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The Social from the Economic: The Emergence of Solidarity within Networks of Economic Exchange

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The PhD programme in Economic Sociology and Labour Studies (ESLS) stems from the collaboration of three Universities, namely Università degli Studi di Brescia, Università degli Studi di Milano, and Università degli Studi del Piemonte Orientale "Amedeo Avogadro". The University of Milan serves as the administrative headquarters and provides the facilities for most teaching activities.

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Ai miei genitori, per avere reso sempre tutto possibile.
Ad Arianna, per avermi ricordato che esiste altro.

Chapter 1

Introduction

This dissertation aims to contribute to our understanding of the link between economic behaviour and social relations. Sociologists and economists have extensively studied how social structures affect economic outcomes. These studies have contributed to one of the most successful sociological theories, that is, the 'social embeddedness' of the economic behaviour (Granovetter 1985). This has allowed sociologists to understand the performance of firms and markets in various socioeconomic systems beyond what is predictable by contract enforcement and institutional rules. The role of trust and social norms to overcome free-riding temptations, as well as the competitive advantage of contextual knowledge shared by economic actors through non-purely instrumental social connections, are only two examples of how social forces might have important economic implications. However, less is known about the opposite direction of the link between the economy and the society. Here, it is reasonable to suppose that, in certain circumstances, economically-oriented interactions with their instrumental nature might even trigger expressive social relations, which might in turn reinforce business outcomes.

Although less is known about the link between economy and society, this problem is crucial in contemporary complex societies. For instance, the process of globalization of the world economy brings a large multitude of people to interact with each other without necessarily sharing a salient collective identity. Nevertheless, economic exchanges, such as co-working, professional collaborations or business relations, are a context where peers can develop relations that go beyond the original instrumental motives and get expressive value. Millions of professionals around the world collaborate everyday on shared projects through internet-based repositories, provide and seek advice on specific technological issues, contribute to improve collectively-managed open-source tools. Moreover, companies in knowledge-intensive tertiary sectors design loose organizational structures to grant employees the freedom to collaborate with peers and share their expertise. Therefore, understanding how solidarity relations can form without group identity is key to address the problem of eliciting solidarity in current societies.

For this reason, this dissertation looks at the emergence of solidarity from economic exchanges as a crucial phenomenon of contemporary societies. In other words, this work aims to help answer the question: "Under which structural conditions do purely instrumental exchange relations develop into expressive ones that are valued in their own right?" (Thye, Yoon, and Lawler 2002, p. 140). In doing this, we aim to challenge the idea that economically-oriented interactions are necessarily detrimental for social relations, which is rooted in foundational works of economic sociology (e.g. Polanyi [1944] 1957). This would be because economic exchange relations are intrinsically motivated by conflicting individuals' self-interest. This tension may yield negative effects on social relations, which instead are often based on non-instrumental motives. In Polanyi's work, economic exchange becomes disruptive when it is 'disembeddeded' from social regulation. However, we argue that individuals who interact for economic purposes, by experiencing each other's behaviour, can indeed develop beliefs on each other that eventually elicit the development of social expressive relations, even without centralized regulation.

In order to understand this problem, we must first disentangle the subtleties of the interplay between instrumental and expressive motivations. On the other hand, the dynamic relational structure that constrains actors' motives must also be considered. This requires to study how individuals use the information they have about others' business behaviour to develop expectations about others' availability to help them in other situations. This is the basic mechanism that could help extend a previously instrumental relation into an expressive one, which may extract social value from the very first business contact between individuals.

Moreover, this work is also motivated by the idea that stable social systems can often emerge thanks to actors' self-organization. Studying mechanisms that let solidarity emerge from the bottom up as a form of self-organization can help us understand how individuals can develop efficient informal institutions that regulate economic and social interaction. These institutions can be even more stable than those coming from top-down regulation or centrally-enforced norms, which can even be detrimental in eliciting dysfunctional motives and behaviour (Simpson and Willer 2015).

Essentially, our epistemological approach here starts from looking at micro-level causal mechanisms to explain emergent social phenomena. This means to explain social phenomena "not merely relating them to other social facts [...] but by detailing in clear and precise ways the mechanisms through which the social facts under consideration are brought about" (Hedström and Bearman 2009, pp. 3-4). Therefore, the following chapters focus on individuals' beliefs and motives which underlie their actions, the dynamic opportunity structure that constrains them and the way these elements affect each other to bring about new 'social entities'. This process cannot be properly understood without accounting for actors' beliefs on others.

Here, it is important to note that studying the emergence of social relations from the bottom up requires the use of formal modelling and computer simulations. These tools are especially useful for a mechanism-based approach to socioeconomic interactions for two reasons. First, they are powerful tools to build empirically-grounded theories. On the one hand, modelling requires clarity in the conception of social entities and mechanisms, which is achieved through theory-driven research design. On the other hand, it translates theory in a form that is comparable with empirically observed reality, so that empirical research can truly help testing explanatory hypotheses. Secondly, computer simulations of formal models allow researchers to go beyond explanations of observed phenomena and explore other possible scenarios. This is achieved by manipulating *in silico* certain aspects of a social system which are either difficult to observe in real settings or may occur in the future. It is worth noting that "future" here has not merely a 'predictive' meaning (e.g., knowing the state of a system at time $t = 0$ to predict its state at $t = 1$), but is a way to conceive the social reality as only one of the possible instantiations of certain social mechanisms. This means that exploring alternative scenarios can also be useful to understand the strength of a social mechanism and its possible generalization to many similar instances in similar contexts.

Passing to the presentation of the work, it is worth saying that this dissertation has been designed as a collection of stand-alone contributions to the analysis of solidarity within economic exchange networks (Chapters 3-5), framed by an introductory literature review (Chapter 2) and followed by a concluding chapter (6). More in detail, the remainder of this dissertation is organized as follows.

Chapter 2 reviews the literature on solidarity and exchange relations in sociology and the behavioural sciences. The chapter aims to elaborate a theoretical framework and working hypotheses for the following chapters. A definition of solidarity at the behavioural level is proposed and various empirical contributions are examined.

Next, Chapter 3 presents an empirical study on the link between professional collaboration and social support relations. In this work, certain hypotheses are tested on a group of independent professionals sharing a 'coworking' space. The work has benefited from the feedback received at several international conferences and workshops, namely the 3rd Doctoral Workshop in Economics of Innovation, Complexity and Knowledge (Turin, Italy, January 21-22, 2016), the XXXVI Sunbelt Conference of the International Network for Social Network Analysis (Newport Beach, California, USA, April 4-10, 2016), the INAS 2016 Conference of the International Network of Analytical Sociologists (Utrecht, The Netherlands, June, 3-5) and the 2nd European Social Network Conference (Paris, France, June, 14-17, 2016). The study has been submitted to an international journal for peer-reviewed publication in a slightly different version, co-authored by Niccolò Casnici and Flaminio Squazzoni (University of Brescia).

Chapter 4 presents an extensive literature review of the use of Agent-Based Models (ABM) for sociological research. Given the key role of this methodology in this dissertation, the chapter aims to provide a comprehensive account of the contributions to sociology given by applications of ABM computer simulations. Moreover, a classification of these contributions is proposed according to the various methodological approaches to ABM in social research. The aim of the chapter is to review ABM as a possible means to overcome some limitations of the study presented in Chapter 3. A slightly different version of this chapter, co-authored by Flaminio Squazzoni, has been published in *Wiley Interdisciplinary Research: Computational Statistics*, Vol. 7[1], after being reviewed by two anonymous referees.

Chapter 5 applies computer simulation to study cohesion and integration of a social support network from economic exchange. In this chapter, an ABM of the mechanisms observed in Chapter 3 is presented. The model is used to simulate the effect of competition and resource distribution on social support networks. The aim of this work is to explore the effects of different environmental conditions and overcome the context-specific properties of empirical data. The work has been done in collaboration with Andreas Flache (University of Groningen, The Netherlands) and Flaminio Squazzoni and has been presented at the 4th Doctoral Workshop in Economics of Innovation, Complexity and Knowledge (Turin, Italy, December 15-16, 2016). This study has benefited from a visiting period at the Department of Sociology / ICS of the University of Groningen, where I was hosted by Andreas Flache. There, I had the opportunity to take part to the working activities of the 'Norms and Networks' and the 'Social Networks' research groups.

Finally, Chapter 6 includes a general discussion of the findings from previous chapters and suggests some concluding remarks.

Coming to acknowledgements, all the work presented in this dissertation has widely benefited of the support provided by the colleagues of the GECS (Research Group on Experimental and Computational Sociology) at the Department of Economics and Management of the University of Brescia. In particular, I am grateful to Marco Castellani and Simone Gabbriellini for their encouragement and suggestions. I am also grateful to Giangiacomo Bravo, who hosted me for a brief visiting period at the Linnaeus University in Växjö, Sweden. Finally, I would like to devote special thanks to Niccolò Casnici, with whom I have been fruitfully collaborating and sharing my office.

This work has greatly benefited from a visiting research period at the University of Groningen. I am very thankful to my host, Andreas Flache, for his great dedication and support to explore innovative ideas. For their hospitality, precious feedback and engaging discussions, I would like to thank Thomas Feliciani, Francesca Giardini, Michael Mäs, Nynke Niezink, Tom Snijders, Gert Stulp and the members of the 'Norms and Networks' research cluster. A special mention goes to Lucas Sage, my office mate.

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1. See Federico Bianchi and Flaminio Squazzoni (2015) "Agent-Based Models in Sociology", *Wiley Interdisciplinary Research: Computational Statistics*, 7: 284–306, doi: 10.1002/wics.1356

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Finally, while working at this dissertation I had the chance to work within the framework of the 'PEERE - New Frontiers of Peer Review' EU-COST Action TD1306 project. In the project, I have applied ABM computer simulations to study the interplay between strategic behaviour and social relations in peer-reviewed scientific evaluation. First, I studied the impact of the number of reviewers on the efficiency and quality of peer review. This work has been selected through peer review for a talk at the 2015 Winter Simulation Conference (Huntington Beach, California, USA) and published in the conference proceedings[2]. Secondly, I analysed how behavioural heterogeneity of scientists affect the peer-review system through resource allocation between publishing and reviewing. This work, co-authored with Francisco Grimaldo Moreno (University of Valencia, Spain), Giangiacomo Bravo and Flaminio Squazzoni, is currently under revision in *Scientometrics*. Finally, in another work I have compared quality and efficiency of open and confidential peer review systems assuming scientists' strategic behaviour. This work, co-authored with Flaminio Squazzoni, has been presented in several conferences and is currently in progress. Furthermore, the PEERE project has given me the tremendous opportunity to participate at regular group meetings in different European countries (Croatia, Greece, Spain, Switzerland) and work in team with brilliant scholars of different disciplines. After various considerations, we decided not to include these works in this dissertation. Although they revolved around a similar 'broad tent view' theme, i.e., the interplay of instrumental and expressive motivations in social behaviour, we thought that the coherence of this work would have been probably compromised by including also these works.

Last but not least, I am deeply grateful to my supervisor, Flaminio Squazzoni, for supporting me in ways that exceed what is to be expected by a good mentor. I am especially thankful to him for granting me the freedom to pursue my scientific interests while providing me the help I needed. Thanks to him I have learnt that science is mostly hard work that cannot be done without a collective effort.

2. See Federico Bianchi and Flaminio Squazzoni (2015), "Is Three Better than One? Simulating the Effect of Reviewer Selection and Behavior on the Quality and Efficiency of Peer Review". In: L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti (eds.), *Proceedings of the 2015 Winter Simulation Conference*, IEEE Press, Piscataway, NJ, pp. 4081–4089. doi: 10.1109/WSC.2015.7408561.

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Chapter 2

Solidarity and Social Exchange

The problem of solidarity is as old as sociology is. In everyday life, we typically find material or emotional support in our closest social groups. We may ask our families or relatives, our inner circle of friends, or we may turn to strangers with whom we share some sort of collective identity. Nevertheless, solidarity can often be found in other situations. In fact, previously unacquainted people sometimes provide each other material resources or emotional help in such a way that a new group of mutual support can emerge.

In current times, the internet has allowed a multitude of people to share resources, without having any group identity. Yet, previously unacquainted individuals develop everyday stable and successful collaborative relationships. For example, consider that now increasingly large shares of the labour force of industrialised countries are freelance workers, who might share their competencies with others on specific projects. In these cases, people coordinate their self-related interests towards a shared goal, often without being compelled by any hierarchical organizational structure.

Interacting for economic purposes is key for unrelated individuals to establish relations that eventually go beyond instrumental motivations. Unfortunately, the social sciences have mainly focused on the other direction of the link, namely the effect of social resources on economic outcomes.

This chapter presents a literature review on the social mechanisms of solidarity among different individuals. Special attention is devoted to understand how solidarity emerges between people who do not necessarily share a salient collective identity. Here, it is important to note that, given that our aim is to study the emergence of solidarity beyond specific normative, organizational or hierarchical structures, we did not consider the effect of norms and rules. Therefore, this review revolves around relational mechanisms[1] of solidarity rather than institutional or normative contexts.

Section 2.1 suggests a definition of social solidarity, by reviewing both classical and recent contributions in sociological theory. The aim is to elucidate behavioural properties of solidarity at the dyadic level. By following the durkheimian concept

1. Simpson and Willer (2015) have classified the social mechanisms of prosocial and cooperative behaviour into three main categories: a) "*rules*", i.e. "prevailing norms and their enforcement", b) "*reputations*", i.e. "the perceptions and rank of individuals in groups", c) "*relations*", i.e. "the character and structure of relations connecting individuals" (p. 44).

of 'mechanical solidarity', Section 2.2 briefly presents experimental and observational evidence about cooperation among individuals who happen to share certain socio-demographic traits or the membership to a social group. Here, evidence is mainly drawn from literature in sociology, cognitive and social psychology and other behavioural sciences. Section 2.3 introduces some concepts about various forms of exchange within the *Social Exchange Theory* paradigm. Section 2.4 reviews experimental literature in sociological social psychology about mechanisms which bring about commitment, relational cohesion and solidarity within networks of social exchange. A special emphasis is given to two competing theories of the emergence of solidarity, namely the *Affect Theory of Social Exchange* (Lawler, Thye, and Yoon 2008) and the *Reciprocity Theory of Solidarity* (Molm, Collett, and Schaefer 2007). Section 2.5 reviews sociological literature on social networks and suggests the need for empirical research on multiplex social networks that bridges Social Exchange Theory and empirical social network research. Finally, Section 2.6 discusses our conclusions by identifying some critical points in the literature, which are addressed in subsequent chapters.

2.1 What is solidarity?

Although rooted in the classic foundations of sociological science (see f.i. Durkheim 1984 [1893]), defining *social solidarity* is still an open analytical task for social research. Moreover, despite the prominent position of solidarity in the history of sociological research, there has been little attention to examine the conditions that generate solidarity among unrelated individuals. Therefore, there is still no convincing theory of the stability of social solidarity. In fact, sociological theory cannot account as to why solidary groups emerge from the interaction of dissimilar individuals, nor does it provide theories on the structural reasons for the fragility of solidarity bonds. As it has been noted by Lindenberg (1998), this depends on the lack of understanding of what constitutes *solidary behaviour*, i.e., the microfoundations of social solidarity.

The way sociological theory has conceived 'social solidarity' has been influenced by the classical durkheimian conception (McPherson and Smith-Lovin 2002). In *La division du travail social*, Émile Durkheim looked at this problem while discussing *mechanical* and *organic solidarity*. While the former is based on similarity of group members' traits and characteristics via psychological attraction ('vitality', see Lindenberg 1998), the latter depends on the structural interdependence of differences created by the economic division of labour.

Unfortunately, the classical durkheimian theory does not provide a microfoundation for solidarity that goes beyond the distinction between mechanical and organic relations (Markovsky and Lawler 1994). Such a dychotomy continued also after Durkheim. Indeed, sociological theory has tended to focus on either an emotional, similarity-based or a utilitarian, rational-choice explanation of group formation.

Following Homans (1950), Fararo and Doreian (1998, p. 16) distinguished four distinct ways to analyse solidarity from a more operational point of view. They suggested to focus on:

1. *sentiment*: the affective bonds which unite members of solidary groups;
2. *activity*: the common behavioural patterns within the group;
3. *interaction*: the patterns of interaction and exchange which are denser within the group as regards to the outside;
4. *norms*: expectations of normative behaviour based on group-level obligations.

This classification shows certain similarities with a narrower one previously proposed by Hechter (1987). According to him, group solidarity could be defined through *behaviour* and *sentiment*. Behaviour referred to contributing with private resources to collective ends, sentiment to love, fellow feeling, or feeling of brotherhood.

Sociological rational-choice theorists have made significant contributions to understand the microfoundations of social solidarity. They have proposed a definition of solidarity as: a) a byproduct of the rational action of actors and their social capital (Coleman 1990; Lin 1999) and b) obligation towards group norms that maintain social order (Hechter 1987; see also Heckathorn and Rosenstein 2002; Fararo and Doreian 1998.

In the first stream of literature, the unit of analysis has been shifted to the dynamical creation, maintenance and dissolution of ties of social capital (Coleman 1990; Lin 1999). The main point is that actors strategically create and maintain ties of social capital in order to secure access to various resources. More precisely, Coleman (1990, p. 309) argued that rational actors strategically accumulate "credit slips", i.e. obligations, by helping others. In this way, *ego* woul bear the cost of providing help to *alter* when *alter* needs *ego*'s resources. This would create some form of assurance for a future exchange, where asymmetry will be reversed, so that future benefits for *ego* would exceed current costs. Suffice to say here that this conception of solidarity is highly related to durkheimian organic solidarity, as asymmetry of costs and benefits are created by specialization, which comes from the social division of labour.

Although pointing at solidary behaviour, thereby providing a more dynamic analytic framework, this account of solidarity shares a typical weakness of rational-choice models of human behaviour, due to lack of realism and a narrow conception of action as strictly related to instrumentalist purposes (Hedström 2005). First, it does not consider symbolic values (Mauss 1925), which are highly important for a person's access to a variety of expressive resources (e.g., emotional support; see Lin 1999). Secondly, it fails to explain risky effects of asymmetries due to time gap between the two sides of a resource exchange, which is explored by social exchange theory (Emerson 1976; Molm and Cook 1995; Molm 2003, see also). Finally, the theory is limited to unpredictable needy situations and it does not address endogenous or exogenous sources of fragility.

An important milestone that looked at the dynamic fragility of solidarity is *The Principles of Group Solidarity* by Michael Hechter (1987). Moving from a critique of macro-level sociological theories, he recognised that, although much sociological work is based on solidarity, neither normative, functional, or structural explanations could provide adequate accounts on its social mechanisms. This brought Hechter to consider the behavioural dimension of group solidarity. Nevertheless, defining solidarity in behavioural terms was more a methodological rather than a theoretical choice about the difficulty of measuring sentiment (Fararo and Doreian 1998; Lindenberg 1998). This led towards defining solidarity as a group-level property, which is backed and maintained through individual contributions to collective goods, whose regulation is specified and enforced by social norms. Conformity to norms is here related to expediency rather than morality, differently from other classical normative sociological theories (e.g., Parsons 1991 [1951]). Actors will contribute to the collective good if norms are enforced by effective sanctions. This accounts also for dynamics and change of group solidarity: If sanctions are not effective, actors can exit the group and join a more benefiting one, or stay in the group and exploit collective resources as free-riders.

Although Hechter's theory deals successfully with internal control of cooperation (see f.i. Fehr and Gintis 2007; Simpson and Willer 2015) and dependency and external sources of precariousness (i.e., exit temptations), it does not account for the production of solidary behaviour. Solidarity is conceived only as a group property. Helping behaviour is completely ignored, since it does not involve cooperation or collective action *per se*. Moreover, here solidarity seems to work only if people face no alternatives and norm enforcement is fully effective. Not surprisingly, Hechter acknowledges that his theory "does not seem capable of accounting for the kind of solidarity that is so often celebrated in our own experience" (1987).

This revealed that a sociological theory of solidarity requires a definition of solidary behaviour that also accounts for its fragility at the group level. To do so, Lindenberg (1998, p. 64) proposed to look at five solidarity-clue behavioural patterns, which can be related towards another actor or a group.

1. *Common good situation*. *Ego* and *alter* both belong to a group that produces a common good. *Ego* will contribute to the common good even if he/she could free ride.

2. *Sharing situation*. If there are joint divisible benefits and costs and if *ego* is the one who can divide them, he/she will not seek to maximize what he/she gets from the benefit and minimize what he/she gets from the costs but take a fair share of both.

3. *Need situation*. *Ego* will help *alter* in times of need.

4. *Breach temptation*. *Ego* will refrain from hurting *alter* even at a cost to herself.

5. *Mishap situation*. Acts can be intended solidary but actually turn out to go against the expectation of solidary behaviour. In that case, *ego* will show that he meant to act differently. If *ego* knows in advance that she will not be able to keep to the agreement, she will warn others in advance, so that they can mitigate the damage.

So, solidary behaviour is not just cooperative behaviour, because it entails a form of voluntary costly transfer of benefits from *ego* to *alter*, without any assurance of future benefits and with a risk structure entailed by the character of unilateral transfer. These five behavioural dimensions have some variable costs for actors. *Common good* situation implies variable contribution costs for collective good, *sharing* situation implies a variable amount of what can be considered as a "fair share" of costs and benefits, *need* situation implies variable meaning of needs and variable expectation of what constitutes help, *breach* temptation entails a variable minimal amount of cost expected that has to be borne for not hurting alter.

In conclusion, Lindenberg's definition of solidary behaviour (1998) provides microfoundations of solidarity that accounts for a relational dimension. More precisely, it encompasses a sufficiently wide spectrum of solidarity-related behaviour, without reducing them to strategic rationality. Moreover, it does not assume the existence of a group-level norm to which individuals have to comply.

2.2 In-group bias and group identity

In-group bias refers to displayed favouritism towards in-group members in prosocial and cooperative behaviour and consequent discriminatory behaviour towards out-group members (e.g., Hewstone, Rubin, and Willis 2002).

Suppose a game where two subjects are provided with a shared endowment of resources. One randomly chosen player has to decide how to divide the resources between himself/herself and the other player. The endowmnent is then split accordingly. Assuming that the subjects were completely self-interested, one should expect that subjects decide to keep the entire endowment for themselves. However, experimental tests showed that players share, on average, between 20% and 30% of their resources. This game, defined as the 'Dictator Game', is usually applied to measure subjects' other-regarding preferences in behavioural experiments (Kahneman, Knetsch, and Thaler 1986; Camerer 2003).

Behavioural research on this game has showed that in laboratory experiments subjects tend to share a larger amount of resources with their kin (Hamilton 1963), or their friends and acquaintances (Goeree et al. 2010; Leider et al. 2009; Brañas-Garza et al. 2010), than with strangers.

Other-regarding preferences can also be biased by shared identities which build on ascribed categories, such as ethnicity (Whitt and Wilson 2007), religion (Adida, Laitin, and Valfort 2010) or political partisanship (Fowler and Kam 2007). These findings confirm observational studies that found that people who are similar in age, education, prestige, social class and ethnicity tend to form ties more preferably among each other due to homophily preferences (McPherson, Smith-Lovin, and Cook 2001). While group attachment can explain prosocial behaviour in strategic situations (Baldassarri and Grossman 2013), understanding of network effects on in-group favoritism is more difficult. A set of studies has shown that individuals are most willing to share their resources with people to whom they are directly connected or are less distant in their social network than towards more distant others (Leider et al. 2009; Goeree et al. 2010; Apicella et al. 2012).

These results are backed by evolutionary research. In complex societies, cooperation and generosity among strangers likely stem from a group-level selection process which favoured prosocial norms sustaining mutually beneficial exchanges beyond kin-based social relationships. This allowed human groups to reach large-size scale, which might have driven important steps of the evolution of human societies (e.g. Henrich et al. 2010).

However, in-group favoritism has been observed not only in cases when group membership was based on ascribed categories, but also when it was randomly assigned (Goette, Huffman, and Meier 2006), as well as in laboratory settings where scholars induced trivial group identities (Tajfel and Turner 1979; Chen and Li 2009).

In this respect, *Social Identity Theory* (SIT) provides a cognitive mechanism underlying in-group bias. Moving from the assumption that a person's sense of self derives from his/her membership in social groups, group identification emerges from a process of categorisation, identification and comparison in which individuals, including oneself, are classified into groups by context-specific attributes (Tajfel and Turner 1979).

However, more recent studies have questioned the robustness of cooperation elicited in the 'minimal group paradigm'. They showed that in-group biased cooperation in social dilemmas (e.g., Bicchieri 2002) arises when the existence of a common group interest is clearly perceived by players in absence of inter-group competition (Charness, Rigotti, and Rustichini 2007). Moreover, the group identification hypothesis, which was tested in experimental research, has been questioned, in favour of an explanation based on group norms built by players within the experimental frames (Bicchieri 2002).

The literature on in-group bias provides some interesting insights on the emergence of solidarity. On the one hand, experiments of the *minimal group paradigm* found that prosocial behaviour is not strongly constrained within salient social groups. On the other hand, common-sense knowledge is rich of examples of occasional prosocial behaviour between strangers. Yet, solidarity requires a relational stability that goes far beyond casual acts of cooperative and prosocial behaviour.

However, given that framing a collective interest is a mechanism that elicits prosocial behaviour (Charness, Rigotti, and Rustichini 2007), then we should expect solidarity to emerge if individuals learn how to coordinate their own interests with others'. This can occur while interacting within an exchange relationship.

2.3 Exchange, commitment and cohesion

In sociology, the relational dimension of solidarity has often been conceived as the *cohesion* of a group, i.e., the stability of the bonding ties among members of a group (Willer, Borch, and Willer 2002; Moody and White 2003).

Some scholars have attempted to study the structural mechanisms that account for the stability of group cohesion. McPherson and Smith-Lovin (2002) have proposed a homophily-based theory of relational stability, which accounts for structural features of group dynamics such as membership duration, internal coherence and group survival in a general ecological framework where groups compete with each other within larger societies. The theory has been further developed by treating the establishment and maintenance of relationships as a form of collective action (Heckathorn and Rosenstein 2002).

Considering the relational facets of solidarity is crucial to understand large-scale social phenomena. However, structural analyses of group cohesion do not seem to overcome the analysis of the structural interdependence of actors within groups. Therefore, by relying on simple assumptions about relational dynamic (e.g., homophily), they cannot open the black box of the interaction mechanisms that underlie the emergence of solidarity.

In this respect, *Social Exchange Theory* (SET) provides a solid theoretical framework to study the emergence of solidarity between interacting individuals (Molm, Collett, and Schaefer 2007; Lawler, Thye, and Yoon 2008). Deeply rooted in classic sociological works (Homans 1958, [1961] 1974; Blau 1964; Emerson 1976), SET has tried to explain important facets of social interaction and the social structures it generates. It has stimulated a large body of experimental studies in the laboratory (see f.i. Molm and Cook 1995; Fehr and Gintis 2007). A structurally oriented formulation of SET goes under the label of *Network Exchange Theory* (NET), which embeds the analysis of social exchange interactions within network structural configurations, by applying tools of *Social Network Analysis* (SNA) (see f.i. Cook and Emerson 1987; Molm and Cook 1995; Walker et al. 2000).

The theory is centred around the concept of *social exchange*, which is defined as a mutual transfer of benefits (f.i., physical goods, including economically valuable goods, or symbolic ones, such as information, aid, affection, etc.) between two or more actors under conditions of incompletely specified obligation (Blau 1964). An *exchange relation* is defined as a longitudinal sequence of opportunities, initiations and transactions, which forms a variably enduring relation between specific partners (Emerson 1976). Finally, a set of two or more connected exchange relations identifies an *exchange network*. Thereby, SET aims at studying social interaction and its link with social structure by treating the social relation as its unit of analysis (Molm and Cook 1995).

Every social exchange relation is viewed as a power-dependence relation, as actor i depends upon actor j as the source of a resource which i values. This mutual dependence occurs as far as i and j need each other in order to engage in a rewarding exchange. It also accounts for its initiation and continuation over time (Emerson 1976; Molm and Cook 1995). Moving from the assumption that actors "behave in ways that increase outcomes they positively value and decrease outcomes they negatively value" (Molm and Cook 1995, p. 210), a social exchange is a mixed-motive relationship (Schelling 1960), in that actors' interest is to cooperate for obtaining other's resource but also to compete for maximizing their own profit.

Here, *cohesion* is defined as a structural attribute of exchange relations and the exchange networks in which they are embedded (Molm and Cook 1995). It is a function of the degree of power-dependence of the relation and is positively correlated with the frequency of exchanges (Emerson 1976). The overall cohesion of an exchange network is the aggregate effect of the stability of ties among network nodes, which in turn depend on the dynamics of exchange opportunities and transactions.

This implies that power-dependence and cohesion as structural attributes of exchange relations allow new emergent relational properties to be generated over time, such as *commitment* (Molm and Cook 1995). SET has provided mixed evidence about both cognitive (see Thye, Yoon, and Lawler 2002 for a comprehensive review) and behavioural (Cook and Emerson 1978; Kollock 1994; Yamagishi, Cook, and Watabe 1998) dimensions of commitment in exchange relations.

Therefore, since power-dependence within exchange relations implies the opportunity for actors to exploit partners, commitment in an exchange relation may emerge between two actors as a strategic mechanism to reduce uncertainty. This leads to repeated exchanges with specific partners, so ignoring potentially more rewarding exchange partners (Cook and Emerson 1978).

An experimental test of this hypothesis was then provided by Kollock (1994), who found that increasing uncertainty and information asymmetries about other players' trustworthiness in simulated market transactions made long-term interaction partners more attractive for future exchanges. So, risk and uncertainty generated emergent commitment among partners, giving actors the opportunity to prove their trustworthiness, thereby stimulating new exchanges. This mechanism cumulatively led to more commitment and increasing mutual dependence between actors, which in turn generates stronger relational cohesion. Further tests were performed across U.S. and Japan by Yamagishi, Cook, and Watabe (1998), who similarly found that committed relations were more likely to develop between people who displayed a lower level of generalized trust towards others. This confirmed that risk and uncertainty reduction are linked to commitment and cohesion. Following these experiments, Back and Flache (2006) showed that strategies based on commitment may be more efficient in avoiding risk of exploitation by free-riders through computer simulations of game-theoretic exchanges. Finally, empirical evidence has then been collected through observational studies of networks of economic exchanges, where it is more likely that commitment is actually caused by strategic behaviour (see f.i. Podolny 2001; Beckman, Haunschild, and Phillips 2004).

In partial contrast with these studies, other scholars have suggested that the emergence of commitment in social exchange relations would be the result of the positive outcomes of exchange. More precisely, commitment could be due to emotions that are intrinsic to a successful exchange (see f.i. Lawler and Thye 1999), rather than on strategic behaviour (Thye, Yoon, and Lawler 2002). Within this research programme, which is called *Theory of Relational Cohesion* (TRC) (Lawler and Yoon 1993, 1996, 1998; Lawler and Thye 1999; Lawler, Thye, and Yoon 2000), *cohesion* is defined as the perception by individuals in an exchange relation that their relationship is an integrative element in the social situation (Lawler and Yoon 1996). *Commitment* is then defined as the perceived strength of the tie existing between a person and a social unit, such as a relation, a group, a network, an organization, a community and so forth (Thye, Yoon, and Lawler 2002).

Lawler and Yoon (1993) developed a causal model which included the positive role of emotions as an intervening mechanism between structural power-dependence factors and commitment behavioural outcomes within exchange relations. Starting from the idea that people tend to attribute responsibility for the emotions which they feel, to some identifiable sources, the model argues that equal relative power and negotiation in a dyadic exchange leads to repeated agreements, which in turn generate satisfaction in the actors, eventually eliciting commitment (Thye, Yoon, and Lawler 2002). First experimental tests showed that individuals who had the possibility to negotiate exchange terms in a face-to-face interaction in a balanced mutual dependence relation, displayed commitment behaviour. For example, they were committed to a relation despite more profitable alternatives and were prone to mutual concessions in the agreement. In short, this study showed that positive emotions are an intervening factor that links successful exchanges to relational cohesion.

Moreover, other experiments showed that emotions, e.g., satisfaction, were proximate causes of exchange outcomes and were generated from the social character of the very joint activity of negotiation. Furthermore, since people tend to attribute responsibility for the emotions they feel to some sources, these experiments showed a positive effect of satisfaction on relational cohesion, i.e., increasing commitment and collective-oriented behaviour (Lawler and Yoon 1996). Later, new experiments compared the effect of different network structures on dyadic exchange. Results showed that greater frequency of exchange in unequal power relations was not sufficient to produce commitment because it did not elicit positive emotions. Group identity also displayed a positive effect on commitment (Lawler and Yoon 1998). Finally, emotional enforcement of commitment in exchange relations was experimentally disentangled from strategic behaviour of uncertainty reduction. This suggests that the two mechanisms, rather than concurrent, might rather be complementary depending on different social situations (Lawler, Thye, and Yoon 2000).

To summarize, TRC has accumulated robust experimental evidence on the occurrence of an endogenous process within dyadic exchange relations via the elicitation of positive emotions in the exchange partners towards their relation. In this way, by interacting exchange partners attach expressive value to their relation, which helps to create the integrative bonds that are necessary to produce relational cohesion in an exchange network (Thye, Yoon, and Lawler 2002). Moreover, unlike strategic uncertainty reduction, these mechanisms tend to trigger stable group cohesion, since they are likely to generate more salient relations for exchange partners. It is important to note that these mechanisms also apply to a wider spectrum of exchange networks.

In conclusion, TRC provides insights on causal mechanisms of solidarity within an exchange network, since the expressive value generated through the interaction can trigger solidary behaviour between the actors. However, this process seems to occur only in equal-power networks, especially when the frequency of exchanges and the elicitation of positive emotions are linked (Lawler and Yoon 1998). Therefore, it might not be suitable for exchange interactions where actors' conflict of interests is more salient.

2.4 Forms of exchange and solidarity

TRC experiments only considered one particular form of dyadic social exchange (with the sole exception of Lawler, Thye, and Yoon 2000), namely one in which actors negotiate an agreement which constraints their exchange. More recent developments in the SET programme have further inquired the emergence of solidarity across different forms of exchange (Lawler 2001; Molm, Collett, and Schaefer 2007; Lawler, Thye, and Yoon 2008). In order to do so, some experimental studies have compared different forms of social exchange, moving from the assumption that each one entails different configurations of power-dependence (Molm, Peterson, and Takahashi 1999, 2001). However, findings have been inconclusive due to the context-dependency of different forms of exchange in actual social settings.

Here, it is important to consider that forms of exchange vary according to the structure of transaction which they entail. They are defined by analytically abstracting from the contingency of actors, resources or network structures (Emerson 1981; Molm and Cook 1995; Molm 2003). First, according to the kind of mutual dependence between actors, a social exchange can be either *direct* or *indirect*. In *direct* or *restricted exchange* actor i provides value to actor j and j to i, so that each actor's outcome depends directly on another actor's behaviour. In *indirect* or *generalized exchange*, a benefit received by j from i is reciprocated indirectly, by j's transferring value to another actor k.

The latter form of exchange has dominated the classical social exchange literature both in sociology and anthropology (see f.i. Blau 1964; Ekeh 1974; Lévi-Strauss 1949; Malinowski 1922; Mauss 1925; Sahlins 1972). The most common form of generalized exchange is what Takahashi (2000) has called *pure-generalized exchange*, in which no fixed structure of giving is entailed, i.e. i might transfer benefits to j and k on a different occasion. On the other hand, in *chain-generalized* exchange, benefits flow in one direction in a circle of transferring which eventually indirectly reciprocates benefits to the initiator. For instance, in a three-actor chain, i transfers benefits to j, j to k and k to i. Structures of chain-generalized exchange underlie classic exchange phenomena such as the *Kula ring* (Malinowski 1922) and matrilateral cross-cousin marriage (Lévi-Strauss 1949; Bearman 1997). Finally, it is worth to outline that while direct exchange implies a dyadic relation, indirect exchange has a collective dimension.

Secondly, direct exchange relations can be further distinguished in *negotiated* or *reciprocal* (Blau 1964; Emerson 1981; Molm 1997; Lévi-Strauss 1949). In a *negotiated exchange*, actors engage in a joint decision process, such as explicit bargaining, in which they typically seek a binding agreement on the terms of exchange. Therefore, the benefits enjoyed by both partners can be conceived as paired events, which identify a *transaction*. In *reciprocal exchanges*, actors' transfers of benefits are separately performed and non-negotiated. Actor i initiates an exchange as the outcome of an independent decision, by unilaterally transferring benefits to actor j without knowing whether, when, or to what extent j will reciprocate in the future. Negotiated exchanges cover most economic exchanges (other than fixed-price trades) as well as many social exchanges (Molm and Cook 1995). Reciprocal exchanges, however, characterize the vast majority of exchanges among family, friends and acquaintances (Homans [1961] 1974). Moreover, scholars in economic sociology have widely shown the importance of reciprocal exchange in business and trade relations (see f.i. Uzzi 1996; Granovetter 1985).

Reciprocal and negotiated forms of exchange differ across three key analytic dimensions (Molm 2003). First, in reciprocal exchanges benefits flow unilaterally from i to j, since each actor's outcomes are contingent solely on the other's individual actions: actors can initiate exchanges which will not be reciprocated, as well as they can profit from another's transfer without reciprocating (Emerson 1981; Molm and Cook 1995). On the contrary, negotiated exchanges entail bilateral flow of benefits, each actor's outcomes being instead contingent on the joint negotiating interaction, so that nobody can profit without an agreement which benefits both sides. Secondly, following from difference on contingency, while communication within negotiation implies shared information about outcomes, in reciprocal exchange actors cannot rely on the same kind of information. Last but not the least, differently from negotiated exchanges, in reciprocal exchanges the degree of equality in exchange outcomes develop only over time, as it does not rely on discrete transactions but on individually performed, sequentially contingent transfers (Molm 2003; Molm, Schaefer, and Collett 2009). Moreover, it is also worth noting that while negotiated exchanges can be formally modeled in terms of cooperative games, in which interdependent agents share a common knowledge of the game, reciprocal exchanges can be modeled as non-cooperative games, in which agents make independent choices (Heckathorn and Rosenstein 2002).

2.4.1 Affect Theory of Social Exchange

Further TRC studies looked at the effects of exchange interaction on the relations and networks (Lawler 2001; Lawler, Thye, and Yoon 2008). Relying on previous experimental evidence, Lawler (2001) proposed a causal model to explain variations in strength and stability of emergent relational cohesion across different forms of exchange networks. The model, which has been called *Affect Theory of Social Exchange* (ATSE), moves from the assumption that emotions perceived in joint social activities are attributed by actors to social units (relationships, networks, or groups), thereby producing stronger or weaker affective attachment. The aim of the theory is to account for the mechanisms which cause the emergence of a *micro social order*, defined as "a recurrent pattern of interaction among a set of actors, from which they come to perceive themselves as a unit (i.e., a group) and to develop feelings about that unit" (Lawler 2002, pp. 4-5). The strength of the group attachment implied by a micro social order may then determine collectively oriented behaviour, such as: providing unilateral benefits without expectation of reciprocity, expanding areas of collaboration beyond the vulnerability to opportunism, forgiving isolated free-riders and staying in the relationship despite more profitable alternatives (Lawler 2001). Another basic assumption of the model is that each form of exchange requires a certain joint activity, which varies according to a structural and a cognitive dimension: a) the degree of separability of actors' task behaviours and contribution and b) the perception of shared responsibility on exchange outcomes. Hence, a causal mechanism is implied so that increasing non-separability generates a higher perception of shared responsibility, which in turn increases the probability that actors attribute emotions to the exchange relation as a social unit. This mechanism could explain why the strength of differences in strength of emergent micro social orders may vary across different forms of exchange. Here, the model predicts that direct forms of exchange produce stronger micro social orders than generalized exchange and that negotiated has stronger effects than reciprocal exchange. Moreover, ATSE predicts that the endogenous process argued by TRC yields a mediating effect on outcomes.

These model predictions were tested through a laboratory experiment through a factorial design that compared different forms of three-actor exchange networks (Lawler, Thye, and Yoon 2008). The emergence of micro social orders were measured by four indicators: 1) frequency of exchange, 2) positive feelings about exchanges, 3) perceptions of the network cohesion, 4) affective attachment about the social unit. Results only partially supported model predictions. Generalized exchange actually yielded the lowest measures of micro social order, with network cohesion decreasing over time, direct exchange was shown to generate stronger across all indicators. In short, unlike ATSE predictions, this study did not find any significant differences between the negotiated and the reciprocal forms of exchange.

Other SET experimental scholars found results that challenged TCR, by shifting the focus on the effects of risk and uncertainty on trust and commitment formation (Molm, Peterson, and Takahashi 1999; Molm, Takahashi, and Peterson 2000; Molm, Peterson, and Takahashi 2001; Molm 2003; Molm, Schaefer, and Collett 2009).

First, in some experiments, negotiated and reciprocal direct exchange relations were compared to look at differences in contingency of benefit flow, information and timing. Especially interesting for the emergence of solidarity, Molm, Takahashi, and Peterson (2000) showed that reciprocal exchange is more effective on the production of affective commitment between actors because of a mechanism linking the risk of non-reciprocity to trust formation. Defined as the "structural or situational potential for incurring a net loss" (Molm, Schaefer, and Collett 2009, p. 5), risk is a necessary condition for trust to develop among actors within an exchange relation, as it provides actors the opportunity of proving to be trustworthy (Dasgupta 1988; Gambetta 1988; Hardin 2002; Kollock 1994; Yamagishi, Cook, and Watabe 1998). This is done by displaying and recognizing signs and signals of trustworthiness (e.g., Bacharach and Gambetta 2001; see also Macy and Skvoretz 1998). Actors can interpret the partner's reciprocation as a sign of his/her trustworthiness, given that it would have been more profitable for the partner to not reciprocate.

Despite the fact that some degree of risk is related to each form of exchange, in situation of negotiation, there is only the risk of being unable to establish an agreement, whereas reciprocal exchange implies a stronger risk of non-reciprocation (Molm 2003). Once an agreement is reached, the risk of being exploited by an opportunistic partner is kept under control by various social mechanisms that can enforce the agreement, e.g., law enforcement in case of a contract, reputation and decentralized social control in case of informal agreements. Thus, if actors succeed in establishing an agreement, trust between actors can be rather unnecessary to get positive outcomes in negotiated exchanges, as they can rely on the assurance provided by an agreement (Yamagishi and Yamagishi 1994).

In an experimental study, Molm, Takahashi, and Peterson (2000) found strong and consistent differences in trust and affective commitment, measured via subjects' self-assessment, between the two forms of direct exchange. They argued that while negotiated exchange provides actors the opportunity to display only a behavioural form of commitment (i.e., the disproportionate exchange with one partner despite more profitable alternatives; Kollock 1994; Lawler and Yoon 1996, 1998), the risk of non-reciprocity in reciprocal exchanges allows actors to display their trustworthiness by reciprocating exchanges over time. This elicits trust formation. Furthermore, in cases there are no assurance structures, actors are more likely to attribute partners' reciprocating to their intentions rather than to exogenous enforcement structures. This generates affective commitment. Moreover, reciprocal exchange can also exacerbate strategic behaviour aiming to reduce uncertainty. Indeed, Molm, Peterson, and Takahashi (1999) had showed that powerful actors were less likely to use their power to maximize their profit in reciprocal rather than in negotiated exchanges, because they tended to avoid risk (see f.i. Kahneman and Tversky 1979) by disproportionately opting for reciprocity. Finally, other experiments supported the importance of the expressive value of reciprocation in itself. Indeed, it is likely that reciprocation is a sign of affective regard to exchange partners beyond trustworthiness (Molm 2003; Molm, Schaefer, and Collett 2007; Molm, Collett, and Schaefer 2007).

In conclusion, although they do not question the occurrence of an emotion-based commitment mechanism, these last studies cast serious doubts on the differences between negotiated and reciprocal exchange in the generation of solidarity. Molm (2003) argued that the same features that make negotiated exchange more structurally cooperative than reciprocal exchange (i.e., joint decision-making, bilateral flow of benefits, the two-party social unit created by the task of negotiation) might also lead to a conflict of interests between exchange partners. While Lawler (2001) suggested that a perception of shared responsibility reduces competition bias in negotiated exchanges, the only fact of having an agreement prevents actors to infer trustworthiness and develop affective regard for exchange partners (Molm 2003). This would explain why some experimental studies found that individuals show greater resistance to unequal negotiated exchanges than to unequal reciprocal exchanges. Moreover it was found that subjects generally perceive that negotiated exchanges are more unfair than reciprocal exchanges even when outcomes are equal and are less positively affected. Finally, actors usually show less affect, less trust and less commitment to the partner in negotiated exchanges (Molm, Peterson, and Takahashi 1999; Molm, Takahashi, and Peterson 2000; Molm, Peterson, and Takahashi 2003; Molm 2003). However, as Lawler (2001) argued, these studies measured levels of commitment towards the exchange partner and not to a larger social unit. This would indicate that these findings cannot help to look at cohesion as group attachment.

Therefore, TRC provides important insights to explain the emergence of solidarity from negotiated exchanges. However, its results seem to be limited to exchange networks where power differences between actors are not relevant, i.e. where competition between partners is not salient. In this context, the success of an economic exchange can trigger an emotional mechanism that enhances solidarity between the partners beyond their trustworthiness. However, it must be said that most economic exchanges in natural settings occur in situation of resource asymmetry and competition.

2.4.2 Reciprocity Theory of Solidarity

The *Reciprocity Theory of Solidarity* (RTS) has challenged the explanation proposed by ATSE for the emergence of solidarity from exchange relations (Molm, Collett, and Schaefer 2007).

Building on previous experimental evidence on the comparison of different forms of exchange (Molm, Takahashi, and Peterson 2000; Molm, Collett, and Schaefer 2006; Molm, Schaefer, and Collett 2007), the RTS predicts that reciprocal exchanges generate stronger solidarity than negotiated ones and that within reciprocal exchange, generalized forms are more important than direct ones. They defined solidarity as "the integrative bonds that develop between persons and between persons and the social units to which they belong" (Molm, Collett, and Schaefer 2007, p. 207).

Their experiment tested the affective components of solidarity by measuring self-assessed subjective feelings of the following aspects: a) "trust", i.e. "the belief that the exchange partner will not exploit the focal actor", b) "affective regard", i.e. "positive feelings and evaluation towards the partner", c) "social unity", i.e. the perception of the exchange relation as a social unit, with actors united in interests and purpose", d) "feelings of commitment to the partner and the relationship" (*ibid.*). The model assumes that each exchange form entails a different *structure of reciprocity*, defined by two dimensions: a) whether benefits are reciprocated directly or indirectly and b) whether benefits flow unilaterally or bilaterally (Emerson 1981; Molm and Cook 1995; Molm 2003). These variations are responsible in the model for the generation of three causal mechanisms: 1) the "risk of nonreciprocity", 2) the "expressive value of reciprocity", 3) the "salience of conflict" (Molm, Collett, and Schaefer 2007, p. 211).

These three mechanisms would affect the different levels of solidarity generated in different forms of exchange. First, the risk of nonreciprocity should be higher in reciprocal than in negotiated exchanges (Molm, Takahashi, and Peterson 2000; Molm 2003). Moreover, generalized exchange would be more risky than direct reciprocal forms. This is because actors are dependent on the actions of multiple others in the generalized exchange, with risk increasing in proportion to the length of the chain. This would affect the production of trust proportionally.

Secondly, the expressive value of reciprocity would increase in the absence of assurance structures. This is especially when benefits flow unilaterally rather than bilaterally (Molm 2003; Molm, Schaefer, and Collett 2007) and with stronger magnitude with generalized rather than direct reciprocity, given that in generalized exchange not even a tacit obligation is implied.

Finally, according to the mixed-motive structure of social exchange, the salience of conflict should decrease feelings of solidarity to be even exacerbated by the bilateral flow of benefits entailed by negotiated exchange (Molm, Collett, and Schaefer 2006). Moreover, indirect reciprocation should reduce the salience of conflict by removing any direct reciprocal relation between the two partners.

An experimental test was run by comparing in a factorial design all three forms of exchange (negotiated, direct reciprocal and chain-generalized) in both three- and four-actor networks. This was to disentangle potential confounding effects of network size and power, according to the typical setting of SET laboratory experiments (see Molm and Cook 1995; Molm, Collett, and Schaefer 2007). Experimental results confirmed the model predictions, according to which generalized exchange generates higher levels of solidarity than direct reciprocal exchange, which in turn is more effective than negotiated exchange.

Therefore Molm, Collett, and Schaefer (2007) and Lawler, Thye, and Yoon (2008) provided conflicting results about the effect of different forms of exchange on the emergence of solidarity. However, a closer look into the two experimental designs reveals that the validity of their results can be extended to different social situations, without necessarily overlapping.

On the one hand, the study run by Molm, Collett, and Schaefer (2007) calls for reconsidering the validity of ATSE, because actors engaged in exchanges within equal-power networks and this could have favoured the activation of the emotion-based mechanism proposed by TRC (Lawler and Yoon 1998), while previous experiments by Molm and colleagues were performed unequal-power networks (Molm, Takahashi, and Peterson 2000; Molm, Peterson, and Takahashi 2001; Molm, Collett, and Schaefer 2006). Moreover, Molm, Collett, and Schaefer (2007) measured subjects' perception of social unity as indicator of solidarity, thereby avoiding the problem of relating to person-to-person commitment instead of group attachment (Lawler 2001). This implies that outcomes contradicted results by Lawler, Thye, and Yoon (2008), although subjects engaging in negotiated exchange indeed experienced the positive emotions argued by TCR.

On the other hand, the experimental design by Molm, Collett, and Schaefer (2007) and Lawler, Thye, and Yoon (2008) differ in one important feature. While in the former study subjects were embedded in a negatively connected network, which implies that actors choose only one exchange partner simultaneously for direct exchanges (Molm and Cook 1995), the latter experiment was set in null-connected networks, where actors could engage in direct exchange with multiple partners at a time. Since generalized exchange always implies the transferring to only one actor at a time, this implied a substantial differences in the salience of conflict between direct and generalized forms of exchange. This discrepancy could have made potential conflicts in direct exchange less salient in the experiment by Lawler, Thye, and Yoon (2008). This would explain higher outcomes in cohesion and perception of social unity.

Here, it is important to note that a more recent experimental study conducted by Molm, Schaefer, and Collett (2009) has provided new insights on the emergent stability of relational cohesion through trust development. This study started from the idea of building more realistic experimental settings where looking at the difference between negotiated and reciprocal exchange. In this study Molm, Schaefer, and Collett studied a form of negotiated exchange with non-binding agreements and a form of reciprocal exchange where actors were allowed to communicate. This was to vary risk and uncertainty within negotiated and reciprocal exchange forms. These experiments showed that even when levels of produced trust were equal across different forms, reciprocal exchange produced a more resilient and affect-based form of trust. Conversely, in negotiated exchange trust was based on cognition and more "fragile". More precisely, actors in reciprocal exchanges were more likely to forgive occasional untrustworthy behaviour, to trust partners who displayed imperfect trustworthiness and to develop stronger affective regard towards the trusted partners. Similar results about the context-dependency of solidarity in negotiated exchanges has been confirmed by experiments by Kuwabara (2011).

Furthermore, these results suggest that trust can be generated also by negotiated exchanges. This confirms findings by an experimental study by Barrera (2007). There, negotiated exchanges in equal-power networks could generate trust between partners, although subjects did not perceive the partners as trustworthy.

To summarize, research in sociology and social psychology has examined causal mechanisms that are relevant for social solidarity in exchange networks. Despite differences in some results, experimental studies in laboratory settings successfully showed that exchange networks might provide opportunities for actors to develop endogenously more or less stable ties, which eventually overcome instrumental individual interests in the exchange. Therefore, exchange relations may yield actors' commitment to the network as a social unity, even when there is no shared group identity between the actors. In some cases, economic exchanges might generate solidarity between the actors, although in contexts where the conflict between their interests is not salient.

In conclusion, experimental studies are key to disentangle the link between instrumental and expressive motivations. Nevertheless, empirical research in natural settings can help us understand the interplay between different forms of exchange and different social contexts.

2.5 Social structure and solidarity

While SET focuses on various forms of social exchange, social network research provides information also about the content of exchange relations, i.e. the exchanged resources. Over the last decades, social network research has examined in detail relational mechanisms that are responsible for evolution and change of social networks over time.

Moreover, social network research has looked extensively at structural processes that make certain social relations turn into different kinds, according to the content of the interaction or the actors' motives.

2.5.1 Heterophily and collaboration

Professional collaborations is a type of economic exchange that has been studied extensively by empirical social network research. In these cases, two or more professionals interact to achieve a common goal by joining their skills and competencies.

Here, resource asymmetry is often one of the drivers of collaboration. This is usually due to the fact that diversity in terms of skills and competencies may be of great advantage in case organizations need the representation of dissimilar functional specializations or connections to different financial or political resources (Westphal and Milton 2000; Mizruchi 2004). Yet, collaboration ties among dissimilar individuals are also formed voluntarily. This process has been called *heterophily* and has been extensively analysed by studies on collaboration networks.

A collaboration network means every group of individuals who work together in teams for a common goal. The diversity of social ties has been studied, for example, in the cases of coauthorship in science (Newman 2001a; Moody 2004; Wuchty, Jones, and Uzzi 2007), codirectorships on the same board (Westphal and Milton 2000) and coperformance in the same artistic production (Watts 1999; Uzzi and Spiro 2005; Uzzi 2008). In creative and economic production, ties connect dissimilar coworkers because collaboration requires different attributes, complementary skills and capabilities. Research on multiplex networks has studied the interacting effects of complementarity and other personal attributes on professional collaborations, providing evidence for what Blau (1974) termed "multiform heterogeneity". This means that network ties may be between individuals who are simultaneously similar and different, sharing similarities on some dimensions and differences on others. A study by Casciaro and Lobo (2008) found that members of different organizations select coworkers whom they perceive to hold complementary skills, only if they evaluate those persons as enjoyable to work with according to similar demographic traits, which signal trustworthiness and ease communication.

In any case, heterogeneous relationships in professional collaborations are oriented towards the completion of a project or goal. Their short-term character often does not permit their evolution in solidarity networks. Moreover, the diversity between collaboration partners might exacerbate the inherent conflict of interests within every kind of economic exchange. Empirical research on multiplex networks is needed to understand how collaboration ties can spill over new ties of non-instrumental relations. This process is mediated by relational mechanisms, which can make actors' beliefs and motives change within the context of one kind of interaction and trigger the development of a new kind of relation (Simpson and Willer 2015; Baldassarri 2015).

2.5.2 Repetition

In order to understand how new social relations can develop from already existing weaker relationships, it is probable that examining frequency and direction of social relations is key. This requires a "within-the-network" approach (Rivera, Soderstrom, and Uzzi 2010). Sociological network research has extensively tried to understand how network change is predicted by the previous structure of a network in a prior time period, as it conditions opportunities of interaction and the flow of trust and information among actors (Stuart and Sorenson 2007).

Repeated interaction allows individuals to learn about each other's beliefs and motives. This, in turn, might generate feedback effects about actors' intentions and determine the maintenance or the dissolution of an exchange relation. This is why the frequency of interaction is an important predictor of network evolution over time.

More precisely, being informed about future interaction repetition can make actors cooperate in order to avoid the partner's retaliation (the so-called "shadow of the future"). In a seminal study, Axelrod (1984) showed that in a two-person iterated Prisoner's Dilemma, self-interested players can find it rational to reciprocate the partner's cooperative behaviour. Conversely, a one-shot interaction would make it more convenient to defect and exploit the partner.

Moreover, the repetition of risky interaction exchanges can also trigger mechanisms of learning and control (Buskens and Raub 2002). Firstly, strategic players might infer from the structure of an exchange that they will be able to sanction the partner's opportunistic behaviour. This would elicit cooperation as actors would expect each other not to defect. Secondly, repetition also allows actors to experience each other's trustworthiness and predict that the partner's future behaviour would be consistent with the past.

Furthermore, repeated interaction provides the opportunity for actors to develop commitment to partners in exchange networks. This holds for cognitive (Cook and Emerson 1978; Kollock 1994; Yamagishi, Cook, and Watabe 1998; Back and Flache 2006) as well as for affective commitment (Thye, Yoon, and Lawler 2002; Molm, Takahashi, and Peterson 2000), as detailed in Section 2.3.

Network research has extensively studied the effects of repetition in many types of ties, both social and economic (Rivera, Soderstrom, and Uzzi 2010). Concerning collaboration ties, research has showed that professionals are more prone to voluntarily select as partners those persons with whom they have previously already worked. This phenomenon has been observed in various fields, ranging from artistic and creative professions (Uzzi and Spiro 2005) to scientific working groups (Guimerá et al. 2005). For instance, this last study developed an agent-based model that showed that the network structure of four scientific disciplines exhibited similarly high rates of repeated ties. By comparing the rate of repeated ties among diverse networks, the rate of repeated ties varied from about 50% to approximately 99%. This suggested that repetition had become a norm across different fields.

The importance of repetition for strategic commitment has been found especially in studies on market transactions, where ties are frequently modelled as one-shot exchanges. These results have inspired the theory of the social embeddedness of the economy (Granovetter 1985). Even big corporations (Baker 1990), investment banks (Podolny 1994) and large law firms (Uzzi and Lancaster 2004) appear to engage in ongoing relationships with a core set of financial partners, adding others on an *ad-hoc* basis for extraordinary or specific deals. Although focusing on corporate actors, network research in economic sociology provides interesting results also for interpersonal exchanges, as it can cast some light on processes that are enabled by individual actors who engage in relationships on behalf of their firms (see also Brailly et al. 2015).

Finally, other empirical studies have testified to the importance of repetition mechanisms for other kinds of exchange. Besides being a measure of the strength of a relationship (Friedkin 1990), repetition is also considered as an indicator of trust (Gulati and Gargiulo 1999; Uzzi and Lancaster 2004), altruism and information exchange in intraorganizational networks (Uzzi 1996).

Empirical network research has found that repetition is key to understand commitment in instrumental exchange relations, where frequent one-shot transactions identify a stable relation. However, other types of social relations are characterized by one's attribution of some status (e.g., friendship or other affective relationships) or discrete transfers of resources (e.g., advice-giving or social support). In order to understand the dynamic of these kinds of social relations, tie direction must be taken into consideration.

2.5.3 Reciprocation

Reciprocation seems to be a basic tendency of most social relations (Blau 1964). This means that an important predictor of some tie formation between an individual, i, and another one, j, is whether or not j previously had a directed tie with i. Yet, reciprocation is possible if the character of a social relation is directional, e.g., an individual transferring a resource to another. The character of the exchanged resource affects the tendency of reciprocating in social relations. More precisely, some relations occur in situations of resource asymmetry or signal the attribution of social status. These processes might prevent reciprocation.

Social network research has extensively studied the dynamic of tie reciprocation (Wasserman and Faust 1994, Chap. 13; Rivera, Soderstrom, and Uzzi 2010). This holds especially for positive expressive ties, such as affective relationships (Ibarra 1992; Lin 1999). By analysing longitudinal data of small groups of previously unacquainted individuals, Doreian et al. (1996) have found that reciprocation is one of the most important drivers of the growth of friendship networks. Moreover, Mollica, Gray, and Trevino (2003) showed that reciprocation observed in empirical friendship networks is much higher than what computer simulations of randomly generated similar networks would predict. Therefore, state-of-the-art statistical models always assume a positive tendency towards reciprocation for the analysis of empirical social networks (e.g. Snijders, Van de Bunt, and Steglich 2010; Lusher, Koskinen, and Robins 2013).

Empirical research has also dealt with unreciprocated ties. This might be affected by underlying dynamics of status attribution and recognition. In case of friendship, if *ego* does not reciprocate an incoming tie from *alter*, he/she would signal weaker commitment to *alter* (Gould 2002). Thereby, if *alter* does not withdraw his/her friendship offer, he/she expresses deference to *ego*'s claimed higher status (see also Lynn, Podolny, and Tao 2009). For example, in a recent study, Ball and Newman (2013) have found that unilateral friendship ties among young people are likely to be directed towards people who rank higher in social status.

Furthermore, non-reciprocation can also be related to differences in resources between individuals. Concerning social support, material help can be provided only by individuals who can provide it, because they own the needed resource. At the same time, people who do not own a specific resource are more likely to ask for material help. Therefore, the reciprocation of material support might be prevented by a static distribution of resources.

These two sources of non-reciprocation may be mixed in actual social systems. Research on social networks has tried to disentangle status and resource complementarity by studying advice exchange within organizations. On the one hand, advice-seeking is important for the individual mobilization of social capital (Coleman 1990; Lin 1999). On the other hand, advice-seeking is also related to social status, as nodes who are sought out for advice are likely to be recognized as high status members by other individuals (Lazega and Duijn 1997; Lazega et al. 2012). This implies that seeking advice from a peer and not being reciprocated means implicitly the establishment of a hierarchical relation between two actors. For instance, in a longitudinal study of an organization, Agneessens and Wittek (2012) found that, although social status bias is at work, advice-seeking among peers can indeed show a positive tendency towards reciprocation.

Finally, all exchange relations face the risk of non-reciprocation at some degree, as noted in Section 2.4. Although repeated interaction may discourage opportunistic behaviour, the risk of non-reciprocation is especially critical for reciprocal exchanges. Unidirectional positive expressive relationships are fragile if they fail to become reciprocal. Indeed, for some types of direct relationships, such as the ones involving solidarity, their directional character is a double-edge sword. If a positive expressive tie is reciprocated, actors can develop a stable bond. However, if a tie from *ego* to *alter* is not reciprocated, *ego* usually reacts by withdrawing his/her outgoing tie.

Therefore, solidarity between individuals is in itself a fragile social formation, because it faces the risk of non-reciprocation that is typical of any reciprocal forms of exchange. This implies that looking at dyadic interdependencies between actors, e.g., repeated interaction, is not sufficient to understand why solidarity relations can emerge from other exchange relations.

2.5.4 Closure and clustering

Considering an exchange network, it is important to look at the structural interdependencies that constrain actors beyond dyadic relations. More precisely, individuals' motives and beliefs might be conditioned by their embeddedness in wider relational structures.

Similarly to reciprocation, most social relations show also a strong tendency towards *network closure*. This means that if there is a tie between i and j and another tie between j and k (i.e., a *two-path*), then it is likely that a tie between i and k will close the path (Davis 1970; Holland and Leinhardt 1971). This would generate a local triangular structure within the network. Moreover, closed triads can cumulate and generate a process of "multiple triangulation", where triadic closure cumulatively occurs within the same subset of nodes, rather than spreading evenly across the network. This process of network *clustering* is at the basis of the formation of "community structures" (Newman and Park 2003) or "cohesive subgroups" (Wasserman and Faust 1994).

Network closure occurs in both undirected (e.g., collaboration) and directed (e.g., friendship) social relations. In the latter case, it occurs in several different versions, according to tie direction. For example, let us consider "transitive closure" (or "transitivity"). In this case, as an example, if i considers j a friend and j considers k a friend, then i is likely to consider k a friend as well. Alternatively, we would call it "cyclic closure" if k is likely to become friends with i in the same triad (e.g. Bearman 1997).

Closure and clustering are especially relevant to understand the emergence and maintenance of cooperation within social systems. First, individuals can learn to trust others by getting information about their reputation from third parties. Similarly, partners' behaviour can be controlled by third parties, who may sanction opportunism even if they are not directly involved in it (Buskens and Raub 2002; see Chapter 4 for more details). Concerning friendship and other affective relationships, explanations of tendency towards closure can be distinguished between opportunity-driven and preference-driven. In the former case, people are expected to create ties preferably with their tie neighbours' neighbours because there is higher probability of encountering them (e.g. Granovetter 1973). In the latter case, triadic closure might reflect in-group biased preferences for similar others or the result of exposure to information about positive reputation from an intermediary (e.g. Goodreau, Kitts, and Morris 2009).

Empirical research has found various economic and social networks that show closure and clustering properties. One of the best examples is a study by Newman and Park (2003), who testified to the importance of clustering. By comparing various kinds of human social networks (f.i., interlocking corporate directorates, the World Wide Web, food exchange), they showed that clustering occurs significantly more than in biological and technological networks.

Classic social network studies provided robust evidence on triadic closure. Besides the famous study by Granovetter on weak ties and job finding (1973), clustering has been observed in cross-cultural settings by Hammer (1980), who found that variously located social networks tend to exhibit higher likelihood of tie creation between unacquainted individuals who shared a common link neighbour. Concerning information sharing within organizations, clustering mechanisms have been observed in a vast digital communication network through the analysis of email exchange among students and faculty members of a large US university. This study found that having a mutual contact dramatically increased the probability of communication between two formerly unconnected students (Kossinets and Watts 2006).

Much research has involved collaboration network. There, evidence of clustering has been collected among members of corporation boards (Davis, Yoo, and Baker 2003), in the cultural industry (Watts 1999; Uzzi and Spiro 2005), in technology and innovation (Fleming, King, and Juda 2007), in scientific research (Newman 2001a) and law firms (Lazega and Pattison 1999; Lazega 2001). Furthermore, triadic closure may have a dramatical effect also in professional collaboration networks, where the need for control via reputation is highly relevant. For instance, by examining a collaboration network among 1.6 million of researchers in biology, physics, medicine and computer science over 4 years, Newman (2001b) found that sharing a common previous co-author increased the probability of collaboration between two researchers by about 30%. Moreover, the effect of sharing a mutual acquaintance in collaboration networks appears to be additive and non-linear, so that the overall network dynamics of scientific collaboration networks often approximate a preferential attachment growth model (Newman 2001b; Barabási and Albert 1999).

It is important to note that clustering effects interact with network distance between nodes. Research has found that closure mechanisms are detectable also among nodes whose distances are greater than 1, though it decreases according to the distance. Kossinets and Watts (2006)'s study on email exchange networks between students found that distance at one point in time is negatively related to the probability of attachment. Among those who did not share one class, dyads separated by two intermediaries were less likely to initiate a new tie than were individuals separated by only one. However, clustering effects were still remarkable. Coherently, current statistical models for social networks assume that the effect of network distance on attachment decays rapidly as the number of intermediaries grows (see also Pattison and Robins 2002; Snijders et al. 2006).

This said, it must also be considered that not all social networks exhibit clustering. In fact, the opposite tendency has been observed in social networks where norms or structural constraints prohibit or hinder some patterns of interaction. Kinship networks where ties represent genealogical descent are an obvious example of taboo norms against closure. Besides kinship systems, however, an interesting study was conducted by collecting data on the romantic and sexual networks of more than 800 students of a US high school. Bearman, Moody, and Stovel (2004) found that closed triads or four-cycles[2] were rare. By simulating a series of agent-based models which implemented different hypothetical micro-level mechanisms, they were able to reproduce the observed spanning-tree network configuration by assuming that an unrecognized norm prohibited actors to engage in a romantic relationship with the former lover of his/her current lover's ex-lover.

To summarize, repeated interaction, reciprocation and triadic closure can explain the formation of social relations between previously unrelated individuals. However, this 'within-the-network' approach cannot overcome the limitations of considering only one kind of relation at a time. Therefore, it cannot account for more complex interdependencies between different kinds of exchanged resources, which are probably more relevant empirically.

2.5.5 Multiplexity

In order to understand how solidarity can emerge from other types of relations, it must be looked at the *multiplex* dimension of social networks. This means to consider

2. A four-cycle is a pattern where there is a tie between i and j, a tie between j and k, a tie between k and l and a tie between l and i.

that different kinds of relations may exist simultaneously within the same set of individuals. For example, i can consider j a friend but trusts k as business partner.

Besides the content of ties, the same logic of 'within-the-network' approaches apply to multiplex relations. The fact that repetition, reciprocity and clustering can generate stabilization of ties of different resource exchanges, suggests the possibility that iterated frequency of a tie between two actors could lead to the creation and maintenance of a different overlapping tie between the same actors (Gould 1991, 1995).

Here, it is relevant to cite one research that has explicitly linked solidarity with the analysis of multiplex relational mechanisms. After an extensive preliminary and posterior ethnographic analysis, Lazega (2001) has studied the structure of cooperation among 71 lawyers who worked in a US lawyering firm (see also Lazega and Pattison 1999). He collected empirical data about the exchange of three different resources, such as: a) coworkers' goodwill, defined as strong commitment to collaborate, b) basic advice seeking (see also Cross, Borgatti, and Parker 2001), c) friendship. The study was guided by the hypothesis that a balance between competition among coworkers for internal status and successful collective action in achieving organizational efficiency were possible only when actors were bounded by structural interdependencies due to their needs for some crucial resources and the constraints for action given by the unequal distribution of those resources. Free-riding temptations to free-ride were neutralized by expectations of reciprocity that actors had in the exchange of various kinds of resources. This created a multiplex internal exchange system. More interestingly, ethnographic study suggested that in order for such a complex cooperation structure to remain stable, exchanges were unlikely to flow within dyads. So, the exchange system was expected to be a *generalized* one.

By analysing interdependencies among the three different networks through Exponential Random Graph Models (ERGMs) (Pattison and Wasserman 1999; Robins et al. 2007; Lusher et al. 2012), Lazega and Pattison (1999) assessed the structural properties of the multiplex exchange system emerging from coworkers' relations. First, they found that the three different kinds of relations were driven by different relational mechanisms. While co-work ties were strongly governed by reciprocation and clustering, which generated a mixed system of restricted and generalized exchange, advice and friendship ties exhibited patterns of local clustering. Secondly, despite diversity between networks, different types of exchange tended to overlap, particularly concerning advice-seeking, which aligned with the other two. Finally, they found some level of direct exchange between different relations. These results strongly support the idea of a multiplex exchange system, where cooperation and solidarity are backed by structural interdependencies among different types of resource exchange, where one type appears to serve as a bridge supporting the other. The combination of advice with either co-work or friendship showed the most robust effect. Moreover, advice ties were observed to connect actors who were indirectly connected through asymmetric co-work ties. Therefore, such an exchange system may be functional to the stability of solidarity internal to a group of peer coworkers, by neutralizing centrifugal tendencies driven by opportunism and status competition.

Finally, other recent network studies have shown the importance of multiplex network analysis when groups and organizations are seen as complex exchange systems. More precisely, advice-seeking in organizations has been analysed in different analytic dimensions, by identifying interdependencies between different kinds of advice and their relation with job satisfaction (Cross, Borgatti, and Parker 2001; Soltis et al. 2013). Trust ties have also been analysed through a full-network study, in order to understand the relations between perceived and expressed trust (Lomi et al. 2014).

In conclusion, social network research points out the possibility of testing theories of solidarity by analysing the actual exchange systems that emerge within multiplex social networks. In particular, by looking at social systems as multiplex exchange networks, it is possible to understand the mechanisms that make certain exchange relations develop into expressive ties.

2.6 Conclusions

This chapter has tried to understand why solidarity can emerge between peers who do not share any group identity. To do so, studies in sociology and behavioural sciences have been reviewed to identify important "relational mechanisms" (Simpson and Willer 2015). Here, we explored the idea that actors interacting for certain purposes may develop beliefs on the interaction partners that go beyond the specific content of the exchange. This may eventually change their motives, develop an expressive value out of an instrumental purpose and transform their relation into another kind of tie.

First of all, classic sociological theories of solidarity have been analysed and a micro-level definition of solidarity as "solidary behaviour" (Lindenberg 1998) has been suggested. This approach is particularly fruitful to analyse relational mechanisms, because it focuses on the behavioural aspects of solidarity within dyadic relations.

We found that social exchange scholars have provided two main theories about the emergence of solidarity from exchange relations, namely the *Affect Theory of Social Exchange* (Lawler, Thye, and Yoon 2008) and the *Reciprocity Theory of Solidarity* (Molm, Collett, and Schaefer 2007). They suggested that individuals find it difficult to develop solidarity between each other if the context of their exchange relation is informed by conflict rather than cooperation (Molm, Collett, and Schaefer 2007; Lawler, Thye, and Yoon 2008; Molm, Schaefer, and Collett 2009; Kuwabara 2011). Besides this, these two theories did not produce univocal results about the link between different forms of exchange and solidarity. In particular, RTS suggested that economic exchanges with bounded agreement might be detrimental for solidarity, because they do not allow partners to learn to trust each other. This would occur especially if actors compete with each other, as this increases the salience of conflict. Nevertheless, RTS suggested that trust is fundamental for the emergence of solidarity.

Although research in Social Exchange Theory has provided insights about relational mechanisms of solidarity, empirical research is needed to look into the content of social relations and their interplay with actors' motives in more detail. Here, social network research has been reviewed to understand which structural configurations can help certain relations to develop into different kinds of ties. These studies suggested the importance of considering the complex interdependencies of actors within exchange networks, which affect the stability of social relations.

In conclusion, our review indicated that the problem of solidarity is twofold. On the one hand, solidary behaviour in the context of other exchange relations needs to overcome conflict of interests. This facet of solidarity shares some critical points with cooperation and prosocial behaviour. On the other hand, emergent solidarity must avoid the risk of disruption brought by the divergence between actors' interests.

Concerning the first aspect, it is probable that trust can trigger the development of solidarity. It is an empirical question whether it is possible to elicit trust in various exchange relations. Interaction contexts where individuals are free to learn about each other's trustworthiness could be favourable for trust formation. More precisely, actors who hold beliefs about exchange partners' trustworthiness might expect that they are available for support as well. At the same time, trust-based solidarity relies upon an inherent conflict of interests. This might prevent expectations of solidarity to be fulfilled and reciprocated, especially in situations of resource asymmetry or competition. For both dimensions of the problem, empirically-grounded research is needed that helps disentangle these mechanisms.

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Chapter 3

Solidarity as Byproduct of Professional Collaboration[1]

3.1 Introduction

The relationship between economic exchange and solidarity is still a subject of debate in social sciences. On the one hand, some scholars suggest that successful economic interactions structured as "negotiated exchanges" (Blau 1964; Emerson 1981; Molm 2003) can generate solidarity, provided that joint bargaining promotes coordination of common interests between partners. The perception of cooperative attitudes would confer expressive value to the relationship (Lawler 2001; Thye, Yoon, and Lawler 2002; Lawler, Thye, and Yoon 2008; Kuwabara 2011). On the other hand, other scholars argue that economic exchanges cannot easily generate solidarity, because negotiated agreements binding subjects' interaction tend to exacerbate conflict between their mutual interests. Moreover, by preventing individuals from mutually exploiting each other, an economic exchange would not allow partners to show their trustworthiness, thereby hindering the development of mutual trust, a crucial component of solidarity (Molm, Takahashi, and Peterson 2000; Molm 2003; Molm, Collett, and Schaefer 2006, 2007; Molm, Schaefer, and Collett 2009).

This paper aims to contribute to this debate, by analysing the multiplex network of relations of economic exchange, trust and solidarity within a group of freelance professionals. In order to measure solidarity at a dyadic level, we studied the subjects' expectations of receiving social support from other members when they were in a situation of need (Lindenberg 1998; see also Flache and Hegselmann 1999a, 1999b). As a proxy for economic exchange, we analysed professional collaboration between partners, resulting from the joint participation of two or more actors to the provision of a good or service for a customer.

In order to disentangle the effects of exchange interactions from particular institutional and organizational contexts, we selected a group of ICT professionals working as independent freelancers, while sharing the same coworking space (DeGuzman and Tang 2011). This setting provided us with the opportunity to observe economic

1. A different version of this chapter, co-authored with Niccolò Casnici and Flaminio Squazzoni, has been submitted with the same title to an international journal as a peer-reviewed article.

exchanges among peers who were free to select their partners outside the constraints of a formal organizational or hierarchical structure. Moreover, the absence of a formal organization allowed us to study emergent solidary behaviour among subjects who did not share any group-related collective interest.

At the same time, we also analysed the *structural logic* (Markovsky, Willer, and Patton 1988; Rank, Robins, and Pattison 2010) of the network of expected social support emerging among collaborating partners. To do so, we assessed the impact of reciprocity (Wasserman and Faust 1994) and closure (Davis 1970; Holland and Leinhardt 1971) independent of the multiplex effects of collaboration and trust.

The rest of the paper is organized as follows. The following section presents our research background, while Section 3.3 describes data collection and analysis. Section 3.4 discusses our results, while the final section summarizes the main findings and discusses limitations and prospects.

3.2 Research background

The importance of the embeddedness of the economy within social structures is a key point of sociological analysis (Granovetter 1985). Social network research has shown that the control and exchange of social resources, such as advice or information, affect the performance of entrepreneurs and organizations through informal interpersonal relationships (e.g. Krackhardt 1992; Ingram and Roberts 2000; Lazega 2001; Brass et al. 2004; Rank, Robins, and Pattison 2010; Brailly et al. 2015), which often entail trust and support (Coleman 1988, 1990; Granovetter 2002). Though it is acknowledged that "most forms of social capital are created or destroyed as a byproduct of other activities" (Coleman 1990, p. 317), we know less about the structural conditions under which instrumental relations, such as professional collaboration, develop into expressive ties (Ibarra 1992), such as social support.

Various institutional and organizational contexts may enhance prosocial behaviour among self-interested individuals by eliciting and enforcing norms or favouring the diffusion of reputation (see Simpson and Willer 2015, for a review). Yet, we still know little about those mechanisms which bring about social support between two individuals within the context of another type of relation.

Social support mainly encompasses a *material* (or tangible) along with an *emotional* (or intangible) component, according to the nature of the resources which one is asked to mobilize in order to help the recipient (van der Poel 1993; see also Lin 1986). Research on personal social support networks (Hall and Wellman 1985) has identified certain regularities in the determinants of social support relations along individual lines. Different kinds of support are expected by *Ego* according to *Alter*'s role status in Ego's personal network (Agneessens, Waege, and Lievens 2006).

While kinship members are usually considered more important as a source of emotional support, workmates are often recognized to play a prominent role in the provision of minor material support (Wellman and Wortley 1989; Wellman et al. 2001).

Moreover, previous research has found gender differences in the provision of material and emotional support (Vaux 1985; Wellman and Wortley 1990), as well as age and gender homophily effects (Feld 1982; Marsden 1987; McPherson, Smith-Lovin, and Cook 2001). Finally, social status affects the size and composition of one's social support network, with higher educated individuals being more likely to rely more on non-kin contacts rather than others (Fischer 1982).

Aside from the literature on personal social support networks (e.g. Fischer 1982; Wellman and Wortley 1989, 1990; Wellman et al. 2001), one of the most important facets of solidary behaviour is that its scope goes beyond one's kinship or proximate social circle. Dyadic exchange relations provide individuals with opportunities to develop beliefs about each other that may trigger the change of that relation into a different one, or to develop new relations of different nature (Emerson 1976; Molm and Cook 1995). Following Granovetter's claim that "[c]ontinuing economic relations often become overlaid with social content that carries strong expectations of trust" (1985, p. 490), we argue that solidary behaviour in the form of social support between two otherwise unrelated individuals might arise as the byproduct of an economic exchange relation between them.

Exchange theorists (Homans [1961] 1974; Blau 1964; Emerson 1976; Molm and Cook 1995) have provided a sound conceptualization of *economic exchange* as a specialized form of social exchange (Homans [1961] 1974), which is often referred to as *negotiated exchange* (Blau 1964; Lawler 2001; Molm 2003). In this conceptualization, economic exchange between two partners is defined as a bilateral transfer of resources which benefits both, upon a jointly negotiated agreement. The benefits yielded to both partners occur as two paired events, although the agreement is reached through a joint bargaining process. The terms of the agreement can be either binding or non-binding (Molm, Schaefer, and Collett 2009; Kuwabara 2011).

This process implies that the ongoing engagement in exchange relations elicits subjects' attribution of expressive value to the relation, which in turn reinforces the duration of the exchange (Blau 1964; Emerson 1976). The repetition of the exchange is key here to provide an opportunity for the development of mutual trust and regard. Beyond forward-looking, "shadow of the future"-like rationality (Axelrod 1984), long-term commitment to exchange partners in market-like situations can emerge as an effect of strategic uncertainty reduction, despite the presence of more profitable exchange partners (Cook and Emerson 1978; Kollock 1994; Yamagishi, Cook, and Watabe 1998). Computer simulations have also shown that commitment is more efficient than other strategies in reducing risk of exploitation by opportunistic partners (Back and Flache 2006). Finally, studies on empirical business networks showed that the repetition of exchanges reinforces strategic commitment between partners (e.g. Podolny 2001; Beckman, Haunschild, and Phillips 2004). Especially relevant for our study is research on interdependency between instrumental and expressive ties (Ibarra 1992) in intraorganizational networks. A seminal study by Lazega and Pattison 1999 (see also Lazega 2001) has shown that the collective efficiency of an organization made by associated professionals rests upon complex interdependencies between collaboration ties, instrumental exchange of valuable resources and friendship. In a similar vein, Rank, Robins, and Pattison (2010) have shown that employees who collaborate frequently are more likely than other employees to exchange information and support each other.

Experimental research in social psychology has provided evidence on the effects of economic exchange on solidarity (Molm, Takahashi, and Peterson 2000; Thye, Yoon, and Lawler 2002; Molm, Collett, and Schaefer 2007; Barrera 2007; Lawler, Thye, and Yoon 2008; Molm, Schaefer, and Collett 2009; Kuwabara 2011). Some scholars suggest that economic exchange does not provide sufficient structural conditions for solidarity to emerge (see Molm 2010 for a comprehensive account). The joint character of the decision-making process inherent in the the negotiating activity and bilateral transfer of benefits during transactions, while providing room for cooperation, may also exacerbate the salience of conflict between the two partners' interests (Molm, Collett, and Schaefer 2006). First, the bilateral structure of exchange heightens the perception of competition between partners, who can frame splitting benefits as a zero-sum game. Secondly, the instrumental and strategic nature of other partners' commitment is made explicit by constraining exchange within the terms of a negotiated agreement (Molm 2003; Molm, Collett, and Schaefer 2007). Finally, the most relevant point is that the act of establishing an agreement in itself reduces the risk of being exploited by an opportunistic partner (Molm, Takahashi, and Peterson 2000; Molm 2003; Molm, Collett, and Schaefer 2007).

The risk of exploitation is a necessary condition for trust to develop within an exchange relation. This is because it provides individuals with the opportunity to prove to be trustworthy (Gambetta 1988; Hardin 2002; see also Kollock 1994; Yamagishi, Cook, and Watabe 1998). If subjects succeed in finding an agreement, trust is not particularly necessary for a positive outcome, as they can rely on assurance provided by the agreement (Yamagishi and Yamagishi 1994; Malhotra and Murnighan 2002).

Nonetheless, other studies suggest that the structure of joint negotiation entailed by economic exchanges generates solidarity between the partners. This is achieved through a cognitive mechanism, which allows them to attribute the positive outcomes to each other and to the relation as a unit (see Thye, Yoon, and Lawler 2002 for a review; see also Lawler, Thye, and Yoon 2008). First, Lawler, Thye, and Yoon (2008) show that the character of 'jointness' entailed by bargaining activity promotes coordination and the partners' collective responsibility, which eventually increases the chances to reach an agreement. In theses cases, the benefit of exchange can trigger positive emotions that subjects tend to link to collective responsibility. The relationship in itself is made more salient by the task-interdependence of the negotiating process, which makes individual contributions difficult to separate (Lawler 2001). However, laboratory experiments have found conflicting evidence of the effects of economic exchange on solidarity (Lawler, Thye, and Yoon 2008; Molm, Collett, and

Schaefer 2007).

Other laboratory experiments have questioned the existence of a negative effect of economic exchange on trust, by providing more flexible versions of the negotiated exchange model. For instance, Barrera (2007) has shown that repeated economic exchange generates trust between subjects with equal distribution of resources. However, it is unclear whether this is due to learning a partner's trustworthiness or to personal characteristics. By loosening the terms of agreement between partners, Molm, Schaefer, and Collett (2009) showed that non-binding economic exchange can successfully generate trust, as partners can prove their trustworthiness to each other. However, the higher risk of opportunistic behaviour undermines the likelihood of success of such exchanges. Finally, Kuwabara (2011) suggests that the structure of joint negotiation underlying economic exchange may either generate solidarity or exacerbate conflict depending on contextual factors. More precisely, varying levels of perceptions of risk-taking, conflict and expressive value entailed by various forms of economic exchanges yield different results in terms of trust and solidarity.

Our aim here is to empirically test the effect of the economic exchange on solidarity. We also wanted to understand the role of trust as a causal mechanism that accounts for the formation of expectations of social support. Here, we hypothesized that where there is no hierarchical structure or formal organization providing top-down incentives, engaging in a professional collaboration among peers is not sufficient alone to develop expectations of support. However, if a trust relation develops between partners, this is enough to develop expectations of social support. Therefore, expectations of social support could emerge from professional collaborations as long as trust develops between partners.

Thus, assuming a group of peers who are independent from each other, we formulated the following hypotheses:

> *Hypothesis 1*: There is no net association between successful collaboration and expectations of social support.

> *Hypothesis 2*: There is a positive association between business-related trust and expectations of social support.

3.3 Research design and method

In order to test our hypotheses, we conducted a full-network study on a group of 29 independent workers sharing the same "coworking space". Our empirical strategy included the collection of relational and individual survey data on the entire population.

3.3.1 Empirical setting

Coworking spaces are office-like working environments where freelancers, entrepreneurs, or employees of small companies are allowed to pursue independent activities while sharing the same working space (DeGuzman and Tang 2011). Members of a coworking space usually get access to self-managed goods (e.g., personal desk, mailbox) and collective goods and services (e.g., kitchen, reception, wi-fi internet connection, etc.). Although the basic entry motivation in coworking spaces is usually cost reduction, sharing a common space generates the opportunity for independent workers to develop business relationships such as professional collaborations or subcontracting, as well as the exchange of information and various social resources.

It is important to note that, since they mostly work as freelancers, members of a coworking space do not usually share any collective economic interest. Moreover, unlike employees in a company, members of a coworking space are not embedded in any formal organizational structure. Thus, the selection of collaboration partners is by no means related to any superimposed directive. Finally, the absence of any hierarchy makes members of a coworking space peers to each other. Thus, studying a coworking space allows us to disentangle the effects of professional collaboration on trust and expectations of social support from confounding factors of an institutional or organizational nature.

As a suitable case, we collected data on the whole population of "Talent Garden Brescia" (TaG), a coworking space located in Brescia, Northwestern Italy. TaG is owned by private shareholders, whose mission is to create and manage coworking spaces for ICT freelancers and small innovative companies. Unlike more politically-oriented coworking spaces, which are explicitly aiming at building forms of solidarity between freelancers, TaG was founded in 2012 with an explicit business-like orientation and attracted an original core of mainly previously unrelated ICT professionals. The lack of a shared collective identity allowed us to control *a priori* for self-selected orientation towards solidarity among the subjects. Moreover, as all TaG members were ICT professionals, skill complementarity allowed us to observe a sufficiently dense network of professional collaborations.

3.3.2 Qualitative fieldwork

Before collecting network data, we conducted a qualitative study of the empirical setting, in order to shed light on the content of interaction between coworkers and the institutional and organizational context in which they worked. This was accomplished through a 4-month participating observation, during which casual contacts with coworkers were established. The aim was twofold: (i) establishing a rapport with the subjects in order to maximize the rate of participation to the survey (e.g. Johnson 1990); (ii) calibrating the survey questionnaire with a meaningful content for subjects in order to maximize validity and reliability of the data. During the fieldwork, qualitative information about organizational and contextual characteristics of TaG were collected via interviewing managers of the holding company. Together with observation, this has contributed to understand the basic mechanisms of collaboration between coworkers. Since the institutional context of the coworking space provided no top-down incentives for cooperation, all collaborations between coworkers were self-organized. They mainly took the form of subcontracting and were enhanced by skill complementarity among coworkers. Besides this, small companies typically tended to outsource a portion of their projects to internal rather than external partners in order to reduce transaction costs, because partner control could be performed easier. As indicated by some interviewees, this occurs even in the presence of more profitable alternatives with external partners (Cook and Emerson 1978; Kollock 1994).

By means of direct observation and administrative data, we reconstructed the structure of company co-membership within TaG. While 10 out of 29 subjects worked as independent freelancers, 19 TaG members were distributed among 7 small companies of 2, 3, or 4 members each. Figure 3.1 shows the network of co-membership to the same company among TaG members.

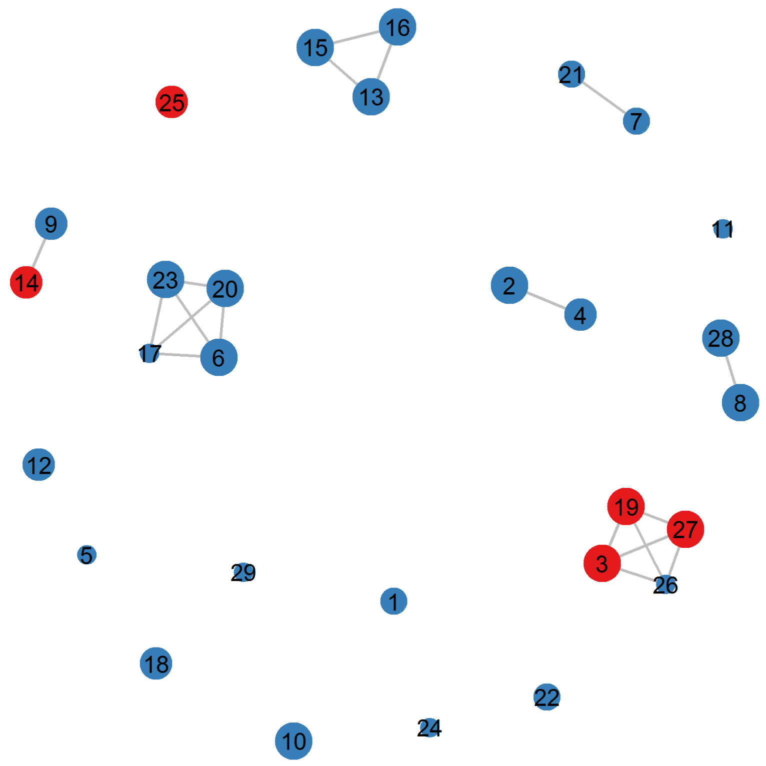

FIGURE 3.1: The *Company co-membership* network. Node colours represent actors' gender (blue = male, red = female). Node size represents seniority in the group.

3.3.3 Data: variables and measures

We collected relational and individual-level data by means of a CAPI questionnaire personally and individually administered to all 29 members of TaG by one interviewer. Since we could not apply leverage on any formal hierarchy to ensure participation to the survey, respondents were invited by casual contact during the fieldwork. Twenty-eight out of 29 interviews were conducted through a 2-week time period,

Number of coworkers	29
Gender	Male = 24, Female = 5
Age (years)	Mean = 31.83 (SD = 6.04)
Family status	Single = 4
	In a stable relationship = 6
	Cohabitant with partner = 11
	Married = 8
Seniority in coworking space (months)	Mean = 29.34 (SD = 14.26)
Educational degree	Middle school or vocational training = 2
	High school = 10
	Bachelor = 7
	Master = 10

TABLE 3.1: Members of Talent Garden Brescia coworking space: Main characteristics.

while one interview was conducted with a 2-month delay. Respondents filled out the questionnaire independently, although the interviewer was always available to help respondents and improve respondent recall (e.g. Brewer 2000). Response rate was 100%.

In order to control for the interplay between coworkers' individual properties and the relationships between them, we collected node-level attribute data about both sociodemographic and business-related characteristics: *Gender*, *age*, *family status*, *seniority* in TaG, *educational degree*. Table 3.1 summarizes the main characteristics of respondents.

Gender distribution was highly skewed in the population, as women were only 5 out of 29. The distribution of *age* was also consistently skewed, as 11 out of 29 were below 30, 15 were between 30 and 39 and only 3 of them were 40 or older. The group was also quite homogeneous in terms of *seniority*, which was measured as the number of months from the beginning of their membership at the time all the interviews were completed. 24 out of 29 subjects had been members for at least 6 months, with nobody with a membership lasting less than 3 months; 20 coworkers had been members for more than 12 months, while a core of 13 of them had a membership of at least 24 months.

Relational data were collected by means of sociometric questions formatted according to the conventional repeated roster method (Kilduff and Krackhardt 2008). English translations of the questions are provided in the Appendix A.

Social support is the *explanandum* of this study (see Figure 3.2). A tie-variable was built by merging the answers to two different questions, addressing respectively the mobilization of *material* and *emotional* resources in the context of out-of-work private life (van der Poel 1993; Lin 1999), so that $x_{ij} = 1$ if i expects j to support him/her with either material or emotional resources and $x_{ij} = 0$ otherwise[2]. Both questions

2. We merged the adjacency matrices of *material* and *emotional support* through a Boolean aggregation procedure, so that the aggregate tie-variable *Social support* was equal to 1 for a given dyad if the same dyad had an edge at least on one of the two original matrices

were formulated as passive and attitudinal measures, in order to minimize social desirability and avoid the biasing effect of the opportunity of being in a situation of need (van der Poel 1993; De Lange, Agneessens, and Waege 2004).

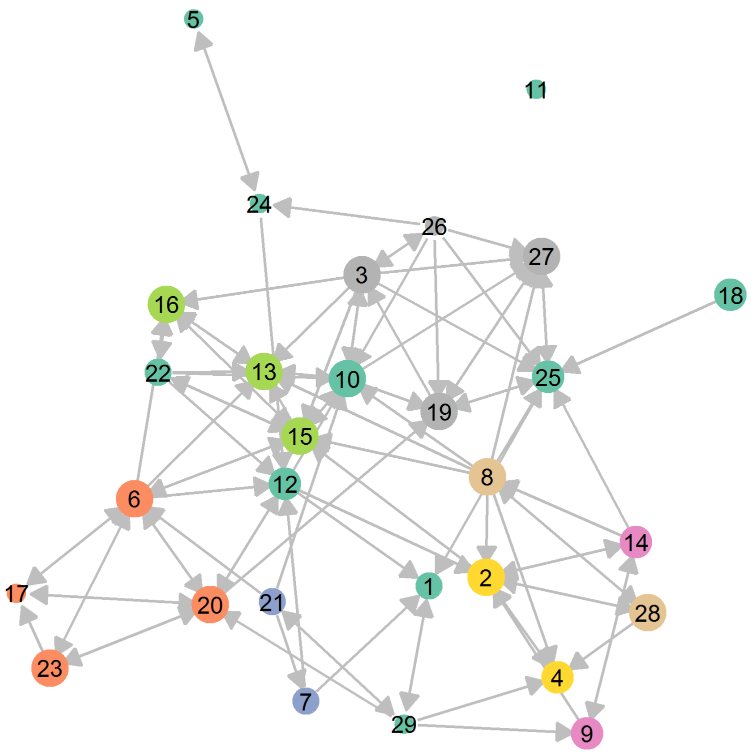

FIGURE 3.2: The *Social support* network. Node colours represent company co-membership (dark green = freelancers).

In the *Trust in business* variable, $x_{ij} = 1$ if i considered j to be trustworthy for a hypothetical risky business partnership and $x_{ij} = 0$ otherwise. This was to relate our measure to the concept of trust in a risky situation (Gambetta 1988; Hardin 2002). Figure 3.4 shows the *Trust in business* network.

Data concerning professional collaboration between TaG members, by asking three questions, according to the types of collaboration observed during the fieldwork. Firstly, we asked about "incoming commissions", where respondents had to select other members offering one or more effectively completed commissions. Secondly, a similar question was asked to measure "outgoing commissions". Thirdly, respondents were asked about other members with whom they worked at jointly designed new projects. We then merged the adjacency matrices relative to the collaboration-related questions and the matrix of *Company co-membership* to build a *Collaboration* network, where $x_{ij} = 1$ if i had collaborated in any form or was company colleague with j and $x_{ij} = 0$ otherwise.

Furthermore, we measured subjects' satisfaction levels of their collaboration partners by asking them to express how much they would recommend them as

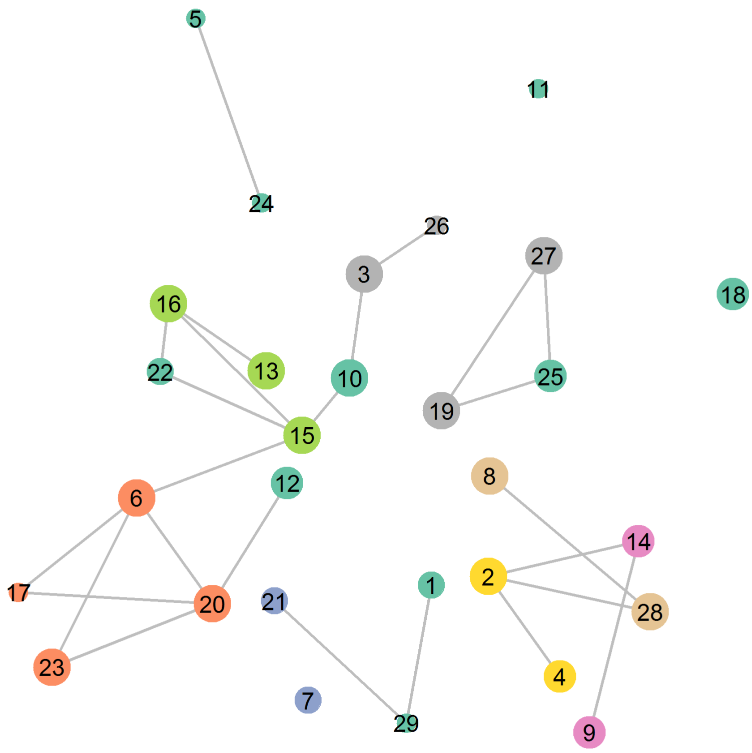

FIGURE 3.3: The Social support network with reciprocated ties only. Node colours represent company co-membership (dark green = freelancers); node size represents seniority in the group. Node coordinates are the same as in Figure 3.2

business partners to others on the basis of their own past experience through a 1-7 Likert scale. We then built a *Positive collaboration* network, where $x_{ij} = 1$ if i has collaborated with j and evaluated her with a value > 4. Otherwise, $x_{ij} = 0$. This was made to create a proxy for "successful" economic exchange relations (Lawler, Thye, and Yoon 2008). Figure 3.5 shows the *Positive collaboration* network.

Finally, as a control variable, we asked subjects to cite those TaG members whom they had already known in person before becoming a TaG member. The resulting answers constitute the *Previous acquaintance* network, which is reported in Figure 3.6.

Table 3.2 reports descriptive graph-level statistics of the *Social support*, *Trust in business* and *Positive collaboration* networks.

3.3.4 Model specification

In order to test our hypotheses, we estimated univariate and multivariate Exponential Random Graph (p^*) Models (ERGMs) for the *Social support* and *Trust in business* networks (Pattison and Wasserman 1999; Snijders et al. 2006; Robins et al. 2007, n.d.; Robins, Pattison, and Wang 2009; Lusher, Koskinen, and Robins 2013). Univariate

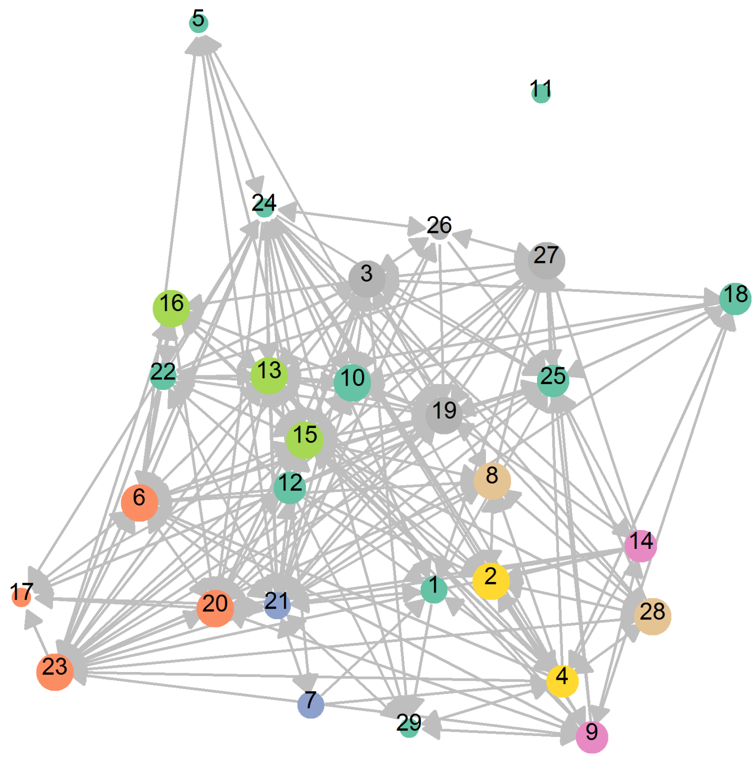

FIGURE 3.4: The *Trust in business* network. Node colours represent company co-membership (dark green = freelancers). Node size represents seniority in the group. Node coordinates are the same as in Figure 3.2

ERGMs for social network analysis have the following general form:

$$Pr(Y = y) = \frac{1}{k} exp\left[\sum_{A} \lambda_A z_A(y)\right], \tag{3.1}$$

where, $Pr(Y = y)$ represents the probability of the tie-variable Y taking the observed value y, $\frac{1}{k}$ is a normalizing quantity, A represents a potential network substructure, λ_A is the parameter corresponding to configuration A and $z_A(y)$ is the graph statistic corresponding to configuration A, which indicates the presence of configuration A in the observed network.

In case of the multivariate model, the statistics $z_A(y)$ are defined within and among ties from different types of networks (Pattison and Wasserman 1999), such that:

$$z_k(y) = \sum_{A \in A_k} \prod_{(i,j,m) \in A} x_{ijm}\,, \tag{3.2}$$

where A_k is a collection of isomorphic configurations A of tie-variables.

For the multivariate ERGMs, we simulated the emergence of the observed networks of *Social support* and *Trust in business* simultaneously, assuming the exogenous occurrence of the observed network of *Positive collaboration*. In order to test our

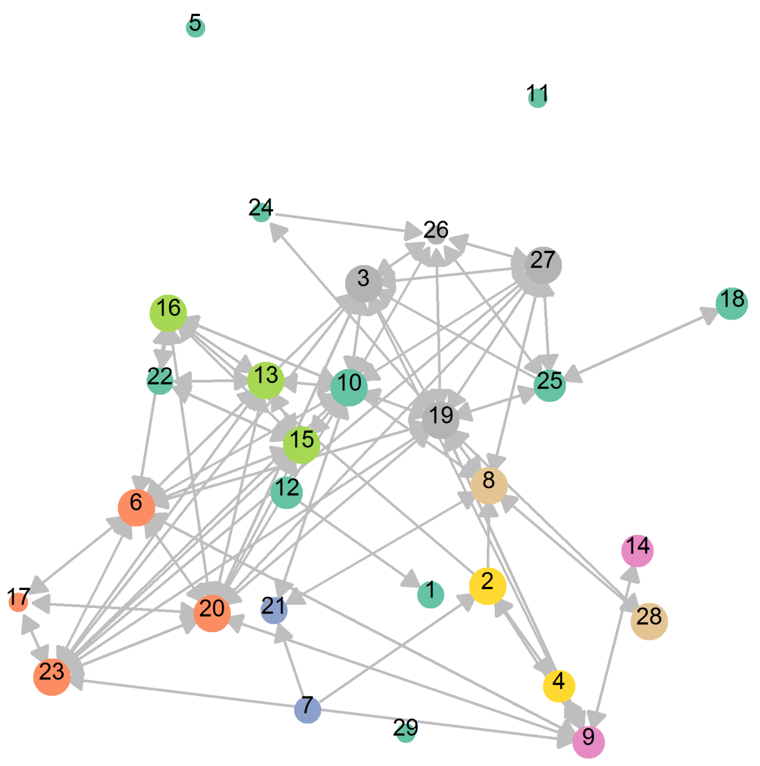

FIGURE 3.5: The *Positive collaboration* network. Node colours represent company co-membership (dark green = freelancers). Node size represents seniority in the group. Node coordinates are the same as in Figure 3.2.

hypotheses, we calculated estimates of the entrainment effect of *Positive collaboration* and *Trust in business* on *Social support*. In the former case, the effect measures how likely i expects support from j if i and j have collaborated and i would recommend j as a partner. In the latter case, the effect measures how likely it is that i expects support from j and considers her trustworthy in business as well. In order to control for the co-occurrence of other confounding processes, we specified the models with endogenous structural effects, exogenous actor-relation effects and exogenous network covariate effects.

For within-network structural effects, we specified the model with basic reciprocity, closure and connectivity parameters for non-directed networks (Robins, Pattison, and Wang 2009; Lusher, Koskinen, and Robins 2013). As regards to actor-relation effects, we included parameters concerning individual demographic properties, namely *gender* and *age*, along with the subjects' working experience, namely *seniority* in the coworking space. For each attribute, the value of the *sender* effect measured the likelihood for a tie to be directed from a subject with a particular attribute rather than another, while the *receiver* effect expressed the likelihood of a tie to be received by a subject with that attribute. The *homophily* effect statistics measure the propensity for subjects to form ties with others of the same categorial attribute. In

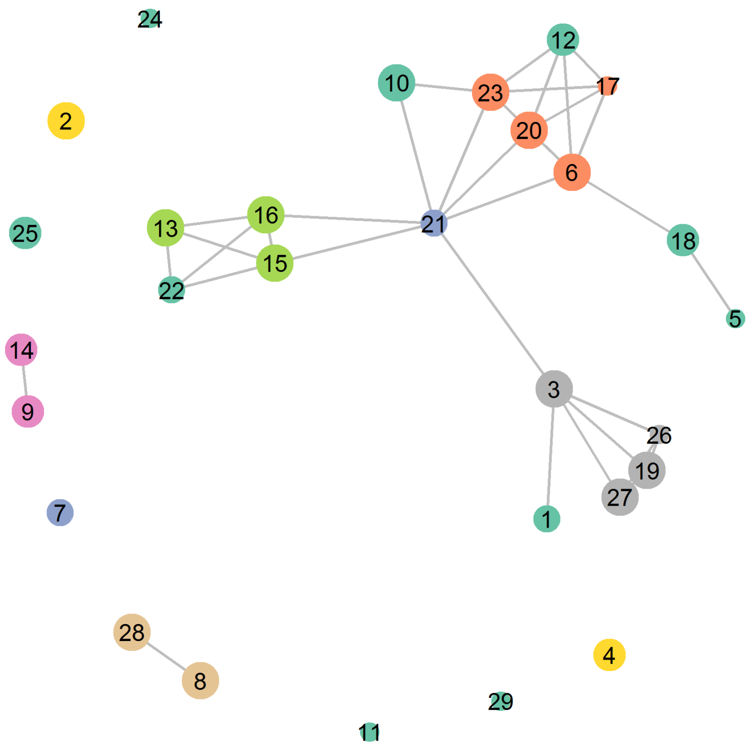

FIGURE 3.6: The *Previous acquaintance* network. Node colours represent company co-membership (dark green = freelancers). Node size represents seniority in the group. Node coordinates are the same as in Figure 3.1

multivariate models, actor-relation effects were also estimated for both *Social support* and *Trust in business* networks.

Finally, the entrainment effect of *Previous acquaintance* as covariate network was estimated as a control factor. We dropped the specification of a similar effect for *Company co-membership* on *Social support* because it was not significant in any of the model configurations.

We estimated our models through Monte Carlo Markov Chain Maximum Likelihood Estimation (MCMCMLE) (Snijders et al. 2006) using the Pnet software (Wang, Robins, and Pattison 2005) for the univariate models and the XPnet software (Wang, Robins, and Pattison 2006) for the multivariate model.

3.4 Results

3.4.1 Descriptive statistics

Table 3.3 shows that both *Positive collaboration* and *Trust in business* were significantly correlated with *Social support*, with slight differences between the two values (Krackhardt 1987). By considering the number of entrained arcs between the three networks,

	Social support	*Trust in business*	*Positive collaboration*
Number of ties	99	235	130
Density	0.122	0.290	0.160
Mean in/outdegree	3.414	8.103	4.483
Minimum outdegree	0	0	0
Maximum outdegree	8	20	12
Outdegree centralization	0.170	0.440	0.278
Minimum indegree	0	0	0
Maximum indegree	7	16	11
Indegree centralization	0.133	0.292	0.241
Number of reciprocated pairs	25	64	58
Number of transitive triads (030T)	11	89	0
Number of cyclic triads (030C)	0	1	0

TABLE 3.2: Basic statistics for *Social support*, *Trust in business* and *Positive collaboration* networks

TABLE 3.3: Pearson graph correlations of *Social support*, *Positive collaboration* and *Trust in business* with Quadratic Assignment Procedure (QAP) tests.

Network	1	2
1. Social support		
2. Positive collaboration	0.433*	
3. Trust	0.443*	0.410*

* $p < 0.001$, QAP test with 1,000 repetitions.

Table 3.4 shows that out of 130 ties of *Positive collaboration*, 58 co-occur with ties of *Social support*, while 72 do not, with a Multiplexity Index $\upsilon = 0.712$ (*z-score*=11.676) (Skvoretz and Agneessens 2007)[3]. A higher multiplexity was observed between *Trust in business* and *Social support*, as 82 out of 99 ties of social support expectations co-occur with trust in business-related situations, with $\upsilon = 0.821$ (*z-score*=12.788).

However, due to complex interdependencies within the data, we were unable to draw any relevant conclusions on our hypotheses on the basis of these descriptive statistics.

3. The index depends on the calculation of the maximum number of multiplex pairs that could occur and of the expected number conditioned on outdegree.

TABLE 3.4: Number of entrained arcs for *Social support*, *Trust in business* and *Positive collaboration*

	1	2
1. Social support		
2. Positive collaboration	58	
3. Trust in business	82	93

3.4.2 ERGM results

Table 3.5 shows estimates and standard errors of univariate ERGMS of *Social support*, while Table 3.6 reports the same values estimated in multivariate ERGMs of *Social support* and *Trust in business*. Good convergence of the MCMCMLE algorithm were reported by all estimates. Following Wang et al. (2008), the goodness of fit of the models are very good, as convergence statistics for the conventional range of non-modelled effects was less than twice the absolute value of the estimated coefficient in all but two effects (see Appendix B).

In order to test *Hypothesis 1*, we first looked at the entrainment effect of *Positive collaboration* on *Social support*, as estimated in Model 1.1 (see Table 3.5). Our results showed that the estimated coefficient was positive and significant. This would mean that the observed proportion of positive collaboration ties which overlapped with expectations of social support was greater than we would expect by chance, controlling for exogenous actor-relation effects and other structural within-network effects of the *Social support* network. Model 1.2 (see Table 3.5) shows that such effect held true even when controlling for the subjects' previous acquaintance. More precisely, the model shows that, although expectations of social support were directed preferably towards those with whom i was previously acquainted, a positively evaluated collaboration made it more probable that i expected support from a partner j rather than from others, even if i did not already know j previously.

Hypothesis 2 can be tested by looking at the entrainment effect of *Trust in business* and *Social support* in the multivariate models reported in Table 3.6. Model 2.1 shows that i was more likely to expect social support from j if the former trusted the latter for business-related issues, beyond the effect of all other processes specified in the model. This effect remained positive and significant even when we controlled for the entrainment effect of *Positive collaboration* (Model 2.2) and *Previous acquaintance* (Model 2.3) on both *Social support* and *Trust in business*.

Our results showed that the likelihood that i expected social support from j if the latter was considered trustworthy by i was greater than we would have expected by chance. This was true even when the two actors had no previous successful collaboration nor were they previously acquainted for any other reasons. These results provide clear support for *Hypothesis 2*.

In addition, the multivariate models reported in Table 3.6 show that the effect of *Positive collaboration* on *Social support* was not significant when we controlled for the endogenous emergence of *Trust in business*. By comparing the entrainment effect of *Positive collaboration* on *Social support* in Models 2.1 and 2.2, we noticed that the estimate was not significant once we controlled for the effect of positive collaboration ties on those pairs with overlapping *Social support* and *Trust in business* ties. More precisely, Model 2.2 shows that *Positive collaboration* yielded a positive and significant effect on *Trust in business*. This means that, beyond other effects in the model, if i had collaborated satisfactorily with j, it was more likely that i trusted j for business-related issues rather than others. Indeed, after including this in the model, the

TABLE 3.5: Parameter estimates and standard errors for multivariate ERGMs of *Social support*.

Parameters	**Estimates (S.E.)** Model 1.1	Model 1.2
Structural effects (endogenous)		
Arc	-3.843 (1.429)∗	-3.938 (1.487)∗
Reciprocity	1.905 (0.551)∗	1.708 (0.532)∗
Simple 2-path	-0.409 (0.166)∗	-0.340 (0.173)
Popularity (in-degree)	-0.442 (0.519)	-0.435 (0.513)
Activity (out-degree)	-0.087 (0.373)	-0.063 (0.420)
Path closure (transitivity)	0.918 (0.228)∗	0.762 (0.240)∗
Cyclic closure	-0.118 (0.196)	-0.138 (0.179)
Multiple connectivity	0.117 (0.189)	0.037 (0.195)
Actor-relation effects (exogenous)		
Gender (sender)	-0.551 (0.529)	-0.527 (0.578)
Gender (receiver)	-0.943 (0.567)	-0.752 (0.597)
Gender (homophily)	0.811 (0.561)	0.552 (0.645)
Age (sender)	0.017 (0.023)	0.025 (0.024)
Age (receiver)	0.070 (0.025)∗	0.073 (0.025)
Age (difference)	-0.028 (0.024)	-0.041 (0.028)
Seniority (sender)	0.002 (0.011)	0.005 (0.013)
Seniority (receiver)	0.023 (0.015)	0.027 (0.016)
Seniority (difference)	-0.009 (0.010)	-0.025 (0.011)∗
Covariate network effects (exogenous)		
Positive collaboration (entrainment)	1.833 (0.294)∗	1.447 (0.312)∗
Previous acquaintance (entrainment)		1.530 (0.388)∗

* |Est.|/S.E. > 2
$\lambda = 2.00$

TABLE 3.6: Parameter estimates and standard errors for multivariate ERGMs of *Social support* and *Trust in business*.

Parameters	Estimates (S.E.)					
	Model 2.1		Model 2.2		Model 2.3	
	Social support	Trust	Social support	Trust	Social support	Trust
Arc	-6.919 (1.730)*	-1.534 (1.652)	-6.292 (1.687)	-1.811 (1.704)	-6.283 (1.787)*	-1.723 (1.655)
Reciprocity	0.842 (0.605)	0.869 (0.348)*	1.102 (0.599)	0.757 (0.343)*	0.999 (0.578)	0.746 (0.339)*
Simple 2-path	-0.464 (0.191)*	0.052 (0.022)*	-0.480 (0.197)*	0.054 (0.024)*	-0.446 (0.206)*	0.056 (0.026)*
Popularity	-0.627 (0.517)	-0.161 (0.528)	-0.600 (0.537)	-0.060 (0.570)	-0.613 (0.524)	-0.036 (0.525)
Activity	-0.344 (0.409)	0.762 (0.462)	-0.339 (0.418)	0.781 (0.481)	-0.331 (0.422)	0.810 (0.481)
Path closure	0.845 (0.236)*	0.653 (0.202)*	0.866 (0.250)*	0.596 (0.207)*	0.747 (0.263)*	0.561 (0.196)*
Cyclic closure	-0.098 (0.197)	-0.263 (0.120)*	-0.097 (0.203)	-0.251 (0.116)*	-0.111 (0.191)	-0.254 (0.118)*
Multiple connectivity	0.134 (0.207)	-0.048 (0.054)	0.148 (0.210)	-0.044 (0.055)	0.111 (0.222)	-0.048 (0.059)
Entrainment	2.249 (0.337)*		2.014 (0.389)*		2.024 (0.398)*	
Exchange	1.079 (0.363)*		0.899 (0.354)*		0.824 (0.344)*	
Gender (sender)	-0.155 (0.598)	-0.652 (0.555)	-0.235 (0.624)	-0.725 (0.617)	-0.135 (0.649)	-0.742 (0.632)
Gender (receiver)	-0.534 (0.638)	-0.716 (0.602)	-0.575 (0.635)	-0.820 (0.652)	-0.349 (0.702)	-0.801 (0.642)
Gender (homophily)	0.387 (0.676)	0.817 (0.623)	0.437 (0.663)	0.944 (0.700)	0.130 (0.710)	0.922 (0.718)
Age (sender)	0.052 (0.025)*	-0.030 (0.014)*	0.046 (0.026)	-0.025 (0.015)	0.049 (0.027)	-0.024 (0.015)
Age (receiver)	0.102 (0.027)*	-0.032 (0.015)*	0.094 (0.027)*	-0.025 0.017	0.096 (0.028)*	-0.027 (0.017)
Age (difference)	-0.039 (0.028)	0.016 (0.016)	-0.036 (0.028)	0.016 (0.019)	-0.048 (0.033)	0.011 (0.018)
Seniority (sender)	0.005 (0.013)	-0.014 (0.006)*	0.009 (0.012)	-0.018 (0.007)*	0.011 (0.014)	-0.019 (0.007)*
Seniority (receiver)	0.019 (0.015)	0.013 (0.007)	0.023 (0.015)	0.009 (0.007)	0.028 (0.016)	0.009 (0.007)
Seniority (difference)	0.009 (0.011)	-0.023 (0.008)*	0.005 (0.011)	-0.022 (0.008)*	-0.012 (0.013)	-0.025 (0.009)*
Positive collaboration	1.828 (0.293)*		0.932 (0.710)	0.868 (0.281)*	0.566 (0.711)	0.771 (0.288)*
Previous acquaintance					2.027 (0.819)*	1.140 (0.471)*

* | Est. | /S.E. > 2

$\lambda = 2.00$

proportion of ties of *Positive collaboration* which co-occurred with expectations of social support was not greater than expected by chance, given other processes at work. More precisely, in 55 out of 58 pairs with entrained ties of *Positive collaboration* and *Social support*, ties of *Trust in business* occurred as well[4]. Furthermore, results did not qualitatively change when we controlled for the entrainment effect of *Previous acquaintance* on both emergent networks (see Model 2.3). Finally, it is also worth mentioning that being previously acquainted with j made i more likely to trust him/her or to expect social support, beyond all other factors, as is shown by Model 2.3 (see Table 3.6).

Therefore, our results suggest that, once we account for the endogenous effect of trust, there is no net association between a successful collaboration and the expectation of social support from the partner, beyond other confounding processes. This would confirm Hypothesis 1. This would also imply that there is an association between positive collaborations and expectations of social support, but only as long as the collaboration generates trust for the partner. If i's collaboration with j, though positively evaluated, does not generate business-related trust for the partner, then i is not more likely to expect social support from j than from other subjects.

An additional point to mentions is the importance of looking at the structural logic of the *Social support* network by examining the endogenous structural parameters of the ERGMs, concerning the structural logic (Markovsky, Willer, and Patton 1988; Rank, Robins, and Pattison 2010) of the *Social support* network.Reciprocity is one of the most interesting effects of the model. In the multivariate models reported in Table 3.6, the estimate is positive but not significant, which allows us to conclude that the amount of reciprocated ties in the *Social support* network was not significantly different from what we would expect by chance. It is interesting to notice that reciprocity was significant if the model was specified without controlling for the emergence of *Trust in business* (see Table 3.5). When not controlling for the presence of other ties, we found a tendency of subjects to reciprocate expectations of social support. However, by taking into account the positive effects of reciprocity within *Trust in business* and entrainment between the latter and *Social support*, we could say that this data supports the view that the direct reciprocation of expectations of social support is mainly due to the co-occurrence of trust ties.

Concerning closure, the model reported the values of two effects. First, the estimate of path closure was positive and statistically significant. This means that there was a tendency for a subject i to expect social support from another subject j, if the same was done by other people who were expected by i to provide support. Moreover, the likelihood of i expecting support from j increased non-linearly with the number of two-paths between i and j, following a law of diminishing returns. Secondly, the value of the cyclic closure effect was negative and non-significant. This

4. It is also meaningful that simulations of Model 2.2 without including the effect of *Positive collaboration* on entrained *Trust in business* and *Social support* ties were sufficient to generate networks with an average of 54.74 overlapping ties of *Trust in business* and *Social support* (see Table B.2 in Appendix B).

would indicate that peers did not share social support because of indirect reciprocity. However, this was also not significantly different from chance, controlling for the other specified parameters, which prevents us from concluding that there was a tendency against cyclic closure. The joint interpretation of the two closure parameters indicates that there was a tendency towards transitivity.

Another interesting point is that the estimates for degree-related parameters were not significant. This would indicate that the in- and out-degree centralization of *Social support* was not significantly different from what we would expect by chance, controlling for other effects.

Finally, certain interesting effects were shown by the multivariate models on the emergence of the *Trust in business* network. The reciprocity effect was positive and significant, in addition to the path closure value, while cyclic closure was negative and significant. This is consistent with previous studies of trust in intraorganizational networks, which found that trust is often reciprocated at the dyadic level, while showing high transitivity closure and anti-cyclicality (e.g. Robins, Pattison, and Wang 2009; Lusher et al. 2012).

3.5 Discussion and conclusions

Eliciting solidarity between strangers is of particular importance in modern complex societies, where an increasing number of individuals interact without necessarily sharing a group identity. Economic exchanges, such as business relations or professional collaborations, can be a means of developing social relations as byproducts of professional or economic interests. However, the conflict between individual interests, intrinsic to strategic motivations and uncertainty, may prevent the formation of expressive ties that can magnify collective outcomes even beyond the original scope of the interaction.

In this paper, we aimed to address this problem by analyzing expectations of social support between independent professionals occasionally collaborating for business-related reasons. We found that successful professional collaborations did not determine support expectations. Yet, our results showed that such expectations are associated with trust that individuals develop while collaborating professionally. This supports the hypothesis that solidarity can emerge from economic interactions only if the partner is considered to be trustworthy for risky exchanges (Molm, Collett, and Schaefer 2007; Molm, Schaefer, and Collett 2009).

More importantly, our study shows that the formation of trust-based solidarity can be triggered by professional collaboration. First, learning partners' trustworthiness typically occurs during professional collaboration. This would confirm the positive effect of negotiated exchanges on trust (Barrera 2007; Molm, Schaefer, and Collett 2009). On the one hand, expectations of social support between collaborators require the formation of trust. On the other, the development of business-related trust is mainly triggered by successful professional collaboration.

Although accepting caveats concerning the context-specific nature of the work, our study has general implications on the analysis of the interplay of economic motivations and social outcomes. First, studying social support among business partners is relevant to understand the microfoundations of cooperation. Along the same lines, Baldassarri (2015) recently suggested looking at how interactions change individuals' motives and expectations towards prosocial behaviour as the key to understand cooperation and social relations. Simpson and Willer (2015) suggested that relational mechanisms of cooperation are critical for the emergence and maintenance of large-scale social formations. This is because social relations can amplify the effect of norms and reputations beyond individual-level characteristics, so contributing to establish contexts that can sustain cooperation.

Secondly, by analyzing solidarity within a network of economic exchanges, we suggest that trust can have a mediating function of turning professional collaboration into ties with expressive value and so even being self-reinforcing (Granovetter 1985). Indeed, it is probable that trust developed while individuals professionally collaborate side-by-side could have expressive value as individuals not only appreciate each other's expertise and skills during a collaborative project but also observe each other's standards of conduct and moral attitude.

Finally, our results imply that solidarity among peers in an organization can emerge from their spontaneous economic interaction. However, this is conditional on decentralized partner selection (see also Grimm and Mengel 2009; Chiang 2010; Bravo, Squazzoni, and Boero 2012). Indeed, the lack of formal enforcement, e.g., top-down directives or hierarchical roles, exposes peers to the risk of exploitation and so requires mutual learning of each others' trustworthiness in direct or mediated relations. Our results suggest that organizational policies aiming to create social relations through top-down incentives might not be the only appropriate design for nurturing social relations. An understanding of the appropriate mix of top-down and bottom-up forces to stimulate collaboration, trust and social support is an important topic to be investigated in the future (Squazzoni 2014).

More research is also needed to further investigate the emergence of solidarity from economic exchange as a general socio-economic phenomenon. Here, synthesizing economic and social analysis is also key to understand the link between individual behaviour and social constraints. In particular, other empirical studies are needed to test existing theories on various organizational contexts, where specific forms of economic exchange could yield different combinations of cooperation and conflict affecting individuals' framing of their partner's motivations (Molm, Schaefer, and Collett 2009; Kuwabara 2011). A potential extension of our study would be to reconstruct the link between collaboration, trust and solidarity in organizational contexts with different degrees of top-down constraints, e.g., hierarchical roles, over-imposed collaboration and the presence of more established status dynamics within a workplace. This would give a more comprehensive picture of the factors which stimulate or inhibit the pivotal function of collaboration-driven trust found here.

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Chapter 4

Agent-Based Models in Sociology[1]

Agent-Based Models (ABMs) are computer simulations of social interaction between heterogeneous agents (e.g., individuals, firms or states), embedded in social structures (e.g., social networks, spatial neighbourhoods or institutional scaffolds). These are built to observe and analyse the emergence of aggregate outcomes (Gilbert 2008; Squazzoni 2012). By manipulating behavioural or interaction model parameters, whether guided by empirical evidence or theory, micro-level mechanisms can be explored that can account for macro-level system behaviour, that is an existing time series of aggregate data or certain stylized facts (Epstein 2006; Hedström and Ylikoski 2010).

The origins of ABMs in sociology can be traced back to pioneering contributions by James S. Coleman (1964, 1964) and Raymond Boudon (1964) and the publication of the first two volumes of *The Journal of Mathematical Sociology* in 1971. These included two important articles by Sakoda (1971) and Schelling (1971) on segregation dynamics. In these contributions, studying social outcomes by modelling agent behaviour and interaction in a computer was considered an alternative to the functionalistic, hyper-theoretical, macro-oriented social system theories that dominated sociology at that time.

However, it was only from the 1990s that ABM applications reached a critical mass. This development was thanks to the increasing computing power and the diffusion of the first open source ABM platforms. These platforms made explicitly individual behaviour models possible for the first time, without requiring excessive computing skills by the modeller. Initial sociological applications in the late 1990s covered the following areas: cooperation and social norms, diffusion, social influence, culture dynamics, residential ethnic segregation, political coalitions and collective opinions, to name but a few (Gilbert and Doran 1994; Gilbert and Conte 1995; Epstein and Axtell 1996; Axelrod 1997; Conte, Hegselmann, and Terna 1997).

All these applications demonstrated that computational models can look at the dynamic nature of social facts better than most other social scientific methods. These include analytical equation-based models, used in standard economics and game theory, statistical regression models, used in macro-sociology and unformalised,

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descriptive accounts, used in qualitative sociology. Due to mathematical restrictions, standard game theory and analytical modelling cannot account for the irreducible heterogeneity of social behaviour or look at out-of-equilibrium social dynamics, which are both intrinsic to the ABM approach. In this sense, the ABM approach is closer to behavioural game theory, which studies a variety of preferences and motivations through experiments, rather than standard rational choice theory, where homogeneous individual selfishness is assumed. While variable-based statistical models cannot easily deal with micro-generative processes, which are key to ABMs, descriptive, qualitative accounts cannot disentangle the effects of social networks and at the same time look at space, time and large scale social processes in the same way ABMs can.

By reviewing the first wave of ABMs in sociology in the 1990s, Macy and Willer (2002) emphasized that ABMs are instrumental when the macro patterns of sociological interest are not the simple aggregation of individual attributes but the result of bottom-up processes at a relational level. Time has progressed since this influential review and advances have been made both in the extent and scope of ABM applications, in the number of sociological publications and in their methodological rigour. This article aims to report on these recent advances by considering examples, which looked at the importance of behavioural factors, cases that tested the effect of structural factors and models that pointed to the dynamic interplay of individual behaviour and social structures.

This chapter is organized as follows. Section 1 looks at ABMs, which investigated social norms in cooperation and competition processes among individuals in stylized interaction contexts. This is one of the most vibrant ABM fields, where sociology and behavioural game theory have usefully interacted (Corten 2014). Their results showed the importance of considering the fundamental heterogeneity of social behaviour, the subtle nuances of individual rationality and the influence of social contexts in understanding aggregate behaviour. They also showed that sociological relevance increases when the interplay between individual behaviour and social networks is looked at in a more dynamic, co-evolutionary way.

Section 2 looks at examples of ABMs, which investigated social influence mechanisms and the influence of certain structural constraints on social outcomes, such as residential segregation, stratification and collective opinions. These examples help us to understand that certain facets of the social structure might influence social connections among individuals. As a result they may have wider implications, including not only pressure towards social uniformity and convergence but also persistence of diversity in culture, norms or attitudes. At the same time, they allow to conceive the constructive role of the interplay of behavioural mechanisms and social structures in understanding the emergence of collective phenomena.

Finally, in Section 3 the key findings are summarized, while methodological implications are discussed.

4.1 Cooperation and social norms

Social life is rich with complex forms of cooperation between unrelated individuals that are channelled through social norms and institutions. Donating blood, being a witness at a trial or reviewing an article for a journal would not be possible if we were not able to overcome the temptation of self-interest to benefit others with our own effort. Given that natural and social selection tend to encourage competition, social norms and institutions must exist to provide a context for cooperation. Understanding in which contexts and for what reasons individuals can collectively generate social welfare despite self-interest, is one of the most important missions of social science.

The social sciences have looked at the importance of certain social mechanisms in promoting cooperation in hostile environments, where there is a conflict between individual self-interest and group outcomes. Examples of these mechanisms could be direct and indirect reciprocity, reputation, social punishment, trust and social conventions. In this field, fruitful cross-fertilization already exists between behavioural game theory and ABM sociological analysis of social norms, with interesting extensions and modifications of standard game theory. Here, simulations were used to complement problems of analytic tractability of standard game theory as well as for exploring departures from its deductive, equilibrium-dominated framework.

4.1.1 Direct reciprocity

A key mechanism of social life is reciprocity, i.e., a form of conditional cooperation between related or unrelated individuals, which can be both direct or indirect (Bowles and Gintis 2011). Direct reciprocity means that two individuals are expected to cooperate if the probability of their future encounter exceeds the cost/benefit ratio of the altruistic act at an individual level. In this case, it is likely that certain aspects of social structure can have significant implications for cooperation as they influence the probability of encounters between two individuals and so the type of behaviour to which they are exposed (Macy and Flache 2009).

It is widely acknowledged that the embeddedness of agents in a spatial structure, dramatically increases cooperation, as this determines a higher probability of encounter between correlated agents (Németh and Takács 2007). An interesting problem is to understand whether this can also happen in non-spatially related structures. A good ABM example of this is a study by Cohen, Riolo, and Axelrod (2001) on an iterated Prisoner's Dilemma (see also Nowak and Sigmund 1992)). They simulated a population of agents, who could cooperate or defect, reciprocate their opponent's behaviour (i.e., cooperating with cooperators and defecting with defectors) and imitate the behaviour of the highest fitted individual they encountered (with some noise), thus learning behavioural strategies from the social environment. They manipulated the initial network topology that connected agents to each other, by testing random encounters, spatial neighbourhoods, small-world networks and fixed networks. Results showed that even the sole persistence of interaction patterns from initially random encounters could make cooperation possible between selfish agents as it preserves favourable conditions for direct reciprocity, e.g., cooperators interacting more frequently among each other and receiving higher payoffs. This situation did not vary when agent behaviour was spatially correlated, i.e., spatial effects existed between neighbouring agents (see also Axelrod et al. 2002).

Although important, these examples neither assume a considerable influence of the social structure in shaping individual behaviour nor look at social mechanisms that exist to help individuals predict other agents' behaviour. If we consider that our life is mostly structured into social groups, it is probable that cooperation is influenced by group identity, so that we prefer to cooperate with in-group members and are less fair with outsiders. Coherently, in many circumstances, we tend to use tags or etiquettes (e.g., colour of skin, group dress style, or any other observational trait) to predict behaviour (Riolo, Cohen, and Axelrod 2001), which can even make us unconscious victims of stereotypes. The point here is that group identity or tags could substitute or magnify direct reciprocity.

Hales (2000) built an evolutionary model which showed that cooperation could emerge in a mixed population of cooperators and defectors with randomly distributed tags playing one-shot Prisoner's Dilemma games with in-group members. Results showed that the formation of same-tag local clusters, in which cooperative groups eventually outperformed non-cooperative ones, could work even without assuming the memory of past experience, nor reciprocity-oriented strategies. Hammond and Axelrod (2006a, 2006b) modelled a population of agents with different tags who could decide whether to cooperate or defect with in-group and out-group agents. Without building in-group favouritism in the model, simulations showed that the evolution of cooperation in a spatial structure could be sustained by the emergence of a dominant "ethnocentric" strategy. That is, by which agents cooperated with in-group members and defected with outsiders, through the formation of local clusters of same-tag agents. Recently, Bausch (2014) has questioned the tag-driven nature of Hammond and Axelrod's results, arguing that higher levels of cooperation might even be obtained by simply constraining interaction and reproduction to occur locally, without modelling different tags and preferential cooperation.

While these examples examined the importance of forward-looking strategies in repeated dyadic interaction, cooperation may also emerge from backward-looking strategies, with individuals capable of learning from past experience and adjusting their behaviour dynamically. Building on previous work on stochastic learning algorithms (Macy 1991), Macy and Flache (2002) built a series of models that included a variety of two-person cooperation dilemmas. Their results showed that adapting backward-looking agents could generate a self-reinforcing cooperative equilibrium but only within a narrow range of intermediate levels of the agents' aspiration. Mutual defection was more likely if agents had low or high aspiration levels as in these cases the context made defection worth-while, due to agent inertia (low aspiration) or individual dissatisfaction (high aspiration).

The situation can change if agents could exploit forms of interpersonal commitment against the risk of being cheated. In this respect, following experimental research about commitment in dyadic exchange, Back and Flache (2006) looked at the viability of committing – i.e., acting unconditionally cooperatively with some partners who have previously proved to be reliable – against a wide spectrum of other exchange strategies in a competitive environment. Results showed that commitment-based strategies are more viable than even tolerant versions of direct reciprocity, as they allow agents to create wider and more efficient exchange networks, while avoiding the vicious cycle of "keeping the books balanced", which makes reciprocity-based strategies vulnerable to cascades of mutual retaliatory defection. It is worth noting that recent ABM studies have analysed the impact of reciprocity also in peer review and found a possible negative side of reciprocity when social sanctioning is absent or weak. Squazzoni and Gandelli (2013) modelled the strategic behaviour of referees in a population of scientists called on to act as authors and referees during the peer review process in different competitive publication environments. Scenarios where referees were randomly reliable (i.e., providing more or less pertinent evaluation of author submissions' quality) were compared with others in which referees could strategically reciprocate past experience as authors by being more or less reliable with new authors. Their simulations showed that if referees' reciprocity is not inspired by fairness (contributing to scientific progress as a public good), but only by past publication or rejection when authors, peer review generates dramatic publication bias and allocates resources inefficiently (see also Thurner and Hanel 2011; Squazzoni and Gandelli 2012).

4.1.2 Indirect reciprocity and reputation

It is worth noting that individuals can also cooperate indirectly via third parties. In these cases, individuals could expect future benefits by cooperating with a counterpart from other partners, e.g., other group members, or by accessing or being subject to reputational information, e.g., cooperating with someone establishes good reputation that will be awarded by others (Nowak 2006).

Behavioural and evolutionary research has recently shown that the complex cooperation scaffolds that characterise social life seem to primarily depend on these complex forms of indirect reciprocity (Bowles and Gintis 2011). This has interesting sociological implications as social relationships pass from a dyadic to a triadic form and network effects are also included. This can help us to understand why social evolution involves the establishment of generalised forms of social exchange and large groups of unrelated individuals beyond direct reciprocity motives.

In this respect, many ABM studies have looked at the impact of reputation as a form of indirect reciprocity (Janssen 2006; Pinyol and Sabater-Mir 2013). These studies emphasised two important functions of reputation: a) learning, i.e., accessing information about unknown partners via third parties which was not previously available and/or was too costly and b) social control, i.e., monitoring and punishing norm violators through socially shared reputational signals (Raub and Weesie 1990; Buskens and Raub 2002).

As regards to learning, Boero et al. (2010) developed an ABM calibrated on behavioural data gathered from a lab experiment where subjects were asked to take investment decisions in a simulated financial market characterized by asymmetries of information and uncertainty. Subjects had different investment options, which were more or less risky and could receive/send information by/to others, so mimicking the formation and circulation of reputational information. Results showed, firstly, that subjects followed three types of behaviour, coherent with behavioural game theory findings, i.e., always cooperating with others by sharing reliable information, reciprocating reliable information only with reliable partners, cheating by always providing unreliable information to others. Secondly, results showed that socially sharing reputational information was beneficial for the exploration capabilities of agents in situations of uncertainty, independent of the quality of the information shared. Finally, they showed that reputation (social sharing of personal evaluation, even if potentially biased) was more effective than personal experience (formation of an opinion on the counterpart in direct interaction) in detecting reliable information partners and reducing the amount of false reputational information in the system.

In regards to social control, Conte and Paolucci (2002) developed a model that also distinguished "image" from "reputation" and focused on social processes of reputation formation and transmission. They simulated a population of agents that followed heterogeneous behaviour, i.e., self-interest, altruism and norm compliance, in a social dilemma situation and manipulated simulation scenarios to add socially shared evaluation of other agents' behaviour. Results showed that, by allowing individuals to share the social cost of sanctioning against self-interested behaviour, reputation provided room for evolutionary stability of cooperation at levels hardly achievable by other mechanisms, e.g., direct reciprocity or cognitively sophisticated trustful partners' detection. Furthermore, they found that the circulation of false bad reputation tended to protect normative behaviour more than leniency (false good reputation) or silence. This work has influenced a large body of ABM research on reputation as a social control device for group behaviour (Hales 2002; Hahn et al. 2007; Wierzbicki and Nielek 2011).

4.1.3 Social punishment

Another form of indirect reciprocity is social punishment. Indeed, while reciprocating bad behaviour with a bad behaviour in some circumstances can create the conditions for cooperation, social life is full of examples of individuals bearing a personal cost for punishing wrongdoers, e.g., an individual reporting misbehaviour to the police to benefit a victim. This behaviour is called "strong reciprocity" as it implies a direct reduction of payoffs imposed on the cheater at the expenses of the punisher without direct reciprocal benefits for the latter (Gintis 2000).

Empirically inspired by the case of mobile hunter-gatherer groups in the Late Pleistocene, Bowles and Gintis (2004) have developed an ABM where a population of agents played an n-player Prisoner's Dilemma that mimicked cooperation problems in hunting, food gathering and common defence without any centralised institution. They explored a mixed population of egoists, cooperators and strong reciprocators. Due to the presence of self-interested agents, group benefits could be eroded by the fact that certain individuals could exploit the collaborative work of others without contributing themselves. They found that the robustness of cooperation depended on the co-existence of these behaviours at a group level and that strong reciprocators were functional in keeping the level of cheating under control in each group. This was due to the fact that the higher the number of cooperators in a group without reciprocators, the higher the chance that the group disbanded due to high payoffs for shirking. This means that group structure may be the key to evolutionary social selection, even more than individual strategies (see also the test on the case of team collaboration in organizations by Carpenter et al. (2009)). This is a relevant finding as it paves the way to consider whether social selection can be multi-level, working not only at a genetic-individual level but also at a social group level.

These findings were extended by Boyd, Gintis, and Bowles (2010) to situations of public punishment (i.e., the establishment of an institution, which monitors people's behaviour and punishes wrongdoers by exploiting economies of scale). Their results showed that also in the case of institutional punishment, the presence of a minimal fraction of strong reciprocators intrinsically motivated by social norms to support institutional punishment by paying fees and help social monitoring is instrumental to maintain cooperation over time.

More recently, Andrighetto et al. (2013) built an interesting ABM based on experimental data in a public goods game similar to the previous examples, where punishment was combined with normative signalling. In this case, agents were called on to decide whether to cooperate by contributing to the public good or defect by exploiting other agents' contribution, punish defectors and send signals to others about the appropriate amount of contribution expected (i.e., the norm). As it is a focal point for what others expect as an appropriate contribution, signalling could affect individual preferences. Their simulations showed that punishment accompanied by norm signalling can ensure more robust cooperation at a lower cost for the group than when acting alone. They also showed that punishment is more effective when norm communication has already proved to be important for the perception of the norm by individuals. This socio-cognitive approach has been followed by other ABM studies to examine the cognitive counterpart of social norms and the importance of social contexts. These provide normative meaning and signals for individuals in typical social dilemmas, using an interesting mix of ABM, experimental and qualitative methods (Poteete, Janssen, and Ostrom 2010; Conte, Andrighetto, and Campennì 2013; Elsenbroich and Gilbert 2014; Xenitidou and Edmonds 2014).

4.1.4 Trust

In many cases, we provide relevant information, time or money to others when we trust they will honour our help. However, in competitive environments and in situations of information asymmetry, distrust could prevail given that the potential benefit of interacting with others could be lower than the future cost of being cheated. On the other hand, when interaction is between strangers, with no previous experience of each other, a set of communication signals or tags might exist. These in turn could help individuals to convey and recognise the degree of trustworthiness of a potential partner and so risk cooperation. This is the case of taxi drivers and their relationships with customers, brilliantly documented by Gambetta and Hamill (2005).

In order to look at the emergence of trust among strangers, Macy and Skvoretz (1998) built a model in which agents could decide whether to engage or not in a Prisoner's Dilemma game by learning to display or mimic and recognise actual or fake signals of trustworthiness and eventually imitating successful strategies from others. They assumed that agents were embedded in a social network structure with neighbours and strangers through strong and weak ties respectively. Couples were randomly paired with a probability correlated with the social distance of agents. They tested the effect of different payoffs for not engaging in a risky exchange (i.e., an exit option) and the degree of the agents' network embeddedness. Results showed that cooperation between strangers could emerge in the long run, due to less costly exit payoffs that allowed agents to build clusters of trustful relationships locally that gradually diffused via weak ties, depending on the level of agent embeddedness.

Following experimental studies on cross-cultural differences on trust and commitment (Yamagishi and Yamagishi 1994), Macy and Sato (2002, 2010), tested the effect of spatial mobility on the emergence of trust and cooperation in a simulated population of learning agents. These played a repeated version of the Prisoner's Dilemma with an exit option and the possibility to choose to play with a neighbour or a stranger with different opportunity and transaction costs. Simulations found a curvilinear effect of mobility on trust. Indeed, the ability to detect trustworthy partners emerged only beyond moderate levels of mobility, which allowed agents to meet other partners. In case of higher levels of mobility, trust decreased because agents could not appropriately discriminate trust any more.

These studies indicate that one of the main challenges for cooperation in trust situations is the capability of agents to detect trustworthy partners and build stable forms of interaction around them. In this respect, some studies have looked at partner selection in dynamic networks (Santos, Pacheco, and Lenaerts 2006; Pacheco, Traulsen, and Nowak 2006). The idea here is that not only might individual behaviour vary from person to person and within the same person over time, but social networks are also constantly changing. This reflects new opportunities or constraints for a person when connected with another one. Behaviour and networks can change dynamically in a complex regime of possibilities/constraints that could have dramatic implications for macro behaviour.

Dynamic networks are also important factors in establishing trust. Bravo, Squazzoni, and Boero (2012) calibrated an ABM on experimental data on the behaviour of real subjects in a repeated trust game. They compared scenarios where agents were embedded in exogenously fixed networks (e.g., random, scale-free and small-world networks) and scenarios with endogenous networks, where agents could select their partners according to a simple happiness function. They found that cooperation dramatically increases in dynamic networks. Trustworthy agents tended to cluster around emerging cooperators, who had more ties and ensured higher profit to their respective partners. On the other hand, "bad apples" tended to be isolated over time losing both profit and opportunities for exchange. Furthermore, while different initial network conditions did not affect this endogenous dynamics, with more cooperative agents benefiting from an exponential growth of number of ties independently of the initial network constraints, the final network topology in case of initial random or regular networks, was different.

These results were confirmed experimentally in an iterated Prisoner's Dilemma (Fehl, Post, and Semmann 2011). It was also confirmed in a model on a helping game where Chiang (2013) allowed agents to use information of network characteristics (e.g., the structural attribute of the nodes) to strategize whether to cooperate or not. The co-evolution of behaviour and network created a crystallized configuration where cooperators had more ties and achieve higher profit so that cooperation outperformed defection over time.

This fact would indicate that social structure can endogenously generate role differentiation that may be relevant in generating conditions favourable to cooperation. For instance, Eguíluz et al. (2005) simulated a spatial Prisoner's dilemma model where diverse social roles emerged from dynamic networks with "leaders", i.e., agents obtaining a large payoff, who were then imitated by many others, "conformists", that is unsatisfied cooperative agents, who keep cooperating and finally, "exploiters", i.e., defectors who have a larger payoff than the average obtained by cooperators. By endogenously converging towards a small-world topology, the network achieved a strong hierarchical structure in which the leaders played an essential role in sustaining cooperation. On the other hand, they found that once disruptions affecting leaders was introduced, a dynamic cascade was found, which propagated defection throughout the network.

4.1.5 Conventions

Social life is full of examples of social interaction where it is of mutual interest for individuals to converge towards a dominant behaviour, rather than compete on certain rewards at stake. We develop certain habits or conventions, e.g., language, monogamy vs. polygamy in marriage, a particular dress-code, that help us coordinate with each other more or less efficiently. Once established, these conventions can even be institutionally enforced, e.g., traffic rules. The challenge here is to understand the origins of these social artefacts, given that any coordination game may have multiple possible equilibria, no initial preferable options exist and outcomes are extremely sensitive to initial conditions, path dependence and increasing returns (Durlauf and Young 2004).

In order to understand this, Hodgson and Knudsen (2004) modelled a population of agents randomly located in a 100 x 2 cell ring that had to decide whether to drive clockwise or counter-clockwise around a ring to avoid collision. Agents were characterised by a limited vision of space, inertia and a habituation level, i.e. the tendency to repeat past behaviour. Their simulations showed that the convergence of agents toward a right/left convention is higher when the level of habituation increases, independent of the error at the agent-level when estimating other agents' behaviour. Furthermore, they confronted agents with different cognitive capabilities of monitoring the environment. They found that although habit had a positive effect on the emergence of conventions even for omniscient agents, the most striking influence was found when agents were boundedly rational, thus showing how habit can complement individuals' cognitive limitations in achieving coordination at a collective level.

Epstein (2001) built a similar model to investigate the link between the strength of a convention and the cognitive costs that individuals have to pay to decide what to do. He simulated a population of agents in a ring, similar to the previous example, which had a heterogeneous sampling radius (i.e., space of vision). They could observe other agents' behaviour within their radius and could generalise global attributes by reducing or extending the search process around it. His simulations showed that two conventions could co-exist, with local conformity vs. global diversity patterns. However, this required considerable cognitive costs for intermediate agents, i.e., agents who continued to shift from one convention to another one. He also found that when a given convention equilibrium emerges, it feeds back to the agent-level by minimising cognitive decision costs and therefore a macro-micro self-reinforcing path.

However, it is reasonable to presume that the emergence of conventions is also influenced by network effects, i.e., how agents are connected. Many studies have examined the influence of exogenous network structures on the diffusion of conventions (Goyal and Vega-Redondo 2005). It is probable that, while engaged in coordination problems, agents try to avoid those who behave differently and prefer relationships with agents similar to themselves. The consequences of these endogenous mechanisms of the formation of a social environment were explored by Buskens, Corten, and Weesie (2008) in a repeated coordination game model. Here, agents were called on to decide which opinion to endorse and their payoffs depended on the choices of other agents they were tied to. The authors examined the importance of initial network conditions on the emergence of conventions. They found that the density of the network had a crucial impact on the final conventions' equilibrium. The more segmented the network was, the higher the likelihood that two groups with different conventions emerged over time. This was due to the fact that certain agents preferred to have ties with agents similar to themselves, rather than adapting their behaviour to dissimilar ones.

The importance of these endogenous network formation mechanisms was also confirmed by Corten and Buskens (2010). Their findings from a repeated, multi-person coordination game model with network embeddedness were tested in a laboratory experiment. Here, subjects played a coordination game with payoffs depending on the choices of other neighbouring agents while they could create, maintain or break their ties depending on a certain cost. Results showed that agents were more efficient in terms of coordination, where the initial networks were less dense and they could endogenously adjust their networks.

Finally, it is worth noting that these results were also empirically tested on a longitudinal survey about alcohol use among adolescents in fourteen Dutch secondary schools, conducted in 2003 and 2004. Here, alcohol use was modelled as a risk dominant inefficient behaviour in a coordination game. Adolescents were motivated to align their behaviour with that of their friends to be approved socially (Ormerod and Wiltshire 2009). While initial alcohol use propensity per class had a positive effect on average alcohol use at a later stage, the initial network density dramatically amplified this tendency (Corten and Knecht 2013).

4.2 Social influence

Individuals rarely make decisions in complete isolation of their social context (Granovetter 2005). The influence of social contexts on individual decisions is something that supporters of rational choice theory often tend to underestimate or conceive simply as information bias. However, in situations of uncertainty, the exposure to social signals from the behaviour of other people might influence our behaviour, as we presume that others know more than we do. At the same time, in group-life, we know that our behaviour is a signal for others who are observing and judging us. This is particularly important when the opinion of others can influence our access to important resources, e.g., economic benefits and social approval.

When the decisions of individuals are not independent but interdependent, choices do not simply aggregate at the macro level. This makes any micro-macro or macro-micro mapping potentially misleading if we do not consider the meso-level between individual choices and social outcomes. For instance, macro patterns can be the result of unintended consequences given that they do not reflect individual preferences but only interaction or propagation effects.

4.2.1 Segregation patterns

A classic example of the analysis of social interdependence is the famous Schelling's segregation model (Schelling 1971). Here, a population of households of two groups, say black and white, was located in a two-dimensional space, characterised by regular neighbourhood structures, representing an idealised urban space. Households had a threshold preference about the group of their neighbours and could stay or move randomly towards new locations in case the number of similar neighbours was below the threshold. Results showed that even moderate preference for similar neighbours could tip a society into a segregated pattern. This was due to the interdependent nature of choices and their spatial and temporal effect on changing the context. Indeed, any household that reached its threshold and moved out of its neighbourhood reduced the number of similar neighbours in the original neighbourhood, leaving whoever was left closer to its threshold. Any movement of households also changed the receiving neighbourhood and indirectly also the neighbourhoods of the neighbourhoods, thus triggering a cascade of reactions towards an equilibrium of household distribution far from the original households' preferences.

If we only looked at the individual level, we could predict macro segregation but with a more mixed residential distribution. If we only looked at the macro level, we should presume the segregational preferences of households, which was not the case. This abstract model allows us to understand that social context is typically a nexus of interdependence, e.g., the choice of A influences the choice of B, which influences the choice of C and subsequently that of A again. This makes it difficult for any linear micro-macro mapping (see also Sakoda 1971). This reminds us of the classic lessons of complex adaptive systems theory: even with simple agent interaction, there is always a possible gap between individual choices and aggregate processes so that looking only at individual levels, whether micro or macro, can lead us to draw illusionary conclusions (Miller and Page 2009).

Thanks to its simplicity and ability to be generalised, the Schelling's model has contributed to a prolific stream of ABM research. Certain authors have extended this original version by modifying important model parameters, e.g., preference thresholds, search for new locations, intentional household preferences toward integration, size of the neighbourhoods or spatial network topologies (Epstein and Axtell 1996; Laurie and Jaggi 2003; Zhang 2004; Fossett and Waren 2005; Fagiolo, Valente, and Vriend 2007; Clark and Fossett 2008). Gilbert (2002) examined the influence of certain social attributes of neighbourhoods, such as crime rate, the neighbourhoods' perceived prestige and certain economic constraints, by providing households with more sophisticated cognitive processes of social environment's detection. Benito et al. (2011) provided an experimental test of the Schelling's findings in a laboratory experiment. In all these cases, the original findings were corroborated and this contributed to make Schelling's model a general example of the unintended consequences of individual choices in social situations.

In a recent article, Bruch and Mare (2006) started from empirical evidence that indicated that individuals tend to respond continuously to variations in the racial makeup of their neighbourhoods. They replicated the Schelling's model, but assumed that households could experience a small increase in desirability of their location for each given percentage increase in the proportion of similar households in their neighbourhood, so removing the threshold shape of households' preference. Their results showed that linear function preferences could soften residential segregation.

In response to Bruch and Mare (2006)'s model, Van de Rijt, Siegel, and Macy (2009) examined the rules that determined how households moved when they were unsatisfied. They showed that in a multicultural population with integrative preferences, threshold preferences at a micro level might help to prevent tipping, on condition that households made mistakes and moved to neighbourhoods that did not necessarily correspond to their preferences. This presumed that they did not have complete information about the real composition of the new targeted neighbourhood. They showed that once agents have a clear preference toward diversity, move to undesirable neighbourhoods or promptly react to the changes in their neighbourhood, segregation is likely to occur. On the contrary, once households have a clear preference toward ethnicity, react promptly to their neighbourhood's changes and rarely make mistakes in selecting their new neighbourhood, integration is more likely. This indicates that the shape of preferences does not have unequivocal implications, but rather that this depends on household preferences. It is worth noting that the importance of the contextual nature of preferences and the possible heterogeneous nature of neighbourhood composition was also found in an empirical calibration of Schelling's model in Israel (Benenson, Hatna, and Or 2009; Hatna and Benenson 2012).

More recently, Bruch (2014) calibrated a segregation model by using empirical data on three cities in the U.S., the Panel Study of Income Dynamics and the 1980-2000 U.S. census data. She found that income inequality affects racial segregation. Given that higher between-group income inequality increases the salience of economic factors in residential mobility decisions, she found that high income blacks live in whiter neighbourhoods than they would otherwise, whereas poorer blacks are racially and economically isolated. The focal mechanism is called "offsetting": under sufficiently high levels of within-race income heterogeneity, increasing between-race income inequality can have opposite effects at the high and low ends of the income distribution. Whether these offsetting processes cause a net increase or decrease in segregation depends on the relative size of the black population, the salience of racial versus economic factors in residential mobility decisions and the shape of the income distribution.

Finally, it is worth noting that Schelling's findings have also been extended into policy and health fields. For instance, Auchincloss et al. (2011) showed that residential segregation might play a role in determining the diffusion of obesity and related illnesses in low-income families. By adding food price and preferences and locating stores across the neighbourhoods in the model, they showed that *ceteris paribus*, residential segregation alone could increase income differential in diet, independent of the low-income households' food preferences. Negative implications of residential segregation were also found in public goods provision (Alesina, Baqir, and Easterly 1999), income distribution (Reardon and Bischoff 2011) and quality of schools and labour market (Nechyba 2003).

4.2.2 Cultural and opinion dynamics

Although social influence would lead us to expect a dominant tendency towards convergence in collective behaviour, social systems often display persistent dynamics of cultural and opinion diversity. Minority beliefs or opinions tend to persist over time, independent of any social force pushing them towards uniformity. This is especially relevant when we observe the persistence of collective misbeliefs and discriminatory stereotypes in certain societies or the impact of extremist groups in politics.

Influenced by Latané's social psychological theory of social impact (Latané 1981), Nowak, Szamrej, and Latané (1990) modelled a population of agents in a lattice with randomly assigned binary values of an opinion variable and heterogeneous levels of persuasiveness and supportiveness. These levels were defined respectively as the ability to make out-group agents change their opinion and in-group agents to resist outsiders' persuasiveness. Agents changed their opinion value according to the relative impact of total persuasiveness or supportiveness exerted on them by other agents, weighted by their distance from the agent within the matrix. Simulations showed that, besides the emergence of a dominant opinion, the formation of strong local minority clusters prevented in-group agents being influenced by the majority. This determined the emergence of a polarized stable equilibrium, with local convergence and global polarization of cultural traits, due to the high sensitivity of persuasiveness and supportiveness to structural embeddedness factors.

This avenue was further explored by Axelrod (1997), who built a more sophisticated model to test the effects of structural embeddedness, cultural heterogeneity and interpersonal influence on convergence and polarization outcomes. Adaptive agents were modelled with heterogeneous cultural characteristics, defined as a combination of a fixed number of cultural features (e.g., language, religion, etc.), each taking n possible trait values (e.g., English, German, Italian; Christian, Muslim, etc.). Agents interacted with neighbours with a probability dependent on the number of identical cultural features they shared. A mechanism of interpersonal influence was added to align one randomly selected dissimilar cultural feature of an agent to that of the partner, after interaction. The author manipulated certain parameters of cultural heterogeneity (number of features and number of traits) and structural embeddedness (interaction range and environment size). Confirming previous studies, Axelrod's simulations showed that global convergence towards a single culture did not occur, despite interpersonal influence mechanism. Moreover, they showed that the number of emergent cultural groups positively correlated with the number of cultural features and negatively correlated with the interaction range. This was because large-distance interaction amplified the effect of interpersonal influence from the local to the global scale. However, cultural diversity was unexpectedly found to negatively correlate with both the number of possible traits and the environment size. More recently, Klemm et al. (2003) found that cultural homogeneity could eventually emerge due to low rates of random cultural perturbations, which caused the collapse of boundaries between otherwise dissimilar neighbours. Moreover, by looking at the co-evolution of network structure and agents' partner selection, Centola et al. (2007) identified a certain size-dependent perturbation parameter region for which interpersonal influence and homophily prevented the evolution of the system into monoculture or unstable global cultural diversity. This in turn generated a stable polarized global equilibrium.

However, the unrealistic narrowness of such parameter region was pointed out by Flache and Macy (2011a), who found a stabilising mechanism for the emergence of a bipolarized global equilibrium. They questioned the assumption of the dyadic character of social influence in favour of a multilateral model of that mechanism (Kuperman 2006). Their results showed that multilateral interaction could be a more robust mechanism for the persistence of cultural diversity, especially in large populations, as local clusters could better resist deviant agent influence under conditions of perturbation and eventually prevent it from spreading globally.

It is worth considering that the local convergence and global diversity pattern can also be generated when homophily or social influence are not expected to play a crucial role. Combining standard game theory and ABMs, Bednar and Page (2007) showed that certain structural characteristics of cultural dynamics might be generated by purposive agents playing multiple games without reacting to evolutionary pressures. Similarly, Bednar et al. (2010) showed that a certain level of diversity could persist within local cultural clusters. By assuming that culturally heterogeneous agents, besides facing social pressure to conformity, also strive for internal consistency among their own different features, they showed that global convergence could emerge in the long run, yet allowed for an intermediate phase in which cultural heterogeneity persisted.

Social influence is also important for the formation and diffusion of political opinions, including the rise and propagation of minority political positions. By extending previous studies on opinion dynamics (Deffuant et al. 2000; Hegselmann and Krause 2002), Deffuant et al. (2002) built a model in which a continuous opinion variable x ($-1 < x < 1$) was distributed within a population of adaptive agents. In this way, moderate and extreme positions on a political issue could be contemplated. Agents were also equipped with an uncertainty value, negatively correlated with the level of the agents' political radicalism, following the assumption that radicals are more confident of their own opinions. Both opinion and uncertainty could change over time through interaction, so that agents randomly coupled and influenced each other if their opinion distance was lower than a threshold, eventually leading to converging opinions. The agents' influence negatively depended on their level of uncertainty. By manipulating the uncertainty distribution and the proportion of radicals in the population, they showed that for low levels of uncertainty, the influence of radicals was effective only on a small proportion of closer agents, eventually leading to convergence around moderate levels. However, for high uncertainty levels, radicals prevailed, causing concentration of opinion distribution either on a single extreme or on both (bipolarization).

By adding a social network structure to the previous model, Amblard and Deffuant (2004) showed that extremists could exploit low connected networks better, as they could spread in local clusters and co-exist with the rest of the population. On the other hand, when connectivity increased around a critical value, the extremists were confined to peripheral regions by core moderate agents. Furthermore, Deffuant (2006) compared different formal models of opinion and uncertainty across three network structures, pointing out that extreme convergence was possible in certain network configurations which favoured the isolation of clusters of moderates and permitted radicals to influence other agents without being influenced in turn.

Polarization can be further influenced by the fact that in social life partner selection might be driven by xenophobia (McPherson, Smith-Lovin, and Cook 2001). This implies that negative interpersonal influence could even exacerbate this tendency. In order to consider this, Macy et al. (2003) developed a model of adaptive agents with binary cultural states, which were embedded in a full-connected network of weighted undirected ties. Weights, w ($-1 < w < 1$), incorporated information about the strength and the valence (positive or negative) of the influence between agents in dyadic interaction, were randomly distributed among the ties and could evolve according to changes in the number of similar traits. By manipulating decision-making flexibility and number of cultural states, results showed that a bifurcating network equilibrium emerged. A stable outcome towards homogeneity would not occur, unless only positive valence of partner selection and social influence were assumed. In a development of this model, Flache and Macy (2011b) tested the effect of the bridging role of "long-range ties" (Granovetter 1973) in fostering cultural convergence, by allowing agents to create dynamic networks within different exogenous network structures. Results showed that long-range ties did generate cultural homogeneity but only when interaction was limited to positive selection and influence. On the contrary, in cases of bivalent influence, long-range ties induced a polarized equilibrium.

By looking at U.S. American public opinion, Baldassarri and Bearman (2007) investigated the bivalent nature of partner selection and social influence mechanisms to explain the mismatch between perceived and actual polarization both at a local and global level. They modelled a population of agents with heterogeneous opinions about multiple political issues, attaching different levels of interest to each of them, whose sign represented the opinion on them (either positive or negative). Interaction partners were selected with a probability inversely depending on the perceived ideological distance between the agents. Moreover, interaction directly depended on the absolute value of the interest level that agents attached to different issues. Agents then interacted by focusing only on the issue in which they were interested in the most and could then update their opinions. Simulation results showed that bivalent selection and influence across multiple issues caused clustered polarization in the emergent interaction structure. However, the overall distribution across multiple issues was not polarized, except for highly salient take-off issues. This can explain why individuals' perception of opinion homogeneity in local interpersonal networks emerges from gradual segregation of interaction partners around take-off political issues, despite the fact that individuals still had heterogeneous opinions about other issues.

Furthermore, it is probable that individualization mechanisms besides homophily-driven social influence can affect collective dynamics, i.e., the tendency of certain individuals to increase their own uniqueness when their group starts to become overcrowded (Mark 2003). For instance, Mäs, Flache, and Helbing (2010) tested the effect of individualization on cultural convergence by building a simple model with mechanisms of choice homophily and non-negative social influence. By assuming a noise parameter that imposed agents' changes of opinion depending on other similar agents in the group, they showed that a phase of stable clusters with diversity between and consensus within tended to emerge. In this same vein, Mäs and Flache (2013) developed and experimentally tested a model of homophily and social influence in which agents interacted through the exchange of arguments instead of adjusting to each other's opinions. Their results showed that interpersonal communication generated a bipolarized equilibrium but only for high levels of choice homophily.

This approach has also been applied to diffusion dynamics of innovation. Deffuant, Huet, and Amblard (2005) extended the continuous opinion dynamic models by simulating agents who held dynamic opinion values about the impact of a particular innovation on society – i.e., its social value. Agents could collect and share information for the assessment of expected individual payoff, only when the social value was considered to be high enough. Their results suggested that under these conditions, innovations with overall high social value but low expected payoffs were more likely to succeed than innovations with low social value but higher individual benefits. Moreover, diffusion dynamics are significantly influenced by at least a minority of radical innovators.

More recently, Van Eck, Jager, and Leeflang (2011) developed an empirically-grounded ABM to study the effects of opinion leaders on the diffusion of innovation via normative and informational influence. The basic concept was that agents could adopt innovation either stemming from social pressure or from social information about quality. A sample of free online game consumers was used to calibrate the behaviour and position of opinion leaders. Opinion leaders were situated in central positions within the network. They were more prone to adopt innovations, could assess the quality of a product better and were also less permeable to normative influence. Comparing network configurations with and without opinion leaders, the authors found a significant effect of opinion leaders on the rapid spread of diffusion. This was because they could spread positive information about the quality of the products and were less likely to be affected by the normative influence exerted by more conservative agents.

4.2.3 Collective behaviour

Our decision to join a social movement or spread a cultural fad depends heavily on the effects of social influence. This is because we are often influenced by observing other people's behaviour before deciding what to do. It is often hard to understand empirically how certain collective behaviour are produced when individuals are subjected to social influence without analysing the effect of social structural factors, such as complex network configurations.

In this field, a seminal model was published by Granovetter (1978), who analysed the dynamics of a type of collective behaviour, such as a riot, by simulating agents deciding whether to join it depending on the decisions of other agents. Agents were modelled to make a binary choice, according to an expected benefit dependent on a heterogeneously distributed threshold value of how many agents were already participating. In a simulation scenario, he added the impact of previous decisions of relevant agents connected to the individual. His results showed that whenever network externalities are added, collective behaviour becomes extremely dependent on non-linear dynamics, which make any prediction of macro behaviour on single individual preferences very hard to make.

Threshold models of collective behaviour have also been used to analyse innovation diffusion dynamics. By integrating Granovetter's classic model with a network structural component, Abrahamson and Rosenkopf (1997) and Rosenkopf and Abrahamson (1999) looked at the differences in bandwagon effects due to certain network communication properties. They found that bandwagon effects in innovation diffusion within a network also depend on particular structural characteristics of nodes that bridge core and peripheral components and the permeability of their boundaries. Furthermore, by weighting social influence with exogenously distributed opinions about the reputation of innovations, they showed that bandwagon effects could override information about their unprofitability, eventually leading agents to converge on inefficient practices.

Hedström (1994) relaxed Granovetter's original assumption of homogeneity of interpersonal influence and added the more realistic dimension of spatial embeddedness to this model. He assumed that agents were more influenced by spatially closer connections. He used data on the extraordinarily rapid diffusion of trade union organizations in Sweden between 1890 and 1940 to test this model. Simulations showed that the spatial-based structures of social contacts could explain the empirically observed behaviour.

A more complex model was elaborated by Kim and Bearman (1997) to explain the participation to social movements. Their model showed that there was no need to assume agents' irrationality to explain why individuals voluntarily engaged in collective action even when this was risky or costly. They simulated the interaction between agents with different interest levels in providing a public good – from whose benefits no agents could be excluded – and the different amounts of resources to produce it, which shaped a dynamic network. Agents decided whether or not to contribute according to the expected marginal benefit, which they calculated upon their interests, the cost of participation and the amount of resources they possessed. However, the agents' interest in the good varied either upward or downward depending on whether their ties had previously contributed or defected. By manipulating various structural parameters, simulations showed that a critical mass of highly interested agents situated in central network positions, even if guided by self-interest, could create a local dense cluster, which eventually neutralised the influence of defecting agents. In particular, network density was more decisive to achieve this critical mass than high concentration of resources.

Chwe (1999) proposed a model in which strategic agents chose to participate in a collective action depending on the expected number of participants among their neighbours. Consequently, expectations of neighbours' participation depended in turn on expectations of neighbours of neighbours' participation and so on. The agents were assigned a fixed number of partners for the whole simulation cycle. By examining the effect of network transitivity on social influence, results showed that transitivity was particularly effective in triggering bandwagon effects among agents with low thresholds, as they could get information from locally small and yet dense clusters. For agents with high thresholds, however, weak ties were especially important as they transmitted information about a larger amount of agents.

4.2.4 Social inequality

It is probable that social influence is responsible for a variety of dysfunctional collective patterns typically observed in macro quantitative sociology. These include inequality in educational opportunities, social stratification, employment traps in the labour market and the co-evolution of social and workplace segregation (Abdou and Gilbert 2009).

For instance, by looking at the labour market, Hedström (2005) built an empirically calibrated ABM to examine how social influence mechanisms can explain aggregate youth unemployment rates. Their hypothesis was that levels of unemployment among neighbourhood peers had an effect on youth unemployment by lowering their expectations of finding a job, reducing the psychological costs of being unemployed and preventing outsiders accessing insider information about job opportunities. Large-scale observational data on youth unemployment in Stockholm between 1993-1999 was used to calibrate the socio-demographic characteristics of individuals and the structural features of the neighbourhood network clusters. Transition probabilities of leaving unemployment were also estimated through maximum-likelihood statistical modelling. The author assumed that agents decided to leave unemployment according to their own socio-demographic characteristics, the unemployment rate in their neighbourhood and the tightness of the job market. Simulations showed that the combination of social influence and agents' educational level provided the most striking effect on the population's rising unemployment rate. Furthermore, the effect of social influence was comparably higher than that exerted by the agents' educational level *per se*.

When looking at social stratification, it is likely that there is a persisting effect of social origin on educational attainment, which has traditionally been explained through rational choice approaches (Breen and Jonsson 2005). Recently, Manzo (2013) proposed an ABM to improve the realism of standard rational choice models by introducing a social influence mechanism within friendship networks. Agents were assigned into four groups, representing background social classes. They were then embedded in a small-world network and took decisions about transitions from an educational level to the next one. These decisions were based on the evaluation of their own ability, the perceived cost/benefit ratio, their probability of success in function of their ability and the effect of the overall social influence exerted by others with whom they were tied. Simulation findings were tested against observational data about the French stratification of educational choices across social origin in 2003. Results showed that only by considering a social influence mechanism could the model generate outcomes sufficiently close to the empirical data.

Another interesting field includes the study of the social influence effects on the reproduction of status. Analytical theories explain the emergence of status hierarchies as the result of a self-reinforcing process driven by the exchange of deference-conferring gestures (i.e., the attribution of a perceived quality evaluation). This amplifies already existing qualitative differences between individuals (Lynn, Podolny, and Tao 2009). Recently, Manzo and Baldassarri (2015) tested the potential inequality-driving effect of social influence on status attribution mechanisms, by hypothesizing a counteracting effect of reciprocity in the exchange of deference-conferring gestures. They modelled a population of agents with heterogeneously distributed "quality" values, assessing each othe's quality and exchanging deference gestures. In addition, they could become biased by other agents' behaviour. The agents interacted on the basis of status homophily, selecting partners within an acceptable range of status dissimilarity (corrected by a heterogeneously distributed "heterophily" constant). They also assessed partners' quality, by considering the partner's previously acquired status, their own tendency to rely on social influence and a noise value. Subsequently, the agents transferred a deference value to their interaction partners, which was equal to the partner's perceived quality, unless the evaluating agent had previously received less deference than expected from the partner. In the latter case, according to a heterogeneously distributed parameter for sensitivity to reciprocity, the evaluating agent reciprocated the partner's previous unfair behaviour by exchanging less deference. Status values were then calculated for each agent as the average deference received. The simulation results suggested that the interaction between the cumulative effects driven by social influence and the counterbalancing effect of conditional deference exchange, was sufficient to generate status hierarchies, qualitatively similar to those observed in empirical research, that is, the increasing gap between actual quality and status asymmetry. Furthermore, if low-status agents were more prone to have mixed interaction with similar and dissimilar agents rather than high-status agents, outcomes tended towards a "winner-takes-all" status hierarchy.

Finally, Gabbriellini (2014) built an empirically-tested model of the emergence of status hierarchies in task-oriented groups as the effect of a network of precedence ties (Skvoretz and Fararo 1996). He modelled the interaction within a disconnected network of agents, who could participate in a discussion with other members by addressing precedence claims in the hierarchy to all others (i.e., asking everyone to accomplish a task). Agents' participation depended log-linearly on the expected consequences of their claim. Permanent precedence ties were established with a probability, which partially depended on comparing agents' external status values, which were activated according to a probabilistic value. He collected empirical data on communication in an online task-oriented discussion forum of a role-playing game community. His simulations showed that highly linear status hierarchies, – similar to those observed – were due to the higher participation of agents in communication and the deference generated by mutual observation of external status.

4.3 Discussion and conclusion

This chapter presents a number of sociologically relevant ABM studies that explain complex social outcomes as effects of agent interaction. Table 4.1 summarises the most important contributions and provides a systematic overview on their main explanatory achievements. These cases combine abstract models, which look at general mechanisms of social phenomena, e.g., cooperation and social norms. It also looks at middle-range models, where specific social puzzles are analysed, such as youth unemployment and education. Although the prevalence is for theoretical approaches, some empirical applications of these models also exist, where important behavioural or structural model parameters have been calibrated with available or ad-hoc generated empirical data. In these cases, these models have been used to complement empirical data by manipulating certain parameters (e.g., complex social networks) that would be difficult to observe empirically (Bravo, Squazzoni, and Boero 2012), or used to generate empirically tested hypotheses (Corten and Buskens 2010). In other cases, models have been used to reproduce certain macro empirical regularity by a given theory (Manzo 2013; Gabbriellini 2014).

Although most sociologists shrink from abstract, formalised theories, these examples show that abstraction can have a crucial role for theory building even in sociology when it is guided by modelling. On the other hand, empirically grounded studies are fundamental to explain well-studied sociological puzzles and stimulate cross-methodological approaches with mutual benefits between, for examples, standard quantitative sociology and ABMs. Furthermore, this type of study is pivotal in persuading traditional sociologists about the advantages of this approach.

At a substantive level, these examples show that exploring the fundamental heterogeneity of individual behaviour is of paramount importance to understand the

TABLE 4.1: Summary of the most sociologically relevant ABM studies (*continues on the following page*)

Reference	Topic	Approach	Manipulation	Findings
Cohen, Riolo, and Axelrod (2001) and Axelrod et al. (2002)	Direct reciprocity	T,T	Macro	Cooperation among forward-looking self-interested agents can evolve as a pure effect of the persistence of dyadic interaction patterns from initially random encounters ('shadow-of-the-future').
Macy and Flache (2002)	Direct reciprocity, learning dynamic	T	Micro	In two-person social dilemmas, cooperation can emerge among backward-looking agents with intermediate levels of aspiration.
Hales (2000), Riolo, Cohen, and Axelrod (2001), Hammond and Axelrod (2006a, 2006b), and Bausch (2014)	Ethnocentrism	T,T,T,T	Micro	The evolution of cooperation can be sustained by the emergence of an in-group-biased dominant strategy. Cooperation can emerge if interaction and reproduction are constrained locally. In-group bias and tags can sustain cooperation even without direct reciprocity.
Back and Flache (2006)	Commitment	T	Micro	Even a moderate form of commitment can be more efficient than direct reciprocity in sustaining cooperation in a competitive environment as it helps to avoid cascades of mutual defection.
Conte and Paolucci (2002) and Boero et al. (2010)	Reputation	T,E	Micro	Socially sharing sanctioning costs provides more evolutionary stability for cooperation than direct reciprocity or trust. Socially sharing false bad reputation sustains cooperation more than false good reputation. Under uncertainty and information asymmetry, sharing reputation is beneficial for agents' exploration capabilities and more effective than direct experience in detecting reliable partners, independent of reputational information quality.
Bowles and Gintis (2004) and Boyd, Gintis, and Bowles (2010)	Strong reciprocity, group selection	T,T	Micro	The mix of self-interested agents, altruistic agents and strong reciprocators at a group level is instrumental to sustain cooperation. Not only individual traits but also group characteristics are relevant for evolutionary social selection.
Macy and Skvoretz (1998)	Trust, signalling	T	Macro	Cooperation can emerge in the long run if agents follow signals of trustworthiness for partner selection, provided that there is a large number of local clusters of trustful relationships. This is due to low exit costs and network embeddedness.
Bravo, Squazzoni, and Boero (2012)	Trust, partner selection	E	Both	Trust and cooperation among strangers dramatically increase if agents can select exchange partners according to their previous experience, independent of the initial network structure.
Epstein (2001) and Hodgson and Knudsen (2004)	Conventions	T,T	Micro	An efficient coordination norm can also emerge with minimally rational agents, if they can rely on habits. Norms can help to save the cognitive costs of decisions.
Buskens, Corten, and Weesie (2008), Corten and Buskens (2010), and Corten and Knecht (2013)	Coordination	T,E,E	Both	An efficient coordination norm can emerge if homophily-driven agents are not constrained in exogenous network structures, but rather can interact within a dynamic network. Network density amplifies the initial behavioural tendency of the population. This can explain the diffusion of alcohol abuse within young people's friendship networks.

TABLE 4.2: Summary of the most sociologically relevant ABM studies (*continues from the previous page*)

Reference	Topic	Approach	Manipulation	Findings
Van de Rijt, Siegel, and Macy (2009) and Bruch (2014)	Segregation	T,E	Both	The interdependence of choice can lead to unintended macro consequences due to non-linear dynamics of aggregation. Even multiculturalist preferences can lead to residential segregation patterns if they are sensitive to small changes in neighbourhood composition. If agents have multiple, correlated attributes, segregation can occur from the non-linear interaction between income inequality, population size and salience of ethnic versus economic factors.
Klemm et al. (2003), Centola et al. (2007), and Flache and Macy (2011a)	Cultural diversity	T,T,T	Both	The persistence of local convergence and global cultural diversity in human societies cannot be fully explained by homophily and interpersonal influence. In large populations, cultural diversity can be brought about by multilateral social influences, which prevent deviant agents spreading out within local clusters.
Deffuant et al. (2002), Hegselmann and Krause (2002), and Amblard and Deffuant (2004)	Opinion dynamics	T,T,T	Macro	Political opinions can converge toward one or both extremes, due to the presence of a radical minority, if agents can influence each other and uncertainty is high, especially within sparse networks.
Macy et al. (2003), Baldassarri and Bearman (2007), and Flache and Macy (2011b)	Opinion dynamics, negative influence	T,E,T	Both	Opinion bipolarization can emerge if agents conform to xenophobia and negative influence, besides homophily and positive influence. Small-world networks can generate cultural homogeneity only if interaction is limited to positive selection and influence; otherwise, a bipolarized equilibrium tends to emerge. The bivalence of selection and influence can explain the mismatch between perceived and actual polarization of public opinion.
Abrahamson and Rosenkopf (1997), Rosenkopf and Abrahamson (1999), Deffuant, Huet, and Amblard (2005), and Van Eck, Jager, and Leeflang (2011)	Innovation diffusion	T,T,T,E	Macro	Innovation can spread as a bandwagon effect within networks with permeable boundaries between core and peripheral components, leading to possible convergence toward inefficient outcome. When information about social value and profitability are decoupled, innovations with high social value but low payoffs are more likely to succeed. Opinion leaders play a significant role in the rapidity of diffusion.
Kim and Bearman (1997) and Chwe (1999)	Collective behaviour	T,T	Macro	A collective action can arise between self-interested agents if a critical mass of highly interested agents are situated in central network positions, even if they do not control a significant amount of resources. Network transitivity can be effective in triggering bandwagon effects among low-threshold agents.
Hedström (2005), Manzo (2013), Manzo and Baldassarri (2015), and Gabbriellini (2014)	Social stratification	E,E,T,E	Both	Social influence can explain variations over time in youth unemployment rates within urban environments and inequality in educational opportunities in industrialized countries. Status hierarchies can emerge as the self-reinforcing outcome of deference gestures exchange and social influence.

emergence of social patterns. Cross-fertilization between experimental and computational research is a useful process. It shows us that by conflating the concept of rationality with that of self-interest, as in standard game theory and economics, we cannot account for the subtle social nuances that characterise individual behaviour in social contexts. In this respect, Gintis (2009) suggested that we questioned the aprioristic assumption of common knowledge that lies behind standard game theory. If we assume that individuals are rational, self-interested as they perceive their counterparts, game equilibria of any social or economic exchange can be predicted. The problem here is that experimental research has repeatedly found that social outcomes are better explained if we recognize that people develop an *epistemic knowledge* within the game based on implicit *shared mind* efforts. Culture, social norms and learning as social scaffolds for individual rationality makes a wider set of behaviour rationalizable, which would otherwise be far from standard self-interest (see also neuro-scientific research on the positive role of emotions, e.g. De Quervain et al. 2004).

Behavioural game theory could help to explore departures from standard rational choice models. Furthermore, they can be used to understand social norms in well controlled experimental scenarios, relevant for sociological research. By concentrating on interaction situations where self-interest is expected to prevail, we can understand the genesis of social norms, their dynamics, in terms of fragility or robustness and the factors that could condition their evolution. This is impossible if we assume that individuals have no individual autonomy (also that of being self-interested) and passively internalise norms by culture, education or social conformism, as in many standard sociological accounts.

Interestingly, most ABM studies mainly look at the self-organization of social groups around social norms and should not be seen as a naive exercise. No one believes that institutions and top-down influences simply do not exist. At the same time, the ABM approach is not a bottom-up "market" ideology. By focussing on micro-macro aspects, ABM studies can offer relevant insights on how groups and communities can coordinate and collaborate in our world. This is more and more fragmented into cultures, contexts and domains and in constant evolution and change. This is to say, the ABM approach is also sociologically timely and can contribute to understanding social change.

These ABM studies show that, if we consider society as an evolutionary system in constant change and adaptation, the co-existence of different behaviours and norms over time is instrumental to promote and maintain social order. This means that institutional policies, which typically assume that individuals are self-interested, end up eliciting self-interest in people. This situation could actually worsen the long-term sustainability of social systems for the following reasons: Firstly, they do not nurture diversity and heterogeneity of behaviour and secondly, they can crowd out pre-existing social norms and intrinsic motivations (Squazzoni 2014). In these cases, ABM studies could be used to understand when incentives, regulations and external institutional design can work, when social norms are beneficial and when institutions and social norms can work in synergy.

Secondly, these ABM studies can help us to understand the importance of social contexts even when looking at individual behaviour in a more micro-oriented perspective. The role of social influence and the fact that we are embedded in complex social networks have implications for the type of information we access and the types of behaviour we are exposed to. At the same time, individual behaviour has a constructive role in endogenously shaping these networks. While the literature on social networks typically looks at structural factors, the ABM approach can enrich the behavioural counterpart of these studies, providing a more dynamic picture of the interplay of individual behaviour and networks. This could help us to understand the evolutionary bases of network structures, ideally considering a complex set of reciprocal influences between micro and macro levels. It is worth noting that this interplay is difficult to understand using standard social science approaches, given that a combination of qualitative and quantitative factors must be considered simultaneously. Furthermore, simulations can provide a vivid picture of space and time processes that might unfold over a long time, also supporting intuitive understanding of the complexity of social systems.

Here, the advent of the big data movement and the increasing convergence between data platforms in various domains of social life (for example, the public, private and social sectors) could allow sociologists to have fine-grained, large-scale data on individual choices but also on social network connections that were impossible even to contemplate before. By applying sociologically-informed computational models to these multi-source, layer data, we could reveal the complex mechanisms of social life in a globally interconnected world (Conte et al. 2012).

Finally, one of the most important sociological advantages of ABMs is that they can help sociologists to achieve more rigorous standards of theorization and empirical analysis. ABM studies have developed a serious methodological debate on standards to improve empirical calibration and validation of models, model documentation and reporting and model replication and test (Grimm et al. 2006; Polhill et al. 2008). Tools such as a public repository of models have been developed (e.g., ABM Open [2]), where researchers are asked to make models public so that replication and model extension is easier. This can increase cumulative findings and create the collective dimension of any rigorous scientific endeavour (Squazzoni 2012).

ABMs can promote a modelling attitude in sociology, including more disciplined theory building and a stronger "testing hypotheses" experimentalist culture. Moreover, they can make sociology a more collective effort, by undertaking the path followed by more mature disciplines. In this regard, it is worth noting that there is still a serious gap in computing skills in the education programmes of sociologists at all levels, from Bachelors to PhD courses and even in top institutions. We need to fill

2. http://www.openabm.org/

this gap in order to equip a new generation of sociologists towards cutting-edge, collaborative research. This is also essential for sociologists to collaborate and compete with external experts, who are increasingly performing relevant sociological research.

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Chapter 5

Solidarity and Competition: Simulating Social Support between Competing Business Partners

5.1 Introduction

This study aims at understanding the consequences of competition between collaborating partners on the emergence of solidarity between business partners. Previous research has suggested that certain social mechanisms can elicit expectations of social support between professional partners (see Chapter 4). Yet, emergent solidarity within economic exchange networks might be favoured by some context-specific properties. In particular, the lack of competition among exchange partners might elicit cooperation rather than conflict. This could ease the production of trust in loose forms of negotiated exchanges (Molm, Schaefer, and Collett 2009) and generate expressive relations between partners.

Here, we examined the effect of competition and resource distribution on social support through a stochastic Agent-Based Model (ABM, Macy and Flache 2009; see also Chapter 3) which includes a multiplex network of collaboration, trust and expectations of support. The model allowed us to manipulate certain structural conditions of the collaboration network and test their impact on the stability of the social support network. By running computer simulations of the model, we looked at the connectivity and integration of emergent networks of social support.

The rest of the paper is organized as follows. In Section 2, we introduced the theoretical background of this study. Section 3 shows a description of the model and the simulation output measures. Then, Section 4 illustrates the design of the computer simulations and shows our results. Finally, Section 5 discusses certain implications of our study for the analysis of social and economic exchange and discusses limitations and future developments.

5.2 Research background

In case of professional collaborations, solidarity between partners can emerge as a byproduct of trust formation within exchange interactions (see Chapter 3). At the dyadic level, solidarity can arise if individuals are prone to provide support to each other at a cost, when requested to do so (Lindenberg 1998; Flache and Hegselmann 1999a, 1999b). An enduring professional collaboration, such as a 'negotiated exchange with non-binding agreements' (Blau 1964; Emerson 1976; Molm 2003; Molm, Schaefer, and Collett 2009) might stimulate the emergence of expectations of support by eliciting mutual trust between partners. Indeed, a trust relation requires a sufficient level of structural risk to let partners prove their trustworthiness to each other (Gambetta 1988; Coleman 1990; Hardin 2002), which elicits trust formation. In fact, if exchanges are too strictly bound by the terms of an agreement, opportunistic behaviour becomes so costly that actors do not free ride on each other. Nevertheless, might perceive cooperative behaviour by partners as due to formal constraints of an agreement rather than revealing a partner's genuine goodwill (Kollock 1994; Yamagishi, Cook, and Watabe 1998; Barrera 2007). Bearing the cost of a cooperative behaviour intentionally may be perceived by others as a sign of intrinsic motivation, which testifies to the genuine interest in the value of a collaboration or a moral obligation of good behaviour that can typically self-reinforce when reciprocated. If actors develop trust in each other within the context of an economic exchange, then solidarity might arise (Molm, Collett, and Schaefer 2007), as trust entails the expectation of getting costly support from a partner in case of need.

Furthermore, besides being elicited through enduring collaboration relationships, trust can also be generated by the diffusion of actors' reputation of trustworthiness (Buskens and Raub 2002; Boero et al. 2009). Here, empirical research on intraorganizational social networks has shown that the evolution of trust between professionals is usually driven by dynamics of transitive closure (e.g., i trusts j because the latter is trusted by one or more persons whom i trusts) (Robins, Pattison, and Wang 2009; Lusher et al. 2012).

In Chapter 3, we found that expectations of support were strongly associated with business-related trust within a group of collaborating ICT freelance workers, while the collaboration network provided the opportunity for partners to develop trust in each other. However, this result might have been affected by the context-specific configuration of the collaboration network. Moreover, the lack of competition between partners, which characterised the empirical context under observation, might have provided a favourable context for collaborations to turn into expectations of support. Otherwise, it could be argued that collaboration relations would not have elicited trust formation, which in turn would not have generated expectations of social support between partners. This argument is consistent with the claim that the structure of joint negotiation which underlies professional collaboration might generate solidarity or exacerbate conflict depending on contextual factors affecting actors' perception of risk-taking, conflict, and a partner's goodwill (Molm, Schaefer, and Collett 2009; Kuwabara 2011).

It is also important to note that differences in resources (f.i. skills, competencies, time, financial capital, etc.) among collaboration partners may affect the dynamic of collaboration and so the collaboration network structure. Actors tend to preferentially select partners with a higher amount of resources, which makes more likely to match one's lack of skills that are needed to perform an activity. Therefore, an unequal distribution of resources generates a competitive framework that makes some collaboration partners looking more attractive than others (Markovsky, Willer, and Patton 1988, e.g.). In these cases, establishing collaboration relations is probably costly. Moreover, high-resource actors tend to become more central than low-resource actors in a collaboration network.

At the same time, differences in resources may influence the dynamic of support relations. For instance, in a series of computer simulation studies, Flache and Hegselmann (1999a, 1999b) studied the emergence of solidarity between agents playing a 'repeated support game'. They modelled solidarity relations as reciprocated social support ties. In the former study, they analysed the effect of behavioural heterogeneity on the formation of social support. They showed that an efficient social support network could emerge even among self-interested agents if resources were distributed unevenly within the population. This was because agents varied in *neediness* – i.e., the need for social support – and capability of providing support. Low-resource agents were more needy than high-resource ones. Then, neediness was inversely related to provision capability. In the second work, they studied the effect of resource distribution on cohesion and integration. They found that dense solidarity networks could emerge among self-interested agents, but these showed patterns of segregation along resource classes.

This suggests that the distribution of resources within a population may affect the development of exchange relations. With regards to the link between collaboration and social support, resource distribution and competition might have a 'double-edge' effect. On the one hand, resource distribution identifies different classes within the population. Competition would make high-resource actors more attractive than those with less resources. On the other hand, resource distribution would make lower-resources actors more needy than those with higher-resources. This double-edge effect of resource distribution would segregate the population in different overlapping resource and neediness classes and yield different outcomes for collaboration and social support.

Concerning social support, this situation could dramatically change the emergent network. On the one hand, actors would tend to establish collaboration relations with high-resource actors, so that these nodes will probably be the most central ones in the collaboration network. This would bring trust to cluster within the same set of nodes that are central in the collaboration network. Finally, the same nodes would form expectations of social support from each other, being this process driven by the occurrence of trust ties. In sum, the disproportionate number of collaboration relations that high-resource actors would establish between each other would prevent low-resource actors to develop trust in others. This would in turn prevent low-resource actors to develop expectations of social support from others. Therefore, competition over most desirable collaborators could generate a highly segregated social support network, where the most social support ties would be concentrated among high-resource actors.

On the other hand, if we assume that low-resource actors are more needy, the disruptive effect of competition could be counterbalanced. More precisely, low-resource actors would tend to develop support expectations towards more partners. This could avoid their isolation in the social support network and might generate a more cohesive and integrated social support network.

The aim of this study was to test the effect of resource distribution on the process observed in Chapter 3 if we assume that actors compete for most profitable collaborations. First, we were interested into assessing the effect of competition with unequal resources on the connectivity and integration of the emergent social support network. Secondly, we looked at the possible effect of letting actors self-organize their social support relations according to their level of resource-related neediness.

5.3 Method

In order to investigate our questions, we developed an ABM which incorporated the empirically observed interplay between collaboration, trust and social support. Therefore, the model is a theoretical ABM, although the specification of the micro-level parameters that govern agent behaviour are grounded on empirical data.

In this way, ABM can complement to the limitations intrinsic to the case-based nature of the study presented in Chapter 3 in a twofold way. Firstly, by this approach context-specific characteristics of the observed mechanisms can be isolated. Then, the robustness of empirical results to macro-level changes can be tested. Secondly, manipulation of environmental configurations is key to understand outcomes of applications of the micro-level processes in real settings, where abstract mechanisms cannot be isolated by contextual factors (e.g., Boero et al. 2010; Bravo, Squazzoni, and Boero 2012; see also Section 4.3). However, we did not calibrate the model with empirical data (Boero and Squazzoni 2005) in order to avoid modelling noise from context-specific properties of the analysed case.

5.3.1 Stochastic Actor-Oriented Models for network dynamics

Modelling the emergence of a network from another requires an approach that can handle the complex interdependencies of a multiplex network. In a recent paper, Snijders and Steglich (2015) have proposed the use of 'Stochastic Actor-Oriented Models for network dynamics' (Snijders 1996, 2001; Snijders, Van de Bunt, and Steglich 2010) as empirically-calibrated ABMs to study the emergence of social networks.

SOAMs are a combination of theoretical and statistical models (Snijders 1996). In fact, they are mainly used for statistical modelling of longitudinal network data to assess the impact of certain network local configurations or nodes' attributes on the formation of an empirically observed network. The model weighted parameters represent actors' preferences for network local configurations in their own personal networks (i.e., their neighbourhood). For example, a positive coefficient value for the 'reciprocity' parameter means that actors on average have a preference for sending ties to those other nodes who already sent them a tie.

Similarly to most methods for statistical inference of network data, SOAMs are not based on random sampling. Therefore, parameter estimates are computed by artificially generating a stochastic distribution of networks. This is achieved by a model component, which is a theoretical stochastic simulation algorithm. This algorithm derives the expected evolution of the network ties from theoretically specified assumptions about agents' preferences and a decision-making mechanism.

For these reasons, the simulation algorithm of SOAMs can be considered an agent-based computational model (Flache and Stark 2009; Snijders and Steglich 2015). The algorithm parameters can be specified in a way that represents the assumed agent micro-level behaviour. Computer simulations of the algorithm can then be performed to generate macro-level network configurations.

Here, it is important to note that the model relies on a few relevant assumptions. Firstly, provided that network ties denote states, the changing network can be interpreted as a Markov process. This means that the current state of the network determines probabilistically the following state, with all relevant information being included in the current state. Secondly, it is assumed that agents control their outgoing ties and have full information about their personal networks. Finally, network changes are assumed to occur sequentially, which prevents actors to coordinate tie changes.

Coming to the algorithm, SOAMs assume a population of n agents. First, at each iteration, one agent i is selected randomly and decides whether to change one of her/his outgoing ties or do nothing. In order to compute decision outcomes, i first calculates the variation in her/his utility related to each possible tie change, according to an *objective function*:

$$f_i(x) = \sum_k \beta_k s_{ik}(x), \tag{5.1}$$

where $\sum_k s_{ik}$ is a set of graph statistics calculated on i's personal network. These statistics represent local configurations of agents' personal networks towards which they can have positive or negative preferences of various magnitude, according to the values of parameter coefficients, β_k.

Secondly, i selects one of the $n-1$ possible new states – including no change – through a multinomial random experiment, in which each possible state has probability

$$p(\text{change in } x_{ij}) = \frac{\exp(f_i(\text{change in } x_{ij}))}{\sum_h \exp(f_i(\text{change in } x_{ih}))}. \tag{5.2}$$

In conclusion, SOAMs provide a useful tool to implement micro-level assumptions about agent behaviour and generate emergent macro-level network configurations. Behavioural assumptions are incorporated in the weighted parameters $\beta_k s_{ik}(x)$. Following the approach of random utility models, SOAMs assume that there is a random component of the utility of an action. This loosens the assumption of agents maximizing the utility of an action. Therefore, agent maximize utility through a multinomial probabilistic choice. The choice of a new state in an agent's personal network is related to the outcome of Equation 5.2, but for all choices there is always a positive probability. This is why the decision-making algorithm of SOAMs is equivalent to a process of *myopic stochastic optimization* of the objective function (Snijders 2001).

5.3.2 The model

The approach adopted in our work is slightly different from that proposed by Snijders and Steglich (2015), as we did not calibrate our model with empirical data. In a previous study, Flache and Stark (2009) have developed a 'Stochastic Agent-Based Model' (SABM) based on the SOAM simulation algorithm (see also Stark 2011). The main difference with the original SOAM algorithm is that one agent is selected randomly at each iteration, instead of being picked according to a rate function λ.

Moreover, our model includes a multiplex network X with three layers: *Collaboration* ($X^{(C)}$), *Trust* ($X^{(T)}$) and *Social support* ($X^{(S)}$). In order to adapt the SABM to our purpose, we implemented an *ad hoc* version based on the simulation algorithm of the SOAM for multiplex network dynamics developed by Snijders, Lomi, and Torló (2013). Figure 5.1 shows the main steps of the model algorithm. At each iteration, one agent i is selected randomly and decides whether to change one of her/his outgoing ties on one of the randomly selected network layers $X^{(r)}$, or do nothing. Each network layer can be selected with fixed equal probability.

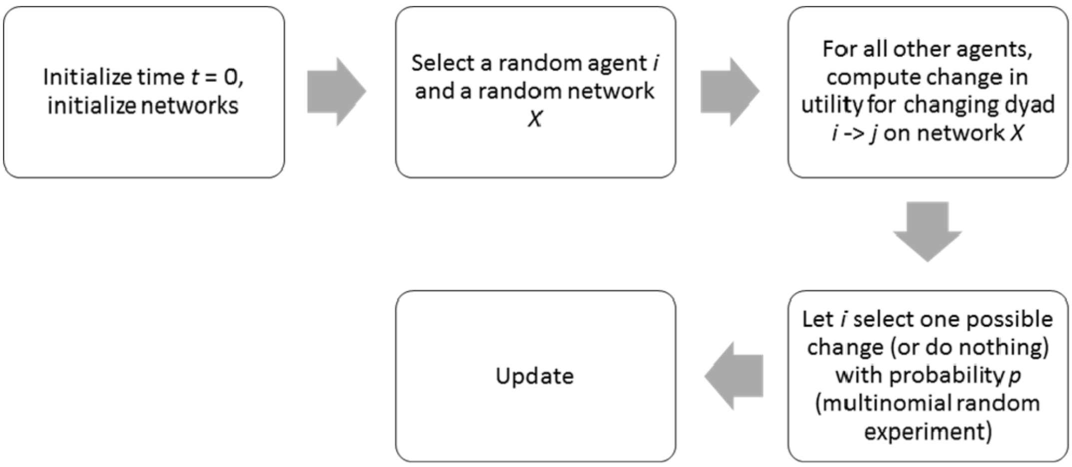


FIGURE 5.1: The algorithm of the multiplex Stochastic Agent-Based Model.

Concerning agent individual properties, we distributed two static vectors of node attributes within the population. A first attribute, R, represented *resources* for collaboration, while another attribute, N, represented *neediness*.

In order to implement the mechanisms observed in Chapter 3 and test the effect of certain factors (i.e., competition and resource distribution), we specified the model with parameters expressing both within-network (i.e., agent preferences for local configurations) and multiplex effects (i.e., cross-network effects) for each of the three network layers. Therefore, the model is composed by three different objective functions.

Unfortunately, this increased the number of the model parameters, which is usually avoided in the 'KISS' approach to ABM building (see Chapter 4). However, modelling network emergence through micro-level behaviour requires simulations to stochastically handle complex network interdependencies. Therefore, like statistical models that require a certain degree of complexity to deal with confounding factors, our stochastic ABM requires as many parameters as necessary to adequately represent the mechanisms that bring about social networks (Snijders and Steglich 2015). In the remainder of this section, we describe the model specification for each network layer[1].

5.3.3 Collaboration

The *Collaboration* network ($X^{(C)}$) is a directed network where $x_{ij} = 1$ if i has sent a request for collaboration to j and 0 otherwise. If $x_i j = 1$ and $x_j i = 1$, i.e., a request for collaboration is reciprocated within a dyad, then we consider a collaboration tie between i and j.

The objective function for $X^{(C)}$ is the following:

$$f_i^{(C)}(x) = \sum_j \beta_0^{(C)} x_{ij}^{(C)} + \beta_1^{(C)} x_{ij}^{(C)} x_{ji}^{(C)} + \beta_2^{(C)} x_{ij}^{(C)} R_j + \beta_3^{(C)} x_{ij}^{(T)} x_{ij}^{(C)} \tag{5.3}$$

The first term of the sum (*outdegree*) represents a baseline preference for sending collaboration requests to other agents. Its coefficient was fixed at a negative value, because we assumed that sending collaboration requests was costly, as it required solving problems of cooperation and coordination. The second term (*reciprocity*) represents agent preference towards incoming tie reciprocation. In order to model the formation of collaboration ties, we set the coefficient to a high positive value. This was to compensate the high cost of baseline request sending with the benefits of accepting others' requests.

The third term (*resource popularity*) represents agents' attractiveness related to their resources. By fixing its coefficient to a positive value, we assumed that agents preferred to request collaborations to high-resource agents rather than to low-resource

1. See Appendix C for the main part of the software implementation code.

ones. This was to model competition between agents for highly-skilled collaboration partners.

Finally, we implemented feedback effects of trust on collaboration by specifying the last term (*direct association with Trust*). By setting the related coefficient to a positive value, agents preferred to send collaboration requests to other agents with whom they already had a trust tie rather than to others.

5.3.4 Trust

The *Trust* network ($X^{(T)}$) is a directed network where $x_{ij} = 1$ if i trusts j and 0 otherwise. The following is the objective function for $X^{(T)}$:

$$f_i^{(T)}(x) = \sum_{j,h} (\beta_{0,0}^{(T)} + \beta_{0,1}^{(T)})\, x_{ij}^{(T)} + \beta_1^{(T)} x_{ij}^{(T)} x_{ji}^{(T)} + \beta_2^{(T)} x_{ih}^{(T)} x_{ij}^{(T)} x_{jh}^{(T)} + \beta_3^{(T)} x_{ij}^{(C)} x_{ij}^{(T)} \quad (5.4)$$

The first term of the sum (*outdegree*) represents the baseline preference for trust. Here, we assumed that trusting other agents yielded marginal diminishing returns (e.g. Flache and Stark 2009; Snijders, Van de Bunt, and Steglich 2010; Sutcliffe and Wang 2012; Sutcliffe, Wang, and Dunbar 2012). This was achieved by setting $\beta_{0,0}$ with a positive value and $\beta_{0,1}$ with a negative value. More precisely, for agents with a low outdegree, the marginal utility of an additional tie exceeded the marginal costs. As outdegree increased, marginal costs grew so that utility for new ties was too low above a certain threshold. The second term (*reciprocity*) represents agent preference towards trust reciprocation. This was achieved by setting a positive value for the related coefficient. The third term (*transitive triplets*), weighted by a positive coefficient, represents agent preference towards transitive path closure, i.e., that i would be more likely to trust j if the former already trusts h, who in turn trusts j. These three parameters represent the agent within-network preferences and have been specified in order to control for other mechanisms at work in the formation of trust. It is worth noting that this specification was based on what has been found in various studies (e.g., Robins, Pattison, and Wang 2009; Lusher et al. 2012; see also Chapter 3).

Finally, we implemented the first step of the mechanism observed in Chapter 3 through the last term of the sum. This effect (*direct association with Collaboration*), associated with a positive coefficient value, reproduced the agents' tendency to trust other agents to whom they have sent a collaboration request.

5.3.5 Social support

The *Social support* network ($X^{(S)}$) is a directed network where $x_{ij} = 1$ if i expects social support from j and 0 otherwise. If $x_ij = 1$ and $x_ji = 1$, i.e., an expectation of social support is reciprocated within the same dyad, we considered a social support relation between i and j. The following is the objective function for $X^{(S)}$:

$$f_i^{(S)}(x) = \sum_{j,h}(\beta_{0,0}^{(S)} + \beta_{0,1}^{(S)} + N_i)\, x_{ij}^{(S)} + \beta_1^{(S)} x_{ij}^{(S)} x_{ji}^{(S)} + \beta_2^{(S)} x_{ih}^{(T)} x_{ij}^{(T)} x_{jh}^{(S)} + \beta_3^{(S)} x_{ij}^{(T)} x_{ij}^{(S)} \tag{5.5}$$

The first term of the sum (*outdegree*) is the baseline preference for trust. Similarly to trust, we assumed that expecting social support from other agents yields marginal diminishing returns (e.g. Flache and Stark 2009; Snijders, Van de Bunt, and Steglich 2010). Here as well, $\beta_{0,0}$ was set to a positive value and $\beta_{0,1}$ to a negative value. The second term (*reciprocity*) represents agents' tendency to reciprocate expectations of social support. This was achieved by setting a positive value for the related coefficient. The third term (*transitive triplets*), weighted by a positive coefficient, represents agent preference towards the closure of transitive paths, i.e., that i would be more likely to trust j if the former already trusts h, who in turn trusts j. These three parameters represent the agent within-network preferences and have been specified in order to control for other mechanisms at work in the formation of trust. Together, they are based on results showed in Chapter 3.

Concerning *neediness*, we modelled this effect so that it changed the slope coefficient for the *outdegree* effect in Equation 5.5. In other words, i's baseline tendency to expect social support from other agents varied according to N_i (see next section for more details).

Finally, the final term in the sum represents the implementation of the second step of the mechanism observed in Chapter 3. This effect (*direct association with Trust*), associated with a positive coefficient value, can be interpreted as the agents' likely expectations of social support from other agents whom they already trust.

5.4 Computer simulations

5.4.1 Simulation design and model specification

We ran computer simulations by manipulating the distribution of *resources* and *neediness* within the population in a 2 X 2 factorial design. Table 5.1 shows the resulting 4-scenario simulation design.

		Neediness	
		Equal	2-class
Resources	Equal	Scenario 1	Scenario 2
	2-class	Scenario 3	Scenario 4

TABLE 5.1: 2 X 2 factorial simulation design.

Concerning *resources*, we compared an equal distribution of R, where all agents had the same level of resources, with an equal 2-class binary distribution, with $R[0, 1]$. In the former case, competition over resources was *de facto* removed from the model, while in the latter case the population was split in two groups of high-resource and low-resource agents of equal size.

Similarly, we tested an equal distribution of *neediness* and a 2-class binary distribution, with $N[-0.5, 0.5]$. In the second case, the utility for high-resource agents to establish new expectations of social support was decreased by 0.5, while utility was increased by the same value for low-resource agents (see Equation 5.5).

In order to implement the 'double-edge' effect of resources (see Section 5.2), we distributed R and N in the population so that the two vectors were inversely related in *Scenario 4*, i.e., high-resource agents had low neediness values and low-resource agents were more needy.

Coming to model specification, with regards to global parameters, simulations were run on a population of $n = 20$ agents. This was done to resemble as much as possible the small scale of the case analysed in Chapter 3. Sensitivity checks with $n = \{30, 50\}$ did not show significant qualitative differences in the results. Therefore, we decided to set $n = 20$ to increase computational efficiency. Moreover, following Flache and Stark (2009), network change rates parameters were kept fixed and equal, so that

$$\lambda^{(C)} = \lambda^{(T)} = \lambda^{(S)} \approx \overline{0.33} \tag{5.6}$$

This means that, at each iteration, the randomly selected agent had an equal probability to pick one of the three network layers to change. For each network statistic specified in the objective functions, parameters $\beta_k^{(r)}$ have been fixed exogenously and kept constant. Table 5.2 shows the parameter values used in our computer simulations.

Calibration has been done by following three criteria. First, we tried to resemble as much as possible the effect magnitude suggested by the ERGM interpretation provided in Section 3.4.2. Secondly, parameters were set according to our theoretical knowledge about micro-level mechanisms of network formation. Finally, values related to *outdegree* slope and *transitive triplets* for *Trust* and *Social support* were also set in order to avoid network degeneracy, by following best practices in statistical modelling of network data (e.g. Snijders et al. 2006; Robins, Pattison, and Wang 2009; Snijders and Steglich 2015).

In order to analyse simulation outcomes, we computed a non-directed graph for each generated *Social support* network, by considering only reciprocated ties. This was to analyse social support relations and not merely agent expectations of social support.

The non-directed networks of social support have been analysed by calculating three graph-level statistics concerning connectivity (Snijders and Steglich 2015). First, we looked at *density*, d. This was done by dividing the number of ties in the network by the number of all possible ties (Wasserman and Faust 1994). Furthermore, we

Parameter	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
Social support	
Outdegree	5
Outdegree slope	-1
Reciprocity	1
Transitive triplets	0.5
Association with Trust	1

TABLE 5.2: Model parameter values for micro-level network effects.

calculated the *number* and *size* of *connected components*, N_C and C_1. A connected component of a non-directed network is a subset of nodes where each node can be reached from all other nodes[2].

5.4.2 Results

Table 5.3 shows results of computer simulations of the four scenarios. Results were averaged over 100 replications for each scenario, by calculating outcome statistics at equilibrium after 20,000 iterations for each replication. Simulations started from an empty initial configuration. Sensitivity analysis of the results to other configurations did not show significant differences qualitatively[3].

Concerning the connectivity of the emergent networks, the distribution of resources did not significantly affect the density of social support ties unless we assumed that agents yielded different marginal returns from support ties depending on their neediness. Unlike other scenarios, in these cases, some agents were more in need of social support than others. This increased the global connectivity of the network globally increase.

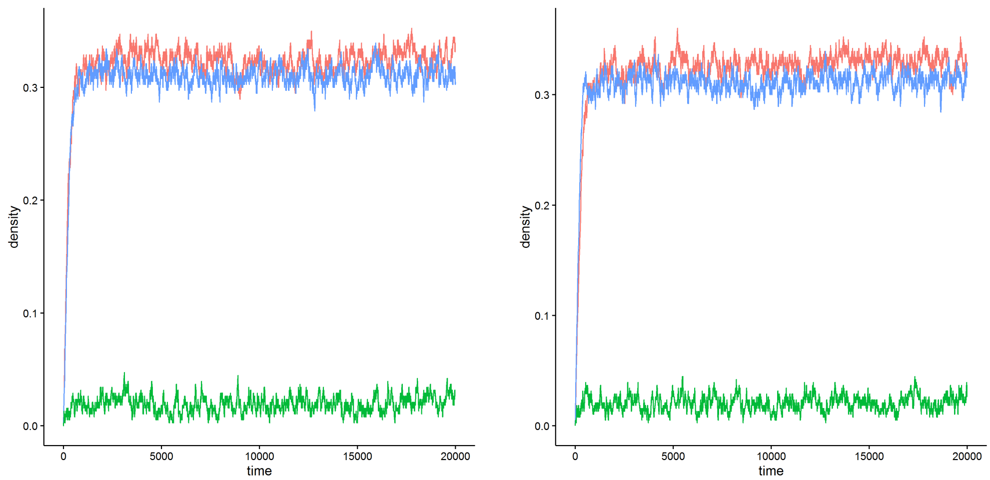
The number of strongly connected components showed a significant increase in global connectivity if we assumed a 2-class distribution of resources and neediness within the population. More precisely, the effect of resource inequality exacerbated

2. Graph-level statistics were computed through the *igraph* package (Csardi and Nepusz 2006) in the statistical computing environment *R* (R Development Core Team 2008).

3. We tested the effect of initial random network configuration of $X^{(C)}$, by running simulations from Erdős-Renyi graphs with increasing density values. We also tested star-like configurations of $X^{(C)}$ with increasing density values.

Outcome	Equal R		2-class R	
	Equal N	2-class N	Equal N	2-class N
Density	0.329 (0.009)	0.326 (0.009)	0.333 (0.009)	0.417 (0.011)
Number of components	7.450 (2.271)	7.570 (2.189)	9.530 (1.732)	2.570 (1.130)
Size of main component	13.440 (2.280)	13.350 (2.222)	11.420 (1.701)	18.360 (1.291)

TABLE 5.3: Results of computer simulations with varying distributions of resources (R) and neediness (N): Mean and standard deviations over 100 replications (20,000 iterations each).



th

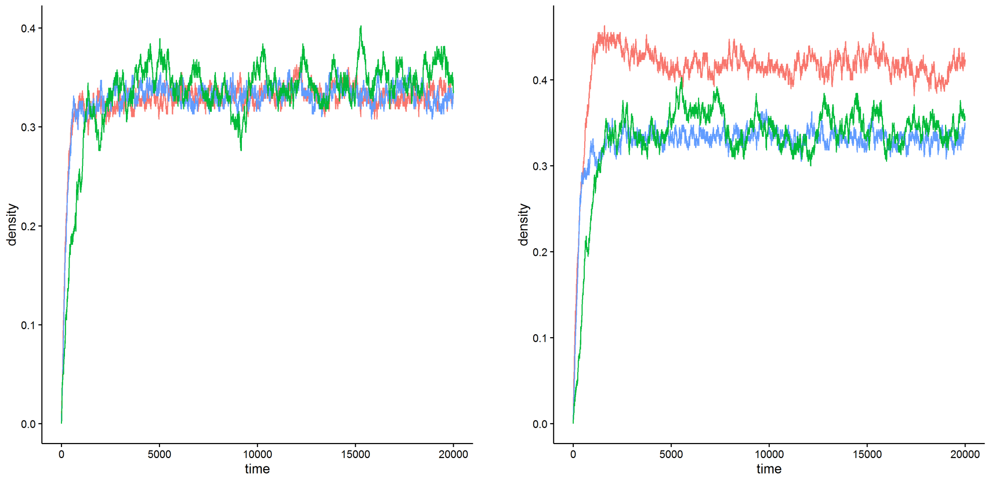
(A) *Equal N.* (B) *2-class N.*

FIGURE 5.2: Evolution of *Collaboration* (green), *Trust* (blue), and *Social support* (red) networks over time with equal distribution of resources: Density values over 20,000 iterations.

agents' tendency towards segregation, due to the fact that expectations of support inherited the patterns of collaboration. This can be seen by looking at the dynamic of the network co-evolution over time (see Figure 5.3a), where the three networks highly overlapped over time.

However, if we assumed that low-resource agents were also more needy than others, results showed a striking reduction of the number of components in the emergent networks. This indicates that the network was much more connected than in other scenarios. These results are mirrored by the differences in size of the largest component across scenarios, with the number of nodes in the core decreasing with an unequal distribution of resources, while increasing strikingly when assuming differences in neediness among agents.

Furthermore, the counteracting effect of differences in neediness is shown by the evolution of expectations of support in Figure 5.3b. Here, it is important to note that the *Social support*network grew beyond the initial core of trust associated with



th

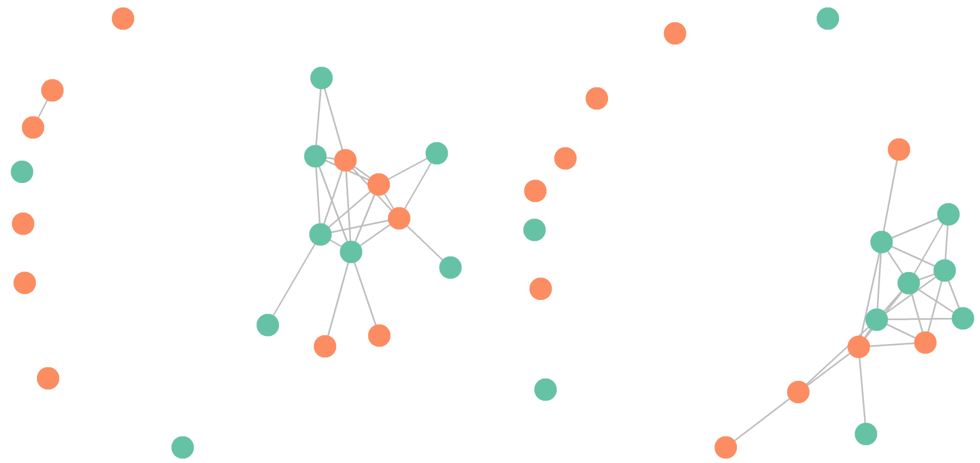
(A) *Equal N*. (B) *2-class N*.

FIGURE 5.3: Evolution of *Collaboration* (green), *Trust* (blue), and *Social support* (red) networks over time with 2-class resource distribution: Density values over 20,000 iterations.

collaboration ties.

Finally, Figures 5.4 and 5.5 show interesting results about class segregation within the emergent support networks. In order to analyse segregation, we added node attributes to the network also in those scenarios where one (*Scenarios 2* and *3*) or both (*Scenario 1*) attributes were distributed equally within the population. This was to study baseline effects of network segregation to be compared with relevant scenarios.

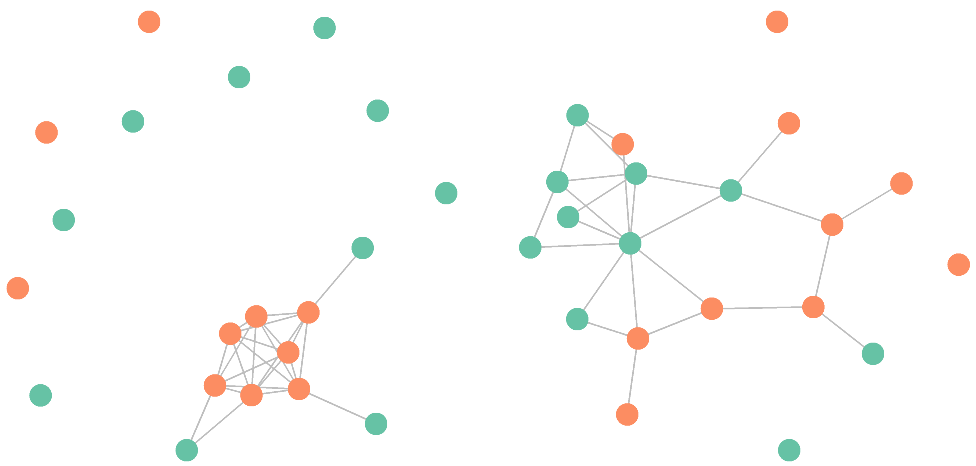
Figure 5.4 show that, when agents did not compete for more profitable collaborations, the main connected component of the support network was composed by a relatively balanced distribution of agents in terms of resource classes.



(A) *Equal N.* (B) *2-class N.*

FIGURE 5.4: Segregation in artificially generated *Social support* networks with reciprocated ties only with equal resource distribution (*100th replication*). Node colours represent resource levels (Green: $R = 0$, $N = 0.5$; Red: $R = 1$, $N = -0.5$).

The situation changed dramatically if we allowed agents to select each other for collaboration based on resource control. This generated a highly segregated largest component, with most of the less resourceful agents with no reciprocated support relations, not even between each other (see Figure 5.5a). However, not only was the support network in *Scenario 4* (see Figure 5.5b) more connected, but even the integration between the two classes is not significantly different from that generated by an equal distribution of resources.



(A) *Equal N.* (B) *2-class N.*

FIGURE 5.5: Segregation in artificially generated *Social support* networks with reciprocated ties only with 2-class resource distribution (*100th replication*). Node colours represent resource levels (Green: $R = 0$, $N = 0.5$; Red: $R = 1$, $N = -0.5$).

5.5 Discussion and conclusions

Our study aimed to discuss the possibility of generating stable and cohesive networks of solidarity between collaborating business partners. Previous research has shown that trust-driven solidarity might emerge as a byproduct of economic exchange relations if the context makes cooperation more salient than conflict. We hypothesized that social support networks arising from economic exchange relations could be stable and cohesive even if actors compete with each other for more profitable collaborations in a situation of resource inequality.

Computer simulations of a stochastic ABM supported our hypothesis. This is because resources have a double-edge effect on the formation of social support relations. On the one hand, low-resource agents are disadvantaged by competition in collaboration, so developing less social support relations with other agents. On the other hand, heterogeneity in neediness among agents counteracts the disruptive effect of competition in collaboration, which otherwise would lead to a rather disconnected and segregated support network.

Our simulations have important implications for theory and for applied organizational issues. First, our study found that allowing individuals to build social support ties according resource inequalities is key not only for balancing the dysfunctional effects of competition on solidarity, but also for generating even more integrated networks than with equal resource distribution. This is because resource heterogeneity drives the formation of new ties of social support which create new clusters where collaboration is generated as feedback effects. These results address the debate on the link between the economic and the social, by showing that solidarity generated as byproduct of economic exchange might be even resilient to competition.

Moreover, our results argue that economic relations are not necessarily detrimental for social relations. This would be caused by the conflict of interests which is intrinsic to the structure of economic interaction, where individuals would behave according to mere self-interest. Our results show that business partners, even if they act upon their own self-interest, might interact in a way that elicits cooperation instead of conflict. This suggests that the discussion about the effects of the economic on the social should be informed by empirical research that looks at the ways economic interdependencies generate the possibility for individuals to self-organize and create efficient social structures. Our study shows that this effect is theoretically possible.

Secondly, our results may be relevant for designing organizational settings. If competition in decentralized collaboration networks elicits resource heterogeneity, inequality could even be instrumental to keep the network relatively connected, given that peers have to collaborate for requested activities.

Unfortunately, our study suffers from a few limitations that narrows the implications of our results. The assumptions about interaction sequentiality and homogeneity of objective functions makes difficult to extend our results to larger-scale populations. However, the aim of this study was primarily to stress the results obtained in Chapter

3, which were obtained by a statistical model which shares similar assumptions and limitations. Moreover, the lack of behavioural heterogeneity in the model is a trade-off of our model's effectiveness in dealing with complex multiplex network interdependencies.

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Chapter 6

Conclusions

In this dissertation, we attempted to contribute to the discussion about the link between the economic and the social. More specifically, we addressed the debate on the consequences of economically-oriented interaction on social relations. Sociological studies have mostly focused on understanding the opposite direction, i.e., the effect of social relations on economic outcomes. Conversely, our work was motivated by the idea that the consequences of the economic on the social is crucial for social sciences and society in general. The reason of this is twofold.

First, interacting for economic purposes is an activity that takes a considerable amount of time in individuals' everyday social life. Working, trading, negotiating are key activities of modern societies. These activities often provide a frame in which people come across each other and interact with others who are not often part of their most intimate social circles, such as family or friends. The relevance of economic activities in everyday social life is an important reason for social sciences to study their consequences on social structures. Here, it is worth to note that the expansion of markets and online transactions in contemporary market economies might indeed yield destabilizing effects on social solidarity. More specifically, the current globalization dynamic could exacerbate the conflict-related content of economic exchanges and so be detrimental for social expressive relations. Institutional deregulation of business relations would amplify disruptive effects on solidarity, by 'disembedding' the economy from the social. However, economic exchanges do not necessarily generate negative consequences on social relations. On the contrary, the interaction frame provided by the exchange allows actors to experience each other's behaviour and develop expressive relations beyond instrumental motives. For these reasons, it is of great importance for social sciences to empirically study those contexts where the social arises from the economic. This is relevant to build tools that can inform policy and organizational design.

Secondly, our study testifies to the importance of empirically analysing economic behaviour, rather than postulating unrealistic context-free assumptions on individuals' strategic rationality. We showed that this is key to disentangle instrumental and expressive motivations in social mechanisms. Moreover, this is useful to inform formal models that go beyond context-specific observations, while simultaneously deriving consequences which are empirically grounded.

In conclusion, our studies showed that economic relations *per se* are not detrimental for social relations. More specifically, we found that social support expectations can arise as a byproduct of professional collaborations, which were originally generated by instrumental motivations between socially unrelated individuals. Furthermore, the development of solidarity expectations is made possible by the risk structure which is intrinsic to the nature of economic exchange. More precisely, our work suggests that if individuals are allowed to choose their partners independently and are exposed to the risk of being exploited, they might learn to identify trustworthy partners. This would eventually bring them to translate their trust in the expectation of getting social support from them. Therefore, economic interaction could nurture interaction contexts that let solidarity emerge outside the boundaries of group identity.

Moreover, our study has shown that solidarity as byproduct of collaboration may be robust to competition between partners. While collaborating because of skill complementarity, competition for the most attractive partners might generate a collaboration structure disproportionately centred on most attractive professionals. This in turn makes it difficult for lower-resource individuals to develop trust relations and, eventually, social support ties. Nevertheless, our research suggested that resource inequality can have a positive effect on keeping the emergent social support network connected and integrated. More precisely, actors' different neediness levels, due to resource inequality, not only integrates weaker collaborators in the social support network, it also increases the network global connectivity.

By studying the link between the economic and the social, we also attempted to contribute to the analysis of the microfoundations of solidarity. In particular, we aimed to understand relational mechanisms that might elicit prosocial behaviour. Although it applied observational techniques, our empirical study was highly inspired by experimental research. This testifies to the importance of designing empirical research that goes beyond methodological boundaries, in order to shed light on substantial issues in a more fruitful way.

In this respect, this dissertation helps to discuss another important methodological point, in that it showed how insightful may be to cross-fertilize ABM computational methods with social network analysis. More specifically, recent advancements in statistical modelling of social network data have addressed the focus of network analysis on microfoundations of network emergence. Unfortunately, these methods often rely on rather strict assumptions about social system equilibria and actors' behaviour. ABM computer simulations can complement to the use of statistical modelling for social networks by either loosening model assumptions or exploring possible scenarios. In this way, statistical analysis can inform with empirical content formal models. On the one hand ABM computer simulations can be auxiliary in widening the scope of statistical models which rely on narrow behavioural assumptions. On the other hand, simulations can go beyond explanation and explore possible scenarios.

Finally, our study provides some insights for organizational design. Studying relational mechanisms provides insights on processes of self-organization that are analytically isolated from hierarchical organizational structures. This suggests that top-down policies aiming at community building in organizations or neighbourhoods might not be the only way to ensure collaboration. This may depend on two conditions. First, people have to be free to choose their interaction partners independently. This might lead to a dynamic of learning about one's trustworthiness and diffusion of reputation, which eventually might generate expressive relations. Secondly, self-organization might be hindered by centralized incentives and norm enforcement which create ambiguity in the interpretation of others' motives. This might eventually neutralize individuals' prosocial motivations and exacerbate collectively inefficient tendencies towards self-interest. Our study shows that conditions for the emergence of social relations can be found in economically-oriented interactions from the bottom up.

Appendix A

Sociometric questionnaire

This questionnaire was administered in Italian, the mother tongue of all interviewees. Here, all the questions related to data analysed in Chapter 3 are shown in the original version (ITA)[1], each followed by an English translation (ENG).

Previous acquaintance

ITA:

> *Quali delle/degli abitanti conosceva già prima di entrare in TaG Brescia? Per "conoscenza" si intende l'essersi conosciuti personalmente, indipendentemente dal contesto. Ad esempio: amico/a, ex collega, familiare, ex compagna/o di scuola o università, semplice conoscente.*

ENG:

> *With which TaG members were you already acquainted before joining TaG? As "acquaintance" we mean having met in person, independent of the context. E.g., friends, relatives, former colleagues or school mates, simple acquaintance.*

Professional collaboration

Incoming commission

ITA:

> *Lei o la Sua agenzia ha mai ricevuto una commessa o un'offerta di collaborazione da un(a) abitante o un'agenzia di TaG Brescia? Se sì, indichi i nomi soltanto nei casi in cui abbiano accettato la proposta. Consideri soltanto le attività regolate da un chiaro accordo (formale o informale) sulla ripartizione delle attività e dei compensi.*

ENG:

> *Have you ever been offered a commission or a collaboration opportunity by another TaG member? If so, please select their names only in case you accepted the offer. Please consider only those cases that were regulated by an explicit (formal or informal) agreement about timing, resources, and payment.*

1. TaG members call themselves "abitanti" (*sing.*, "abitante"), which means "resident" in Italian.

Outgoing commission

ITA:

> *Lei o la Sua agenzia ha mai offerto una commessa o un'opportunità di collaborazione a un(a) abitante o un'agenzia di TaG Brescia? Se sì, indichi i nomi soltanto nei casi in cui abbiano accettato la proposta. Consideri soltanto le attività regolate da un chiaro accordo (formale o informale) sulla ripartizione delle attività e dei compensi. Non consideri i casi di informazione o intermediazione offerta gratuitamente a un membro o un'agenzia di TaG Brescia.*

ENG:

> *Have you ever offered a commission or a collaboration opportunity to another TaG member? If so, please select their names only in case they accepted the offer. Please consider only those cases that were regulated by an explicit agreement about timing, resources, and payment. Please do not consider simple information sharing with other TaaG members.*

Common projects

ITA:

> *Lei o la Sua agenzia ha mai intrapreso un progetto comune con un(a) altra/o abitante o agenzia (es. una nuova attività in partnership, una nuova iniziativa imprenditoriale)? Se sì, indichi i nomi, indipendentemente dal successo finale. Consideri soltanto le attività regolate da un chiaro accordo (formale o informale) sulla ripartizione delle attività e dei compensi.*

ENG:

> *Have you ever started a new common project with another TaG member (e.g., a new partnership, a joint venture, etc.)? If so, please select their names, independently of the outcome. Please consider only those cases that were regulated by an explicit agreement about time, resources, and payment.*

Partner evaluation

ITA:

> *Consideri le/gli abitanti di TaG Brescia citate/i finora con cui ha collaborato professionalmente (commesse ricevute, commesse offerte, progetti comuni). Sulla base dell'esperienza diretta maturata nell'ambito di tali collaborazioni, quanto raccomanderebbe ad altri queste persone come potenziali partner professionali? Nel caso di collaborazioni con agenzie, risponda solo per quelle persone con le quali ha effettivamente interagito nell'ambito delle collaborazioni avvenute.[1 = "Assolutamente no" - 7 = "Assolutamente sì"]*

ENG:

Please consider all TaG members whom you cited so far as collaborators (incoming or outgoing commissions, common projects). Based on your personal experience, how much would you recommend them as business partners to others? In case you collaborated with agencies, please rate only those people with whom you actually interacted. [1 = "Absolutely not" - 7 = "Yes, absolutely"]

Social support

Material support

ITA:

Immagini di avere un problema pratico che riguarda la Sua vita quotidiana. Per risolverlo, immagini di avere bisogno di un aiuto da parte di un'altra persona, che implichi tempo, impegno o il prestito di attrezzature (es. un aiuto per un trasloco o piccole riparazioni in casa). A quali delle/degli abitanti si rivolgerebbe?

ENG:

Suppose that you need to solve some practical problems related to your private life. In order to accomplish this, you needed help from another person, who will provide time, effort, or tools. To which TaG member would you turn?

Emotional support

ITA:

Immagini di avere un problema relativo alla Sua vita privata e di volerne parlare con qualcuna/o per ricevere un consiglio o del conforto. A quali tra le/gli abitanti si rivolgerebbe?

ENG:

Suppose that you have a problem related to your private life and you needed to talk about it with someone for advice or comfort. To which TaG member would you turn?

Trust in business

ITA:

Immagini di poter coinvolgere le/gli abitanti in un Suo progetto lavorativo personale, potenzialmente aperto a tutte le competenze presenti all'interno di TaG Brescia. Di quali abitanti si fiderebbe come eventuali partner o collaboratori? Non consideri, per favore, la compatibilità delle competenze delle/degli abitanti.

ENG:

Suppose that you needed to involve other TaG members in a new personal business project, potentially open to all competencies supplied within TaG. Whom would you trust as business partners? Please, do not consider the competencies needed for your actual business.

Appendix B

ERGM goodness of fit

In this appendix, we provide tables for assessing goodness of fit of the ERGMs showed in Chapter 3.

Univariate ERGM

Parameter (*PNet* name)	Obs.	Mean	Std. Dev.	t-ratio
Arc	99	99.183	6.283	-0.029
Reciprocity	25	25.061	3.431	-0.018
2-In-Star	190	198.59	32.647	-0.263
2-Out-Star	179	176.227	24.882	0.111
3-In-Star	240	297.832	110.244	-0.525
3-Out-Star	217	208.115	59.67	0.149
Mixed-2-Star	306	306.789	39.5	-0.02
030T	114	111.159	19.447	0.146
030C	25	26.336	6.42	-0.208
Sink	0	1.417	1.109	-1.277
Source	1	1.789	1.144	-0.69
Isolates	1	0.187	0.415	1.959
K-In-Star(2.00)	108.375	108.568	11.06	-0.017
K-Out-Star(2.00)	105.266	105.455	10.438	-0.018
K-L-Star(2.00)	72.859	71.423	5.003	0.287
K-1-Star(2.00)	150.797	149.178	14.187	0.114
1-L-Star(2.00)	154.758	154.036	14.843	0.049
AKT-T(2.00)	86.5	86.518	12.071	-0.001
AKT-C(2.00)	62.375	62.434	12.664	-0.005
AKT-D(2.00)	81.344	81.428	11.368	-0.007
AKT-U(2.00)	86.75	84.295	11.825	0.208
A2P-T(2.00)	259.625	260.261	30.82	-0.021
A2P-D(2.00)	145.344	144.425	18.515	0.05
A2P-U(2.00)	154.688	165.438	25.248	-0.426

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Parameter (*PNet* name)	Obs.	Mean	Std. Dev.	t-ratio
Interaction (gender)	67	67.324	5.604	-0.058
Sender (gender)	80	80.203	6.336	-0.032
Receiver (gender)	76	76.287	5.928	-0.048
T2u11 (gender)	18	16.585	2.987	0.474
T1u11 (gender)	22	20.945	3.335	0.316
T1au14 (gender)	140	144.955	29.451	-0.168
T1au13 (gender)	239	227.891	33.745	0.329
T1au12 (gender)	145	141.944	24.561	0.124
Sender (age)	3107	3110.8	199.906	-0.019
Sender (seniority)	3195	3183.338	207.256	0.056
Receiver (age)	3261	3266.29	220.673	-0.024
Receiver (seniority)	3458	3470.842	233.313	-0.055
Single Sum (age)	6368	6377.09	413.234	-0.022
Single Sum (seniority)	6653	6654.18	410.792	-0.003
Single Difference (age)	580	581.754	65.418	-0.027
Single Difference (seniority)	1131	1137.274	153.983	-0.041
Single Product (age)	103048	102735.861	7004.307	0.045
Single Product (seniority)	115719	114859.503	7806.12	0.11
Mutual Sum (age)	1599	1600.261	224.067	-0.006
Mutual Sum (seniority)	1714	1797.349	240.269	-0.347
Mutual Difference (age)	125	124.543	29.079	0.016
Mutual Difference (seniority)	264	222.243	62.569	0.667
Mutual Product (age)	25692	25667.497	3792.406	0.006
Mutual Product (seniority)	30599	33164.653	4662.229	-0.55
CovariateArc (Positive collaboration)	58	57.85	5.031	0.03
Std. Dev. in-degree dist.	2.205	2.298	0.303	-0.306
Skew in-degree dist.	0.26	0.699	0.455	-0.966
Std. Dev. out-degree dist.	2.026	1.942	0.243	0.346
Skew out-degree dist.	0.424	0.343	0.368	0.22
Global Clustering Cto	0.318	0.317	0.043	0.043
Global Clustering Cti	0.3	0.282	0.043	0.409
Global Clustering Ctm	0.373	0.362	0.043	0.237
Global Clustering Ccm	0.245	0.257	0.051	-0.233

TABLE B.1: Goodness of fit of Model 1.1. Observed values (Obs.) relate to empirical data, while mean and standard deviations (Std. Dev.) relate to simulated networks.

Multivariate ERGM

Parameter (*XPNet* name)	Obs.	Mean	Std. Dev.	t-ratio
Social Support (S)				
Arc	99	98.956	7.759	0.006
Reciprocity	25	24.745	3.68	0.069
2-In-Star	190	202.335	39.496	-0.312
2-Out-Star	179	178.813	30.448	0.006
3-In-Star	240	323.422	143.082	-0.583
3-Out-Star	217	222.626	77.354	-0.073
Mixed-2-Star	306	304.054	42.341	0.046
030T	114	110.731	19.145	0.171
030C	25	25.68	6.214	-0.109
Sink	0	1.395	1.128	-1.237
Source	1	1.743	1.197	-0.621
Isolates	1	0.187	0.452	1.799
K-In-Star (2.00)	108.375	108.375	13.282	0
K-Out-Star (2.00)	105.266	105.338	12.705	-0.006
K-L-Star (2.00)	72.859	71.093	5.748	0.307
K-1-Star (2.00)	150.797	148.608	16.155	0.136
1-L-Star (2.00)	154.758	153.262	16.905	0.088
AKT-T (2.00)	86.5	86.188	12.755	0.024
AKT-C (2.00)	62.375	61.722	12.702	0.051
AKT-D (2.00)	81.344	81.29	11.864	0.005
AKT-U (2.00)	86.75	84.192	12.504	0.205
A2P-T (2.00)	259.625	258.056	34.41	0.046
A2P-D (2.00)	145.344	146.011	22.927	-0.029
A2P-U (2.00)	154.688	167.954	30.735	-0.432
Interaction (gender)	67	67.072	6.789	-0.011
Sender (gender)	80	80.097	7.889	-0.012
Receiver (gender)	76	75.936	7.09	0.009
T2u11 (gender)	18	16.494	3.205	0.47
T1u11 (gender)	22	20.843	3.571	0.324
T1au14 (gender)	140	146.94	35.252	-0.197
T1au13 (gender)	239	226.655	37.054	0.333
T1au12 (gender)	145	144.968	30.692	0.001
Sender (age)	3107	3102.865	244.173	0.017
Sender (seniority)	3195	3194.875	229.79	0.001
Receiver (age)	3261	3263.14	275.065	-0.008
Receiver (seniority)	3458	3449.828	266.409	0.031
Single Sum (age)	6368	6366.005	512.288	0.004

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Parameter (*XPNet* name)	Obs.	Mean	Std. Dev.	t-ratio
Single Sum (seniority)	6653	6644.703	469.256	0.018
Single Difference (age)	580	580.951	76.11	-0.012
Single Difference (seniority)	1131	1126.441	168.186	0.027
Single Product (age)	103048	102669.023	8617.597	0.044
Single Product (seniority)	115719	114882.142	8108.209	0.103
Mutual Sum (age)	1599	1583.479	243.173	0.064
Mutual Sum (seniority)	1714	1756.718	253.027	-0.169
Mutual Difference (age)	125	123.155	31.936	0.058
Mutual Difference (seniority)	264	226.834	68.519	0.542
Mutual Product (age)	25692	25475.012	4137.941	0.052
Mutual Product (seniority)	30599	32135.806	4898.239	-0.314
Covariate Arc (Positive Collaboration)	58	57.724	4.72	0.058
Trust in Business (T)				
Arc	235	234.511	37.112	0.013
Reciprocity	64	63.885	13.099	0.009
2-In-Star	1117	1082.513	301.306	0.114
2-Out-Star	1272	1053.804	284.091	0.768
3-In-Star	3795	3487.628	1361.527	0.226
3-Out-Star	5321	3180.507	1222.039	1.752
Mixed-2-Star	2035	2028.035	577.11	0.012
030T	1016	878.978	283.677	0.483
030C	256	252.885	92.48	0.034
Sink	0	1.502	1.271	-1.182
Source	0	0.476	0.696	-0.684
Isolates	1	0.109	0.342	2.602
K-In-Star (2.00)	361.773	360.786	70.809	0.014
K-Out-Star (2.00)	364.252	363.242	69.337	0.015
K-L-Star (2.00)	101.976	99.647	8.293	0.281
K-1-Star (2.00)	452.906	446.531	79.58	0.08
1-L-Star (2.00)	443.899	443.749	82.064	0.002
AKT-T (2.00)	386.483	385.088	84.723	0.016
AKT-C (2.00)	337.897	336.355	88.949	0.017
AKT-D (2.00)	387.013	367.925	84.673	0.225
AKT-U (2.00)	381.768	378.235	86.622	0.041
A2P-T (2.00)	1005.271	1001.814	179.191	0.019
A2P-D (2.00)	588.603	515.491	86.392	0.846
A2P-U (2.00)	496.693	522.431	96.259	-0.267
Interaction (gender)	152	151.913	27.711	0.003

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Parameter (*XPNet* name)	Obs.	Mean	Std. Dev.	t-ratio
Sender (gender)	188	187.798	32.593	0.006
Receiver (gender)	184	183.585	31.501	0.013
T2u11 (gender)	44	39.731	9.669	0.442
T1u11 (gender)	58	57.395	12.81	0.047
T1au14 (gender)	836	821.152	245.382	0.061
T1au13 (gender)	1602	1552.817	477.868	0.103
T1au12 (gender)	1030	834.611	242.315	0.806
Sender (age)	7301	7287.379	1186.675	0.011
Sender (seniority)	7169	7145.751	1004.079	0.023
Receiver (age)	7351	7333.256	1174.509	0.015
Receiver (seniority)	7935	7920.101	1095.391	0.014
Single Sum (age)	14652	14620.635	2358.295	0.013
Single Sum (seniority)	15104	15065.852	2081.84	0.018
Single Difference (age)	1368	1362.361	258.828	0.022
Single Difference (seniority)	2984	2972.606	595.907	0.019
Single Product (age)	228472	227739.29	37588.917	0.019
Single Product (seniority)	248713	249839.812	30809.089	-0.037
Mutual Sum (age)	3933	3952.397	823.167	-0.024
Mutual Sum (seniority)	4331	4389.353	773.956	-0.075
Mutual Difference (age)	341	350.231	91.486	-0.101
Mutual Difference (seniority)	733	634.439	198.038	0.498
Mutual Product (age)	60050	61112.376	13011.957	-0.082
Mutual Product (seniority)	75315	78607.431	12489.15	-0.264
Covariate Arc (Positive Collaboration)	93	92.885	7.057	0.016
Multiplex effects ST				
Arc ST	82	81.909	9.157	0.01
Reciprocity ST	70	69.939	8.936	0.007
Reciprocity SST	45	45.573	7.195	-0.08
Reciprocity STT	60	63.619	8.951	-0.404
Reciprocity SSTT	20	21.383	3.658	-0.378
In2Star ST	886	878.443	174.135	0.043
Out2Star ST	801	837.669	163.768	-0.224
Mix2Star ST	762	797.135	158.519	-0.222
Mix2Star TS	805	841.067	166.763	-0.216
T-STS	174	160.968	26.969	0.483
T-STT	336	361.45	85.138	-0.299
T-TTS	466	381.339	88.335	0.958
T-TST	354	362.896	88.978	-0.1

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Parameter (*XPNet* name)	Obs.	Mean	Std. Dev.	t-ratio
T-SST	178	177.441	33.486	0.017
T-TSS	186	194.141	39.241	-0.207
C-SST	768	768.153	26.845	-0.006
C-TTS	319	330.427	83.956	-0.136
Isolates ST	1	0.017	0.129	7.6
TKT-STS (2.00)	140.875	129.503	20.522	0.554
CKT-STS (2.00)	119.625	118.503	20.519	0.055
DKT-STS (2.00)	135.063	135.097	23.791	-0.001
UKT-STS (2.00)	144.938	152.081	29.003	-0.246
TKT-TST (2.00)	154.552	155.258	23.206	-0.03
CKT-TST (2.00)	148.003	145.254	23.752	0.116
DKT-TST (2.00)	169.73	155.119	22.365	0.653
UKT-TST (2.00)	150.421	154.343	23.643	-0.166
mrs (gender)	65	64.777	8.967	0.025
mrr (gender)	62	61.107	8.264	0.108
ex ST (gender)	56	53.94	8.491	0.243
ex TS (gender)	54	51.556	7.967	0.307
mrb (gender)	55	53.707	7.859	0.165
mrbm (gender)	49	45.022	7.629	0.521
mSum (age)	5921	5952.229	611.506	-0.051
mSum (seniority)	6114	6256.93	541.738	-0.264
mdiff (age)	539	558.999	79.736	-0.251
mdiff (seniority)	1032	991.322	174.534	0.233
mSumm Miss. Attr. (age)	3683	3665.371	590.461	0.03
mSumm Miss. Attr. (seniority)	4165	4369.018	547.694	-0.373
mdiffm Miss. Attr. (age)	267	265.647	76.603	0.018
mdiffm Miss. Attr. (seniority)	569	500.394	161.101	0.426
Covariate Arc ST (Positive Collaboration)	55	54.739	4.873	0.054
Std. Dev. in-degree dist. S	2.205	2.352	0.348	-0.42
Skew in-degree dist. S	0.26	0.826	0.497	-1.138
Std. Dev. out-degree dist. S	2.026	1.989	0.269	0.137
Skew out-degree dist. S	0.424	0.464	0.429	-0.094
Global Clustering Cto S	0.318	0.312	0.045	0.134
Global Clustering Cti S	0.3	0.278	0.044	0.502
Global Clustering Ctm S	0.373	0.365	0.043	0.18
Global Clustering Ccm S	0.245	0.254	0.052	-0.163
Std. Dev. in-degree dist. T	4.413	3.94	0.439	1.077
Skew in-degree dist. T	0.22	0.013	0.294	0.701

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Parameter (*XPNet* name)	Obs.	Mean	Std. Dev.	t-ratio
Std. Dev. out-degree dist. T	5.492	3.679	0.447	4.058
Skew out-degree dist. T	0.645	-0.324	0.354	2.741
Global Clustering Cto T	0.399	0.412	0.032	-0.394
Global Clustering Cti T	0.455	0.402	0.03	1.774
Global Clustering Ctm T	0.499	0.43	0.026	2.655
Global Clustering Ccm T	0.377	0.367	0.037	0.278

TABLE B.2: Goodness of fit of Model 2.2. Observed values (Obs.) relate to empirical data, while mean and standard deviations (Std. Dev.) relate to simulated networks.

Appendix C

Model code

Here follows the part of the software code that implemented the main algorithm of the model. The software has been written in Delphi 5 by Andreas Flache.

```
const
 _X = 3;
 _N = 100;

{**************************************************}
{**            Global Variables    :              **}
{**            State variables of MODEL           **}
{**************************************************}
 attribute1 , attribute2: array[1.._N] of extended;

 net: array[1.._X,1.._N,1.._N] of integer;

 //graph statistics within network
 outDi: array[1.._X,1.._N] of integer;
 recTi: array[1.._X,1.._N] of integer;
 popRecTi: array[1.._X,1.._N] of integer;
 actClosTriadsI: array[1.._X,1.._N] of integer;
 genExTriadsI: array[1.._X,1.._N] of integer;
 transTripletsI: array[1.._X,1.._N] of integer;
 resourcesCollabI: array[1.._X,1.._N] of extended;

 //network statistics cross network
 assCollTrust: array[1.._N] of integer;
 assTrustColl: array[1.._N] of integer;
 multTrustSupp: array[1.._N] of integer;
 recTrustSupp: array[1.._N] of integer;

 //objective function etc
 fij: array[0.._N] of extended;
 prIJ ,prIJChoice: array[0.._N] of extended;
 netProb ,netProbAv: array[1.._X,1.._N,1.._N] of double;

 netProb ,netProbAv: array[1.._X,1.._N,1.._N] of double;
```

```
{**********************************************}
{**           Global Variables   :          **}
{**           Parameters of MODEL           **}
{**********************************************}
N: integer;
rateT, rateC: extended;
odIntc,odSlope,rec,popRecT,actClosTriads,
       genExTriads,transTriplets: array[1.._X] of extended;
aCT,aTC,mTS,rTS: extended;
resPopC: extended;

odSlopHetS: boolean;
odSlopeIndS: array[1.._N] of extended;

begin

Synchronize(SetParameters);
writeCountStatic:=1;

expCount:= initExp;
experimentFinished:= false;
para1:= p1Min;
while para1 <= (p1Max+1/1000000) do

begin
para2:= p2Min;
while para2 <= p2Max do
begin
para3:= p3Min;
while para3 <= p3Max do
begin
para4:= p4Min;
while para4 <= p4Max do
begin

rep:= initRep;

dataSet.initOutputData;

for xNet:= 2 to 3 do
for k:= 1 to N do for j:= 1 to N do
       netProbAv[xNet,k,j]:= 0;

repeat
  controlForm.edCurRep.text:= IntToStr(rep);

 odIntc[2]:= para1;
 rec[2]:= para2;
```

```
actClosTriads[2]:= para3;
odIntc[3]:= para4;
odIntc[1]:= para17;
rec[1]:= para19;
popRecT[1]:= para20;

//Trust network
odSlope[2]:= para15;
transTriplets[2]:= para13;

//support expectation network
odSlope[3]:= para16;
for i:=1 to N do odSlopeIndS[i]:= odSlope[3];
rec[3]:= para5;
genExTriads[3]:= para6;
transTriplets[3]:= para14;
odSlopHetS:= controlForm.ckHetNeediness.checked;

//cross network effects
aCT:= para7;
aTC:= para22;
mTS:= para8;
genExTriads[2]:= para9;
rTS:= para10;

//actor attribute effects
resPopC:= para24;

//change rates
rateC:= para21;
rateT:= para12;

InitState;

iter:=0; writeCount:=1;
updateOutputMeasures;

iter:=1; writeCount:=1;

repeat

//*******************************************//
//HERE FOLLOWS THE ACTUAL SIMULATION ENGINE****//
//*******************************************//

 i:= Random(N)+1;
 ranNum2 := Random;
 if ranNum2 <= rateC then xNet:= 1 else
```

```
    if ranNum2 <= rateC+rateT then xNet:=2 else xNet:= 3;

   //count activity closure triads ik-jk-ij,
   //only needed for trust network
   if xNet=2 then actClosTriadsI[xNet,i]:=
       countActCloseTriadsI(i,xNet);

   //count "generalized exchange" triads jk-ki-ij,
   //needed for both trust and support expectation network
   if ((xNet=2) or (xNet=3)) then genExTriadsI[xNet,i]:=
       countGenExTriadsI(i,xNet);

    //count "transitive triplets" triads ij-ih-hj,
       //needed for both trust and support expectation network
   if ((xNet=2) or (xNet=3)) then transTripletsI[xNet,i]:=
       countTransTripletsI(i,xNet);

   //update count of reciprocated dyads of the j's to which
   //there is i->j
   //this requires that the recTi statistic is up to date
   if xNet=1 then popRecTi[xNet,i]:= countPopRecI(i,xNet);

   //compute value of objective function for tie
   //change corresponding to j.
   cumPrIJ:= 0;
   for j:= 0 to N do
   begin
    if j>0 then
    begin
     oldIJ:= net[xNet,i,j];
     newIJ:= Abs(net[xNet,i,j]-1);

     //*************************************************** //
     //Below here: calculate changes of relevant ***********//
        //graph statistics that would result if ij were toggled *//
     //****************************************************//

     outDiNew:= outDi[xNet,i]+(newIJ-oldIJ);
     recTiNew:= recTi[xNet,i]+((newIJ*net[xNet,j,i])
                -(oldIJ*net[xNet,j,i]));

     //calculate change in popRecTi and resourcesCollabI
        //statistic if dyad ij were toggled, only needed for
        //collaboration network
     if xNet=1 then
     begin
      popRecTiNew:= popRecTi[xNet,i]+(newIJ-oldIJ)*recTi[xNet,j];
      if newIJ=0 then popRecTiNew:= popRecTiNew+1;
```

```
      resourcesCollabINew:= resourcesCollabI[xNet,i]+
                (newIJ-oldIJ)*attribute1[j];
     end; // if xNet=1

     //calculate change in number of  actClosTriadsI ij-ik-jk
        //if dyad ij were toggled, only needed for trust network
     if xNet=2 then
     begin
      actClosTriadsINew:= 0;
      for k:= 1 to N do
      if (k<>i) and (k<>j) then
      begin
       if (net[xNet,j,k]=1) and (net[xNet,i,k]=1) then
        actClosTriadsINew:= actClosTriadsINew+(newIJ-oldIJ);
      end;
      actClosTriadsINew:= actClosTriadsI[xNet,i]+actClosTriadsINew;
     end;

     //calculate change in number of genExTriadsI ij-jk-ki
        //if dyad ij were toggled, both trust and
        //support exp network
     if (xNet=2) or (xNet=3)  then
     begin
      genExTriadsINew:= 0;
      for k:= 1 to N do
      if (k<>i) and (k<>j) then
      begin
       if (net[xNet,j,k]=1) and (net[xNet,k,i]=1) then
        genExTriadsINew:= genExTriadsINew+(newIJ-oldIJ);
      end;
      genExTriadsINew:= genExTriadsI[xNet,i]+genExTriadsINew;
     end;

     //calculate change in number of transTripletsI ij-ih-hj
        //if dyad ij were toggled, both trust and
        //support exp network
     if (xNet=2) or (xNet=3)  then
     begin
      transTripletsINew:= 0;
      for k:= 1 to N do
      if (k<>i) and (k<>j) then
      begin
       if (net[xNet,i,k]=1) and (net[xNet,k,j]=1) then
        transTripletsINew:= transTripletsINew+(newIJ-oldIJ);
      end;
      transTripletsINew:= transTripletsI[xNet,i]+transTripletsINew;
     end;
```

```
    //Below here changes in cross-net graph statistics
        //if dyad ij in xNet were toggled

    //assCollTrust: number of dyads in trust network
        //in which ijC-ijT
    if (xNet=2) then assCollTrustNew:= assCollTrust[i]+
                net[1,i,j]*(newIJ-oldIJ);

    //assTrustColl: number of dyads in collaboration network
        //in which ijT-ijC
    if (xNet=1) then assTrustCollNew:= assTrustColl[i]+
                net[2,i,j]*(newIJ-oldIJ);

    //multTrustSuppNew: number of dyads in support network
        //in which ijT-ijS
    if (xNet=3) then multTrustSuppNew:= multTrustSupp[i]+
                net[2,i,j]*(newIJ-oldIJ);

    //recTrustSuppNew: number of dyads in support network
        //in which jiT-ijS
    if (xNet=3) then recTrustSuppNew:= recTrustSupp[i]+
                net[2,j,i]*(newIJ-oldIJ);
   end
   else

   begin
    oldIJ:= 0;
    newIJ:=0;
    outDiNew:= outDi[xNet,i];
    recTiNew:= recTi[xNet,i];
    if (xNet=1) then popRecTiNew:= popRecTi[xNet,i];
    if (xNet=1) then resourcesCollabINew:=
                resourcesCollabI[xNet,i];
    if (xNet=1) then assTrustCollNew:= assTrustColl[i];
    if (xNet=2) then actClosTriadsINew:=
                actClosTriadsI[xNet,i];
    if (xNet=2) or (xNet=3)then genExTriadsINew:=
                genExTriadsI[xNet,i];
    if (xNet=2) or (xNet=3)then transTripletsINew:=
                transTripletsI[xNet,i];
    if (xNet=2) then assCollTrustNew:= assCollTrust[i];
    if (xNet=3) then multTrustSuppNew:= multTrustSupp[i];
    if (xNet=3) then recTrustSuppNew:= recTrustSupp[i];
   end;

   //Calculate resulting value of objective function
       //for potential ij dyad state change:

```

```
    //first part that is equal for all networks:
    //except that in support expectation network the slope
        //parameter can vary between indivdiuals i
    if (xNet=3) then odSlopePara:= odSlopeIndS[i] else
                odSlopePara:= odSlope[xNet];
    fij[j]:= (odIntc[xNet]+odSlopePara*outDiNew)*outDiNew+
             rec[xNet]*recTiNew+
             genExTriads[xNet]*genExTriadsINew+
             transTriplets[xNet]*transTripletsINew;

    //Now add elements that are specific for collaboration
        //network to objective function:
    if (xNet=1) then fij[j]:= fij[j]+
        popRecT[xNet]*popRecTiNew +
        aTC*assTrustCollNew +
        resPopC*resourcesCollabINew;

    //Now add elements that are specific for trust network
        //to objective function:
    if (xNet=2) then fij[j]:= fij[j]+
        actClosTriads[xNet]*actClosTriadsINew +
        aCT * assCollTrustNew;

    //Now add elements that are specific for support expectation
        //network to objective function:
    if (xNet=3) then fij[j]:= fij[j]+
        mTS * multTrustSuppNew +
        rTS * recTrustSuppNew;

    //Now store corresponding exp(...) values and
        //update cumulative probability
    //prIJ[j] is to hold cumulative probability
        //for toggling ij, thus prIJ[j]-prIJ[j-1]
        //is probability density.
    prIJ[j]:= Exp(fij[j])+cumPrIJ;
    if i<>j then cumPrIJ:= cumPrIJ+Exp(fij[j]);
    if i=j then prIJ[j]:=prIJ[j-1];
   end;

   //**************************************************************//
   // At this point new values obj function for all j's are known.
   //Below here: Multinomial random choice experiment **//
   //**************************************************************//

   for j:= 0 to N do
    if j = 0 then prIJChoice[j]:= prIJ[j]/cumPrIJ else
                prIJChoice[j]:= (prIJ[j]-prIJ[j-1])/cumPrIJ;

```

```
    //Now determine choice according to SIENA decision algorithm
    ranNum:= random*cumPrIJ;
    j:= 0;
    while ranNum > prIJ[j] do inc(j);
    if i=j then
      if (random > 0.5) then inc(j) else dec(j);
    //at this point j is the index of the dyad for
        //which the state will be toggled

     //*****************************************************//
    // At this point dyad to be toggled has been found: j.
    //Now adapt networks and graph statistics accordingly  **//
    //*****************************************************//
    //now update network accordingly.
    if j > 0 then
    begin
     oldIJ:= net[xNet,i,j];
     net[xNet,i,j]:= Abs(net[xNet,i,j]-1);

     //Adapt network statistics for actors affected by
         //this dyad change
     outDi[xNet,i]:= outDi[xNet,i]+(net[xNet,i,j]-oldIJ);
     recTi[xNet,i]:= recTi[xNet,i]+((net[xNet,i,j]*net[xNet,j,i])
                  -(oldIJ*net[xNet,j,i]));

     //change of dyad ij can also change count of reciprocated
         //ties in xNet for j
     recTi[xNet,j]:= recTi[xNet,j]+((net[xNet,i,j]*net[xNet,j,i])
                  -(oldIJ*net[xNet,j,i]));

     //calculate change in popRecTi and resourcesCollabI statistic,
         //only needed for collaboration network
     if xNet=1 then popRecTi[xNet,i]:= countPopRecI(i,xNet);
     begin
       popRecTi[xNet,i]:= popRecTi[xNet,i]+
                  (net[xNet,i,j]-oldIJ)*recTi[xNet,j];
       if net[xNet,i,j]*net[xNet,j,i]=1 then popRecTi[xNet,i]:=
                  popRecTi[xNet,i]-1;
        resourcesCollabI[xNet,i]:=
                  resourcesCollabI[xNet,i]+
                  (net[xNet,i,j]-oldIJ)*attribute1[j];
     end;

     //assCollTrust: number of dyads in which ijC-ijT
     if xNet=2 then
      assCollTrust[i]:= assCollTrust[i]+((net[xNet,i,j]*net[1,i,j])
                  -(oldIJ*net[1,i,j]));

```

```
      //assTrustColl: number of dyads in which ijT-ijC
      if xNet=1 then
       assTrustColl[i]:= assTrustColl[i]+((net[xNet,i,j]*net[2,i,j])
                  -(oldIJ*net[2,i,j]));

      //multTrustSupp for changes in trust network: number
          //of dyads in which ijT-ijS
      if xNet=2 then
          multTrustSupp[i]:= multTrustSupp[i]+((net[xNet,i,j]*net[3,i,j])
                  -(oldIJ*net[3,i,j]));

      //multTrustSupp for changes in support expectation network:
          //number of dyads in which ijT-ijS
      if xNet=3 then
       multTrustSupp[i]:= multTrustSupp[i]+((net[xNet,i,j]*net[2,i,j])
                  -(oldIJ*net[2,i,j]));

      //recTrustSupp for changes in trust network:
          //number of dyads in which jiT-ijS
      if xNet=2 then
          recTrustSupp[j]:= recTrustSupp[j]+((net[xNet,i,j]*net[3,j,i])
                  -(oldIJ*net[3,j,i]));

      //recTrustSupp for changes in support expectation network:
          //number of dyads in which jiT-ijS
      if xNet=3 then
          recTrustSupp[i]:= recTrustSupp[i]+((net[xNet,i,j]*net[2,j,i])
                  -(oldIJ*net[2,j,i]));
    end;

    updateOutputMeasures;
    //note: this procedure change global variables for output statistics

    if ((iter mod 100) = 0) then controlForm.edCurIt.text:= IntToStr(iter);

    //var1 .. var10 contains variables used in displayState
    if ((iter mod itPerOutput) = 0) or (iter=1) or (iter=maxIter) then
    begin
     Synchronize(displayState);
    end;

    inc(iter);
   until Terminated or (iter > maxIter);
   inc(rep);
  until Terminated or (rep > (initRep+maxRep-1));

   //experimentFinished:= (minSize>=p1Max) and (para2>=p2Max)
   //and (para3>=p3Max) and (para4>=p4Max);
```

```
   Synchronize(displayStateStatic);
   inc(expCount);
   para4:= para4 + p4Step;
  end;
   para3:= para3 + p3Step;
  end;
   para2:= para2 + p2Step;
  end;
   para1:= para1 + p1Step;
  end;

  experimentFinished:= (para1>=p1Max) and (para2>=p2Max) and
         (para3>=p3Max) and (para4>=p4Max);
  if experimentFinished then Synchronize(displayStateStatic);

  with controlForm do
  begin
   btnStopClick(controlForm.btnStop);
  end;
 end;
```