if both already trusted the same third agent, h, i.e., transitive path closure. These four parameters represented agents' within-network preferences. Finally, the last term ($\sum_j x_{ij}^{(C)} x_{ij}^{(T)}$, *association with Collaboration*) indicated agents' tendency to trust other agents to whom they had sent collaboration requests.

3.3. *Support expectations*

We modeled *Support expectations* as a directed network $X^{(S)}$ where $x_{ij} = 1$ if i expected social support from j and 0 otherwise. The objective function of $X^{(S)}$ was as follows:

$$\begin{aligned} f_i^{(S)}(x) = \beta_{0,0}^{(S)} \sum_j x_{ij}^{(S)} + \beta_{0,1}^{(S)} (\sum_j x_{ij}^{(S)})^2 + \beta_1^{(S)} \sum_j x_{ij}^{(S)} x_{ji}^{(S)} \\ + \beta_2^{(S)} \sum_j \sum_h x_{ij}^{(S)} x_{ih}^{(S)} x_{jh}^{(S)} + \beta_3^{(S)} \sum_j x_{ij}^{(T)} x_{ij}^{(S)}. \end{aligned} \tag{5}$$

The first term of the sum ($\sum_j x_{ij}^{(S)}$, *outdegree*) represented agents' baseline tendency to expect support from others, while the second term ($\sum_j (x_{ij}^{(S)})^2$, *outdegree slope*) modeled the utility change of an additional support expectation tie change when the outdegree increased. Similarly to Equation 4, the third and fourth terms represented agents' tendency to respectively reciprocate expectations of support ($\sum_j x_{ij}^{(S)} x_{ji}^{(S)}$, *reciprocity*) and expect support from an agent j if both already expected support from the same third agent, h ($\sum_j \sum_h x_{ij}^{(S)} x_{ih}^{(S)} x_{jh}^{(S)}$, *transitive triplets*). Finally, last term ($\sum_j x_{ij}^{(T)} x_{ij}^{(S)}$, *association with Trust*) implemented agents' tendency to expect support from trusted agents.

4. Model specification and simulation design

Simulations were run on a population of $n = 20$ agents, i.e., in a small-scale population. Note that results from sensitivity analysis on $n = \{50, 100\}$ did not show any significant qualitative difference (see Figures A1 and A2 in the Appendix Section). We fixed network change rate parameters throughout all our simulations equal for all three network layers, so that

$$\lambda^{(C)} = \lambda^{(T)} = \lambda^{(S)} = \frac{1}{3}. \tag{6}$$

We ran computer simulations by manipulating the distribution of *resources* and the correlated *neediness*. This required to examine three different scenarios depending on different parameter specifications.

4.1. *Baseline*

Table 1 shows the coefficient values of a *Baseline* scenario, following Equations 3, 4 and 5. Concerning $X^{(C)}$, we specified a negative *outdegree* parameter to indicate that requesting collaboration was costly for agents as this involved managing cooperation and coordination with partners. The cost of sending collaboration requests was balanced by a positive *reciprocity* parameter, which considered the general benefit of receiving a collaboration opportunity. By assuming a negative baseline tendency to create an additional tie, together with a positive tendency toward reciprocation,

Table 1. Model specification in the *baseline* scenario.

Parameter	Coefficient value
Collaboration	
Outdegree	−4
Reciprocity	3
Resource popularity	3
Association with Trust	1
Trust	
Outdegree	5
Outdegree slope	−1
Reciprocity	1
Transitive triplets	0.5
Association with Collaboration	1
Support expectations	
Outdegree	5
Outdegree slope	−1
Reciprocity	1
Transitive triplets	0.5
Association with Trust	1

we modeled marginal diminishing returns of collaboration requests. In this way, a collaboration request yielded a negative marginal impact on the sender's utility, unless it reciprocated an incoming request, or it was sent to either a high-resource or a trusted agent. This was to reflect the notion that collaborations as such are costly to establish and increase utility only if they create an additional form of benefit. In order to model agent preferences to target resourceful partners, we assumed *resource popularity* as a positive tendency. Finally, by specifying a positive coefficient for the *association with Trust* parameter, we assumed that agents preferred to request collaboration to trusted agents.

Concerning $X^{(T)}$, we assumed that agents had cognitive constraints while managing personal networks in that trust ties yielded marginal diminishing returns. Following Flache and Stark (2009), we set $\beta_{0,0}^{(T)}$ and $\beta_{0,1}^{(T)}$ of Equation 4 with a positive and a negative value, respectively. This allowed us to introduce marginal utility of any additional trust tie exceeding the marginal cost for agents with a low outdegree. As outdegree increased, marginal costs grew so that the expected utility of any new tie was below a certain low threshold. Following previous research on trust networks, we assumed that agents tended to reciprocate trust (*reciprocity*) and that agents who trusted the same third-party tended to trust each other (*transitive triplets*) (e.g. Bianchi et al., 2018; Lusher, Robins, Pattison, & Lomi, 2012; Robins, Pattison, & Wang, 2009). Moreover, by assuming transitive closure of trust ties, together with agents' preference for sending collaboration requests to trusted agents (*Association with Trust*; see above paragraph), we also aimed to model processes of transitive closure in $X^{(C)}$ without adding an *ad hoc* parameter for it. Finally, we assumed that agents preferentially trusted agents to whom they had sent a *Collaboration request* tie (*association with Collaboration*).

Concerning $X^{(S)}$, we assumed that expecting support from different sources yielded marginal diminishing returns, similarly to $X^{(T)}$. Following Bianchi et al. (2018), we assumed that agents preferred to reciprocate expectations of support (*reciprocity*), were inclined to closing paths of support expectation ties (*transitive triplets*), and preferentially expected support from trusted agents (*association with Trust*).

Note that we explored a wider range of coefficient values to approximate previous empirical findings by Bianchi et al. (2018), while trying to avoid problems of network degeneracy, which are related to tie closure (Frank & Strauss, 1986). We reported sensitivity analysis results on alternative coefficient values of *outdegree slope, reciprocity*, and *transitive triplets* in a Supplementary Information document (SI).

In order to manipulate the distribution of *resources*, we varied agents' R_i level of resources. In the *baseline* scenario, we assumed that

$$R_i = 0 \quad \forall i.$$

This implied that agents' preference to collaborate with more resourceful partners did not yield any effect on network dynamics (see Equation 3 and Table 1).

4.2. *Competition*

We simulated a *Competition* scenario, in which we divided the population in two classes of equal size, high-resource (H) and low-resource (L) agents. In this scenario, R was distributed among agents as a 2-class attribute, as follows:

$$R_i = \begin{cases} 0 & \text{if } i \in L \\ 1 & \text{if } i \in H \end{cases}$$

Combined with agents' preference for resourceful collaborators, this distribution allowed us to model competition among agents for attracting the most resourceful collaboration partners.

4.3. *Competition/neediness*

Finally, we simulated a third scenario, defined *Competition/neediness*, where we assumed that agents were heterogeneous in terms of *neediness* (N), which was negatively correlated to R, as follows.

$$N_i = \begin{cases} 0.5 & \text{if } i \in L \\ -0.5 & \text{if } i \in H \end{cases}$$

In this case, we assumed that N_i changed agents' baseline tendency of expecting support from different sources by redefining agents' objective function for $X^{(S)}$ as follows:

$$\begin{aligned} f_i^{(S)}(x) = \beta_{0,0}^{(S)} \sum_j x_{ij}^{(S)} + (\beta_{0,1}^{(S)} + N_i) \left(\sum_j x_{ij}^{(S)} \right)^2 + \beta_1^{(S)} \sum_j x_{ij}^{(S)} x_{ji}^{(S)} \\ + \beta_2^{(S)} \sum_j \sum_h x_{ij}^{(S)} x_{ih}^{(S)} x_{jh}^{(S)} + \beta_3^{(S)} \sum_j x_{ij}^{(T)} x_{ij}^{(S)}. \end{aligned} \tag{7}$$

Therefore, the coefficient of the *outdegree slope* parameter changed according to the level of agents' resources. More precisely, the marginal returns of ties related to expectations of support diminished faster for H-agents than for L-agents, as follows:

$$\beta_{(0,1)i}^{(S)} = \begin{cases} -0.5 & \text{if } i \in L \\ -1.5 & \text{if } i \in H \end{cases}$$

Table 2 summarizes our three simulation scenarios, which depended on the manipulation of the distribution of R and N.

Table 2. Simulation design.

Scenario	Distribution of R	Distribution of N
Baseline	equal	–
Competition	heterogeneous	–
Competition/Neediness	heterogeneous	heterogeneous

4.4. Simulation design

We simulated each scenario for 1,000 realizations. For each realization, we ran the simulation algorithm for 20,000 iterations in order to achieve robust outcome measures at approximate equilibrium levels for all scenarios. Agents were initialized in empty networks.[1]

We analyzed simulation outcomes by obtaining non-directed networks of *Mutual support expectations* ($X^{(MS)}$), where $x_{ij} = 1$ if both i and j had *Support expectation* ties to each other, while $x_{ij} = 0$ otherwise. We calculated the average degree of $X^{(MS)}$ to test our hypothesis on connectivity (see Propositions 1a and 1b in Section 2). In order to measure segregation, we calculated *gross segregation* values, as proposed by Moody (2001). The index considers the probability that network ties occur between nodes with the same value of a certain attribute more likely than between nodes with dissimilar values. In this case, A denoted the number of *Mutual support expectation* ties between agents with the same level of resources, while C was the number of pairs of agents with the same level of resources without these ties. This meant that A/C measured the odds that i and j had a *Mutual support expectation* tie, provided that i and j had a similar level of resources. Similarly, B/D indicated the odds of a *Mutual support expectation* tie between i and j if they had different levels of resources, where B was the number of ties between agents of different levels of resources, and D was the number of pairs of agents having different levels of resources without any tie. We defined the *gross segregation* index as an odds ratio and calculated it as follows:

$$s = \frac{AD}{BC}.$$

5. Results

Table 3 shows mean results on average degree and gross segregation of the *Mutual support expectation* network in the three simulation scenarios, while Figure 1 shows distributions. Outcome measures were averaged over 1,000 realizations for each scenario, by calculating outcome statistics at approximating equilibrium after 20,000 iterations. For the sake of readability, we log-transformed distributions of *gross segregation* of each scenario.[2]

Simulation results show that the average connectivity of the *Mutual support expectation* network decreased in the *Competition* scenario compared to the baseline, while resource-driven segregation increased. These results corroborate our propositions (see Propositions 1a and 1b in Section 2). While the effect on segregation was relatively strong, that on connectivity was considerably weak. This was because H-agents increased their popularity, so receiving more ties, whereas L-agents were less popular, so receiving less ties. Therefore, overall degree did not change significantly.

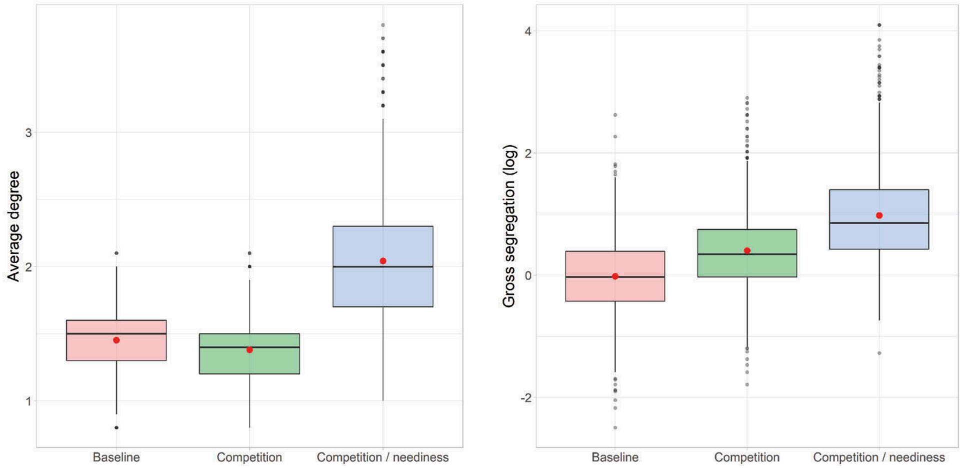
We then examined degree dynamics of each network layer in more detail. Figure 2 shows the mean evolution of the average outdegree of $X^{(C)}$, $X^{(T)}$, and $X^{(S)}$ in each scenario, while Figure 3

Table 3. Average degree and gross segregation (log-transformed) of *Mutual support expectations* networks in simulation scenarios. Mean values were averaged over 1,000 realizations, standard deviation are reported in parentheses.

	Outcome	
Scenario	Average degree	Gross segregation
Baseline	1.45 (0.24)	−0.02 (0.63)
Competition	1.38 (0.24)	0.40 (0.66)
Competition/neediness	2.05 (0.47)	0.98 (0.80)

[1]We performed robustness tests by initializing the model with $X^{(C)}$ being an Erdös-Renyi random network with density values$d = [0.1, 0.2, 0.3, 0.4, 0.5]$. We did not observe any relevant qualitative differences of simulation results.

[2]In order to calculate average values of *gross segregation* we did not consider those simulation outcomes with $s = +\infty$ values, which occurred in those cases where $BC = 0$ because$B = 0$, i.e. there were no between-group *Mutual support expectation* ties. The amount of such cases accounted for 0.012% of the simulation realizations in the worst case (*Competition/neediness* scenario).



(a) *Average degree* (b) *Gross segregation*

Figure 1. Boxplots of average degree and gross segregation across simulation scenarios (1,000 realizations each). Bold horizontal lines indicate median values, red dots indicate mean values.

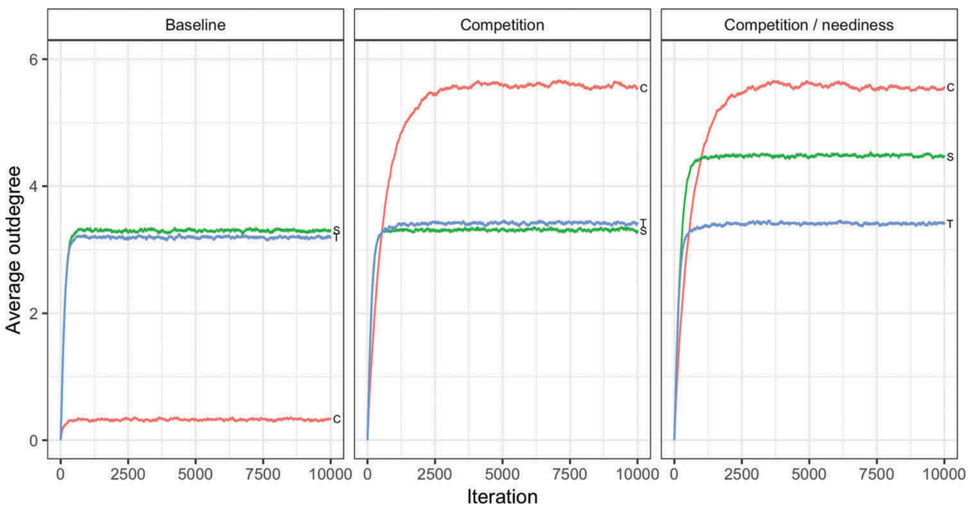


Figure 2. Simulated dynamics of average outdegree of *Collaboration, Trust*, and *Support expectations* networks. (Values averaged over 100 replications).

shows the average outdegree of $X^{(C)}$ and $X^{(S)}$ between and within resource classes across scenarios. By comparing the first and second panels in Figure 2, it is possible to observe that competition with unequal resource distribution boosted the number of collaboration requests, while the average number of trust and support expectation ties remained about the same.

The top left panel in Figure 3 shows a disproportionately higher amount of collaboration requests in the *Competition* scenario between H-agents. This was due to agents' preference of targeting resourceful agents for collaboration combined with the positive tendency of reciprocating collaboration requests. On the one hand, the assumed association between network layers caused *Trust* ties to develop disproportionately between H-agents, which eventually generated a higher concentration of *Support expectation* ties within the H class (see top right panel in Figure 3). On the other hand, building collaboration ties was difficult for L-agents, because their collaboration requests to H-agents

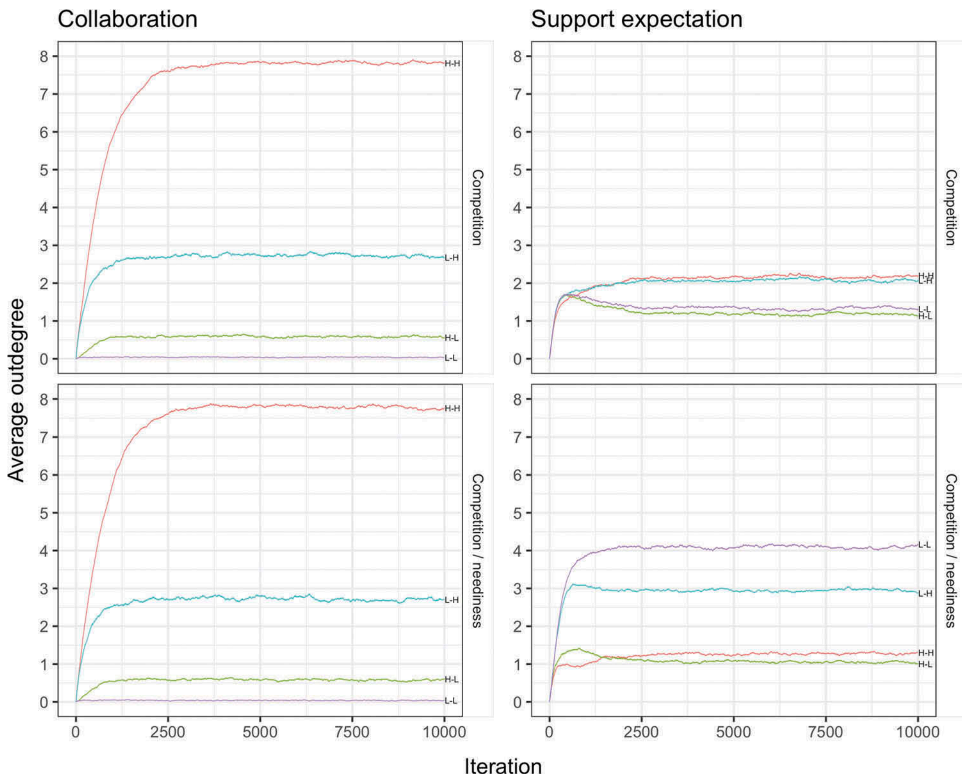


Figure 3. Simulated dynamics of average outdegree of *Collaboration* and *Support expectations* within and between resource classes across scenarios. (Values are averaged over 100 replications).

were less likely to be reciprocated, while their probability of receiving collaboration requests was low as well. This means that *L*-agents were out of the core of the emerging *Collaboration* network. This implied that they had less opportunities to build *Mutual expectation support* ties. Furthermore, the top right panel in Figure 3 shows that *L*-agents tended to expect less support from other in-group agents, while sending their *Support expectation* ties to *H*-agents, who reciprocated only occasionally. Therefore, under a competition regime with unequal resource distribution, agents' preferences of building *Trust* and *Support expectation* ties with collaboration partners generated a core-periphery *Mutual support expectation* network, with *L*-agents confined to peripheral network regions (see Figure 4 for illustrative examples). This result reflects the core-periphery networks generated by Flache & Hegselmann's models of support exchange among unequal actors (1999b), unless it was assumed that agents were driven by partially altruistic preferences (1999a).

The picture changed when we assumed neediness heterogeneity and a negative correlation of neediness with resources. Table 3 shows that our theoretical expectations (see Proposition 2 in Section 2) consistently follow from the dynamics generated by the behavioral assumptions of our model. Results showed that overall connectivity increased consistently in the *Competition/neediness* scenario, with some simulations generating *Mutual support expectation* networks with relatively highly connected networks. It is interesting to note that the increase in connectivity was not accompanied by higher integration. In fact, mean gross segregation significantly increased, with a slightly right-skewed distribution (see Figure 1b). This was due to the fact that we assumed a steeper marginal decrease of *H*-agents' tendency to expect support from other agents than for *L*-agents. This resulted in *L*-agents directing support expectations at a larger number of other agents than *H*-agents did. These expectations were primarily reciprocated by other *L*-agents, which resulted in the emergence of a more dense network of *Mutual support expectations* among *L*-agents. Figure 3 (bottom right panel) shows that *L*-agents had

(a) *Baseline.*

(b) *Competition.*

(c) *Competition / neediness.*

Figure 4. Instances of simulated *Mutual support expectation* networks across scenarios. Node colors represent resource classes. Green: *L*-agents; red: *H*-agents.. In the Printed version Black: L-agents; white: H-agents

on average a higher outdegree of *Support expectations* than H-agents, especially directed toward other L-agents. This changed the peripheral position which L-agents occupied in the *Competition* scenario in the *Support expectation* network into a highly connected position.[3] This further strengthened the segregation process already observed in the *Competition* scenario (see bottom right panel in Figure 4).

6. Discussion and conclusions

Our computational findings from a stochastic ABM supported our propositions on the effect of resource heterogeneity and competition on the link between collaboration and solidarity. We found that resource heterogeneity has a double-edged effect on the formation of social support relations (Flache & Hegselmann, 1999a, 1999b). On the one hand, competition generates slightly less connected and highly

[3]By setting *Transitive triplets* parameter of $X^{(S)}$ to 0, we did not obtain qualitatively different results. This suggests that the observed dynamics could not be attributed to transitive closure (see SI for more information).

segregated networks of support expectations. This is because if professionals compete for collaboration, preference for high-resource partners and a positive tendency toward reciprocation push low-resource individuals to peripheral network positions. Furthermore, if professionals develop trust preferentially toward collaboration partners, low-resource individuals cannot form an amount of trust ties equal to high-resource ones. Considering that support expectations are preferentially directed toward trusted others (Bianchi et al., 2018; Molm et al., 2009), low-resource individuals are marginalized in peripheral regions of support expectation networks. While the overall generation of support expectations is only slightly decreased by competition for collaboration, a considerable level of segregation is expected. On the other hand, while heterogeneity in neediness can in principle counteract the decrease in connectivity, given that support expectations are preferably reciprocated by others having similar resources, resourceful individuals tend to cluster in collaboration-based relationships while low-resource individuals segregate among each other. Then, network segregation follows resource distribution triggered by reciprocity tendencies.

Our findings have important implications for sociological theory and applied organizational research. First, our study allows to define more precisely constraints and context-dependent conditions that can lead to the emergence of solidarity from economic exchange (Bianchi et al., 2018; Kuwabara, 2011). Our results point to the possibility that competitive contexts and resource inequality could still generate relatively dense social support networks, although highly segregated. This is also pivotal to understand certain negative aspects of solidarity, as solidary behavior toward in-group members also leads to the exclusion of out-group individuals from potential benefits (Komter, 2001).

Second, while our results are in line with studies indicating possible detrimental effects of network centralization on group-level cooperation (Molm, 1994) and performance (Mora-Cantallops & Sicilia, 2019), our model suggests that individual interests in building support ties can counter-balance certain dysfunctional effects of competition in organizational settings. However, if skills and competencies are distributed unequally in professional networks or complex organizations, competition and multiplexity effects between trust and support could trigger network segregation. This is because resourceful individuals would rarely reciprocate support expectations of low-resource individuals (Flache & Hegselmann, 1999b). This has relevant implications for designing organizational settings. While the lack of social support by resourceful partners could be detrimental for learning, social approval and professional confidence of low-resource professionals, a segregated support network could yield undesired effects also in organizational settings by backfiring on collaboration relations (Mora-Cantallops & Sicilia, 2019; Sparrowe, Liden, Wayne, & Kraimer, 2001).

While theoretically highlighting intriguing complexities in the interplay of collaboration, trust and support expectations in economic exchange and organizations, our study also has some limitations, which make any generalization problematic and call for empirical tests. While we added behavioral heterogeneity to network modeling (Bojanowski & Buskens, 2011; Bravo, Squazzoni, & Boero, 2012; Xiong, Payne, & Kinsella, 2018) and a dynamic picture to network effects, which is difficult in behavioral research (Takács, Bravo, & Squazzoni, 2018), our findings require extensions to understand larger-scale populations. Here, we aimed to extend previous empirical findings (Bianchi et al., 2018) by developing well-controled theoretical explorations that looked at richer behavioral assumptions. However, the capacity of a model to examine complex multiplex network interdependencies must be completed by considering the dynamic interplay of behavioral and structural factors. Finally, a more explicit attention to status, recognition and signals, as well as to the strategic management of positive and negative ties, would enrich our understanding of the link between competition and solidarity in professional collaborations (Grow, Flache, & Wittek, 2015; Rubineau, Lim, & Neblo, 2019).

In conclusion, despite these limitations, our study testifies to the fruitfulness of ABM for theory development, in particular to explore the consequences of artificial, experimental manipulations on social network dynamics (Raub, Buskens, & van Assen, 2011; Snijders & Steglich, 2015; Stadtfeld, 2018; see also examples by Anjos & Reagans, 2013; Stadtfeld et al., 2020). By manipulating variations of environmental configurations, computer simulation helps to observe aggregate consequences of micro-level processes while controlling for factors that empirical research cannot always fully isolate.

While our study was only indirectly informed by previous empirical research (Bianchi et al., 2018), we hope that it can inspire future empirical tests and stimulate further theoretical extensions (Boero & Squazzoni, 2005; Flache et al., 2017) so that we can cross-fertilize case-based empirical network studies and social network theoretical work.

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Appendix: Sensitivity analysis

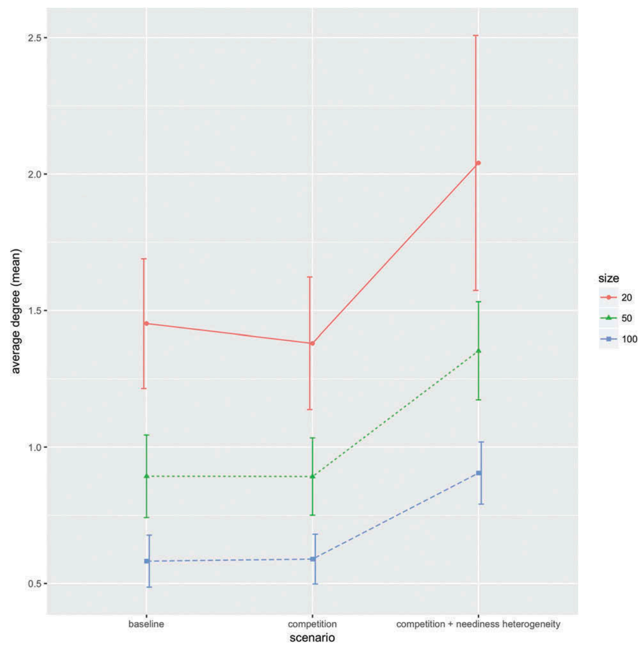

Figure A1. Average degree of *Mutual support expectations* across scenarios for $n =$ 20, 50, and 100. (Mean values over 1,000 realizations).

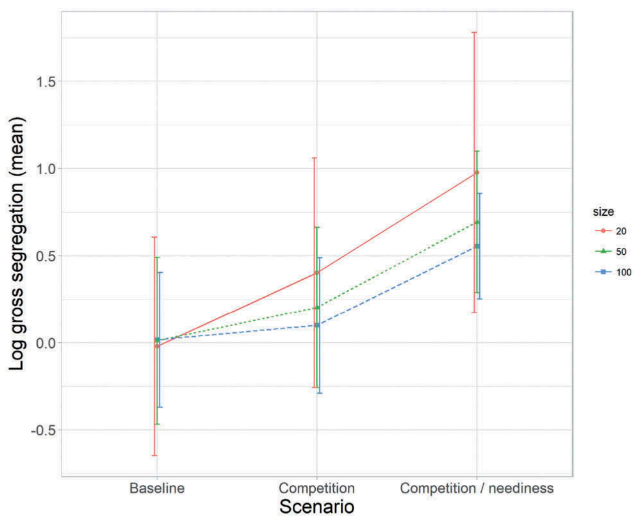

Figure A2. Gross segregation (log) of *Mutual support expectations* across scenarios for $n =$ 20, 50, and 100. (Mean values over 1,000 realizations).