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Trust and partner selection in social networks: An experimentally grounded model

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ABSTRACT

This article investigates the importance of the endogenous selection of partners for trust and cooperation in market exchange situations, where there is information asymmetry between investors and trustees. We created an experimental-data driven agent-based model where the endogenous link between interaction outcome and social structure formation was examined starting from heterogeneous agent behaviour. By testing various social structure configurations, we showed that dynamic networks lead to more cooperation when agents can create more links and reduce exploitation opportunities by free riders. Furthermore, we found that the endogenous network formation was more important for cooperation than the type of network. Our results cast serious doubt about the static view of network structures on cooperation and can provide new insights into market efficiency.

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1. Introduction

Recent experimental studies have acknowledged the relevance of trust for cooperation in human societies (e.g., Barrera and Buskens, 2009; Berg et al., 1995; Boero et al., 2009a,b; Camerer, 2003; Keser, 2003). From a sociological perspective, the problem with these studies is that they considered only highly unrealistic interaction structures, e.g., random coupled subjects, and did not investigate the endogenous forces that might influence structure formation. On the other hand, certain formal models with more concrete sociological content have examined how structural embeddedness affected trust and cooperation, but without referring to empirically verified assumptions on agent behaviour (e.g., Cohen et al., 2001; Pujol et al., 2005).

This article aims to study the link between interaction outcomes and social structure formation by combining experimental data on individual behaviour and social network simulation. Unlike certain influential studies that emphasized the relevance of the interaction continuity to understand cooperation (e.g., Axelrod et al., 2002; Cohen et al., 2001), we investigated whether the robustness of cooperation depended on the agent's capability of selecting good partners, whether this could be influenced by the particular network structure where agents were embedded, and what was the effect of endogenous forces of network formation.

Our aim was to tackle certain important and unsolved issues in the experimental and simulation literature. First, there is no consensus about the role that network structures play on cooperation. On the one hand, some authors argue that conditional cooperators could reinforce pro-social behaviour when they are linked with each other and cooperation could even increase when network structures convey social contagion (e.g., Fowler and Cristakis, 2010). On the other hand, others have argued that network structures could cause reciprocal defection and that the tightness required by social networks to favour contagion cascades was highly unrealistic (Suri and Watts, 2011). Furthermore, most experimental and simulation studies on networks and cooperation have not considered under what circumstances and forces individual behaviour and social network configurations might influence each other endogenously (Takács et al., 2008).

To fill this gap, we have extended the scope of a standard experimental economics game, i.e., the repeated investment game, to situations that were impossible to test in the lab, by introducing complex network structures endogenously. Our results show, first, that exogenously fixed network structures do not lead to more cooperation than the experiment where subjects played in random dyadic networks. This confirms Suri and Watts (2011), whose results indicated that, by varying the network structure, no significant differences were found in contribution levels in a public good game. More importantly in our case, a substantial increase in cooperation occurred only when partner selection and dynamic structure formation were endogenously introduced. This allowed cooperators to break their links with free-riders, benefit from a

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higher number of interactions and constantly re-shape their networks. It is important to note that in our case, cooperation increased even if we did not include social imitation or contagion, agent behaviour was largely heterogeneous and signalling was not possible (e.g., Santos et al., 2011).

This means that cooperation, rather than being fostered by the stability of the interaction structure, as suggested by previous simulation studies (e.g., Axelrod et al., 2002), has more to do with the selective intelligence of agents when they endogenously create networks composed of trustworthy partners, which can isolate bad apples. Our results confirm certain findings of the Eguiluz et al. (2005) model, where the cooperative equilibrium in a Prisoner's Dilemma played on a dynamic network was guaranteed by "leaders" (agents in central position) who played a crucial role in sustaining cooperation in the system. We found the same result even if we did not assume the presence of self-reinforcing cooperation mechanisms, such as social imitation, which were of paramount importance for Eguiluz et al.'s findings. The key-importance of central agents and the efficiency of centralized structures to promote cohesion, cooperation and collective action was also emphasized, among others, by Knoch (1991), Gould (1993) and Diani (1995).¹ Previous experimental studies showed that leadership could increase cooperation in small groups, especially when leaders were endogenously determined (e.g., Güth et al., 2007). Our results allow us to consider that this could also happen in larger and more complex groups, if networks dynamically re-adjust following positive interactional experience of individuals and bad apples risk social isolation (Takács et al., 2008).

The rest of the article is organized as follows: The next section presents the research background, Section 3 describes the experiment used to gather behavioural data, Section 4 presents the estimation of agents' parameters and Section 5 introduces the models and presents the results. Finally, Section 6 discusses our findings.

2. Background

A prominent social mechanism that allows agents to decrease the risk of being cheated in many real social interactions is partner selection. It is likely that in concrete social situations, individuals have a preferential choice and can opt out of given interactions (e.g., Slonim and Garbarino, 2008). Partner selection is not just a means for individuals to make good preferential choices, but also provides an incentive for counterparts to be reliable and committed to others so as to avoid social isolation (e.g., Ashlock et al., 1996). For example, Joyce et al. (2006) built a simulation model largely inspired by Axelrod's well-known tournament. This showed that a conditional association strategy (i.e., agents left partners who defected them and stayed with cooperative partners) can outperform TIT-FOR-TAT, i.e., the conditional altruism strategy suggested by Axelrod. A similar finding on the relevance of contingent strategies which discriminated good and bad partners was also found by Aktipis (2004) and Helbing and Yu (2008).

These interactional aspects have been explained by two arguments: strategic uncertainty reduction and commitment bias. While the former emphasizes rational strategic aspects, the latter points to intrinsic other-regarding or emotional motivation. The first position was stressed by Kollock (1994) in an experimental study on market transactions. Here, the challenge to deal with information asymmetries and uncertainty about other agents' trustworthiness made long-term interaction partners look more attractive than others. Podolny (2001) suggested that investment

bankers who operated in markets characterized by a higher degree of uncertainty were likely to interact with colleagues they had interacted with in the past. Gulati (1995) found the same in an empirical study on corporate alliances. More recently, Beckman et al. (2004) conducted an empirical study on interlocking and alliance networks for the 300 largest US firms during the period 1988–1993. They found that there was a strong correlation between the type of market uncertainty and the stability or instability of partner selection networks: organizations facing firm-specific uncertainty were less selective and more open to new ties than those facing collective market uncertainty.

Hauk (2001) developed a simulation model of an iterated prisoner's dilemma where partner selection was a learning strategy for agents in uncertain environments. Agents learnt how to discriminate between trustworthy and untrustworthy partners and to reward/punish others. By revising strategies according to selected partners, cooperators learnt how to stop the exploitative strategies of agents in the population. In two experiments conducted in the US and Japan, Yagamashi et al. (1998) also found that uncertainty promoted commitment between partners. In particular, individuals who trusted others more often established committed relations less frequently than sceptics, as they relied on generalized trust more.

The second point was that the risk and uncertainty of exchange provided the opportunity for partners to demonstrate their trustworthiness. Therefore, behavioural commitments and trust signals sustained cooperation informally and spontaneously, without negotiations, bargaining and binding agreements as assumed in social exchange research (e.g., Molm et al., 2000). Recent simulation studies have indicated that partner selection could generate a "commitment bias", so that commitment to existing partners increased beyond instrumental reasons. This is due to the strength of intrinsic other-regarding motivation (Back and Flache, 2006, 2008). Back (2010) confirmed this hypothesis in a lab commitment-dilemma game based on a market exchange between subjects who played in artists selling paintings roles and computer-simulated collectors buying them, in six locations of three countries, i.e., the Netherlands, China, and the US. He showed that the initial commitment of buyers had a positive effect on partner selection, even when controlling for uncertainty and material benefits.

Although full of important insights, these studies did not seriously consider the importance of complex social structures. In particular, they undervalued the consequences of partner selection within certain social structure configurations. Moreover, most of the experimental literature on partner selection typically investigated the internal aspects of the selection decision, rather than its consequences over time (e.g., Haruvy et al., 2006; Kagel and Roth, 2000). Recently, Slonim and Garbarino (2008) examined the relevance of partner selection for trust and altruism in the lab by playing an investment game and a variant of the dictator game. Here, partners were exogenously imposed or endogenously chosen. They found the positive effect of partner selection even on market efficiency. Nevertheless, they underestimated the relevance of studying partner selection sociologically, i.e., within network formation processes and by looking at how network structure and partner selection could influence each other. The idea that partner selection is a driving force for network formation, stability and change has not explicitly been acknowledged in the experimental literature (Beckman et al., 2004).

On the other hand, most studies on endogenous tie formation, which explains important aspects of cooperation in social and economic situations, are more analytically oriented than explicitly based on experimental data (e.g., Skyrms and Pemantle, 2000). Moreover, they did not look at the importance of the complexity and large scale of social structures (e.g., Calvó-Armengol, 2001; Dutta et al., 2005; Jackson and Watts, 2002; Jackson and Wolinsky,

¹ For a recent overview on this topic, see Janky and Takacs (2010).

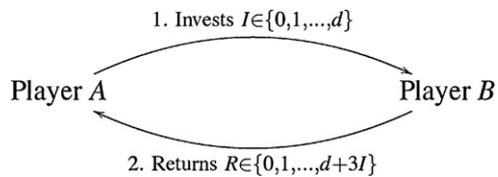


Fig. 1. The investment game: player A profit = $d - I + R$; player B profit = $d + 3I - R$.

1996) or the crucial role of partner selection as a driving force for network formation and dynamics (e.g., De Vos et al., 2001). A noticeable exception was Eguíluz et al. (2005), who created a social network simulation based on a spatial prisoner's dilemma to investigate the co-determination of individual strategies and networks. Unfortunately, they did not look at partner selection at the agent level and did not follow lab data for modelling agent behaviour realistically.

To fill this gap, we worked on an experimentally grounded agent-based model that investigated the link of social interaction and social structure in trust situations. Our assumption was that although an Axelrod-like “shadow of the future” situation can provide a reason for cooperation, agents more probably select each other in reality following past behaviour information. Moreover, by introducing partner selection, we looked at social mechanisms that might explain why social structure changes over time. Indeed, we know that, in reality, social interaction structures, especially in strategic and economic exchange situations, tend to have certain ordered shapes and properties rather than random encounters. Our idea was to use and extend experimental data to look at possible generative mechanisms of network structures.

3. The experiment

Our goal was to look at individual behaviour in asymmetric trust situations, i.e., where an investor had to choose whether to trust another individual (the trustee), who had a rational incentive to cheat (Coleman, 1990, 177–180). The investment game is a standard experimental framework well-suited to investigate trust in economic interaction characterized by information asymmetries and uncertainty (Berg et al., 1995). The game was repeated many times using different samples and under a vast range of different conditions (e.g., Cronk, 2007; Keser, 2003; King-Casas et al., 2005; Knoch et al., 2009; Ortmann et al., 2000) and, recently, it has gained terrain also among sociologists (e.g., Barrera and Buskens, 2009; Boero et al., 2009b; Buskens and Raub, 2008; Molm et al., 2000).

Fig. 1 is a schematic representation of a typical investment game. Each round, participants were coupled and randomly assigned to different roles, called player A (the investor) and player B (the trustee). Both players received an initial endowment of d ECU, with a fixed exchange rate in real money. First, player A had to decide the amount I between 0 and d to send to B, keeping for him/herself the part $(d - I)$. The amount sent by A was tripled by the experimenter and sent to the trustee, in addition to his/her own endowment, who decided whether to return to A all, some or none of the amount received. As before, the amount returned by B could be any integer between 0 and $(d + 3I)$. The amount $(d + 3I - R)$ not returned represented B's profit, while R was summed to the part kept by A to form the final profit of the latter, which was calculated as $(d - I + R)$.

At the end of the game, the final payoff of each player was the sum of the payoffs of the game rounds. All profits were counted in experimental currency units (ECU), translated into real money using a fixed exchange rate and paid immediately after the end of the experiment. The game was called the “investment game” as the rule of multiplying the amount sent by investors implied that (a) investors dealt with the uncertainty of paying a cost at the

beginning of the interaction to possibly gain higher revenues at the end, and (b) trustees had a return from investors' decisions.

The game was a sequence of one-shot interactions with no information on past behaviour, the players knew the structure of the game and could anticipate the behaviour of their opponent only by backward induction. The prediction of the rational choice theory was that, as B were expected to maximize their utility and had no rational incentive to return anything to A, the dominant strategy for A players was to invest zero. This led to a unique sub-game perfect equilibrium, where both players kept their entire endowments. However, this was inefficient as any sum greater than zero invested by A was tripled by the experimenters and could lead to a Pareto superior outcome, with the optimum represented by A investing the whole endowment. However, despite any equilibrium prediction, a quite robust result of investment games played both in the laboratory and in the field was that A players invested a substantial amount of their endowments (usually around 40%) and that B players returned slightly less than the amount invested by A, although much less than a fair share of the overall amount $(d + 3I)$ received (e.g., Berg et al., 1995; Boero et al., 2009b; Cronk, 2007; Keser, 2003; Ortmann et al., 2000).

Our experiment was based on a repeated version of this investment game. One hundred and eight subjects were recruited through public announcements and played the game in six groups of 18 individuals. Half of the subjects were students from the University of Brescia, half from the University of Torino (Cuneo campus). The experiment took place in Spring 2009 in the computer laboratories of the two Faculties of Economics, both equipped with the experimental software z-Tree (Fischbacher, 2007). All groups received the same instructions (available as supplementary materials) and played a repeated investment game using an identical computer interface. The endowment d was 10 ECU with an exchange rate of 1 ECU = 2.5 Euro. Participants earned, on average, approximately 15 Euros, including a show up fee of 5 Euros, which were paid immediately after the experiment. The experiment, including instruction reading, took approximately one hour.

All interactions took place through the computer network and the subjects were unable to identify their counterparts. Participants played 10 periods and were informed in advance of the number of periods to play. The experiment followed a “stranger” matching protocol, i.e., randomly re-coupling subjects after each period. This protocol allowed us to control for the use of direct reciprocity strategies among participants. The players' roles were randomly assigned at the beginning of the first period and subsequently changed on a regular basis (ABAB... or BABA...), so that each subject played the same number of periods in each role.

The results showed that subjects invested, on average, 3.48 ECU (i.e., about 35% of their endowment) and returned 2.79 ECU or about 32% of the amount received (excluding the fixed B endowment of 10 ECU).² The modal investment was 2 ECU while the modal return was 0 ECU, with both investments and returns tending to decrease during the game (Fig. 2).

This result is in line with previous experiments based on investment games, although both investments and returns were somewhat lower than average. In their review of 162 replications of the investment game, Johnson and Mislin (2011) calculated that, on average, investors sent 50% of their endowment (range 22–89%) and trustees returned 37% (range 11–81%). Following their analysis, at least three factors can explain the relatively low levels of trust and trustworthiness in our experiment: (i) our subject pool was composed of undergraduate students, who usually return lower amounts than older people (Yen, 2002); (ii) previous experiments

² All statistical analysis were conducted using the R 2.11.1 platform (R Development Core Team, 2010).

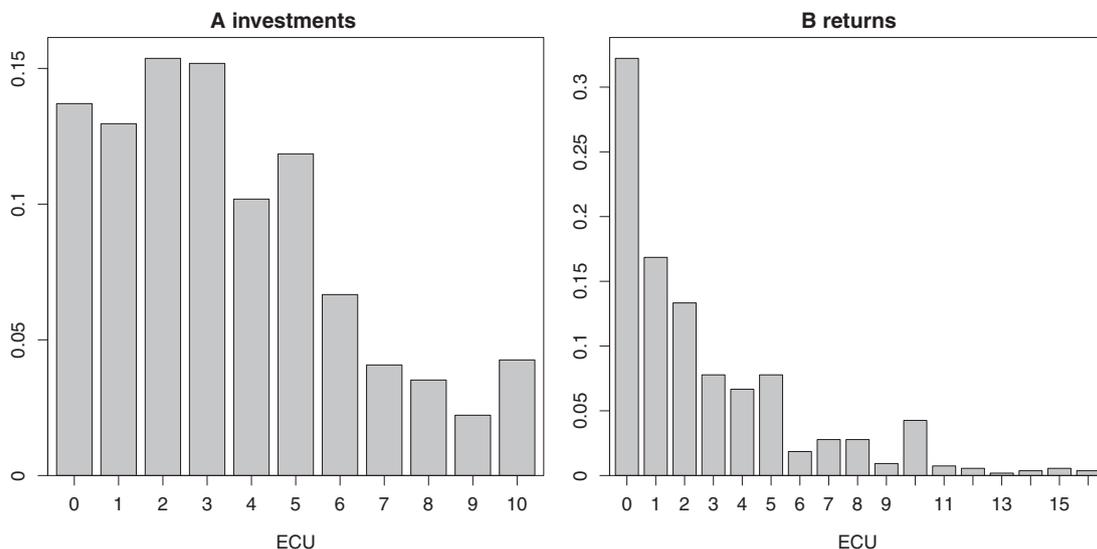


Fig. 2. Distribution of investments and returns in the experiment.

in Italy already led to below average investments and returns (e.g., Johnson and Mislin, 2011); (iii) our subjects played in both roles, which was necessary for our modelling purposes but is a further factor reducing cooperation in the game (e.g., Greiner and Levati, 2005). This given, our results fell fully within the range of standard investment game outcomes, and the fact that we recorded slightly below average investment and returns did not alter our confidence in the general reliability of our model.

4. Parameter estimation

We used these experimental data to calibrate an agent-based model that reproduced the behaviour of the subjects in the lab to investigate the impact of more complex interaction structures. By following the idea that, in the Investment game, trust and reciprocity play a crucial role in explaining subject behaviour (McCabe and Smith, 2000; Ostrom and Walker, 2003), we estimated a coefficient β_i which indicated how much investors modified their investment each period in function of the difference between the amount invested and the amount received by *B* players in the previous round. For any player *i* and period *t*, we calculated the difference $X(i, t) = R(i, t - 1) - I(i, t - 1)$, where $I(i, t - 1)$ and $R(i, t - 1)$ were the amounts that *i* invested and received as return from their investment in the previous round, respectively. We subsequently came up with the model

$$Y(i, t) = \alpha_i + \beta_i X(i, t) + \varepsilon \quad (1)$$

where $Y(i, t)$ was the amount invested by player *i* in round *t*, so that the two parameters α_i and β_i were obtained for each subject when playing as investor. Eq. (1) took into account the fact that investors could have had an individual constant propensity to trust represented by the individual intercept α_i , but also the capability of reacting upon past experience represented by the β_i coefficient. On the other hand, *B* players were supposed to react mainly against what they received from *A* players. To look at this behaviour, we estimated a third coefficient γ_i defined as the average amount returned by each subject as proportion of the amount received in each round plus the fixed endowment. Therefore, the parameter γ_i represented an estimate of the player's trustworthiness.

We were able to successfully estimate the parameter for 105 out of the 108 subject that participated in the experiment. It is worth noting that, while β_i did not significantly correlate with the other parameters, the correlation between α_i and γ_i was significant and

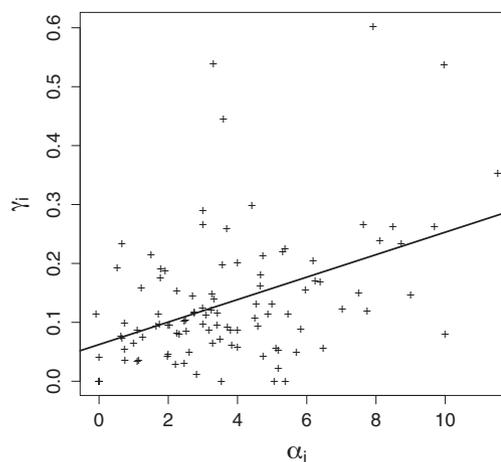


Fig. 3. Distribution of α_i and γ_i with regression line.

positive ($r = 0.44$, $p < 0.001$) (Fig. 3). In other terms, trusting subjects were also trustworthy: they tried to cooperate and responded by cooperating to others' cooperation. This result confirmed previous findings on the correlation between trusting behaviour and trustworthiness (Colquitt et al., 2007) and the idea of reciprocal behaviour at the base of our model.

5. The models

5.1. Experiment replication

We built an *experimentLike* model that exactly replicated the original experiment with calibrated parameters.³ In each round, agents were coupled and played an investment game either as *A* or as *B* players. At the end of each round, they were randomly re-coupled while their roles alternated on a regular basis just as in the original experiment. The behaviour of each agent depended on the

³ Note that we drew 105 valid estimations out of 108 subjects. As the game was played in dyads, we decided to randomly remove one of the experiment participants at the beginning of each run of the model, which, as a result, included only 104 agents.

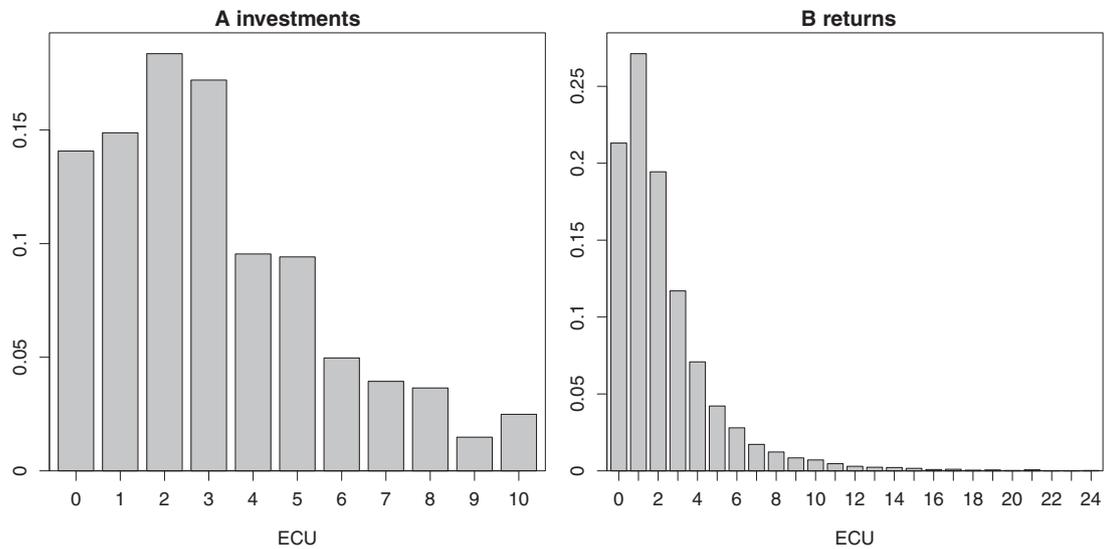


Fig. 4. Distribution of investments and returns in the *experimentLike* model.

coefficient estimated from the experimental data. More specifically, each agent i playing in the role of A in round t invested an amount

$$I(i, t) = \alpha_i + \beta_i [R(i, t - 1) - I(i, t - 1)] \quad (2)$$

where α_i and β_i were the coefficients of the corresponding participant while $I(i, t - 1)$ and $R(i, t - 1)$ were the amounts invested and received in the previous period. In the first round of the game, we set $I(i, 0), R(i, 0) = 0$ for each agent so that agent's first move was chosen only on the basis of α_i . Indeed, α_i reflected the intrinsic propensity of the participants (and, therefore, of our agents) to trust others, while β_i represented the effect of their past experience. On the other hand, when playing as B , agents returned

$$R(i, t) = \gamma_i [3I(i, t) + d] \quad (3)$$

which was their endowment multiplied by the individual parameter γ_i estimated on the experimental data.

Following this procedure, we built an *experimentLike* model, which successfully reproduced the experimental data.⁴ The average investment over 100 runs of the *experimentLike* model was 3.57 ECU and the average return 2.76 ECU (see Table 2). A t test over individual investments/returns, averaged over the game periods, confirmed that the experiment/model figures did not significantly differ (respectively, $t = 0.288, p = 0.774$ two sided, and $t = -0.085, p = 0.933$ two sided). It is worth noting that also the distribution of investments and returns followed a pattern similar to the experiment (Fig. 4).

5.2. The simulation scenarios

We then designed other scenarios where we modified the interaction structure. Each scenario used the experimental data as input and, more generally, was identical to *experimentLike* model, except for the specific characteristic(s) under examination. Table 1 provides an overview of all simulation scenarios.

A first simple variation was to increase the number of rounds played by agents. This was done for all scenarios, including the *experimentLike* model, which were tested both using a 10 and a 30 rounds game. Then, we introduced a two way interaction between agents, i.e., in each round, agents played both as A and B with their

Table 1
The simulation scenarios.

Model name	Main characteristics
<i>experimentLike</i>	<ul style="list-style-type: none"> • Random coupling in each period • One way interaction
<i>twoWays</i>	<ul style="list-style-type: none"> • Random coupling in each period • Two way interaction
<i>fixedCouples</i>	<ul style="list-style-type: none"> • Fixed couples • Two way interaction
<i>denseNetwork</i>	<ul style="list-style-type: none"> • Fixed fully connected network • Two way interaction
<i>smallWorld</i>	<ul style="list-style-type: none"> • Fixed small-world network • Two way interaction
<i>scaleFree</i>	<ul style="list-style-type: none"> • Fixed scale-free network • Two way interaction
<i>dynamic1Couples</i>	<ul style="list-style-type: none"> • Dynamic network • Broken links are replaced only for isolated agents • Two way interaction • Start from random coupling
<i>dynamic1Dense</i>	<ul style="list-style-type: none"> • Dynamic network • Broken links are replaced only for isolated agents • Two way interaction • Start from dense network
<i>dynamic2Couples</i>	<ul style="list-style-type: none"> • Dynamic network • Broken links are replaced only by one of the two formerly linked agents • Two way interaction • Start from random coupling
<i>dynamic2k10</i>	<ul style="list-style-type: none"> • Dynamic network • Broken links are replaced only by one of the two formerly linked agents • Two way interaction • Start from a regular network of degree 10

opponent (*twoWays* model). Note that, while this extension may be of no special interest in itself, it provided a baseline for subsequent scenarios where we extended the interaction to a number of agents greater than two.

Since we knew that differences in the network structure could have crucial consequences for the cooperation at a macro level, we built four models that explored the effect of different network structures. The *fixedCouples* model simply maintained the initial couples throughout the whole run. The *denseNetwork* model introduced a fully connected network where, in each round, each agent interacted with all others. In the *smallWorld* model, we introduced

⁴ All models were programmed in Java using the JAS Library (<http://jaslibrary.sourceforge.net/>). Source codes are provided as supplementary material.

Table 2
Average investments and returns in the original experiment and in the static network simulation scenarios. Standard deviations are in parenthesis.

Model name	10 period game		30 period game	
	A investments	B returns	A investments	B returns
<i>experimentLike</i>	3.57 (2.50)	2.76 (2.62)	3.56 (2.53)	2.76 (2.63)
<i>twoWays</i>	3.57 (2.52)	2.76 (2.61)	3.57 (2.54)	2.76 (2.61)
<i>fixedCouples</i>	3.65 (2.53)	2.91 (3.13)	3.67 (2.56)	2.92 (3.17)
<i>denseNetwork</i>	3.57 (2.54)	2.76 (2.61)	3.57 (2.54)	2.76 (2.61)
<i>smallWorld</i>	3.58 (2.54)	2.76 (2.62)	3.57 (2.54)	2.76 (2.62)
<i>scaleFree</i>	3.61 (2.54)	2.80 (2.68)	3.61 (2.54)	2.80 (2.69)
Experiment	3.48 (2.69)	2.79 (3.58)	–	–

a fixed “small-world” network structure with initial degree 4 and re-wiring probability 0.01, two parameter values able to lead to typical “small-worlds” phenomena (Watts and Strogatz, 1998; Watts, 1999). The *scaleFree* model was based on a “scale-free” network that followed Barabási algorithm with exponent $\gamma=3$, which represents a value falling close to the centre of the [2.1, 4] interval identified as typical for empirical cases of large networks (Barabási and Albert, 1999). In all these cases, the network structure remained fixed throughout the whole game. Note that agents now could have more than one interaction per round. More specifically, each round they played an investment game both as A and as B with all other agents with whom they were linked.

Finally, we investigated the introduction of a dynamic network. Basically, these scenarios added the criterion of partner selection to the formation of couples, so that interaction structure was dynamically shaped by the outcome of the interaction (e.g., Corten and Buskens, 2010; Eguíluz et al., 2005; Flache, 2001). Since there was no way to derive the algorithms that agents used to break their links and create new ones from the experiment, we identified certain plausible algorithms by using as few assumptions as possible. We built two different models, both based on simple mechanisms but with a different focus. The first one (called *dynamic1*) was designed to avoid any agent becoming isolated—i.e., no longer linked to any other agent—while the second (*dynamic2*) was aimed at maintaining the total number of links in the network constant (Table 1).

Both models were based on the idea that “unsatisfied” agents could break their links. In short, we assumed that agents had a threshold happiness function so that they changed partners when they were unhappy. The threshold function was very simple: A agents were happy when B returns were higher or equal to the ones in the previous time step. This is coherent with certain behavioural attitudes of individuals found in economic psychology, e.g., the so-called *Prospect theory* introduced by Kahneman and Tversky (2000). This theory suggested that individuals often use what happened in the past as a reference to estimate future outcomes. Note also that a similar strategy for determining agents’ satisfaction was assumed, for instance, in Bravo (2011), where the emergence of institutions in common-pool-resource situations was modelled. We assumed that a couple could be broken when at least one agent of the couple was unhappy. When there was no past information to evaluate happiness – i.e., in the first two rounds – the couple remained fixed.

The only difference between the two dynamic models was the algorithm for the definition of new links. In the *dynamic1* model, broken links were replaced only when an agent became isolated. In this case, a new link was formed between the isolated agent and a new random agent different from the one with whom it was linked before. In the *dynamic2* model, after each link break, one of the two formerly connected agents was randomly chosen to initiate a new link. In this case, no check was made and agents could become isolated. This second algorithm maintained the number of links in the network constant, while changing its structure.

Both the *dynamic1* and the *dynamic2* model were tested starting from different initial network structures. More specifically, we

used random coupling and a fully connected network as starting point for the former and random coupling and a random network of average degree 10 for the latter. The difference was due to the fact that the second re-coupling algorithm implied that each agent was connected to everyone else and there was no other possibility of re-linking than re-building the broken connection. Having two link replacement algorithms and two initial network structures, we tested four dynamic models named, respectively, *dynamic1Couples*, *dynamic1Dense*, *dynamic2Couples* and *dynamic2k10*. All dynamic models were run for 30 periods in order to see the evolution of the network in a longer period than the original experiment.

5.3. Static network model results

For each scenario, we ran 100 replications to consider the stochastic elements of the models. Table 2 presents the average investments and returns in all models, comparing them with the experiment.

The first important point is that neither the modification of the network structure, nor more rounds significantly changed the outcome of the game. In most runs, models reached their equilibrium before the 10th round, with no significant change. Even introducing two-way interactions, which increased the number of investment games played by agents in every run, only accelerated reaching an equilibrium without altering results. Similarly, letting agents play over a fully connected network, where each agent interacted with all other agents in every single round (resulting in a total of 214,240 interactions per run in the 10 rounds game and in 642,720 interactions in the 30 rounds) did not change the overall results. In all cases, according to a *t* test, the average investments and returns of the models did not significantly differ from the experiment.

The introduction of networks where not all agents had an equal number of interactions, posed a challenge to our analysis. Up to now, to check the statistical significance of the difference between the simulation results and the experiment, we used a *t* test over individual averages. This was a good solution only when agents interacted the same number of times. However, it led to an overestimation of the weight of agents with a lower number of interactions in case of networks where the number of links for each agent was different. For instance, the average investment in the 10 period *scaleFree* model was 3.61 when considering each single interaction. However, considering the average contribution for each agent, the average was 3.57. Although little, this difference could have affected the significance of our results. Moreover, this difference was likely to increase when moving from static to dynamic networks. To consider this problem seriously, we conducted our *t* tests on the weighted means, where the weights depended on the number of interactions performed by each agent.

The *smallWorld* and *scaleFree* model results were very similar to the previous cases: the average investments were slightly higher than the experiment, but a *t* test showed that this difference was not significant. Furthermore, the average returns were almost identical to the experiment.

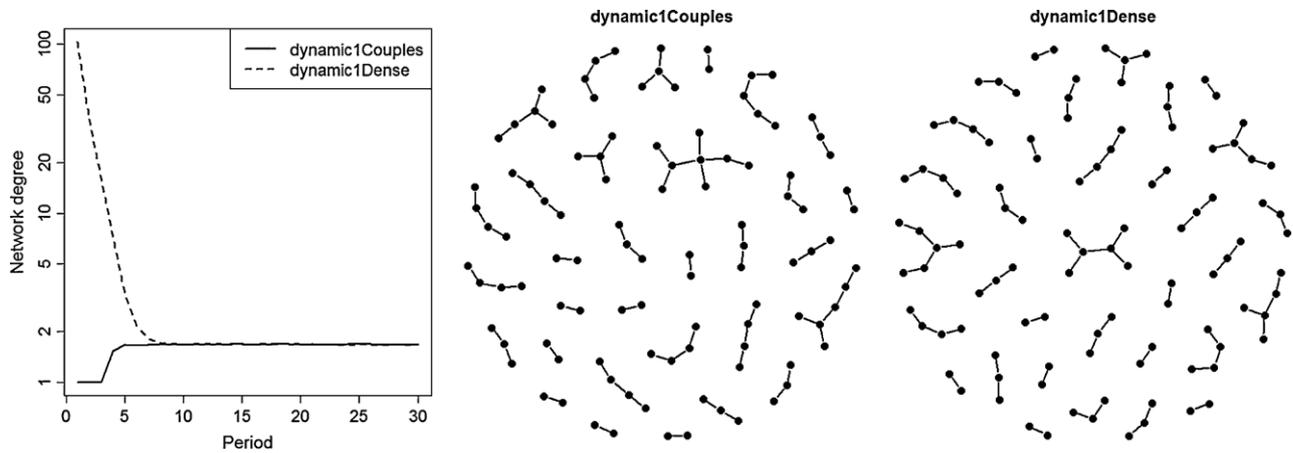


Fig. 5. The system resulting from the *dynamic1* models converged to a fixed equilibrium independently from the starting point. The left panel shows the average degree of the networks in the two models. The center and the right panels show the networks after 30 rounds of a typical run of the *dynamic1Couples* and the *dynamic1Dense* model, respectively.

Table 3
Correlation between average payoffs per run and agents' parameters.

Model name	α_i	β_i	γ_i
<i>experimentLike</i>	-0.75***	0.08	-0.91***
<i>twoWays</i>	-0.74***	0.10	-0.92***
<i>fixedCouples</i>	-0.71***	0.22*	-0.85***
<i>denseNetwork</i>	-0.73***	0.12	-0.92***
<i>smallWorld</i>	-0.72***	0.11	-0.91***
<i>scaleFree</i>	-0.46***	0.14	-0.69***

*** Significant code: $p < 0.001$.
** Significant code: $p < 0.01$.
* Significant code: $p < 0.05$.

An interesting question was whether the change in the network structure would have changed the relative advantage of cooperators (i.e., trustful and trustworthy individuals) over free-riders. We estimated the relation between the value of the three parameters defining each agent and the payoff earned in the different scenarios. Since average investments and returns did not change moving from a 10 to a 30 period game, we considered only the 10 rounds game. Table 3 reports the correlation coefficient between the agent parameters and its earnings.

In most models, earnings significantly and negatively correlated with both α_i and γ_i , while the correlation with β_i was not significant. In other words, both trustful and trustworthy individuals earned lower payoffs in all games, while the agent's ability to react to other actions made little difference. One noticeable exception was the *fixedCouples* model, where the correlation coefficient relative to β_i , although small, was positive and significant at the 5% level. This means that, by increasing their investments after a higher return and decreasing them following a lower return, reactive agents were favoured. Our explanation is that the fixed couple structure of the game tended to favour reciprocity based strategies. Another interesting exception was in the *scaleFree* model. In this

case, the relation between the agents' trust (measured by α_i) and their earnings was significantly weaker than in any other situation. The same was true for their trustworthiness (γ_i).

5.4. Dynamic network model results

Moving from a static to a dynamic network led to interesting results (see Table 4). Note that, as the network was no longer static, the amount sent and returned in the different parts of the game varied. Therefore, we separately analysed the results of rounds 1–10, 11–20 and 21–30 of the game. The average cooperation in the *dynamic1* models slightly increased, even if a *t* test (performed on the weighted means for the reasons given above) showed that the difference was significant only for returns in the first ten periods of the *dynamic1Dense* model ($t = 1.446$, $p = 0.075$, one sided). The *dynamic1Dense* model initially implied higher cooperation than the *dynamic1Couples* as cooperative agents, starting from 103 links each, were able to initially sever most of them and therefore to avoid exploitation by free-riders. However, this strategy was no longer possible when the situation converged towards an average of 1–2 links per agent, with the consequence that final cooperation levels approximated the *Dynamic1couples* model results.

The network dynamics was especially interesting. Apparently, the system had a single equilibrium, which was reached independently of the starting point. From round 9 onwards, the average degree of the networks in the *dynamic1Couples* and the *dynamic1Dense* models converged towards the value of 1.67 ± 0.02 (Fig. 5, left panel). This occurred even if the initial degrees of the two networks were, respectively, 1 and 103. The final network structure of the two models was also very similar: in both cases, all agents were linked in small groups of 2–8 (Fig. 5, center and right panels).

Looking at these simulations, it was evident that the centre of each group was represented by a highly cooperative agent. This

Table 4
Average investments and returns in the original experiment and in the dynamic network models. Standard deviations are in parenthesis. Averages significantly different (at the 10% level) from the experiment are marked in bold.

Model name	Period 1–10		Period 11–20		Period 21–30	
	A invest.	B returns	A invest.	B returns	A invest.	B returns
<i>dynamic1Couples</i>	3.65 (2.58)	2.92 (2.96)	3.67 (2.60)	2.95 (2.90)	3.68 (2.62)	2.96 (2.93)
<i>dynamic1Dense</i>	3.79 (2.67)	3.32 (3.20)	3.66 (2.60)	2.96 (2.96)	3.68 (2.62)	2.97 (2.94)
<i>dynamic2Couples</i>	3.82 (2.68)	3.37 (3.42)	4.48 (3.01)	5.02 (4.50)	4.63 (3.11)	5.58 (5.12)
<i>dynamic2k10</i>	4.11 (2.82)	4.00 (3.59)	4.43 (3.01)	4.85 (4.30)	4.49 (3.04)	5.02 (4.50)
Experiment	3.48 (2.69)	2.79 (3.58)	–	–	–	–

Table 5
Correlation between average payoffs per run and agents' parameters.

Model name	Period	α_i	β_i	γ_i
<i>dynamic1Couples</i>	1–10	-0.78***	0.11	-0.80***
	11–20	-0.78***	0.16	-0.67***
	21–30	-0.68***	0.21*	-0.66***
<i>dynamic1Dense</i>	1–10	0.02	-0.18	0.64***
	11–20	-0.72***	0.17	-0.66***
	21–30	-0.66***	0.15	-0.61***
<i>dynamic2Couples</i>	1–10	-0.13	-0.05	0.53***
	11–20	0.37***	-0.14	0.96***
	21–30	0.37***	-0.14	0.95***
<i>dynamic2k10</i>	1–10	0.32***	-0.19	0.87***
	11–20	0.36***	-0.18	0.96***
	21–30	0.35***	-0.19	0.97***

*** Significant code: $p < 0.001$.
**Significant code: $p < 0.01$.
* Significant code: $p < 0.05$.

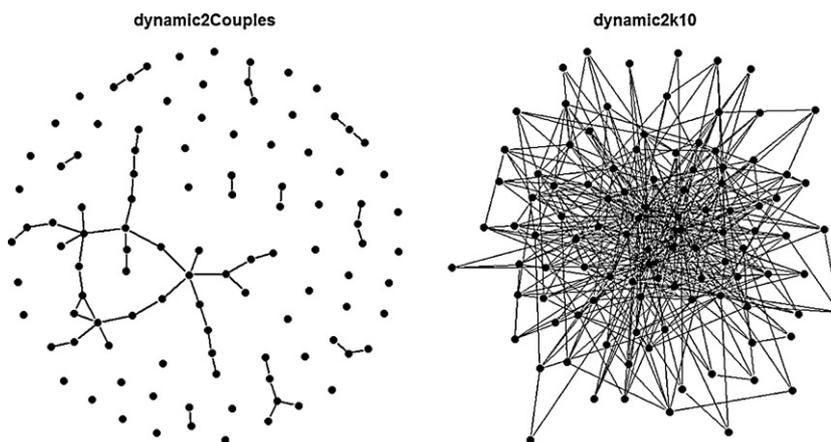


Fig. 6. Networks after 30 rounds of a typical run of the *dynamic2Couples* model (left) and of the *dynamic2k10* model (right).

confirms certain findings of Eguíluz et al. (2005) model, where agents played a Prisoner's Dilemma on a dynamic network and the equilibrium was guaranteed by "leaders" (agents in central positions), who played an essential role in sustaining cooperation. In the network plotted in the middle of Fig. 5, agents with more than two links had an average α_i of 4.02, while agents with two links or less had 3.75. Similarly, agents with more than two links had an average β_i of -0.21 (vs. 0.22) and an average γ_i of 0.21 (vs. 0.13). More generally, both α_i and γ_i of agents were positively correlated with the number of interactions in the last 10 rounds of the game. In the *dynamic1couples* the correlation coefficients were, respectively, 0.42 and 0.86, while in the *dynamic1dense* they were 0.40 and 0.78.⁵ To sum up, agents with more links and so performing a higher number of interactions, were both more trustful and more trustworthy.

We also looked at the relation between the agents' parameters and their earnings. Table 5 shows our estimates. The results of the *dynamic1* models were the same as the static networks. Again, trustful and trustworthy agents were disadvantaged, while the capacity to react made little difference. There was one noticeable exception in the last rounds of the *dynamic1Couples* model, where the coefficient related to the β_i parameter was significant. This was little surprising as the small stable emerging groups (Fig. 5, center panel) were not very different from the dyads which characterized the *fixedCouples* model, which also produced a significant correlation between β_i and agents' earnings.

⁵ It is worth noting that all estimates were significant at the 1% level.

Another exception was found in the initial rounds of the *dynamic1Dense* model, where the correlation coefficient for α_i was almost zero and the one for γ_i was positive and highly significant. However, this situation changed and in rounds 11–20, the coefficient was already positive and highly significant. The initial advantage for trustworthy agents was due to their capacity to maintain their links longer, while untrustworthy ones lost theirs because of their opponents' unsatisfied reaction. Similarly, trustful agents did better than others as they quickly broke their unsatisfying links. However, once the network stabilized, the situation changed and the coefficients converged towards values similar to the *dynamic1Couples* model.

In the *dynamic2Couples* model, cooperation significantly increased (Table 4). Returns were already significantly higher than in the experiment in the first 10 rounds of the game and further increased subsequently. Investments were significantly higher than in the experiment from the 10th round onwards. Starting from the same round, returns were higher than investments. In other words, investments became profitable for A players. This was also clear when looking at the correlations shown in Table 5. The correlation between the agents' payoffs and both their α_i and γ_i was positive and significant, i.e., trustful and trustworthy agents earned, on average, higher payoffs. The explanation is that more trustful and trustworthy agents had more links, so enjoying a higher number of exchanges than less trustful/trustworthy ones. More precisely, the correlations between α_i and γ_i of each agent and the number of interactions that the same agent performed during the whole 30 rounds game, were both positive and significant ($r=0.38$, $p < 0.001$ and $r=0.92$, $p < 0.001$, respectively). Vice

versa, less cooperative agents became easily isolated and earned, on average, lower payoffs.

The resulting network was also remarkably different from the *dynamic1* model (Fig. 6, left). Considering all model runs, the link distribution was strongly right-skewed (skewness = 2.73) with many isolated agents and a limited number of highly connected ones. It is worth noting that a large cluster tended to emerge around the most cooperative agents. For instance, the average α_i of agents with zero or one link in Fig. 6 (left) was 3.41, while the average α_i of agents with two or more links was 4.57. Similarly, the average γ_i of agents with zero or one link was 0.10, while the average γ_i of agents with two or more links was 0.22. More generally, a positive correlation existed between the agents' α_i and γ_i parameters and the average number of links they maintained in the last period of all *dynamic2Couples* model runs ($r=0.37$, $p<0.001$ and $r=0.91$, $p<0.001$, respectively). The correlation was not significant for β_i ($r=-0.14$, $p=0.159$).

The *dynamic2k10* model showed a strong increase of cooperation (Table 4). Unlike before, both the average investments and returns were higher than in the experiment already in the first 10 rounds. Investments and returns further increased in the subsequent periods, even if they eventually converged towards a slightly lower value than in the *dynamic2Couples* model. As before, investments became profitable for *A* players from round 10 onwards. The correlations between agents' parameters and payoffs followed a similar path to the *dynamic2Couples* model, with the exception that the correlation between the agents' α_i and their payoffs was positive and significant from the beginning of the game (Table 5). Overall, trustful and trustworthy agents enjoyed a larger number of interactions. The correlation between the agents' parameters and the number of interactions over the whole simulation was positive and significant at the 0.1% level for both α_i and γ_i (while it was negative and significant only at the 10% level for β_i).

The networks from the *dynamic2k10* model runs also showed a right-skewed link distribution. The skew coefficient of the link distribution was higher than in the previous case (3.64), with cooperative agents maintaining a higher number of links than untrustful and (especially) untrustworthy ones. For instance, in Fig. 6 (right), the average α_i of agents with five or less links was 2.73, while for agents with more than five links was 4.17. Similarly, the average γ_i of the former group was 0.07, while that of the latter group was 0.17. The correlation between α_i and γ and the number of links maintained by each agent on the last period of all the *dynamic2k10* model runs, was positive and highly significant ($r=0.36$, $p<0.001$ for α_i

and $r=0.93$, $p<0.001$, respectively), while the correlation between β_i and the number of links was not significant ($r=-0.16$, $p=0.107$).

It is interesting to note that, despite the differences in their overall number, the final link distribution of the two *dynamic2* models was similar. Fig. 7 plots the number of links maintained by each agent in the last period averaged over 100 runs for each model. In both cases the number of links grew exponentially. A fitting of the curves using the exponential model $\ln(y) = \ln(a) + bx$ produced similar coefficients, $b=0.0158(0.0009)$ for the *dynamic2Couples* model and $b=0.0134(0.0008)$ for *dynamic2k10* (standard errors are reported in parenthesis). This means that, despite the constraint on the total number of links, the *dynamic2* models converged on networks with comparable structures.

6. Discussion

In this article, we have presented an experimentally grounded agent-based model that extended the results of a lab experiment on trust to study the impact of the interaction structure on cooperation. Our results showed that it is not the stable or unstable nature of the interaction structure *per se* that may have a relevant impact on trust diffusion and cooperation. We found that what really matters for cooperation is the endogenous link of interaction outcome and structure formation. While a simple change of the network structure did not significantly alter the outcome of our game, confirming recent experimental findings (Suri and Watts, 2011), the introduction of a dynamic network led to higher cooperation when cooperative agents could create more links and isolate free-riders. It is interesting to note that this contrasts with the popular network literature, which over-emphasises the positive effects of network structures on interaction outcomes without seriously considering where the network generative mechanisms came from (e.g., Barabási, 2009; Buchanan, 2002; Watts, 1999).

Doubtlessly, the “shadow of the future” postulated by Axelrod (1984) and Cohen et al. (2001) is an important factor explaining cooperation in hostile environments. The point is that, when applied to static social networks and once trust has been eroded by cheating, the stability of links between agents following conditional strategies can only cause a never ending sequence of mutual defection. On the other hand, by permitting agents to leave their partners, cooperation increases as the exploitation opportunities of free-riders are reduced and cooperators are not bound to reciprocate defection.

It is important to note that this was also confirmed by recent experimental findings about assortative interaction by Grimm and Mengel (2009) and Chiang (2010): when voluntary partner selection is permitted, conditional cooperators are assured that they interact with the like and free riders should adapt to avoid segregation (see also Güreker et al., 2006; Page et al., 2005). Recently, Rand et al. (2011) found that “fluid” dynamic networks can stabilize cooperation, which declines progressively under static configurations. Besides the fact that, compared to Rand et al. (2011), we included a higher number of agents, the *dynamic2* conditions led to similar results. Trustful and trustworthy agents were no longer bound to reciprocate defection as they were in a position to find new partners with whom they started cooperative relationships. The network dynamics allowed them to use “link reciprocity” instead of simple tit-for-tat, with the consequence that cooperation increased, bringing higher fairness and efficiency into the system.

Obviously, other social mechanisms can boost partner selection and make networks more stable, such as tags (e.g., Axelrod et al., 2004; Hales, 2000) and interpersonal commitment. Everyday we use tags to classify and identify the behaviour of others, as well as to signal certain personal attributes to others. In sociological terms, tags can be viewed as socially shared communication signals that connote certain attributes of individuals or groups. For

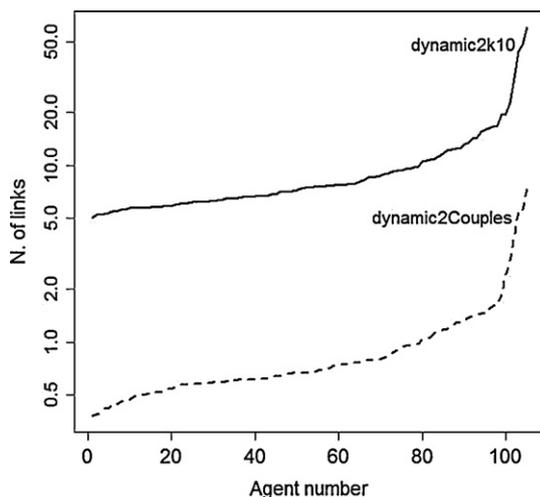


Fig. 7. Average number of links per agent in the *dynamic2Couples* and *dynamic2k10* models.

instance, they can include speaking dialects or particular accents, dressing elegantly, driving garish customized sport-cars or publishing a self-important ethical code in a company's website. These attributes or actions might be used socially as predictors of others' behaviour, in particular when we interact with unknown partners. Although they can channel unintentional, inaccurate, arbitrary or false information, tags can favour cooperation in the absence of past interaction experience, memory, reciprocity motives or reputational signals. Therefore, they can substitute past direct experience of partner selection. As such, they have been widely investigated in agent-based research under different social interaction situations (e.g., Riolo et al., 2001; Edmonds and Hales, 2003; Hammond and Axelrod, 2006; Kim, 2010).

This makes partner selection different from our case, where it was based on past experience of each agent individually. The point is that, if individuals can detect tags or exchange communication signals before interacting, it is likely that the intelligibility of partner selection and the consequent structure formation can be strongly influenced. This also is where the 'dark side' of partner selection enters the picture, i.e., when tag-based selection is biased by discriminative social belief and causes inefficient network formation by preventing unknown partners from potential interaction benefits. If this is reasonable, future laboratory experiments capable of comparing the impact of social tags and past experience on partner selection and structure formation should be particularly welcomed.

The same is true for interpersonal commitment, i.e., the building of long-term cooperative links among partners based on unconditional cooperation. This cannot directly help partner selection when relationships are formed, but can help to maintain them over time. As shown by De Vos et al. (2001) and Back and Flache (2006), interpersonal commitment can exert more robust evolutionary pressures towards cooperation than reciprocity and conditional cooperation, in selective environments where cheaters are likely to exploit cooperators. For instance, by modelling an exchange dilemma game of mutual help, Back and Flache (2006) showed that interpersonal commitment outperformed conditional cooperation strategies against defection exactly because it avoided the vicious cycle of 'keeping the books balanced' of the latter. Obviously, it is essential that the bundles of these mechanisms are more precisely dissected in future lab experiments which could guide new simulation studies.

Another point is that, if it is reasonable to expect that interaction outcomes can influence social structures, it must also be essential to investigate empirically and experimentally how social expectations about the trustworthiness of potential partners and the trusting-other attitudes of individuals can be influenced by cultural aspects, institutions and normative values at a social level. This is of particular interest to understand the nature and evolution of markets, which involve a complex long-term interplay of social norms and formal institutions (North, 2005). First, particular market scaffolds might be more efficient than others exactly because they have institutionalised partner selection as a relatively low-cost sanctioning for cheaters.

Recent experimental findings by Chiang (2010) suggest that, when combined with partner selection as a social sanctioning mechanism, market matching tends to reduce free riding and favour fair strategies. This is because, by pairing less generous proposers with more demanding responders, the risk of free riders' rejection and isolation increases cooperation. Secondly, particular market structure configurations might have historically evolved out of partner selection mechanisms, as suggested also by Watts (2004). Therefore, complex market structures could be viewed as a magnification of relatively simple social mechanisms, not to mention the case of the role of partner selection in the establishment of modern hierarchical corporate organizations.

Another interesting insight from our study is the importance of partner selection. The increase of cooperation via partner selection has implication both for the efficiency of the system and its fairness. In the *dynamic2* conditions, the average investment increased by one third and the average return almost doubled in comparison with both the experiment and the static networks. While it is standard in the experimental literature on trust and cooperation to assume randomly re-matching couples, our results suggest that cooperation can crystallize in stable interaction structures, which depend on positive outcomes generated by agent interaction. This means that it is reasonable to suppose that individual action and interaction structure tend to co-evolve in the social life (e.g., Buskens and Weesie, 2000; Buskens et al., 2008; Mark, 1998). Our experimentally grounded model allows us to emphasize that one of these self-reinforcing co-evolutionary links could be driven by partner selection (e.g., Corten and Buskens, 2010; Flache, 2001; Eguíluz et al., 2005). If this is so, it follows that excluding these aspects from the experimental research means losing something crucial for explaining social mechanisms of cooperation.

A final point concerns our research method. We combined lab experiments and agent-based models to exploit the advantages of both. On the one hand, lab experiments provided sound and clean data on agent behaviour on which to build informative micro-macro models. On the other hand, agent-based models allowed us to extend experimental data by providing for the impossibility of exploring complex interaction structures and long-term macro dynamics and evolution in the lab. Our idea was that, in this mutual benefit, cross-fertilization can be established that could be largely beneficial for sociological research (e.g., Boero et al., 2010; Boero and Squazzoni, 2005; Chmura and Pitz, 2007; Dal Forno and Merlone, 2004; Deadman et al., 2000; Ebenhöf and Pahl-Wostl, 2008; Jager and Jansen, 2003; Jansen and Ostrom, 2006; Rauhut and Junker, 2009; Rouchier, 2003), helping sociologists to appreciate the importance of working with well-specified micro-foundations for micro-macro models. Indeed, being empirically defined, the strategies used by our agents were heterogeneous and more plausible than what is standard for social science research based on formalized models.

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Appendix A. Supplementary Data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.socnet.2012.03.001.

References

- Aktipis, A., 2004. Know when to walk away: contingent movement and the evolution of cooperation. *Journal of Theoretical Biology* 231, 249–260.
- Ashlock, D., Smucker, M.D., Stanley, E.A., Tesfatsion, L., 1996. Preferential partner selection in an evolutionary study of prisoner's dilemma. *Biosystems* 37, 99–125.

- Axelrod, R., Riolo, R., Cohen, M.D., 2002. Beyond geography: cooperation with persistent links in the absence of clustered neighborhood. *Personality and Social Psychology Review* 6 (4), 341–346.
- Axelrod, R., Hammond, R.A., Grafen, A., 2004. Altruism via kin selection: strategies that rely on arbitrary tags with which they evolve. *Evolution* 58 (8), 1833–1838.
- Axelrod, R., 1984. *The Evolution of Cooperation*. Basic Books, New York.
- Back, I.H., 2010. Commitment bias: mistaken partner selection or ancient wisdom? *Evolution and Human Behavior* 31, 22–28.
- Back, I.H., Flache, A., 2006. The viability of cooperation based on interpersonal commitment. *Journal of Artificial Societies and Social Simulation* 9 (1), 12.
- Back, I.H., Flache, A., 2008. The adaptive rationality of interpersonal commitment. *Rationality and Society* 20 (1), 65–83.
- Barabási, A., 2009. Scale-free networks: a decade and beyond. *Science* 325, 412–413.
- Barabási, A., Albert, R., 1999. Emergence of scaling in random networks. *Science* 289, 509–512.
- Barrera, D., Buskens, V., 2009. In: Cook, K., Snijders, C., Buskens, V., Cheshire, C. (Eds.), *eTrust: Forming Relationships in the Online World*. Russell Sage, New York, pp. 37–72.
- Beckman, C.M., Haunschild, P.R., Phillips, D.J., 2004. Friends or strangers? Firm-specific uncertainty, market uncertainty, and network partner selection. *Organization Science* 15 (3), 259–275.
- Berg, J., Dickhaut, J., McCabe, K.A., 1995. Trust, reciprocity and social history. *Games and Economic Behavior* 10, 122–142.
- Boero, R., Squazzoni, F., 2005. Does empirical embeddedness matter? Methodological issues on agent-based models for analytical social science. *Journal of Artificial Societies and Social Simulation*, 8 (4) 6.
- Boero, R., Bravo, G., Castellani, M., Laganà, F., Squazzoni, F., 2009a. Pillars of trust: an experimental study on reputation and its effects. *Sociological Research Online* 14 (5), 5.
- Boero, R., Bravo, G., Castellani, M., Squazzoni, F., 2009b. Reputational cues in repeated trust games. *Journal of Socio-Economics* 38 (6), 871–877.
- Boero, R., Bravo, G., Castellani, M., Squazzoni, F., 2010. Why bother with what others tell you? An experimental data-driven agent-based model. *Journal of Artificial Societies and Social Simulation*, 13 (3) 6.
- Bravo, G., 2011. Agents' beliefs and the evolution of institutions for common-pool resource management. *Rationality and Society* 23 (1), 117–152.
- Buchanan, M., 2002. *Nexus: Small Worlds and the Groundbreaking Science of Networks*. W.W. Norton, New York.
- Buskens, V., Weesie, J., 2000. Cooperation via social networks. *Analyse und Kritik* 22, 44–74.
- Buskens, V., Corten, R., Weesie, J., 2008. Consent or conflict: coevolution of coordination and networks. *Journal of Peace Research* 45, 205–222.
- Buskens, V., Raub, W., 2008. In: Wittek, R., Snijders, T.A.B., Nee, V. (Eds.), *Handbook of Rational Choice Social Research*. Russell Sage, New York.
- Calvo-Armengol, A., 2001. On bargaining partner selection when communication is restricted. *International Journal of Game Theory* 30, 503–515.
- Camerer, C.F., 2003. *Behavioral Game Theory. Experiments in Strategic Interaction*. Russel Sage Foundation/Princeton University Press, New York/Princeton.
- Chiang, Yen-Sheng, 2010. Self-interested partner selection can lead to the emergence of fairness. *Evolution and Human Behavior* 31, 265–270.
- Chmura, T., Pitz, T., 2007. An extended reinforcement algorithm for estimation of human behaviour in experimental congestion games. *Journal of Artificial Societies and Social Simulation*, 10 (2) 1.
- Cohen, M., Riolo, R., Axelrod, R., 2001. The role of social structure in the maintenance of cooperative regimes. *Rationality and Society* 13, 5–32.
- Coleman, James S., 1990. *Foundations of Social Theory*. Harvard University Press, Harvard.
- Colquitt, J.A., Scott, B.A., Lepine, J.A., 2007. Trust, trustworthiness, and trust propensity: a meta-analytic test of their unique relationships with risk taking and job performance. *Journal of Applied Psychology* 92 (4), 909–927.
- Corten, R., Buskens, V., 2010. Co-evolution of conventions and networks: an experimental study. *Social Networks* 32, 4–15.
- Cronk, Lee, 2007. The influence of cultural framing on play in the trust game: a Maasai example. *Evolution and Human Behavior* 28, 352–358.
- Dal Forno, A., Merlone, U., 2004. From classroom experiments to computer code. *Journal of Artificial Societies and Social Simulation*, 7 (2) 2.
- De Vos, H., Smaniotto, R., Elsas, D.A., 2001. Reciprocal altruism under conditions of partner selection. *Rationality and Society* 13, 5–32.
- Deadman, P., Schlager, E., Gimblett, R., 2000. Simulating common pool resource management experiments with adaptive agents employing alternate communication routines. *Journal of Artificial Societies and Social Simulation*, 3 (2) 2.
- Diani, M., 1995. *Green Networks. A Structural Analysis of the Italian Environmental Movement*. Edinburgh University Press, Edinburgh.
- Dutta, B., Ghosal, S., Ray, D., 2005. Farsighted network formation. *Journal of Economic Theory* 122, 143–164.
- Ebenhöh, E., Pahl-Wostl, C., 2008. Agent behavior between maximization and cooperation. *Rationality and Society* 20 (3), 227–252.
- Edmonds, B., Hales, D., 2003. Replication, replication, replication: some hard lessons learnt from model alignment. *Journal of Artificial Societies and Social Simulation* 6 (4), 11.
- Eguíluz, V.M., Zimmermann, M.G., Cela-Conde, C.J., San Miguel, M., 2005. Cooperation and the emergence of role differentiation in the dynamics of social networks. *American Journal of Sociology* 110 (4), 977–1008.
- Fischbacher, Urs, 2007. z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics* 10, 171–178.
- Flache, Andreas, 2001. Individual risk preferences and collective outcomes in the evolution of exchange networks. *Rationality and Society* 13, 304–348.
- Fowler, J.H., Cristakis, N.A., 2010. Cooperative behaviour cascades in human social networks. *Proceedings of the National Academy of Sciences of the United States of America* 107, 5334–5338.
- Gould, Roger V., 1993. Collective action and network structure. *American Sociological Review* 58, 182–196.
- Greiner, Ben, Levati, Vittoria, 2005. Indirect reciprocity in cyclical networks: an experimental study. *Journal of Economic Psychology* 26, 711–731.
- Grimm, Veronika, Mengel, Friederike, 2009. Cooperation in viscous population: experimental evidence. *Games and Economic Behavior* 66, 202–220.
- Gulati, R., 1995. Performance, aspirations and risky organizational change. *Administrative Science Quarterly* 43, 58–86.
- Gürrer, Ö., Irelenbusch, B., Rockenbach, B., 2006. The competitive advantage of sanctioning institutions. *Science* 302, 108–111.
- Güth, W., Levati, M.V., Sutter, M., van der Heijden, E., 2007. Leading by example with and without exclusion power in voluntary contribution experiments. *Journal of Public Economics* 91 (5–6), 1023–1042.
- Hales, D., 2000. In: Moss, S., Davidsson, P. (Eds.), *Multi-Agent Based Simulation*. Springer Verlag, Berlin/Heidelberg, pp. 157–166.
- Hammond, P.A., Axelrod, R., 2006. Evolution of contingent altruism when cooperation is expensive. *Theoretical Population Biology* 69 (3), 333–338.
- Haruvy, E., Roth, A., Ünver, M., 2006. The dynamics of law-clerk matching: an experimental and computational investigation of proposals for reform of the market. *Journal of Economic Dynamics and Control* 30 (3), 457–486.
- Hauk, Esther, 2001. Leaving the prison: permitting partner choice and refusal in prisoner's dilemma games. *Computational Economics* 18, 65–87.
- Helbing, D., Yu, W., 2008. Migration as a mechanism to promote cooperation. *Advances in Complex Systems* 11 (4), 641–652.
- Jackson, M.O., Watts, A., 2002. The evolution of social and economic networks. *Journal of Economic Theory* 106, 265–295.
- Jackson, M.O., Wolinsky, A., 1996. A strategic model of social and economic networks. *Journal of Economic Theory* 71, 44–74.
- Jager, W., Janssen, M.A., 2003. In: Janssen, M.A. (Ed.), *Complexity and Ecosystem Management: The Theory and Practice of Multi-Agent Systems*. Edward Elgar, Cheltenham, pp. 75–102.
- Janky, B., Takacs, K., 2010. Efficient and inefficient social control in collective action. *CEU Political Science Journal* 5 (3), 316–354.
- Janssen, M.A., Ostrom, E., 2006. Empirically based, agent-based models. *Ecology and Society* 11 (2), 37.
- Johnson, N.D., Mislin, A.A., 2011. Trust games: a meta-analysis. *Journal of Economic Psychology* 32, 865–889.
- Joyce, D., Kennison, J., Densmore, O., Guerin, S., Barr, S., Charles, E., Thompson, N.S., 2006. My way or the highway: a more naturalistic model of altruism tested in an iterative prisoners' dilemma. *Journal of Artificial Societies and Social Simulation*, 9 (2) 4.
- Kagel, J., Roth, A., 2000. The dynamics of reorganization in matching markets: a laboratory experiment motivated by a natural experiment. *Quarterly Journal of Economics* 115, 201–235.
- Kahneman, D., Tversky, A. (Eds.), 2000. *Choices, Values and Frames*. Cambridge University Press/Russell Sage Foundation, Cambridge.
- Keser, Claudia, 2003. Experimental games for the design of reputation management systems. *IBM Systems Journal* 42, 498–506.
- King-Casas, B., Tomlin, D., Anen, C., Camerer, C.F., Montague, S.R., Read, Q.P., 2005. Getting to know you: reputation and trust in a two-person economic exchange. *Science* 308, 79–83.
- Kim, J.-W., 2010. A tag-based evolutionary prisoner's dilemma game on networks with different topologies. *Journal of Artificial Societies and Social Simulation* 13 (3), 2.
- Knoch, D., Schneider, F., Schunk, D., Hohmann, M., Fehr, E., 2009. Disrupting the prefrontal cortex diminishes the human ability to build a good reputation. *Proceedings of the National Academy of Sciences of the United States of America* 106 (49), 20895–20899.
- Kollock, P., 1994. The emergence of exchange structures: an experimental study of uncertainty, commitment, and trust. *American Journal of Sociology* 100 (2), 313–345.
- Macy, Michael W., 1991. Chains of cooperation: threshold effects in collective action. *American Sociological Review* 56, 730–747.
- Mark, N., 1998. Beyond individual differences: social differentiation from first principles. *American Sociological Review* 63, 309–330.
- McCabe, K.A., Smith, V.L., 2000. A comparison of naïve and sophisticated subject behavior with game theoretic predictions. *Proceedings of the National Academy of Sciences of the United States of America* 97, 3777–3781.
- Molm, L.D., Takahashi, N., Peterson, G., 2000. Risk and trust in social exchange: an experimental test of a classical proposition. *American Journal of Sociology* 105 (5), 1396–1427.
- North, D.C., 2005. *Understanding the Process of Economic Change*. Princeton University Press, Princeton, NJ.
- Ortmann, A., Fitzgerald, J., Boeing, C., 2000. Trust, reciprocity, and social history: a re-examination. *Experimental Economics* 3, 81–100.
- Ostrom, E., Walker, J. (Eds.), 2003. *Trust & Reciprocity: Interdisciplinary Lessons from Experimental Research*. Russel Sage Foundation, New York.
- Page, T., Putterman, L., Unel, B., 2005. Voluntary association in public goods experiments: reciprocity, mimicry and efficiency. *The Economic Journal* 115, 1032–1053.

- Podolny, J., 2001. Networks as the pipes and prisms of the market. *American Journal of Sociology* 107, 33–60.
- Pujol, J.M., Flache, A., Delgado, J., Sanguesa, R., 2005. How can social networks ever become complex? Modelling the emergence of complex networks from local social exchanges. *Journal of Artificial Societies and Social Simulation*, 8 (4) 12.
- Development Core Team, R., 2010. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria, ISBN 3-900051-07-0.
- Rand, D.G., Arbesman, S., Christakis, N.A., 2011. Dynamic social networks promote cooperation in experiments with humans. *Proceedings of the National Academy of Sciences* 108 (48), 19193–19198.
- Rauhut, H., Junker, M., 2009. Punishment deters crime because humans are bounded in their strategic decision-making. *Journal of Artificial Societies and Social Simulation*, 12 (3) 1.
- Riolo, R.L., Cohen, M.D., Axelrod, R., 2001. Evolution of cooperation without reciprocity. *Nature* 414, 441–443.
- Rouchier, J., 2003. Re-Implementation of a multi-agent model aimed at sustaining experimental economic research: the case of simulations with emerging speculation. *Journal of Artificial Societies and Social Simulation*, 6 (4) 7.
- Santos, F.C., Pacheco, J.M., Skyrms, B., 2011. Co-evolution of pre-play signaling and cooperation. *Journal of Theoretical Biology* 274 (1), 30–35.
- Skyrms, B., Pemantle, R., 2000. A dynamic model of social network formation. *Proceedings of the National Academy of Sciences* 97 (16), 9340–9346.
- Slonim, R., Garbarino, E., 2008. Increases in trust and altruism from partner selection: experimental evidence. *Experimental Economics* 11, 134–153.
- Suri, S., Watts, D.J., 2011. Cooperation and contagion in web-based, networked public goods experiments. *PLoS ONE* 6 (3), e16836.
- Takács, K., Jankó, B., Flache, A., 2008. Collective action and network change. *Social Networks* 30, 177–189.
- Watts, D.J., 1999. Networks, dynamics and the small-world phenomenon. *American Journal of Sociology* 105 (2), 493–526.
- Watts, D.J., Strogatz, S.H., 1998. Collective dynamics of 'small-world' networks. *Nature* 393, 440–442.
- White, H.C., 2004. *Markets from Networks: Socioeconomic Models of Production*. Princeton University Press, Princeton.
- Yagamashi, T., Cook, K.S., Watabe, M., 1998. Uncertainty, trust, and commitment formation in the United States and Japan. *American Journal of Sociology* 104 (1), 165–194.
- Yen, S.T., 2002. An econometric analysis of household donations in the USA. *Applied Economics Letters* 9 (13), 837–841.