23 Social Networks*

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Summary. Social networks affect individual behavior as well as social phenomena. Conversely, when actors can choose with whom to interact, social networks are also themselves affected by individual behavior. This chapter provides an overview of two main classes of formal theoretical models for the analysis of network effects and network formation, namely, game-theoretic models and agent-based simulation models. We first discuss models in which networks are assumed to be exogenous and focus on network effects. More specifically, we focus on models predicting effects of social networks on behavior in social dilemmas. Second, we summarize main approaches to network formation and the dynamics of networks. Third, we review models on the co-evolution of networks and behavior that provide an integrated analysis of network formation and network effects, again focusing on social dilemma problems. The chapter ends with an evaluation of the state of the art of theoretical models for social networks, including open problems and suggestions for future research.

1 Introduction

Theoretical and empirical research from sociology and other disciplines reveals that social networks have important effects for micro-level individual behavior as well as macro-level social phenomena. This includes – but is not limited to – individual search behavior on the labor market and labor market outcomes (Granovetter 1973, 1974), individual adoption and macro-level diffusion of innovations (Coleman et al. 1966),

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the spread of diseases (Kretzschmar & Wallinga 2007; Morris et al. 1995), social inequality (Coleman 1988; Flap 2004; Lin 2001), and trust in social and economic exchange (Coleman 1990) as well as behavior in social dilemmas and the "solution" of such dilemmas (Raub & Weesie 1990). This research implies that actors benefit from occupying certain individual positions in a network and from certain network structures, while other positions and structures affect them negatively. Sometimes dense networks will be beneficial, for example, to solve trust- or cooperation problems (Buskens 2002; Raub & Weesie 1990). In other settings, open structures are more beneficial, for example, in competitive settings where access and control of information is important (Burt 1992; Granovetter 1973; for comparison of these two contexts also see Burt 2005). A similar message emerges from the social capital literature, which argues that social inequality can be explained in part by differences in resources that people derive from their personal networks (Coleman 1988; Flap 2004; Lin 2001).

Often, networks are not exogenous. Rather, actors can affect their position in a network and the network structure, at least to some degree, by establishing, maintaining, or severing relations with others. For example, actors can often choose with whom to exchange goods or information and with whom to collaborate. The notions that actors have opportunities to choose their relations and that networks have important consequences suggest that actors also have incentives for "networking". Namely, goal-directed and incentive driven behavior then implies that actors will try to form relationships with an eye on optimizing their individual benefits from their network: they will tend to strategically invest in establishing and maintaining relations that are beneficial and would end relations that are not (see, e.g., Flap 2004).

However, from the premise that network structures are the results of actors' decisions, it does not follow that socially beneficial network structures will emerge spontaneously (e.g., Büchel & Hellman 2012; Doğan et al., 2009; Jackson & Wolinsky 1996). Although actors may be able to choose their own relations, the network structure is the result of the combined choices of all actors. Actors are thus interdependent. Relational choices of one actor may have consequences for other actors. For instance, by breaking just one relation, an actor may interrupt many indirect connections between other pairs of actors, thereby changing the flow of information in the network. Thus, although network structures may be the consequences of individual decisions, they are often unintended consequences of individual action (cf. Merton 1936; Schelling 1978).

For quite some time, the literature on social networks focused primarily on effects of social networks, while systematic research on the emergence and dynamics of networks is more recent and presumably still scarcer. This is understandable since the emergence and dynamics of networks is inherently – and even more so than network effects – due to interdependent behavior of actors, thus complicating theoretical and empirical analysis (Flap & Völker 2013; Snijders 2013). However, since the mid-1990s the situation has changed and a meanwhile sizeable literature makes progress in studying the emergence and dynamics of networks. This literature has roots in sociology (e.g., Doreian & Stokman 1997; Stokman & Doreian 2001) but is meanwhile very interdisciplinary, with core contributions also from disciplines such as economics, mathematics, physics, and biology. As a result, models have been formulated on the dynamics of "small world" networks (Watts & Strogatz 1998), scale-free networks

(Barabási & Albert 1999; see also Stauffer's chapter in this Handbook), communication networks (Bala & Goyal 2000; Buskens & Van de Rijt 2008), and other topics. By now, the literature also includes major edited volumes (e.g., Dutta & Jackson 2003; Demange & Wooders 2005; Jackson & Zenou 2013) and textbooks (see Goyal 2007; Vega-Redondo 2007; Jackson 2008). The topic of network dynamics has also found its way into popular science literature (e.g., Buchanan 2002; Christakis & Fowler 2011).

Much of this literature studies causes for network dynamics that lie solely in the network structure itself. However, it is likely that the choice of network relations also depends on the content of relations and on actual behavior in relevant interactions. After all, one of the reasons to study social networks in the first place is that networks affect behavior. For example, when facing cooperation problems, actors may want to avoid defectors, while in other settings, actors may simply want to avoid those who behave differently and prefer relations with those who behave similarly (cf. McPherson et al. 2001). Thus, on the one hand, networks influence the way people behave in their interactions. On the other hand, individual behavior in interactions also affects the network such that actors "themselves constitute each others' changing environment" (Snijders 2001: 363; see also Snijders 2013). Hence, the co-evolution of networks and behavior has become the object of study in a new research program *in statu nascendi* (e.g., Eguiluz et al. 2005; Pujol et al. 2005; Vega-Redondo 2006; see Corten 2014 for a more detailed survey).

The general picture emerging is that three kinds of related questions on social networks have to be addressed, namely, (1) the effects of networks on behavior as well as on the macro-outcomes of behavior, (2) how networks are themselves affected by purposeful behavior, and (3) how networks and behavior co-evolve. Whether one wants to consider the effects of networks, the emergence and dynamics of networks, or the co-evolution of networks and behavior, the interdependence of actors will always require systematic model building to understand the implications of assumptions on the social context and on individual properties. In particular, network models intrinsically incorporate macro-micro-macro links, because one tries to understand how macro-conditions such as network structures affect behavior and how individual behavior in turn shapes macro-outcomes, including the dynamics of networks.

Coleman (1987, 1990) provided a stylized scheme that has become a standard way of representing macro-micro-macro links. In his scheme, depicted in Figure 1, nodes A and D represent propositions describing macro-conditions and, respectively, macro-outcomes. Arrow 4 represents propositions about an empirical regularity at the macro-level, say, an association between macro-conditions and macro-outcomes. The macro-outcomes D as well as the empirical regularity 4 represent explananda. Node B represents (descriptions of) micro-conditions, i.e., independent variables in assumptions about regularities of individual behavior or, more ambitiously, in a theory of individual behavior. Arrow 1 represents assumptions on how social conditions affect these variables. Social networks are paradigmatic examples of social conditions that can be conceived as opportunities or, conversely, constraints that affect the feasible alternatives between which actors can choose. Networks likewise shape the incentives associated with various feasible alternatives and shape actors' information. Various labels have been suggested for such assumptions on macro-to-micro relations. Here, we follow Lindenberg (1981; Wippler & Lindenberg 1987) and label them “bridge assumptions”. Node C represents micro-outcomes, i.e., descriptions of individual behavior. Assumptions about regularities of individual behavior or a theory of individual behavior are represented by arrow 2. Thus, arrow 2 represents a micro-theory. Finally, arrow 3 represents assumptions on how actors’ behavior generates macro-outcomes such as changes of network structures. Again following Lindenberg (1977; Wippler & Lindenberg 1987) we use “transformation rules” as a label for such assumptions on micro-to-macro relations. It is evident from the scheme that the explananda, i.e., descriptions of macro-outcomes (D) or macro-regularities (4), follow from an explanans comprising assumptions on individual behavior (2), macro-conditions (A), as well as bridge assumptions (1) and transformation rules (3). For a more extensive discussion of macro-micro-macro modeling in general see Raub et al. (2011).

$$\begin{tikzcd}
\text{A: Macro-conditions} \arrow[rrr, dashed, "4"] \arrow[dr, "1"'] & & & \text{D: Macro-outcomes} \\
& \text{B: Micro-conditions} \arrow[r, "2"'] & \text{C: Micro-outcomes} \arrow[ur, "3"'] &
\end{tikzcd}$$

Fig. 1: Coleman’s scheme.

It is clear that networks can enter Coleman’s scheme as macro-conditions (node A) and as macro-outcomes (node D). All three types of network questions to be discussed in this chapter thus seamlessly fit in Coleman’s scheme. When considering effects of networks, the network is one of the macro-conditions. The micro-conditions then typically involve the different payoffs that actors may derive from different behaviors in a network. Micro-assumptions often depend on the type of models considered: for example, are these game-theoretic models (see also the chapters by Tutić and Rieck in this Handbook) assuming forward-looking rationality or simulation models in which actors are assumed to exhibit more backward-looking adaptive behavior. Propositions on individual behavior, i.e., on micro-outcomes, follow from assumptions on macro- and micro-conditions, bridge-assumptions, as well as assumptions about micro-level regularities of behavior. Examples of micro-outcomes addressed in research on effects of social networks have been provided above, while micro-outcomes will include choice behavior with respect to establishing, maintaining, or severing relations with other actors when it comes to research on network dynamics. In co-evolution models, both types of micro-outcomes are relevant. Finally, propositions on macro-outcomes such as macro-effects of social networks mentioned above but also the dynamics of networks themselves or the efficiency of an emerging network structure then follow from micro-outcomes and transformation rules. Again, in co-evolution models, one would like to address both macro-outcomes in the sense of macro-effects of social networks as well as the dynamics of network characteristics.

Note, too, that Coleman's scheme, by directing attention to addressing how micro- as well as macro-outcomes depend on macro- and micro-conditions, bridge-assumptions, regularities of behavior, and transformation rules, naturally induces a focus on the mechanisms through which networks have effects on micro- and macro-outcomes and a focus on the mechanisms producing network dynamics. Therefore, models that fit into Coleman's scheme and are thus part of the "analytical tradition" in social science (Hedström 2005) quite naturally avoid the "theory gap" (Granovetter 1979) that characterizes much purely descriptive network research.

The models considered in this chapter have in common that they employ the assumption of goal-directed and incentive-guided behavior on the individual level. This includes game-theoretic models as well as agent-based simulation models (see also the chapter by Flache & Mäs in this Handbook). We will see that the demarcation between these types of models is ambiguous. In the remainder of this chapter, we first sketch models of network effects (Section 2). Thereafter, we address models on the emergence and dynamics of networks (Section 3). Subsequently, we describe some models on the co-evolution of networks and behavior (Section 4). We conclude with some general observations, open questions for future research, and some suggestions for further reading (Section 5). Throughout, we provide informal sketches of the models and refer to the literature for technical details.

2 Network effects

By "network effects" we refer to implications of characteristics of social network structure for individual and social outcomes in the network. In terms of substantive applications, our discussion of models of network effects focuses on such effects for social dilemma problems.[1] We distinguish between game-theoretic models[2] of such network effects and simulation studies.

2.1 Game theory: games on networks

Social dilemmas are situations with strategic interdependencies between a set of actors such that cooperative behavior has socially desirable macro-effects in the sense of Pareto-optimality for those actors,[3] while at least one actor has an incentive for "defection" in the sense of opportunistic behavior, thus improving own outcomes, while

[1] Due to the focus on network effects on social dilemma problems, this chapter can also be used as companion chapter to Raub et al. in this Handbook. Conversely, Raub et al. provides background for and additional information on various concepts and assumptions related to models of social dilemmas that are used in the present chapter.

[2] See Tutić's chapter in this Handbook and a textbook such as Rasmusen (2007) for game-theoretic terminology and assumptions.

[3] But, as indicated in Raub et al. in this Handbook, this does not necessarily imply that it is desirable for third parties.

impairing the outcomes for other actors. If all actors follow individual incentives, they end up with a Pareto-suboptimal outcome that is worse for all than had they cooperated. More specifically, in a social dilemma individually rational behavior yields a Pareto-suboptimal outcome. Individually rational behavior is equilibrium behavior in the sense of the theory of non-cooperative games – each actor chooses a strategy that maximizes the actor's (expected) payoff, given the strategies of all other actors (a Nash equilibrium) – and, in the case of a game with multiple Nash equilibria, behavior that is consistent with the equilibrium that can be considered as the "solution" of the game. Cooperation by all actors is more beneficial for each actor and is Pareto-optimal but cooperative behavior of all actors is either inconsistent with equilibrium behavior or, in the case of a game with multiple equilibria such as a coordination game, it can be consistent with equilibrium behavior but does not qualify as the solution of the game. Or, using Rapoport's (1974) more intuitive characterization, individual rationality (in the sense of equilibrium behavior that is consistent with the solution of a non-cooperative game) conflicts with collective rationality (in the sense of Pareto-optimality) in a social dilemma.

Consider simple models for social dilemmas with two actors such as the Prisoner's Dilemma or the Trust Game (depicted in Figure 2) that can be used, for example, to study problems of social and economic exchange as well as, more generally, the "problem of social order".[4] In the Prisoner's Dilemma, both actors can choose between cooperation and defection. For each actor, defection is a dominant strategy so that mutual defection is the unique equilibrium and can thus be assumed to be the solution of the game. Mutual cooperation is more beneficial for each actor than mutual defection and is Pareto-optimal but is inconsistent with equilibrium behavior. In the Trust Game, the trustor moves first and can choose between placing or not placing trust. The game ends if trust is not placed. If trust is placed, the trustee can choose between honoring and abusing trust. For the trustor, honored trust is the best outcome and preferred to the no trust outcome, while the no trust outcome is preferred to abused trust. For the trustee, abused trust is the most preferred outcome, followed by honored trust, while the no trust outcome is least preferred by the trustee. Honored trust is Pareto-optimal and preferred by both actors to the no trust outcome. However, if trust is placed, equilibrium behavior requires that the trustee abuses trust. Anticipating that the trustee would abuse trust, though, not placing trust is the trustor's best-reply and, while Pareto-suboptimal, not placing trust is the unique subgame perfect equilibrium outcome of the game and not placing trust, while placed trust would be abused, is the solution of the game.

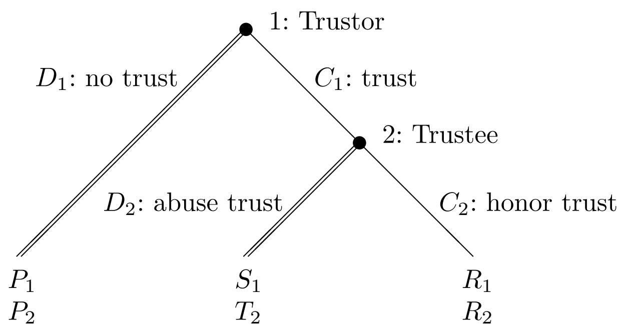
Note that in terms of Coleman's scheme individual cooperation and defection are the micro-outcomes in the case of the Prisoner's Dilemma. In the case of the Trust Game, placing or not placing trust and, respectively, honoring or abusing trust are the micro-outcomes. In both games, Pareto-optimality or Pareto-suboptimality is the relevant macro-outcome. The core assumption on behavioral regularities, represented by arrow 2, is the assumption of game-theoretic equilibrium behavior.

[4] Quite some results for games such as the Prisoner's Dilemma and the Trust Game generalize in principle to a much larger class of games with two or even more actors.

The game theory literature provides a broad range of mechanisms that "solve" social dilemmas, that is, provide actors with incentives such that Pareto-optimal outcomes become equilibria. Such mechanisms include (but are not limited to) iteration of the game, incomplete information, and sanctioning and reputation mechanisms. In Raub et al. in this Handbook, we discuss a number of these mechanisms from a more general perspective. In the current chapter, we focus on how social networks can facilitate the working of these more general mechanisms.

		Actor 2	
		Cooperation (C_2)	Defection(D_2)
Actor 1	Cooperation (C_1)	R_1, R_2	S_1, T_2
	Defection (D_1)	T_1, S_2	$\boldsymbol{P_1, P_2}$

a) The Prisoner's Dilemma ($S_i < P_i < R_i < T_i$); the bold-faced payoffs indicate the unique equilibrium.



b) The Trust Game ($S_1 < P_1 < R_1$, $P_2 < R_2 < T_2$); double lines indicate behavior in the unique subgame perfect equilibrium.

Fig. 2: Two social dilemma games.

We now assume "embeddedness" (Granovetter 1985) of a social dilemma like the Prisoner's Dilemma or the Trust Game in a network of relations. This could be repeated interactions between the same two actors to which we refer as *dyadic embeddedness*. A more complex and in the context of this chapter more interesting case is *network embeddedness*: The actors involved in the social dilemma also interact with third parties and there may be also relations connecting some of those third parties with each other. For example, a trustee interacts with a number of trustors who maintain relations with each other that allow for exchange of information about the trustee's behavior. Or, the actors in the Prisoner's Dilemma are likewise involved in Prisoner's Dilemmas with third parties and each actor has relations with third parties that allow for information exchange about the partner's behavior in his interactions with other actors.[5] Characteristics of the network of relations of the actors with third parties and relations between the third parties are macro-conditions in terms of Coleman's scheme and we are interested in network effects – or effects of network embeddedness – on micro- as well as macro-outcomes.

Buskens & Raub (2002; see also Yamagishi & Yamagishi 1994) distinguish two mechanisms through which networks affect behavior and thus macro-outcomes in social dilemmas such as the Prisoner's Dilemma and the Trust Game. First, there is a *control effect* due to the network. Given embeddedness, a rational actor will not only consider his short-term incentives for opportunistic behavior, i.e., defection in the Prisoner's Dilemma and abuse of trust in the Trust Game. Rather, he[6] will likewise consider the long-term effects of his present behavior on the behavior of the partner and of third parties in future interactions. After all, the partner and third parties may sanction the actor's present behavior in future interactions. Positive sanctioning may entail that the partner or third parties cooperate themselves or place trust in the future if the actor cooperates or honors trust today. Conversely, the partner and third parties may apply negative sanctions if the actor defects or abuses trust today. More precisely, the partner and third parties may defect themselves or may no longer place trust in future interactions if the actor defects or abuses trust today. This mechanism is also known as conditional cooperation (Taylor [1976] 1987; Axelrod 1984) and reciprocity (Gouldner 1960; Blau [1964] 1996; Diekmann 2004; see also the chapter by Berger & Rauhut in this Handbook).[7]

A second mechanism underlying network effects in social dilemmas can be interpreted as a *learning effect*. Assume that an actor in a social dilemma is incompletely informed about the partner. For example, the actor does not know for sure the partner's feasible actions and strategies. In the Trust Game, this would be the case if the trustee may have no opportunity to abuse trust and the trustor only knows the probability for this contingency. Another case of incomplete information is that the actor does not know for sure what the partner's incentives are. In the Trust Game, this would be the case if the trustee, with some positive probability, has no incentive to abuse trust because he suffers from a bad conscience due to internalized norms and values after abusing trust and because his bad conscience provides sufficient disutility so that honoring trust is after all more attractive than abusing trust for such a trustee.

[5] Since a dyad could be considered as a small network (Wasserman & Faust 1994), dyadic embeddedness could be considered as network embeddedness in a broad sense. In the following, we use "network embeddedness" always in the sense of "a network that includes the actors in the focal social dilemma as well as third parties". However, one should keep in mind that effects of dyadic embeddedness are network effects, too.

[6] Throughout, we use male pronouns to facilitate readability and without intending any gender-bias.

[7] See Raub et al. in this Handbook for a more detailed discussion of the control effect due to dyadic embeddedness. Much the same logic applies, too, for the case of network embeddedness.

Again, the trustor has only information about the probability for such an unobservable characteristic of the trustee. Then, information on the partner's behavior in previous interactions can be useful for adapting the actor's assumptions about the partner's unobservable characteristics. In the case of dyadic embeddedness, such information derives from the actor's own previous interactions with the partner. Network embeddedness provides information about the partner's behavior in previous interactions with third parties that may likewise allow for adapting assumptions about characteristics of the partner. Diffusion of information, in turn, is likely to be influenced by the network structure, as a vast literature on this topic shows (e.g., Valente 1995; Buskens & Yamaguchi 1999; also see Jackson 2008: chap. 7 for a review).

Diffusion of information due to network embeddedness is not unproblematic, particularly under the assumption of rational behavior of the actors (e.g., Raub & Weesie 1990: 648; Buskens 2002: 18-20). In a social dilemma context, providing information on other actors' behavior is evidently a contribution to the production of a collective good, namely, mitigating opportunistic behavior in a network and thus fostering the Pareto-optimal solution of social dilemmas. If providing information is costly, the diffusion of information could itself be conceived as a social dilemma. Note that this is often considered as a core problem for institutions used on Internet platforms such as eBay's Feedback-Forum (e.g., Bolton & Ockenfels 2009). Moreover, information that an actor receives from third parties may be inconsistent with his own experiences. Finally, information received from third parties may be biased due to misunderstandings and also due to strategic misrepresentation. For example, consider that trustors interacting with the same trustee are competitors and may thus have incentives to negatively affect each other's position. On the whole, one would expect that effects of network embeddedness are attenuated when such problems associated with information diffusion become more serious.

Game theory has been a useful tool for developing models of network effects in social dilemmas. More precisely, the literature on *games on networks* (Goyal 2007: chap. 3; Jackson 2008: chap. 9) assumes the network as given and exogenous and analyzes effects of the network on individual behavior and on macro-outcomes. Raub & Weesie (1990) seems to be the first game-theoretic model of network effects for a social dilemma, namely, the Prisoner's Dilemma. Buskens (2002) provides models of network effects for trust problems. These models combine dyadic and network embeddedness and show that network effects facilitate trust and cooperation since they complement and strengthen the effects of dyadic embeddedness. The models assume indefinitely repeated games with complete information and thus allow for analyzing control effects, while learning effects are neglected. Buskens (2003) provides a model using games with incomplete information that allows for an integrated analysis of control and learning effects. Examples of more recent and further refined models include Fainmesser (2012) and Jackson et al. (2012).

The game-theoretic models yield testable hypotheses on network effects. Testable hypotheses can be derived (see Buskens & Raub 2013 for discussion) by first of all proving theorems that specify conditions such that, given network embeddedness, there is an equilibrium of the social dilemma game that can be assumed to be the solution and implies cooperative behavior of the actors and thus also Pareto-optimality as a macro-outcome. In the next step, comparative static analysis is used for deriving implications on how changes in characteristics of network embeddedness affect the conditions for the existence of such a "cooperation equilibrium". Roughly, the analysis aims at deriving implications that specify if "increasing" embeddedness provides for less restrictive conditions for the existence of the cooperation equilibrium. Typical hypotheses derived in this way include that cooperation becomes more likely with more positive and less negative information about the partner, for example, more information that the partner has honored trust as a trustee, be it information from one's own interactions or information one receives from third parties about the partner. These are clearly hypotheses about learning effects due to dyadic embeddedness and network embeddedness. Other hypotheses that can be derived from these models include that cooperation becomes more likely with increasing network density as well as with an increasing in- as well as outdegree of the actors involved, with network density affecting learning as well as control, while in a network with directed ties indegree is related to the learning effect and outdegree is related to the control effect.

Such hypotheses have meanwhile been tested in numerous empirical studies of network effects. These studies cover domains such as economic sociology and organization studies. Empirical studies employ different and complementary designs, including survey research as well as experimental and quasi-experimental designs (see Buskens & Raub 2013 for an overview). Empirical research does reveal considerable evidence for network effects in laboratory settings as well as in social and economic interactions that resemble social dilemmas. A drawback of many studies is that they hardly allow for disentangling different mechanisms through which networks have effects. An overall impression is, though, that learning effects are often stronger than control effects and also – not surprising in the light of our discussion of conditions that can attenuate network effects – that effects of dyadic embeddedness are typically stronger than effects of network embeddedness.

2.2 Simulation: games on networks

The models discussed in the previous section, all assume that actors are perfectly forward looking and anticipate in a repeated game context all the consequences of their actions in terms of behavior of the other actors. This might seem an unrealistic assumption at the individual level to start with, but that is only one reason to consider also simulation models. The other reason is that deriving analytical results for networks in general is often very cumbersome. Buskens (2002: chap. 3) uses simulations to extend the implications of analytical solutions of a game-theoretic model of repeated Trust Games in which trustors organized in a network play Trust Games with the same trustee. The analytic results provide explicit formulas for the extent to which rational trustors can trust a rational trustee given any network, but it remains implicit in these formulas, which network characteristics lead to more trust. Buskens derives further hypotheses on control as well as learning effects through calculating the implications of the analytical solutions for many different networks. By regressing predicted trust levels on network characteristics for this large set of networks, Buskens obtains "approximate theorems" on the effects of network characteristics on trust.

Buskens (2002: chap. 4; see Buskens & Yamaguchi 1999) also provides a stochastic model for information diffusion in social networks. This is a model of learning effects. Simulating the speed of information diffusion in many different networks and additionally assuming that information is positive in the sense that the information refers to cooperative behavior, one again obtains hypotheses on the effects of network characteristics on trust. Relevant network characteristics include, for example, network density, centralization, and transitivity as well as trustors' outdegrees and indegrees.

Most simulation models that analyze games on networks use agent-based approaches (see also the chapter by Flache & Mäs in this Handbook). Actors in these models have predefined strategies, for example, "always defect" or Tit-for-Tat (Axelrod 1984). Note that predefined strategies might be conditional on what other actors do as in the case of Tit-for-Tat. Then, these actors play together and the emergence of cooperation is studied given the strategies of the actors. Initially, the interaction structures were relatively simple. In Axelrod (1984) everyone plays with everyone else, while in Nowak & May (1992) actors are placed on a regular grid. Still, more and more studies investigate the effects of more structure on who plays with whom. For example, Ohtsuki et al. (2006) show that, for many structures, the average number of neighbors in a network is a crucial parameter for whether cooperation can be maintained. We refer to Szabó & Fáth (2007) for an extensive overview of this type of models. In their chapter 6, they discuss at length models related to Prisoner's Dilemmas, but they discuss also more general principles as well as other applications.

Although the simulation models seem to apply a completely different modeling strategy as the game-theoretic models, the models are formally quite closely related. Weibull (1995), for example, shows that so-called evolutionary stable strategies are a subset of the Nash equilibria of the underlying game. Still others (e.g., Macy & Flache 2002) suggest that exploring different learning mechanisms in social simulations provides much more informative solutions than just considering the Nash equilibria. This claim is probably even more important if one considers interactions that have a rather irregular spatial structure such as interactions on irregular networks. On the other hand, outcomes of simulations might also strongly depend on subtle specifications of the underlying assumptions.

3 Network formation

The notion that networks have important effects on behavior of actors embedded in these networks has drawn attention to the question how networks emerge. Recent developments in game theory have led to the specification of models of network *formation.* In such models, actors do not choose strategies in a game that is embedded in a network, but instead choose the relations in the network. A core assumption in network formation models is that actors choose relations after consideration of the benefits and costs of relations, where the benefits of particular relations depend on properties of the resulting network. This means that actors prefer certain network positions to others, and actively try to reach such positions. One example of network benefits we have seen above: in denser networks actors can trust each other more easily. Another example is Burt's (1992) argument that network positions rich in structural holes provide actors in these positions with structural advantages. Balance theory (Cartwright & Harary 1954; see Antal et al. 2005; Van de Rijt 2011) stating that a friend of a friend should be a friend is yet another argument that could play a role when actors form relations and that argument can be modeled using game theory as well.

However, from the premise that network structures are the results of actors' conscious decisions, it does not necessarily follow that socially beneficial network structures spontaneously emerge. As we have argued above, although actors may be able to choose their *own* relations, the larger network structure is the result of the combined choices of all actors, and relational choices of one actor may have consequences for other actors. As a result, establishing network relations may be akin to producing a collective good. If, for example, a network is mainly used to obtain information and this information travels easily between actors in the network, two actors establishing a relation will also facilitate further information diffusion between two actors that are connected to one of the actors who established the relation but who are not connected to each other. This property is evident in the so-called "connections model" introduced by Jackson & Wolinsky (1996) as discussed below.

3.1 Game theory: strategic network formation

In game-theoretic modeling, one can distinguish two important types of models for strategic network formation. Both types of models start from the idea that there is a well-defined utility function for the actors in the network that only depends on the position of actors in the network. So, if we know all the relations in the network and a particular position of a given actor, then we know the utility of this actor in this position. Both types of strategic formation models are then based on the assumption that actors try to optimize their utility in this network by choosing relations with others. First, there are the models related to Jackson & Wolinsky (1996). They define equilibrium of the network by considering (sets of) relations and establishing whether actors involved in these relations can increase their utility by changing the set of relations among them. In particular, they define a network as *pairwise stable* if no actor wants to remove a relation and no pair of actors wants to add a relation to the network, using the idea that actors can unilaterally delete relations, but need consent of another actor to establish a relation with this actor. This equilibrium concept has a cooperative flavor because pairs of actors have to consider whether they do or do not want to add a relation.

Second, the class of models exemplified by Bala & Goyal (2000) starts from a completely non-cooperative perspective and defines the strategic network formation game as a game in which all the actors in the network simultaneously propose a set of relations they would like to have. Based on all these proposals, a network is formed. As indicated above, actors' utilities are completely determined by the network position they obtain in this network. This conceptualization has some flexibility, because it allows for different ways in which network relations are formed based on the choices of the actors. For example, one can assume that a relation is formed when at least one actor indicates to be willing to form the relation (one-sided tie formation). A more common assumption, which is also closer to the idea of Jackson & Wolinsky, is that a relation can only be formed if both actors want to have the relation (two-sided tie formation). Under the second assumption for formation of relations, the issue arises that due to coordination problems many Nash equilibria exist. For example, whatever the utility function on the network, no actor proposing a relation is always a Nash equilibrium, simply because given that no other actors propose relations, an actor is indifferent between proposing or not proposing any relation, since these relations will not materialize anyway. If one refines the set of Nash equilibria by excluding Nash equilibria in which there are pairs of actors who are not connected, but would prefer to be connected, the set of Nash equilibria reduces to a subset of the pairwise stable networks (Calvó-Armengol & İlkiliç 2009).

Many early examples of game-theoretic models on network formation can be found in Dutta & Jackson (2003), including the following variant of the connections model (Jackson & Wolinsky 1996). Suppose that actors in some population are connected by a social network and that worthwhile information can flow freely through this network. Then, individuals might be interested in being (directly or indirectly) connected to as many other actors as possible, because this allows them to access the largest amount of information. Furthermore, assume that actors may change the network by unilaterally initiating or removing relations. Finally, assume that maintaining relations is not free: every actor who initiates a relation has to pay a certain maintenance cost and after the relation is established information can flow in both directions through this relation. This is comparable to making a phone call: although both actors participating in the relation benefit from it, only one of them bears the cost. Thus, in this setup, actors would try to obtain access to as many other actors as possible, while at the same time trying to *minimize* the number of relation they have to maintain themselves. The network that eventually emerges is the result of the *combined* actions of the actors. This creates the strategic interdependence that makes the situation suitable for game-theoretic analysis. Moreover, there is clearly a tension between individual incentives on the one hand (minimizing individual maintenance costs) and the collective interest on the other hand (creating a network that allows optimal information flows).

In this example, an actor's strategy consists of his relational choices. Using the concept of Nash equilibrium outlined above, a network is considered to be in equilibrium if no actor can improve his benefits by initiating a new relation or removing an existing relation, given the relations others have. It is possible to show that in the situation described above there are only two types of equilibrium networks. First, the empty network is an equilibrium if the costs of the first relation are larger than the benefits of a single relation. Second, networks that are minimally connected, i.e., networks in which no relation can be removed without disconnecting the network, can be an equilibrium.

Another example is related to the by now almost classic notion of structural holes as introduced by Burt (1992, 2005). Burt's constraint formula makes the underlying intuition precise: actors are more constrained by their network if they have many relations who are also connected among each other. Using a series of empirical studies on network positions of employees in firms, Burt provides empirical evidence that if someone's network is very constrained, the actor has a smaller likelihood to obtain, for example, a promotion in the firm. If an actor has many relations that are not connected one can say that this actor's network is rich in structural holes. Buskens & Van de Rijt (2008) study equilibrium networks using different equilibrium concepts if all actors strive for brokerage positions in the sense of having structural holes in their personal networks. They show that many of the equilibrium networks are bipartite networks: these are networks in which one can divide the actors in two groups such that relations exist only between the two groups, but not within the groups. Moreover, the two groups are mostly of similar size. Because actors who are in the same group do not have connections with each other, but only to actors in the other group, there are no closed triads in these networks and they emerge exactly due to actors' effort to avoid closed triads. The interesting macro-property of these networks is that there are no or only limited strategic advantages for the actors in the network. Everyone has relatively many relations and no one has relations that are connected among each other. This implies that even though the constraint of each network position is low, there are no actors who have a much lower constraint than others. Therefore, no actor has a substantially better network position than another actor.

Note the conflicting incentives between actors in the connections model and in the structural holes model. In the connections model, others often profit from relations a given actor established. So there are positive externalities of network formation. In the structural holes model, relations formed between two actors can have negative externalities for others because structural holes are removed. A general finding is that if relations between others in general have negative externalities for others in networks, networks tend to be over-connected, while if relations between others have positive externalities, networks tend to be under-connected (see Büchel & Hellman 2012). This shows that the network formation process often implies a type of social dilemma in which it is difficult to reach or maintain a socially optimal structure.

3.2 Simulation: strategic network formation

Buskens & Van de Rijt (2008) also show that it can be rather unfeasible to characterize the complete set of equilibrium networks for a given utility function implied by the network. This also implies that it is not always feasible to provide a complete overview of the theoretical implications of the assumptions in the model. This can be due to the complexity of the network utility function or the complexity of the equilibrium concept that is considered. Especially the equilibrium concepts as introduced by Jackson & Wolinsky (1996) can be readily used to develop dynamic simulation models (see Watts 2001; Jackson & Watts 2002) by starting from any network, checking in some order stability of relations, and changing relations until no pair of actors wants to change their relation anymore. Using such agent-based models, the implications of the network formation model can often be extended. Buskens & Van de Rijt use these models to reach two goals. First, for small networks, checking all possible network structures, they specify the equilibrium networks for different equilibrium concepts. Second, for larger networks, they simulate the network formation process starting from a large set of networks. As soon as no actor wants to remove a relation anymore and no pair of actors wants to add a relation, the network is, by definition, pairwise stable. With this approach, one can not only show that the bipartite networks are by far the most likely networks to emerge, but also that the specific set of bipartite networks in which the two groups have an as equal as possible size are even more likely to emerge than more unevenly distributed groups. This reconfirms that one can hardly expect that some actors obtain strategic advantages in the network due to the network formation process.

Similar analyses are meanwhile available for other assumptions on what actors strive for in networks, such as the assumption that all actors in the network strive for (betweenness and closeness) centrality (Büchel & Buskens 2013), closure (Burger & Buskens 2009), or prepare their network for social exchange (Doğan et al. 2009). Note that there are also limitations to this approach. If only pairwise stability is considered, rather straightforward changes in the network through which all the involved actors can obtain better positions can be easily overlooked. Examples are cases in which one actor moves a relation from one partner to another partner. Because this involves three parties, the pairwise stability notion cannot account for this issue. Buskens & Van der Rijt (2008), therefore, pay some attention to refinements of pairwise stability. Another limitation of these simulations is that actors are actually considered as myopic. Actors change relations if this immediately pays off. However, a relational change of one pair of actors often causes that another pair of actors also want to change, and this second change is not necessarily beneficial for the first pair of actors. Therefore, the equilibrium concept has also been extended to versions that assume either perfect (Herings et al. 2009) or limited farsightedness of actors in the network (Morbitzer 2013; Morbitzer et al. 2014).

A growing and flourishing literature on network formation models has also been developed in physics, such as random graph models, preferential attachment models, and percolation models (see also Stauffer's chapter in this Handbook). Superficially, these models seem to be rather mechanistic, because they mostly do not assume strategic behavior of actors. However, the difference with the game-theoretic models is smaller than it seems at first sight. For example, preferential attachment models can be defined as models in which actors are just more likely to connect to others who have already more relations, but one could also define the utility function on the network in such a way that relations to actors with more relations are more valuable. Still, discussing these models is beyond the scope of this chapter and would not do justice to this rich literature. For an introduction to these models, we refer the reader to Newman (2010, in particular chapters 14-16).

4 Co-evolution of networks and behavior

Until now, we have discussed models for effects of networks on the outcomes of games (networks as explanans) and models for network formation (networks as explananda). In many situations, however, we see both types of processes at work: behavior in games is influenced by the network structure, and actors also have opportunities to change the network. In these cases, we can speak of *co-evolution* of networks and behavior.

As an example, consider the model by Raub & Weesie (1990), which shows that network embeddedness can promote cooperation in repeated Prisoner's Dilemmas by means of reputation effects. This model might be applied to R&D collaboration, in which firms share knowledge to create value but also run the risk of opportunistic behavior by their partners. In this situation, it seems plausible that firms would have the opportunity to pick their own interaction partners, and thus change the network. What is more, they also have *incentives* to do so: firms who had a bad experience with an opportunistic partner may want to abandon the interaction with this partner and instead seek a partner with a good reputation for cooperation, thereby (perhaps unintentionally) changing the network structure. In addition, if network embeddedness promotes cooperation via reputation effects, firms that want to engage in cooperative relations might actively pursue such network embeddedness by starting new interactions within densely knit clusters, while firms that intend to be opportunistic would do better to avoid embeddedness and instead seek interaction partners who do not interact with each other. Conversely, co-evolution of networks may also undermine reputation effects. If actors react to defection by a given partner by ending their relation with this partner, this change of the network may (again, unintentionally) prohibit the flow of information through the network, thereby limiting the effectiveness of reputation effects.

The example illustrates how network structure and behavior in strategic situations are likely to be interdependent. The example also gives an indication of the complexity of the mechanisms involved. As a result of this added complexity, theoretical understanding of the co-evolution of social networks and behavior in games is currently limited. Models of co-evolution tend to quickly become analytically intractable, and consequently, analyses relatively often rely on computational approaches.

4.1 Game theory: co-evolution of networks and behavior

An important distinction among co-evolution models, just as with games *on* networks as discussed above, is the choice of the underlying game. Earlier models of co-evolution focused on coordination games, perhaps for their relative simplicity (see Skyrms & Pemantle 2000). In coordination games, the actors' main aim is to play the same strategy as their interaction partners, there are no opportunities for opportunistic behavior, and hence there is little reason to model reputation effects such as in the Raub & Weesie (1990) model. For similar reasons, co-evolution of coordination and networks can often be modeled rather adequately by assuming myopic best reply behavior.

Typically, the Coordination Game assumed is a 2×2 game with a risk-dominant equilibrium and a payoff dominant equilibrium (i.e., a Stag-Hunt game). As such, these models build on the earlier models by Ellison (1993) and Young (1998) who study coordination in a fixed social structure and find that long-run stochastic dynamics always favor the risk-dominant (but socially suboptimal) equilibrium.

Jackson & Watts (2002) introduce a model in which actors not only choose their strategy in a repeated coordination game, but also choose their interaction partners, while relations are costly to maintain. They use the concept of stochastic stability to characterize equilibrium states. In this setup, also other states than the risk-dominant equilibrium turn out to be stable, depending on the cost of maintaining relations. Goyal & Vega-Redondo (2005) study a variation of this setup in which actors unilaterally create relations rather than bilaterally, as in Jackson & Watts (2002). Likewise, they find that the introduction of network dynamics allows for new types of equilibria, depending mostly on the cost of relations. However, this also leaves a problem of *equilibrium selection* in both models; within the boundaries of very general characterizations of equilibria, many different equilibria are possible, and formal game-theoretical approaches are typically insufficient to predict equilibria in specific cases. Simulation studies, addressed in the next section, address this issue.

4.2 Simulation: co-evolution of networks and behavior

Computational approaches to co-evolution of networks and behavior tend to complement analytical approaches in at least two respects. First, they help address the equilibrium selection problem sketched above. An example of this angle is the simulation study by Buskens et al. (2008), who consider a non-stochastic variant of the Jackson & Watts (2002) model of coordination in dynamic networks. Whereas Jackson & Watts provide a general characterization of a multitude of equilibria, Buskens et al. simulate the co-evolution process for a broad range of model parameters and initial conditions, and use statistical regression methods to predict which equilibria are more or less likely given these parameters and conditions, thereby partly solving the equilibrium selection problem. The simulation results show, for instance, that equilibria in which groups in a population coordinate on different actions (i.e., polarization) are less likely if the network is initially dense.

A second use of simulation studies is to obtain results for models that are too complex to study analytically. Typically, such complex models are the result of relaxing strong assumptions on interdependence and rationality that are made to keep models analytically tractable. An example of such complex assumptions are mechanisms of reputation effects in cooperation problems in dynamic networks, as discussed above. Consequently, studies of cooperation in dynamic networks tend to be computational rather than analytical. A good example of such studies is presented by Vega-Redondo (2006), who examines the role of volatility in a situation in which networks and cooperation co-evolve. In this model, actors play dyadic Prisoner's Dilemmas with multiple partners, and receive information about the behavior of other actors via the interaction network. At the same time, actors have the possibility to choose their own interaction partners. Volatility of the environment is introduced by drawing payoffs for each interaction afresh in each round of the game with some probability ε. Equilibrium of the network is defined in terms of pairwise stability, as defined earlier in this chapter. Using simulations and mean field analysis,[8] Vega-Redondo is able to show

[8] Mean field analysis is a technique in which the behavior of a complex system of interacting individuals is approximated by averaging individual effects.

that as volatility increases, the network endogenously adapts by becoming denser, thereby sustaining high cooperation levels. This result emphasizes the role of networks as an emergent phenomenon, or unintended consequence of individual action. Similarly, Hanaki et al. (2006) use a simulation model to study the co-evolution of cooperation and networks assuming that actors imitate their best-performing neighbor in the network. Somewhat counter-intuitively, they find that cooperation is most likely to emerge if costs of relations are relatively high.

A somewhat similar situation is studied by Corten & Cook (2009), who model reputation effects on cooperation in dynamic networks under the assumption that actors use learning heuristics to determine their choices of relations and cooperation levels. In contrast to Vega-Redondo (2006), they explicitly study the effect of reputation effects (i.e., the importance of information diffusion) on cooperation. They find that reputation does not necessarily promote cooperation, but rather increases the range of possible equilibria. Another conclusion is that network density is more likely to be a result of successful cooperation than vice versa.

The above discussion indicates that despite existing efforts, many aspects of the co-evolution of behavior and networks remain unexplored. In concluding this section, we point at two open questions that we think deserve further attention. First, in most existing co-evolution models, information diffusion through networks is at best a "by-product" of network formation, which actors then use to optimize their choices in games played on the networks. However, arguments about social capital suggest that actors would strategically invest in network relations, with the explicit intention of influencing the flow of information in the network (we already hinted at such mechanisms above). Some first steps in this direction are taken by Frey et al. (2013) and Raub et al. (2013) who study investments in network relations in co-evolution with behavior in trust games and other social dilemmas.

A second restricting assumption in existing models is that the network of information exchange typically coincides with the interaction network; that is, actors exchange information if and only if they also play a game together. For many applications, however, it seems reasonable that these decisions can be taken more or less independently.

5 Conclusions and suggestions for further reading

Models of social networks as sketched in this chapter have obvious strengths. Assumptions are clearly specified, with an eye on a clear distinction between assumptions on macro- and micro-conditions, assumptions that relate the macro- with the micro-level, and assumptions on behavioral regularities. Thus, the explicit focus on macro-micro-macro links is an appealing feature of these models. In this way, progress has been made in closing Granovetter's (1979) "theory gap". Analytical methods and simulations are employed to systematically derive implications from the model assumptions. Implications include testable hypotheses and also often include non-obvious or even counter-intuitive predictions. Indeed, empirical research actually testing hypotheses is in full swing in the field of research on social networks. Goldthorpe (2007) has offered influential arguments for an alliance of rational actor models and quantitative survey research in sociology. Goldthorpe's program can be broadened at the theoretical end by including not only rational actor models but also alternative assumptions on behavioral regularities that fit into macro-micro-macro models. Also, the program can be broadened at the empirical end by complementing survey research with experimental research and the use of quasi-experimental designs. Finally, the program seems not only attractive for sociology but also for other social sciences. Quite some of current theoretical and empirical research on social networks can then be seen as an implementation of such a broad version of Goldthorpe's program (see also various contributions in Wittek et al. 2013).

Typical problems of models for social networks likewise become transparent. For example, consider problems related to assumptions on micro-level regularities of behavior (arrow 2 in Coleman's scheme). In a sense, current research faces a trade-off concerning these assumptions. On the one hand, it would be desirable for various reasons to use the same and preferably parsimonious assumptions on micro-level regularities in different models. After all, for methodological reasons, one would *ceteris paribus* prefer assumptions on micro-level regularities with high testability that are consistently applicable in a broad class of models. Also, it seems hard to defend that individual behavior obeys different behavioral *regularities* in different contexts. While it seems natural that actors behave differently under different circumstances, it would be surprising if the regularities underlying individual behavior in social dilemma situations are inherently different from those underlying behavior when it comes to establishing, maintaining or severing relations with partners. Such concerns provide reasons for using perfect rationality assumptions with respect to behavioral regularities. These assumptions are in principle broadly applicable and parsimonious.

On the other hand, in network contexts, these assumptions are also problematic, often more so than in other contexts. For example, game-theoretic models for learning effects of network embeddedness on behavior in social dilemmas assume that incomplete information is updated using Bayes' rule (see also the chapter by Benner & Poppe in this Handbook). Thus, such models use very strong assumptions concerning the strategic rationality of actors. Also, when it comes to network formation, let alone network formation in a sizeable network, assuming perfect strategic rationality implies that actors behave as if they can foresee all the consequences of their own decisions with respect to establishing, maintaining, or severing relations for future networking decisions by other actors, since these future decisions may be affected by previous networking decisions and may have repercussions for payoffs of other actors (see Page et al. 2005; Dutta et al. 2005; Herings et al. 2009; Pantz 2006 for work in this direction). It is not only doubtful whether actors can optimize in this way, it is also often impossible for the *modeler* to solve such optimization problems. These problems are exacerbated since macro-outcomes in interdependent contexts and certainly so in network contexts are often *not* robust when assumptions on behavioral regularities are modified (see Raub et al. 2011 for further references).

Problems associated with using perfect rationality assumptions in social network research have induced the use of alternative behavioral models, such as pure learning models or the assumption of myopic best-response behavior in models of network formation. The drawback then is that different assumptions on behavioral regularities are used for different contexts and also that such behavioral assumptions might be too radical in assuming away any kind of strategic rationality. Also, empirically observed outcomes are not always consistent with the predictions following from models that employ extreme assumptions on myopic behavior (e.g., Callander & Plott 2005; Pantz 2006; Berninghaus et al. 2012; Corten & Buskens 2010). Research on models that assume "some" but less than perfect strategic rationality thus seems attractive but is still in its infancy (see Berninghaus et al. 2012 and Morbitzer 2013; Jackson 2008: chap. 8 provides an overview and further references).

This chapter provides a selective overview of models on network effects, network formation, and the co-evolution of networks and behavior. Quite some models could not be addressed. This includes, for example, theoretical refinements and empirical applications of Coleman's (1973) exchange model in network contexts (e.g., Marsden 1983; Braun 1993), the sociological literature on network exchange (see Willer 1999 and Braun & Gautschi 2006 for overviews), and models of collective decisions in policy networks (e.g., Stokman et al. 2000). Another important and relatively recent development are actor-oriented models for the statistical analysis of network data that have strong links to the theoretical models discussed in this chapter and provide important tools for closely integrating theoretical and statistical modeling (see Snijders 2013 for an overview). Finally, there is a presumably seminal literature emerging that studies online social networks: web-based services that allow users to maintain social relations. These services – such as Facebook or Twitter – have become immensely popular and since relations via these services are mediated by technology, they allow in principle for detailed longitudinal observations of networks and certain types of behavior (see Leskovec et al. 2008 and Corten 2012 for examples of models and empirical applications).

References

Antal, T., P. L. Krapivsky and S. Redner (2005) "Dynamics of Social Balance on Networks." *Physical Review E* 72: 036121.

Axelrod, R. (1984) *The Evolution of Cooperation.* New York: Basic Books.

Bala, V. and S. Goyal (2000) "A Noncooperative Model of Network Formation." *Econometrica* 68: 1181–1229.

Barabási, A.-L. and R. Albert (1999) "Emergence of Scaling in Random Networks." *Science* 286: 509–512.

Berninghaus, S. K., K.-M. Ehrhart and M. Ott (2012) "Forward-Looking Behavior in Hawk-Dove Games in Endogenous Networks: Experimental Evidence." *Games and Economic Behavior* 75: 35–52.

Blau, P. M. ([1964] 1996) *Exchange and Power in Social Life.* New Brunswick, NJ: Transaction Publishers.

Bolton, G. E. and A. Ockenfels (2009) "The Limits of Trust in Economic Transactions. Investigations of Perfect Reputation Systems." Pp. 15–36 in: K. S. Cook, C. Snijders, V. Buskens and C. Cheshire (Ed.) *eTrust: Forming Relationships in the Online World.* New York: Russell Sage.

Braun, N. (1993) *Socially Embedded Exchange.* Frankfurt a.M.: Lang.

Braun, N. and T. Gautschi (2006) "A Nash Bargaining Model for Simple Exchange Networks." *Social Networks* 28: 1–23.

Buchanan, M. (2002) *Nexus: Small Worlds and the Groundbreaking Science of Networks.* New York: Norton.

Büchel, B. and V. Buskens (2013) "Dynamics of Closeness and Betweenness." *Journal of Mathematical Sociology* 37: 159–191.

Büchel, B. and T. Hellmann (2012). "Under-Connected and Over-Connected Networks: The Role of Externalities in Strategic Network Formation." *Review of Economic Design* 16: 71–87.

Burger, M. and V. Buskens (2009) "Social Context and Network Formation: An Experimental Study." *Social Networks* 31: 63–75.

Burt, R. S. (1992) *Structural Holes. The Social Structure of Competition.* Cambridge, MA: Harvard University Press.

Burt, R. S. (2005) *Brokerage and Closure: An Introduction to Social Capital.* Oxford: Oxford University Press.

Buskens, V. (2002) *Social Networks and Trust.* Boston, MA: Kluwer.

Buskens, V. (2003) "Trust in Triads: Effects of Exit, Control, and Learning." *Games and Economic Behavior* 42: 235–252.

Buskens, V., R. Corten and J. Weesie (2008) "Consent or Conflict: Coevolution of Coordination and Networks." *Journal of Peace Research* 45: 205–222.

Buskens, V. and W. Raub (2002) "Embedded Trust: Control and Learning." *Advances in Group Processes* 19: 167–202.

Buskens, V. and W. Raub (2013) "Rational Choice Research on Social Dilemmas: Embeddedness Effects on Trust." Pp. 113–150 in: R. Wittek, T.A.B. Snijders and V. Nee (Ed.) *Handbook of Rational Choice Social Research.* Stanford, CA: Stanford University Press.

Buskens, V. and A. van de Rijt (2008) "Dynamics of Networks if Everyone Strives for Structural Holes." *American Journal of Sociology* 114: 371–407.

Buskens, V. and K. Yamaguchi (1999) "A New Model for Information Diffusion in Heterogeneous Social Networks." *Sociological Methodology* 29: 281–325.

Callander, S. and C. R. Plott (2005) "Principles of Network Development and Evolution: An Experimental Study." *Journal of Public Economics* 89: 1469–1495.

Calvó-Armengol, A. and R. İlkiliç (2009) "Pairwise-Stability and Nash Equilibria in Network Formation." *International Journal of Game Theory* 38: 51–79.

Cartwright, D. and F. Harary (1956) "Structural Balance: A Generalization of Heider's Theory." *Psychological Review* 63: 277–293.

Christakis, N. and J. Fowler (2011) *Connected. The Amazing Power of Social Networks and How They Shape Our Lives.* London: Harper.

Coleman, J. S. (1973) *The Mathematics of Collective Action.* London: Heinemann.

Coleman, J. S. (1987) "Microfoundations and Macrobehavior." Pp. 155–173 in: J. C. Alexander, B. Giesen, R. Münch and N. J. Smelser (Ed.) *The Micro-Macro Link.* Berkely, CA: University of California Press.

Coleman, J. S. (1988) "Social Capital in the Creation of Human Capital." *American Journal of Sociology* 94: S95–S120.

Coleman, J. S. (1990) *Foundations of Social Theory.* Cambridge, MA: Belknap Press of Harvard University Press.

Coleman, J. S., E. Katz and H. Menzel (1966) *Medical Innovation: A Diffusion Study.* Indianapolis, IN: Bobbs-Merrill.

Corten, R. (2012) "Composition and Structure of a Large Online Social Network in the Netherlands." *PLoS ONE* 7: e34760. doi:10.1371/ journal.pone.0034760

Corten, R. (2014) *Computational Approaches to Studying the Co-evolution of Networks and Behavior in Social Dilemmas.* Chichester: Wiley.

Corten, R. and V. Buskens (2010) "Co-evolution of Conventions and Networks: An Experimental Study." *Social Networks* 32: 4–15.

Corten, R. and V. Buskens (2011) "Game Theory and Networks." Pp. 303–306 in: G. A. Barnett (Ed.) *Encyclopedia of Social Networks.* London: Sage.

Corten, R. and K. S. Cook (2009) "Cooperation and Reputation in Dynamic Networks." in: M. Paolucci (Ed.) *Proceedings of the First International Conference on Reputation: Theory and Technology* – ICORE 09, Gargonza, Italy.

Demange, G. and M. Wooders (Ed.) (2005) *Group Formation in Economics. Networks, Clubs, and Coalitions.* Cambridge: Cambridge University Press.

Diekmann, A. (2004) "The Power of Reciprocity." *Journal of Conflict Resolution* 48: 487–505.

Doğan, G., M. A. L. M. van Assen, A. van de Rijt and V. Buskens (2009) "The Stability of Exchange Networks." *Social Networks* 31:118–125.

Doreian, P. and F. N. Stokman (Ed.) (1997) *Evolution of Social Networks.* Amsterdam: Gordon and Breach.

Dutta, B., S. Ghosal and D. Ray (2005) "Farsighted Network Formation." *Journal of Economic Theory* 122: 143–164.

Dutta, B. and M. O. Jackson (Ed.) (2003) *Networks and Groups. Models of Strategic Formation.* Berlin: Springer.

Eguiluz, V. M., M. G. Zimmermann, C. J. Cela-Conde and M. San Miguel (2005) "Cooperation and Emergence of Role Differentiation in the Dynamics of Social Networks." *American Journal of Sociology* 110: 977–1008.

Ellison, G. (1993) "Learning, Local Interaction, and Coordination." *Econometrica* 61: 1047–1071.

Fainmesser, I. P. (2012) "Community Structure and Market Outcomes: A Repeated Games-in-Networks Approach." *American Economic Journal: Microeconomics* 4: 32–69.

Flap, H. (2004) "Creation and Returns of Social Capital." Pp. 3–23 in: H. Flap and B. Völker (Ed.) *Creation and Returns of Social Capital.* London: Routledge.

Flap, H. and B. Völker (2013) "Social Capital." Pp. 220–251 in: R. Wittek, T. A. B. Snijders and V. Nee (Ed.) *Handbook of Rational Choice Social Research.* Stanford, CA: Stanford University Press.

Frey, V., V. Buskens and W. Raub (2013) "Embedding Trust: A Game-Theoretic Model for Investments in and Returns on Social Capital." Forthcoming in: *Journal of Mathematical Sociology.*

Goldthorpe, J. (2007) *On Sociology.* Stanford, CA: Stanford University Press.

Gouldner, A. W. (1960) "The Norm of Reciprocity." *American Sociological Review* 25: 161–178.

GOYAL, S. (2007) *Connections. An Introduction to the Economics of Networks.* Princeton, NJ: Princeton University Press.

GOYAL, S. AND F. VEGA-REDONDO (2005) "Network Formation and Social Coordination." *Games and Economic Behavior* 50: 178–207.

GRANOVETTER, M. S. (1973) "The Strength of Weak Ties." *American Journal of Sociology* 78: 1360–1380.

GRANOVETTER, M. S. (1974) *Getting a Job. A Study of Contacts and Careers.* Cambridge, MA: Harvard University Press.

GRANOVETTER, M. S. (1979) "The Theory-Gap in Social Network Analysis." Pp. 501–518 in: P. W. HOLLAND AND S. LEINHARDT (Ed.) *Perspectives on Social Network Research.* New York: Academic Press.

GRANOVETTER, M. S. (1985) "Economic Action and Social Structure: The Problem of Embeddedness." *American Journal of Sociology* 91: 481–510.

HANAKI, N., A. PETERHANSL, P. S. DODDS AND D. J. WATTS (2006) "Cooperation in Evolving Social Networks." *Management Science* 53: 1036–1050.

HEDSTRÖM, P. (2005) *Dissecting the Social. On the Principles of Analytical Sociology.* Cambridge: Cambridge University Press.

HERINGS, P. J.-J., A. MAULEON AND V. VANNETELBOSCH (2009) "Farsightedly Stable Networks." *Games and Economic Behavior* 67: 526–541.

JACKSON, M. O. (2008) *Social and Economic Networks.* Princeton, NJ: Princeton University Press.

JACKSON, M. O., T. RODRIGUEZ-BARRAQUER AND X. TAN (2012) "Social Capital and Social Quilts: Network Patterns of Favor Exchange." *American Economic Review* 102: 1857–1897.

JACKSON, M. O. AND A. WATTS (2002) "The Evolution of Social and Economic Networks." *Journal of Economic Theory* 106: 265–295.

JACKSON, M. O. AND A. WOLINSKY (1996) "A Strategic Model of Social and Economic Networks." *Journal of Economic Theory* 71: 44–74.

JACKSON, M. O. AND Y. ZENOU (2013) *Economic Analyses of Social Networks.* London: Edward Elgar.

KRETZSCHMAR, M. AND J. WALLINGA (2007) "Editorial: Networks in Epidemiology." *Mathematical Population Studies* 14: 203–209.

LESKOVEC, J., L. BACKSTROM, R. KUMAR AND A. TOMKINS (2008) "Microscopic Evolution of Social Networks." Pp. 462–470 in: *Proceeding of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '08, ACM, New York, USA.

LIN, N. (2001) *Social Capital: A Theory of Social Structure and Action.* New York: Cambridge University Press.

LINDENBERG, S. (1977) "Individuelle Effekte, kollektive Phänomene und das Problem der Transformation." Pp. 46–84 in: K. EICHNER AND W. HABERMEHL (Ed.) *Probleme der Erklärung sozialen Verhaltens.* Meisenheim: Hain.

LINDENBERG, S. (1981) "Erklärung als Modellbau." Pp. 20–35 in: W. SCHULTE (Ed.) *Soziologie in der Gesellschaft.* Bremen: Zentraldruckerei der Universität.

MACY, M. W. AND A. FLACHE (2002) "Learning Dynamics in Social Dilemmas." *Proceedings of the National Academy of Sciences USA* 99: 7229–7236.

MARSDEN, P. V. (1983) "Restricted Access in Networks and Models of Power." *American Journal of Sociology* 88: 686–717.

McPherson, M., L. Smith-Lovin and J. M. Cook (2001) "Birds of a Feather: Homophily in Social Networks." *Annual Review of Sociology* 27: 415–444.

Merton, R. K. (1936) "The Unanticipated Consequences of Purposive Social Action." *American Sociological Review* 1: 894–904.

Morbitzer, D. (2013) *Limited Farsightedness in Network Formation.* PhD thesis, Utrecht.

Morbitzer, D., V. Buskens, S. Rosenkranz and W. Raub (2014) "How Farsightedness Affects Network Formation." *Analyse & Kritik* 36: 103–133.

Morris, M., J. Zavisca and L. Dean (1995) "Social and Sexual Networks: Their Role in the Spread of HIV/AIDS among Young Gay Men." *AIDS Education and Prevention* 7: 24–35.

Newman, M. E. J. (2010) *Networks: An Introduction.* Oxford: Oxford University Press.

Nowak, M. A. and R. M. May (1992) "Evolutionary Games and Spatial Chaos." *Nature* 359: 826–829.

Ohtsuki, H., C. Hauert, E. Lieberman and M. A. Nowak (2006) "A Simple Rule for the Evolution of Cooperation on Graphs and Social Networks." *Nature* 441: 502–505.

Page, F. H. Jr., M. H. Wooders and S. Kamat (2005) "Networks and Farsighted Stability." *Journal of Economic Theory* 120: 257–269.

Pantz, K. (2006) *The Strategic Formation of Social Networks: Experimental Evidence.* Aachen: Shaker.

Pujol, J. M., A. Flache, J. Delgado and R. Sangüesa (2005) "How Can Social Networks Ever Become Complex? Modelling the Emergence of Complex Networks from Local Social Exchanges." *Journal of Artificial Societies and Social Simulation* 8 `http://jasss.soc.surrey.ac.uk/8/4/12.html`.

Rapoport, A. (1974) "Prisoner's Dilemma – Recollections and Observations." Pp. 18–34 in: A. Rapoport (Ed.) *Game Theory as a Theory of Conflict Resolution.* Dordrecht: Reidel.

Rasmusen, E. (2007) *Games and Information: An Introduction to Game Theory.* (4th edition) Oxford: Blackwell.

Raub, W. (2010) "Theorien und Theoreme der Netzwerkforschung: Rational Choice." Pp. 269–280 in: C. Stegbauer and R. Häussling (Ed.) *Handbuch der Netzwerkforschung.* Wiesbaden: VS Verlag für Sozialwissenschaften/Springer Fachmedien.

Raub, W., V. Buskens and M. A. L. M. van Assen (2011) "Micro-Macro Links and Microfoundations in Sociology." *Journal of Mathematical Sociology* 35: 1–25.

Raub, W., V. Buskens and V. Frey (2013) "The Rationality of Social Structure: Cooperation in Social Dilemmas through Investments in and Returns on Social Capital." *Social Networks* 35: 720–732.

Raub, W. and J. Weesie (1990) "Reputation and Efficiency in Social Interactions: An Example of Network Effects." *American Journal of Sociology* 96: 626–654.

Schelling, T. C. (1978) *Micromotives and Macrobehavior.* New York: Norton.

Skyrms, B. and R. Pemantle (2000) "A Dynamic Model of Social Network Formation." *Proceedings of the National Academy of Sciences USA* 97: 9340–9346.

Snijders, T. A. B. (2001) "The Statistical Evaluation of Social Network Dynamics." *Sociological Methodology* 2001: 361–395.

Snijders, T. A. B. (2013) "Network Dynamics." Pp. 252–279 in: R. Wittek, T. A. B. Snijders and V. Nee (Ed.) *Handbook of Rational Choice Social Research.* Stanford, CA: Stanford University Press.

Stokman, F., M. A. L. M. van Assen, J. van der Knoop and R. C. H. van Oosten (2000) "Strategic Decision Making." *Advances in Group Processes* 17: 131–153.

Stokman, F. N. and P. Doreian (Ed.) (2001) *Evolution of Social Networks. Part II. Special issue of Journal of Mathematical Sociology* 25.

Szabó, G. and G. Fáth (2007) "Evolutionary Games on Graphs." *Physics Reports* 446: 97–216.

Taylor, M. ([1976] 1987) *The Possibility of Cooperation.* Cambridge: Cambridge University Press. Rev. ed. of *Anarchy and Cooperation.* London: Wiley.

Valente, T. W. (1995) *Network Models of the Diffusion of Innovations.* Cresskill, NJ: Hampton Press.

Vega-Redondo, F. (2006) "Building up Social Capital in a Changing World." *Journal of Economic Dynamics and Control* 30: 2305–2338.

Vega-Redondo, F. (2007) *Complex Social Networks.* Cambridge: Cambridge University Press.

Wasserman, S. and K. Faust (1994) *Social Network Analysis. Methods and Applications.* Cambridge: Cambridge University Press.

Watts, A. (2001) "A Dynamic Model of Network Formation." *Games and Economic Behavior* 34: 331–341.

Watts, D. J. and S. H. Strogatz (1998) "Collective Dynamics of 'Small World' Networks." *Nature* 393: 440–442.

Weibull, J. W. (1995) *Evolutionary Game Theory.* Cambridge, MA: MIT Press.

Willer, D. (Ed.) (1999) *Network Exchange Theory.* Westport, CN: Praeger.

Wippler, R. and S. Lindenberg (1987) "Collective Phenomena and Rational Choice." Pp. 135–151 in: J. C. Alexander, B. Giesen, R. Münch and N. J. Smelser (Ed.) *The Micro-Macro Link.* Berkely, CA: University of California Press.

Wittek, R., T. A. B. Snijders and V. Nee (Ed.) (2013) *Handbook of Rational Choice Social Research.* Stanford, CA: Stanford University Press.

Yamagishi, T. and M. Yamagishi (1994) "Trust and Commitment in the United States and Japan." *Motivation and Emotion* 18: 129–166.

Young, H. P. (1998) *Individual Strategy and Social Structure.* Princeton, NJ: Princeton University Press.