Limited Farsightedness in Network Formation

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Chapter 1

Introduction and Discussion

1.1 Two examples of network formation

Example 1: Co-authors

Imagine a network of researchers who collaborate in pairs. The success of a project, in terms of each researcher's benefits, depends on the time both researchers invest in the joint project and a synergy effect. As time of each researcher is scarce, he[1] will spend more time on a given project the less projects he is simultaneously involved in. Therefore, it is beneficial for each researcher to work with colleagues who only have few other projects. An individual's optimal situation would be to work with many others who themselves only work on the joint project with the first individual. Researchers thus have an incentive to connect to less connected researchers.

Consider the following situation as shown in figure 1.1: researchers A and B are working together on a project, both receiving a total benefit of 60.[2] Also, researchers C and D are working together on a project. Researchers A and C both benefit if they start working on a project with each other. Both would then receive a total benefit of 65. However, if they establish this relation, this will also influence the project A has with B, and C has with D. Both

[1] I use masculine pronouns throughout the book for readability without intending any gender-bias.

[2] The precise calculation of the benefits will be described in later chapters.

researchers A and C work on two projects now, and have to divide their time over the projects. Therefore, the projects of A and B, and C and D become less beneficial for the researchers involved. Researchers B and D would now receive a benefit of 40. B and D also have an incentive to work together on a project, and even more so if A and C already work together. If B and D do so, this again has a negative influence on the joint projects with both A and C. In the final network situation (see figure 1.1), where each researcher receives a benefit of 50, everybody is worse off than in the initial situation, where only A and B, and C and D were working together. If researchers A and C would have been farsighted and anticipated the consequences of their initial decision, they would have refrained from working together, and everybody would have been better off.

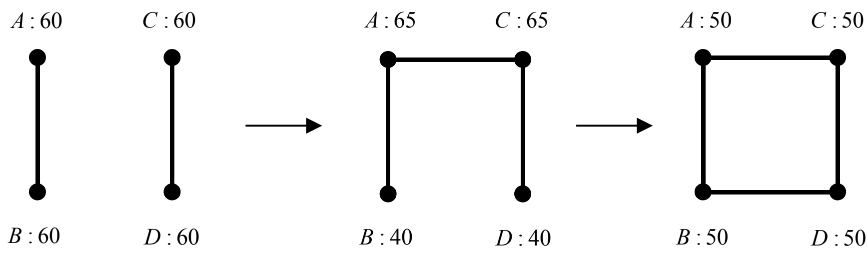


Figure 1.1: Network formation example 1: Co-authors

Example 2: Finding a job

Students A, B, C, and D share information about job openings after graduation. Assuming that there is no competition for job openings among the students, the students receive potentially valuable information about an interesting open position from other students with whom they are directly or indirectly connected. Suppose that being indirectly connected to another student (a friend of a friend) will give a student less valuable information than information from a direct contact (a friend). However, direct relations need to be maintained, which takes time and effort. If these costs of maintaining direct relations become rather high, then it is best to be connected to few other students, who themselves have many other contacts.

Imagine that in such a situation student A has direct relations to B, C, and D, but all of them only have a direct relation to A. In that case B, C, and D are in the most beneficial position, as they get information from indirect contacts via A, but only have to maintain the relation to A. This gives them a net benefit from the information of 110 (see figure 1.2). For student A, however, this situation is less favorable, as he must maintain all relations to the other students, giving him a net benefit of 30. If student A would only look at the immediate consequence of his decision, then he would not cut a relation to one of the other students, because this would be an even less beneficial situation for student A. Therefore, the initial network would be stable because no student has an incentive to create or cut relations. However, after student A would cut a relation, students C and D might establish a relation, and thereby also benefit student A who now would have an indirect relation as well. This network position would give him information with a benefit of 70. So a farsighted student A would maneuver himself out of the central position in order to end up in a different position where he is better off. Given this context, farsighted students would even prevent becoming a central actor and try to connect to a central actor instead.

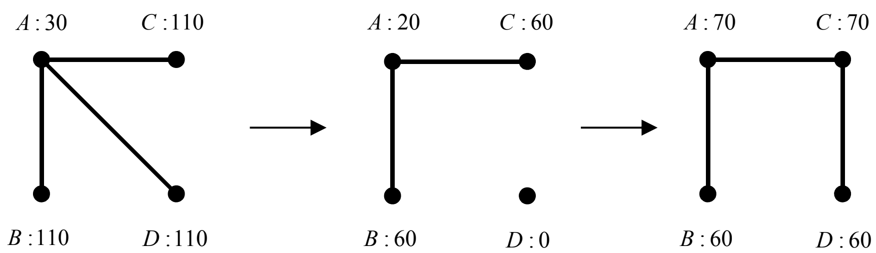


Figure 1.2: Network formation example 2: Finding a job

Naturally, questions arise: Which networks are formed by the actors in the examples described above, and how do the networks look like? Who has the most beneficial network position, and is the network societally efficient?

As the examples show, the answers depend on whether we assume actors to be only looking at the immediate consequence of their decisions, i.e., to be myopic, or whether we assume that they anticipate reactions of other actors, i.e., that they are farsighted.

The two situations described above correspond with two well-known models for how networks generate utility for actors, namely, the co-author and the connections model (Jackson and Wolinsky, 1996). The highly stylized examples capture several aspects that are important in situations in which people strategically form networks. People nowadays use the term "networking" to describe such behavior. Strategic social networking is an important explanatory mechanism concerning the social fabric and cohesion of today's societies (Buskens and Van de Rijt, 2008). In the following section we introduce the relevant literature on social and economic network formation and the role of farsightedness in this literature so far.

1.2 Limited farsightedness in network formation

Because social relationships can be beneficial, actors have incentives to strategically invest in their relations (Flap, 2004). Within these networks of relations, actors maintain different positions, which can influence their outcomes (Burt, 1992; Uzzi, 2008). Given that network positions matter for the attainment of goals, and given that actors have an idea of the structure of relations between each other, they arguably try to maneuver themselves into beneficial network positions (Krackhardt, 1987; Burt, 1992). Decisions of actors in networks do not only have an effect on their own positions and outcomes, but they also have an effect on the positions and therefore the outcomes of others in the network. It is often assumed that actors in such complex and dynamic network situations neglect subsequent decisions of other people. This is referred to as myopic best response behavior. The main motivation to assume such bounded rationality (Rubinstein, 1998) is descriptive plausibility (Goyal, 2007). Standard rationality models would assume actors to be perfectly rational and in that sense perfectly farsighted. Perfectly rational actors who are able to foresee all possible reactions of others in a complex setting like in dynamic networks appear unrealistic, as humans are unlikely to be capable to perform such complex cognitive tasks. However, as described in the examples above, if actors are not only looking at their immediate gain, but anticipate the reactions of others at least to a limited extent, this already might have consequences for the formation of social networks. As Jackson (2008) argues, actors might be more farsighted when they have a good idea of the setting and the incentives that drive actors when creating and deleting links. Therefore, it is worthwhile to study how individual behavior, in terms of actors' farsightedness, changes the formation of social networks.

We systematically study the effects of individual decision-making on the emergence of networks. Formal modeling is necessary to analyze the non-trivial consequences of micro-level behavior on macro-level outcomes. This relates to a broader discussion on model building in sociology (see Raub et al., 2011). Coleman's scheme (see figure 1.3 and figure 1.4 as a specification for network models) is the standard way of representing such micro-macro models (Coleman, 1990).

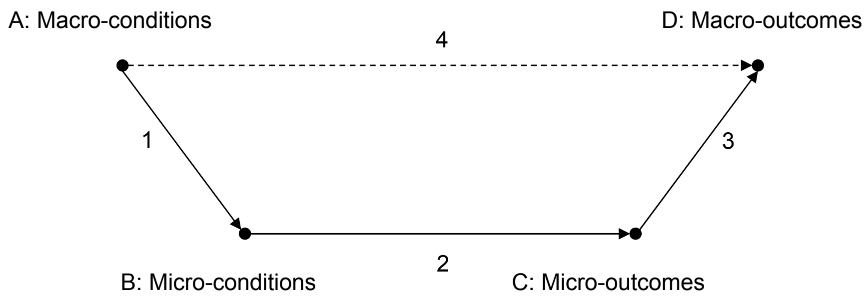


Figure 1.3: Coleman's scheme

The scheme illustrates how social macro-level phenomena (node D in figures 1.3 and 1.4) can be explained. Social macro-level conditions (node A in figures 1.3 and 1.4), in which actors are embedded, such as networks or institutions, can be conceived as opportunities or constraints for the actors. Macro-level conditions shape incentives and information related to alternatives between which actors can choose (arrow 1, also referred to as bridge assumptions). Social phenomena are explained as results, and often as unintended consequences, of purposive behavior of actors. In social network formation, macro-level conditions and macro-level phenomena are the networks actors are embedded in (node A in figure 1.4). Micro-conditions (node B in figure 1.3 and 1.4) might include assumptions or theories on actors' preferences. As a consequence of their purposive behavior of choosing relations with others, actors can alter their own links in the network (node C in figure 1.4). Arrow 3 represents assumptions how actors' behavior generates macro-outcomes, also referred to as transformation rules. It is obvious how the scheme can be expanded to social networks and their dynamics. The new network, as the macro-level outcome, can be seen as the macro-level condition in a subsequent step of explanation (see figure 1.4).

Figure 1.4: Network formation in Coleman's scheme

Micro-level theories about regularities of individual behavior such as assumptions on myopic best response behavior or, respectively, assumptions on perfect or limited farsightedness are needed in micro-macro models. These assumptions are represented by arrow 2. Rational choice theory and game theory can be interpreted as specifications of the idea of incentive-driven and goal-directed behavior. They are examples of microfoundations of these models. Arrow 2 in figures 1.3 and 1.4 then represents the assumption of equilibrium behavior. While some researchers claim that system behavior is robust to many individual level modifications (Coleman, 1986; Becker, 1976), we argue that elaborating on microfoundations indeed can have non-trivial implications on macro-level outcomes (cf. Schelling, 1978; Raub and Snijders, 1997). The examples presented above show that in the context of network formation, farsightedness of actors affects the formation process and therefore potentially its outcome. Additionally, standard rationality assumptions are far from being undisputed. Many experimentally observed macro-outcomes, for instance in public good games, can hardly be explained with micro-level theories such as standard rationality assumptions (see Camerer, 2003, for an overview of results and alternative micro-level theories).

In recent years, game-theoretic tools have been developed to analyze possible outcomes of social network formation processes. Game theory describes situations where rational actors make strategic decisions in which their own outcome also depends on the decisions of other actors and vice versa. It is assumed that actors take the interdependence of decisions into account. In game-theoretic terms, assuming purposive behavior, every actor maximizes own utility, given the other actors' strategies. Rationality of actors is assumed to be common knowledge such that all actors know that all actors are rational, all know this, all know *this*, and so on ad infinitum (see e.g. Aumann, 1995). Additionally, in situations where actors are embedded in networks, it also must be assumed that actors take the structural component of networks into account, in order to put themselves in an optimal network position. Only in recent years researchers started to investigate how and why specific network structures emerge the way they do, assuming that people have the discretion to change their network (Goyal, 2007; Vega-Redondo, 2007; Jackson, 2008). More specifically, strategic network formation models build upon assumptions that actors derive utility from networks and from network effects. Also, actors have the means to choose with whom to interact, i.e., with whom to maintain a relation. Thus, networks and their characteristics are not perceived as exogenously fixed structures but as resulting endogenously from the decisions of actors who can build, maintain, or delete links with others (Jackson and Wolinsky, 1996; Bala and Goyal, 2000). In what is often referred to as *pure* network formation models, utility is a function of the network itself, i.e., actors receive benefits from specific positions within these networks. The predefined way in which network structure determines an actor's outcome, is referred to as the utility function of the network formation process. The way in which links are built and deleted can follow different kinds of protocols (in the terminology of micro-macro models, this would be referred to as the bridge assumptions and the transformation rules). Such rules might include assumptions on the set of links actors can change, or the ordering in which actors make decisions. For instance, models such as the one described in Bala and Goyal (2000), depict network formation as a one-shot game in which all links are established at the same time. In other models, including the one we build upon in the following chapters, actors build or remove their links one at a time, in a dynamic process (Jackson and Watts, 2002). The latter approach seems better suited for modeling social network formation processes, because in real life situations linking decisions hardly occur at the same time, but rather happen over time. A network is considered stable when no pair of actors wants to change their relation anymore. In such dynamic models, the standard micro-level assumption is the so-called myopic best response assumption. Myopic best response is a behavioral heuristic used in dynamic models. In network formation, myopic actors look one step ahead and only consider whether they are better off after adding or severing one link, neglecting possible future reactions of other actors. Yet, creating or deleting a link might lead to the subsequent creation or deletion of other links through other actors' decisions. Therefore, actors might also use more complex heuristics to determine which links with others they want to change, e.g., actors might use more farsighted strategies in these processes, taking subsequent decisions of others into account.

In the literature on network formation we encounter extensions of the myopia assumption. The first alternative is to go to the opposite extreme and assume that actors are perfectly farsighted (Page et al., 2005; Dutta et al., 2005; Herings et al., 2009; Pantz, 2006). This implies that actors consider sequences of changes of arbitrary length in the network towards a given destination network. Such a sequence of changes is feasible if all actors who determine a change in the intermediate steps prefer their position in the destination network to their network position at the moment they implement the change. Here, the assumption that rationality is common knowledge is crucial. As argued before, the increasing complexity of larger networks makes the assumption of perfect farsightedness unrealistic. In addition, the existing models with perfectly farsighted actors do not provide clear-cut predictions for arbitrary networks, but mostly provide general theorems on conditions for stability with some examples for specific utility functions.

Next to the theoretical arguments to develop network formation models with farsightedness, experimental research on network formation shows that myopia models sometimes fail to predict empirically observed outcomes (Callander and Plott, 2005; Pantz, 2006; Berninghaus et al., 2012; Van Dolder and Buskens, 2008; Corten and Buskens, 2010). The observed deviations from myopic best response behavior may be explained when assuming at least some anticipatory behavior of actors. Furthermore, the results of Pantz (2006) and Berninghaus et al. (2012) suggest that actors are neither completely myopic, nor perfectly farsighted, suggesting some form of limited farsightedness of actors.

Remark 1. *We also find support for limited farsightedness in related fields. Foreseeing reactions of changing relations means that people have to consider possible countermoves of others and of themselves. This ability is related to the ability of iterated reasoning. To investigate iterated reasoning of subjects, researchers use dominance-solvable games such as the beauty contest game (see Nagel, 1999, for a survey). Camerer (2003) shows that in games in which it is rather easy to reason ahead, actors use more than one step but still are less than perfectly farsighted. Iterated reasoning and the beauty contest game will be discussed in more detail in later chapters.*

We build a model of network formation, where we vary assumptions about actors' level of farsightedness: actors are not necessarily myopic but are limited when looking ahead. We use computer simulations to derive predictions on stable networks under the new behavioral heuristics. Agent-based simulation techniques are used for several reasons. Given the complexity of our model assumptions, we are unable to derive general analytical results. With agent-based modeling we are able to gain more comprehensive insight into the specific network structures that will likely form under different behavioral assumptions on actors (cf. Buskens and Van de Rijt, 2008). Another advantage of using agent-based modeling is to predict how changes in initial conditions such as cost and benefit variations, or changing network size can change the likelihood of different network outcomes when multiple stable networks exist (see e.g. Cederman, 2005; Flache and Macy, 2006; Epstein, 2007, for introductions and discussions on computer simulations as a theoretical tool in the social sciences).

Predictions of the simulation models are tested experimentally. Experimental studies, while nowadays less common in sociology than in economics, have a long tradition in sociology (Diekmann, 2008). Laboratory experiments allow controlling many factors that are less easy to control in real world settings, by manipulating conditions of theoretical interest and also by keeping other conditions constant. Moreover, the laboratory provides an appropriate environment for studying individual decision-making as well as for observing macro-level outcomes. Network formation processes are much more difficult to investigate using field studies due to the limited availability of adequate longitudinal data on many complete networks and the ambiguity on the precise benefits for each network position. In addition, theoretical models of network dynamics imply complex interdependencies between actors. For studying the behavioral regularities in this context, we need to implement the theoretical mechanisms, and directly observe the individual decisions that lead to the network outcomes. In our context, we have limited knowledge about the individual-level decision-making mechanisms. Individual decision-making, however, is crucial for the understanding of the macro-level predictions. Furthermore, experimental data on individual decisions can be used to study heterogeneity of actors in terms of their ability to look ahead. Discovering such heterogeneity is an important research task: including assumptions on heterogeneity among actors into models of strategic network formation might lead to predictions of more heterogeneous networks that better resemble empirically observed networks. One problem with theoretically modeling heterogeneity in terms of the level of farsightedness is that the outcome depends on the assumed proportion of myopic and farsighted actors in the populations. With information on these empirical distributions it would be possible to fine-tune future theoretical models that incorporate such heterogeneity. In an exploratory analysis we will have a deeper look at the heterogeneity of individuals in terms of their ability to look ahead. The theoretical model presented here applies to homogeneous populations of actors.

1.3 Research problems

In the following we introduce the research problems that are tackled in the different chapters. We start with characterizing the way actors make decisions when they are limitedly farsighted. Assumptions about how actors anticipate others' behavior have to be carefully developed and precisely formulated. The model is built in the context of pure network formation models. Farsightedness is understood as anticipating subsequent linking decisions of other actors. The first research problem relates to the micro level and reads as follows:

- *How can we model limited farsightedness in network formation?*

To study the effects of limited farsightedness on the outcome of the network formation process, we analyze stability of networks when actors are myopic as compared to when actors are limitedly farsighted. Stable networks can then be analyzed in terms of characteristics such as efficiency. Studying effects of farsightedness on specific network characteristics is of interest as farsightedness might have different effects, depending on the context. There may be counter-intuitive effects. For instance, higher levels of farsightedness will not necessarily lead to more efficient networks. This is of course also not necessarily the case in other games. In the centipede game, actors who are more farsighted will actually produce less efficient outcomes (see e.g. Rosenthal, 1981; McKelvey and Palfrey, 1992). We study the effects of farsightedness in different contexts of network formation by applying the model of limited farsightedness in different utility functions. We also vary initial conditions such as costs for maintaining relations and network size. By considering many contexts with different initial conditions we are able to identify more general patterns of implications of farsightedness in network formation. Consequently, the second research problem relates to the macro level and reads as follows:

- *What are the implications of limited farsightedness assumptions on outcomes of the network formation process?*

Subsequently, we empirically test the theory using laboratory experiments. Since we develop a theoretical model that allows for macro-level predictions, via new assumptions on the micro level, the empirical research problems deal with both, micro-level behavior and macro-level outcomes. On the micro level, we analyze individual behavior of subjects. In the laboratory, we can track every single decision. The decisions can be compared to the predicted behavior in the myopia model and the model of limited farsightedness. This enables us to test which model can better describe behavior of subjects. Furthermore, we expect that subjects in the laboratory are heterogeneous with respect to their ability to look ahead. Using an exploratory approach, we classify subjects into types of actors, based on their level of farsightedness. Therefore, the third research problem focuses on the micro level and reads as follows:

- *Which farsightedness assumptions correspond better with actual behavior of subjects in network formation games?*
- *How can we classify individuals into types depending on their level of farsightedness when they make network decisions?*

The second part of the empirical research problems concerns macro-level outcomes. The myopia model and the model of limited farsightedness make different predictions on stable networks. We compare the theoretical predictions with the networks that are formed by groups of subjects in the laboratory to test which model can better predict the macro-level outcomes. Furthermore, concerning heterogeneity we try to assess the empirical distribution of subjects in terms of levels of farsightedness and the composition of subpopulations. Therefore, the fourth research problem focuses on the macro level and reads as follows:

- *Which farsightedness assumptions correspond better with networks formed by groups of individuals?*
- *How heterogeneous are groups of subjects in terms of their level of farsightedness?*

In the box below the research problems are summarized per chapter. Chapters 4 and 5 combine the micro- and macro-level part of the questions above.

Overview of the research problems per chapter:

Chapter 2: How can we model limited farsightedness in network formation?

Chapter 2/3: What are the implications of limited farsightedness assumptions on outcomes of the network formation process??

Chapter 4: Which farsightedness assumptions correspond better with actual behavior of subjects in network formation games and which farsightedness assumptions correspond better with networks formed by groups of individuals?

Chapter 5: How can we classify individuals into types depending on their level of farsightedness when they make network decisions and how heterogeneous are groups of subjects in terms of their level of farsightedness?

Remark 2. *With respect to terminology, note that we distinguish between myopic behavior and limitedly farsighted behavior. We also refer to myopic behavior as thinking one step ahead, to limitedly farsighted behavior as thinking two or more steps ahead, and to perfectly farsighted behavior as the ability of thinking fully ahead. Details with respect to terminology will be explained in chapter 2.*

1.4 Approach and results

1.4.1 Theoretical model: chapters 2 and 3

In chapter 2, we develop the theoretical model of network formation when actors are limitedly farsighted. Drawing from ideas of level-k-thinking theory (Stahl and Wilson, 1995), we assume that each actor takes subsequent actions of other actors into account, assuming further that others are one step less farsighted than he himself. For example, actors who think two steps ahead assume that other actors think only one step ahead. We thus assume that actors do not realize that other actors may look exactly as far ahead as they do. Note that this assumption creates an “inconsistency” between actors’ own behavior and their beliefs about others’ behavior. This will be important for the discussions of the theoretical model, also related to the empirical results of chapters 4 and 5.

Computer simulations are used to derive the stable network structures that are likely to emerge under the assumptions that actors look one, two, or three steps ahead. In each step of the formation process, two randomly picked actors decide to build, remove or keep a link. Because the decisions of the actors in the network involve uncertainty about which subsequent changes in the network will occur, additional assumptions about how actors make decisions under uncertainty are necessary. We introduce three decision rules actors can use as a behavioral heuristic. A risk averse rule, a risk neutral rule, and a risk seeking rule. For the risk neutral decision rule we use the principle of insufficient reason (PIR, see also Luce and Raiffa, 1958; Weesie et al., 2009). The co-author model by Jackson and Wolinsky (1996) is used as an example for a context of network formation. The co-author model implies a tension between stability and efficiency when actors are myopic. The simulation model yields that myopic actors end up in over-connected and therefore inefficient networks. Limitedly farsighted actors can overcome this tension but only if the network is small enough. For larger networks, myopic and limitedly farsighted actors mostly create the same stable, inefficient networks. Regarding the three decisions rules that were implemented, we argue that the PIR decision rule offers the best interpretable results. Addressing the second research problem, we show that changing the microfoundations of the network formation model leads to new implications at the macro-level in the sense that different networks are predicted to be stable.

In chapter 3, the model of limited farsightedness as developed in chapter 2 is applied to two other contexts of network formation, the connections model by Jackson and Wolinsky (1996) and the structural holes model by Buskens and Van de Rijt (2008). Both models focus on information as a resource that can be obtained through social networks. Information is an important resource that is often passed on and obtained within social networks. Jackson and Wolinsky's (1996) connections model captures the idea that being connected to others is beneficial. There is a spillover effect of valuable information from indirect connections in a network. Having close relations comes at a cost (e.g.

time or effort). On the other hand, Buskens and Van de Rijt's (2008) utility function models Burt's (1992) idea of structural holes. It captures the idea that actors who fill intermediate positions between otherwise not connected groups of actors can benefit by brokering the flow of information or other resources. These intermediate positions are the so-called structural holes. Predictions on stable networks show that myopic actors in the connections model build under-connected and therefore inefficient networks. With increasing cost of links, the efficiency of networks decreases. When actors are limitedly farsighted, they build more efficient networks at higher costs, as compared to myopic actors. In the structural holes model, myopic actors end up most often in efficient networks. When actors look two or three steps ahead, the likelihood of building these efficient networks is even higher as compared to myopic actors.

1.4.2 Experimental studies: chapters 4 and 5

In chapter 4, we experimentally investigate whether subjects act myopically or whether subjects' networking decisions are more consistent with limitedly farsighted behavior. Subjects play a network formation game in groups of four. Subjects decide sequentially with whom to connect in their group. As treatments we use the utility functions of the connections model and the co-author model by Jackson and Wolinsky (1996). The beauty contest game is used to measure the ability of iterated reasoning, as a proxy for subjects' level of farsightedness. Results indicate that the model of limited farsightedness predicts macro-level outcomes of the experiment better than the myopia model. A majority of the emerged networks in both treatments are predicted quite accurately by the model of limited farsightedness. The simulation model allows for predictions on the likelihood of specific networks to emerge, in case of multiple stable networks. These likelihoods cannot be supported by the data. On the micro level, we observe both, myopic and farsighted behavior. Analyzing linking decisions where it is possible to differentiate between myopic and farsighted behavior, we find that subjects with higher levels of iterated reasoning, as measured in the beauty contest game, are more likely to behave farsightedly in the co-author model treatment, and are less likely to behave farsightedly in the connections model treatment. This result, however, strongly depends on specific assumptions on how limited farsightedness is modeled. What we classify as farsighted decisions depends on the assumption that limitedly farsighted actors assume that everybody else is less farsighted. The opposing effects of the beauty contest game measure between the two treatments relate to different implications this assumption has. Furthermore, we argue that the often observed myopic behavior in the connections model might actually be consistent with slightly different assumptions on farsighted behavior such that subjects seem to assume others are farsighted as well.

In chapter 5, we classify subjects into types of actors, based on their level of farsightedness when they choose with whom to connect in the network formation experiment. Previous experimental results suggest that subjects differ in terms of their ability to look ahead. Latent class models (LCM) are used to identify this unobserved heterogeneity among subjects. LCM assume categorical latent variables that represent subpopulations where population membership is not known but is inferred from the data. In this chapter, we investigate the observed proportion of myopic and farsighted actors in the laboratory. We explore whether the ability to look ahead is a personal trait of the individual, or whether subjects' behavior is context dependent. Also, we analyze whether subjects' behavior can be better described with pure types, classes of subjects who look either one, two, or three steps ahead, or whether subjects behavior can be better described with mixed types, classes of subjects with levels of farsightedness that might differ depending on e.g., the context or timing in the experiment. Results show that subjects are heterogenous in terms of the ability to look ahead. Also farsightedness is context dependent. Subjects apply different levels of farsightedness in different treatments. We observe that subjects' linking decisions are better described with mixed types of actors than pure types of actors.

Remark 3. *Chapters 2 to 5 are written as articles meant for being publications in peer-reviewed journals. Therefore, this introduction chapter overlaps with the introduction sections of the remaining chapters. Also note that chapters 2 to 5 apply the same theoretical model of limited farsightedness. This implies some overlap in the sections that introduce the theoretical models. Chapters 4 and 5 experimentally test the theoretical models. Analyses of chapters 4 and 5 are performed using data from* *the same experiment. Therefore, there is overlap between these two chapters in the sections on the experimental set-up.*

1.5 Discussion and future research

In this section we offer conclusions on the core findings from the theoretical and empirical studies and discuss possible extensions for future research. Our first research problem focuses on how limited farsightedness in network formation can be modeled. We set up a theoretical model, using ideas from level-k-theory. With our second research problem we were interested in the effect this new micro-level assumption has on the macro-level outcome. The results of the simulation studies show that changing micro-level assumptions on actors' levels of farsightedness indeed has consequences on the network formation process. Different networks can be stable when actors look two or three steps ahead rather than being myopic. The theoretical network formation processes, presented in chapters 2 and 3, show that stable networks are more efficient when actors look ahead as compared to the stable networks built by myopic actors. However, the effects of limited farsightedness are context dependent. Research problems three and four were concerned with testing the theory, on the micro level as well as on the macro level. Empirically, the results are mixed. In chapter 4, we see that the model of limited farsightedness predicts macro-level outcomes in the experiment better than the myopia model. Micro-level analyses of chapters 4 and 5 show that subjects differ in their abilities to look ahead. Additionally, subjects apply different levels of farsightedness in different treatments, thus, the extent to which subjects look ahead is context dependent. The level of farsightedness that is dominantly applied by subjects, differs in the contexts of network formation. Myopic behavior is dominant in the connections model treatment, while limitedly farsighted behavior is dominant in the co-author model treatment. We argue that the different behavior in the two contexts of network formation is related to the predicted sets of stable networks and the assumptions for myopic and farsighted behavior (see discussion above and in chapter 4).

1.5.1 Theoretical extensions

Generalizability of the theoretical findings is one fundamental problem of the approach presented here. One solution is to apply the simulation model to further utility functions in order to make more general statements on the effect of farsightedness on specific network outcomes and characteristics. The co-author model and the connections model generate a conflict between stability and efficiency, because of over- and under-connectedness of stable networks (see above). Our model shows that when actors look two or three steps ahead, they indeed build more efficient networks. A related question is whether increasing the level of farsightedness, such that actors can look more and more steps ahead, also increases efficiency of networks. It might be of interest to analyze whether the benefit of being farsighted decreases, such that the benefit of looking further and further ahead at some point approaches a limit. This might depend on the context of network formation. Such questions can be analyzed with further simulation studies, where the level of farsightedness is steadily increased. This might also add to our understanding of why subjects apply different levels of farsightedness in different contexts.

Different assumptions on risk preferences do affect predictions about stable networks. We adopted three decisions rules, a risk averse, a risk neutral and a risk seeking decision rule. The assumptions of risk averse and risk seeking actors produce extreme results. A further step could be to implement risk aversion as a parameter which can be varied from risk averse to risk seeking, taking all possible future network outcomes into account. For the risk neutral decision rule we used the principle of insufficient reasoning. Future models could also take the different likelihoods of future events into account: since different network paths differ in their attractiveness for other actors, some paths are more likely to be followed than others. This might influence decisions of actors. Kovářík and Van der Leij (2010) study the effect of individuals' risk aversion on their network position in a network formation setting similar to the model of Jackson and Rogers (2007). Their study shows that heterogeneity of individuals in terms of risk preferences has an important impact on the formation of social networks such that individuals connect differently, depending on their risk preferences. Simulation models in the contexts presented in this book, assuming that actors are heterogeneous in terms of risk preferences, would be worthwhile studying. Heterogeneity of actors in terms of their risk preferences might have effects on, e.g., the individuals' payoff or on characteristics of stable networks.

Studying heterogeneity in terms of actors' ability to look ahead, as argued in chapters 4 and 5, is of importance for future research. Subjects differ in terms of their ability to look ahead. They are also likely to apply different levels of farsightedness, depending on the context. So subjects might also differ in terms of their ability to apply different levels of farsightedness in different contexts. Studying such mechanisms presupposes more theoretical work. This could not only help to explain the macro-outcomes of the experiment presented here, but could also shed more light on questions in other settings. For instance, in a setting where structural holes are beneficial, this can help to explain which individuals are more likely to occupy broker positions (Burt, 1992).

Another, yet unresolved theoretical issue is the inconsistency problem, discussed in the theoretical and empirical chapters. In the model of limited farsightedness, we assume that everybody thinks that he is smarter than everybody else. It appears that this technically helpful though substantively problematic and less than plausible assumption resulted in problems when analyzing micro-level behavior. Myopic decisions in the connections model can better be interpreted as farsighted decisions when actors assume other actors to be farsighted as well. The assumption of limited farsightedness is thereby not refuted, but future models need to elaborate more on actors' farsightedness as well as actors' beliefs about farsightedness of others. Studying heterogeneity is also related to questions about the assumptions about beliefs on the distribution of the levels of farsightedness. This could also include the distribution on risk preferences in the population.

We studied limited farsightedness in pure network formation. Another important application of limited farsightedness is in the context of the co-evolution of networks and behavior (Corten, 2009). Subjects in experimental situations when behavior and networks co-evolve often deviate from myopic best response behavior. Alternative models assuming some form of limited farsightedness are necessary to explain the observed behavior. For instance, Berninghaus et al. (2012) present an alternative decision rule, which they call anticipatory best response and a related stability criterion, namely, reaction-anticipating stability. This is a promising approach to explain behavior of subjects in coordination games played in dynamic networks. More theoretical work on the effects of farsightedness in such games is necessary.

Myopic best response behavior is also an important assumption in statistical models for analyzing dynamic networks (Snijders, 2001). The so-called stochastic actor-driven models for network change often rely on myopic updating. As Snijders (2001, p. 390) points out, it would be interesting to develop statistical models "incorporating a sociologically more interesting behavioral model". Our research shows that limited farsightedness is of importance and that it is context dependent. Therefore, there are applications where there are good arguments to assume that actors are not myopic. For longitudinal, dynamic network data, alternative statistical models will be necessary in order to adequately analyze such empirical data.

1.5.2 Suggestions for empirical research

With the experimental studies presented in chapters 4 and 5 we hope to have made some contributions to the empirical validation concerning alternative micro-level theories on network formation. Of course, more empirical studies are needed.

Future experimental work should further focus on studying micro-level behavior. More evidence on individuals' ability to look ahead in complex settings like network formation will be of interest, and especially how the level of farsightedness of decisions is related to individuals' beliefs about the level of farsightedness of others. Research investigating behavior of subjects in relation to subjects' beliefs about behavior of others often shows that decisions are based on the belief that others are similar to oneself (Aksoy and Weesie, 2012). We used the beauty contest game as a proxy to measure farsightedness of individuals. However, with this measure it is impossible to disentangle the individuals' level of iterated reasoning and the individuals' beliefs about others' level of reasoning. More research is necessary to investigate both effects and how they interrelate, also in different strategic social interactions. Such experiments also could test how and under which circumstances it is safe to assume that subjects are overconfident about their own skills, in relation to their beliefs about the skills of others (Camerer and Lovallo, 1999).

With the statistical analysis presented in chapter 5, we made a first step to answer the question whether farsightedness is more a personal trait or is more context dependent. Therefore, it is important to study the macro-level conditions that influence individual-level behavior, and to understand the mechanisms that determine whether individuals are more likely to act myopically or farsightedly, given the context they are embedded in. If farsightedness is to a large degree context dependent, then to understand what triggers farsightedness is of great importance. For instance, myopic behavior might be more prevalent in situations with a high level of complexity, so that individuals tend to apply more simple heuristics. The simulation results of chapter 2 showed that when the network gets larger, myopic and limitedly farsighted actors build similar networks. This effect of growing network size could be tested experimentally. In general, experimental research is well suited to test such context effects systematically. Treatments that vary the level of complexity could be applied, as well as treatments varying the benefits of being farsighted. Berninghaus et al. (2012) show that when short-term benefits are high, individuals are more likely to make myopic decisions.

Furthermore, farsightedness is related to learning and experience. When subjects play the beauty contest game multiple times, they learn how the game works and steadily apply more steps of iterated reasoning until reaching the Nash equilibrium (Nagel, 1999). Nash equilibrium behavior can be interpreted as being perfectly farsighted. Thus, how farsighted actors are might be related to the experience they have in the decision-making situation. Experiments of Palacios-Huerta and Volij (2008) show that professionals play optimal, i.e., farsighted strategies, chess players act more farsighted in the centipede game (Palacios-Huerta and Volij, 2009), and soccer professionals optimize their penalty shooting strategies (Berger and Hammer, 2007). Then the questions arises, whether subjects in network formation games play myopic strategies as long as they are inexperienced with the incentive structure of the situation or similar situations, and whether they become more farsighted when they gain experience. In our experiment we observed some effects that might be related to learning and experience. However, more experimental studies will be necessary.

Chapter 2

How Farsightedness Affects Network Formation*

2.1 Introduction

Previous research demonstrates how networks affect social and economic life. People find jobs more easily through weak ties (Granovetter, 1973; De Graaf and Flap, 1988; Mouw, 2003). Artists perform better if they are organized in networks that are neither too dense nor too sparse (Uzzi, 2008). Firms are more innovative if they organize their strategic alliances well (Stuart, 1998). A so-called broker benefits from being in a position between otherwise not connected actors (Burt, 1992).

Because social relationships can be beneficial and people are to some degree aware of the relational structure between them (Krackhardt, 1987), actors have incentives to strategically invest in their relations and might try to obtain an optimal position within such a network (Burt, 1992; Flap, 2002). People nowadays use the term *networking* to describe this strategic behavior. Only more recently, researchers started to investigate, how and why specific network structures emerge assuming that people have the discretion to change their network. Individuals choose with whom they are friends (Van Duijn

*This chapter was written in collaboration with Vincent Buskens, Stephanie Rosenkranz, and Werner Raub, with Dominik Morbitzer being the first author. An earlier version has been submitted to the *Journal of Mathematical Sociology* et al., 2003; Van de Bunt et al., 1999), firms decide with whom they form alliances (Gulati, 1995). Strategic models of network formation are developed for analyzing these processes, using game-theoretic tools to predict which type of network structure emerges in these interactions (see Bala and Goyal, 2000; Jackson and Wolinsky, 1996).

The models that are developed can be distinguished in terms of their assumptions about how actors make their networking decisions given the macro-conditions in which network formation takes place. We refer to these assumptions about how actors make decisions as the "microfoundations" of the model (see Raub et al., 2011). One group of models considers network formation as a dynamic process in which pairs of actors decide sequentially on whether to change the relation between them (Jackson and Watts, 2002). A network is considered stable when no pair of actors wants to change their relation anymore. In most of these dynamic models, it is assumed that actors make their decisions myopically, implying that they neglect subsequent decisions of other actors: actors look one step ahead and only consider whether they are better off after adding or severing one link, playing so called myopic best response. Yet, adding or severing one link might lead to the subsequent addition or severance of other links. Therefore, actors might also use more complex heuristics to determine which links with others they want to change, e.g., actors might use more farsighted strategies in these processes, taking subsequent behavior of others into account. Farsighted actors look more than one step ahead, and anticipate subsequent changes after an initial decision. They then choose a response that produces the best anticipated outcome.

In the literature on network formation there are already some extensions of the myopia model. One alternative is to go to the other extreme and assume that actors are perfectly farsighted (Page et al., 2005; Dutta et al., 2005; Herings et al., 2009; Pantz, 2006). This implies that actors consider sequences of changes in the network of arbitrary length towards a given destination network. Such a sequence of changes is feasible if all actors who determine a change in the intermediate steps prefer their position in the destination network over their network position at the moment they implement the change. Here, the assumption that rationality is common knowledge is crucial. The increasing complexity of considering such sequences in larger networks makes the assumption of perfectly farsighted actors unrealistic. Jackson (2003) indicates that perfect farsightedness might be feasible only in very small networks (networks of size 2 to 4). We define networks with $n > 4$ as "larger". The number of possible different network structure increases drastically as networks become larger and with that the complexity of the decision situation.[1] We argue that limited farsightedness is a plausible assumption for such settings. We further argue that the assumption of limited farsightedness does not solely depend on network size but can be applied to small and large networks. In addition, the existing models that apply perfect farsightedness do not provide clear cut predictions for arbitrary networks, but mostly provide general theorems on conditions for stability with some examples for specific utility functions in small networks. We know of only one paper by Berninghaus et al. (2012) that tries to model limited farsightedness in a coordination game with network formation. Therefore, we feel that there is still considerable work to be done to further develop the microfoundations of network formation models particularly in the direction of limited farsightedness.

Experimental research on network formation shows that myopia models sometimes fail to predict empirically observed outcomes (Callander and Plott, 2005; Pantz, 2006; Berninghaus et al., 2012; Van Dolder and Buskens, 2008; Corten and Buskens, 2010). The observed deviations from myopic best response behavior may be explained with *anticipatory* behavior of actors. In addition, we know from other experiments on strategic decision-making, specifically on iterated reasoning, that subjects indeed tend to anticipate others' behavior, but in a *limited* way (see Camerer, 2003). To investigate iterated reasoning of subjects, when putting themselves into the shoes of others, researchers apply (dominance-solvable) games such as the beauty contest game (see Nagel, 1999, for a survey). Camerer (2003: ch. 5) shows that in such games in which it is rather easy to reason ahead, actors still are limited in that respect. In the beauty contest game, actors have to choose numbers be-

[1] See for instance table 2.2 which reports the number of non-isomorph network structures for each network size. Note that for $n = 5$ there are already 34 different network structures an actor would have to consider.

tween 0 and 100. The actor who chose the number closest to some proportion p of the average number chosen by all actors wins a prize.[2] Stahl and Wilson (1995) and later Camerer et al. (2004) developed a model (the so-called cognitive hierarchy model), which assumes that actors think n steps ahead, implying that actors assume that other actors think only $n-1$ steps ahead. By applying this model for different values of n, they could show with experimental results (mainly on beauty contest games) that, on average, people think two steps ahead.[3] The results demonstrate that models of human action assuming limited farsightedness predict the behavior of humans in some situations better than, for instance, standard Nash equilibrium predictions, i.e., perfect farsightedness (for more references see Nagel, 1999; Costa-Gomes et al., 2001; Camerer, 2003; Camerer and Fehr, 2006).

For developing our model, we build on these assumptions and findings, but change the context of the game to networks; we ask how farsighted people act in strategic *network* situations. There are qualitative differences between decision-making within a network as compared to most game-theoretic situations in which farsightedness has been studied so far. The network formation process is not a straightforward dominance-solvable game where actors anticipate over others' choices and make their (simultaneous) decisions based on what they belief others will choose. A *dynamic* network formation game consists of many rounds of pairs of actors updating their relations sequentially, therefore a farsighted actor has to consider many different actions of many others while the others are typically not in equivalent positions and the order of who changes links is uncertain. So the cognitive demand is even higher in network formation games. Therefore, we develop a simple form of farsightedness, assuming that actors do not look more than two or three steps ahead.

Summarizing, our research question is: How does the assumption of *limitedly* farsighted actors affect predictions concerning emerging networks and the

[2]The only Nash equilibrium in the beauty contest is all actors choosing 0. If $p = 2/3$, many people choose numbers around 33. This can be seen as thinking one step ahead and assuming others choose randomly, which implies the others choose 50 on average. The most common choice is numbers around 22, which can be seen as thinking two steps ahead.

[3]This result holds for beauty contest games. In general, the level of reasoning in other dominance-solvable games is between two and three steps.

efficiency of these structures? We compare the model of network formation with myopic actors (looking only one step ahead towards the immediate change in outcomes from changing the network position) with models in which actors look two or three steps ahead, following a path of possible subsequent network decisions. In this way, we can determine how changing the microfoundations affects macro-outcomes.

The model will be outlined in section 2.2. Section 2.3 illustrates the model using the co-author model introduced by Jackson and Wolinsky (1996) and shows that different networks are stable under the assumption of limited farsightedness compared to the stable networks when actors are assumed to be myopic. Using computer simulations, we enumerate all stable networks for different sets of assumptions for network size 3 through 8. We use simulation techniques as a theoretical tool since the complexity of our model assumptions makes the derivation of analytical results largely unfeasible. Using simulation techniques provides the advantage that we are able to predict the likelihood of different stable networks to emerge when multiple stable networks exist. The simulation procedure is explained in section 2.4, while the results are summarized in section 2.5. Section 2.6 concludes and illustrates possibilities for further research.

2.2 Model

In the following section we describe our network formation model and how actors make their networking decisions.

2.2.1 Actors, networks, stability, and efficiency

The set $N = \{1, \ldots, n\}$ is the set of nodes representing actors. A network g indicates which actors in N are connected via a link. Formally, g is a set of unordered pairs of actors $\{i, j\}$. For any pair i and j, $\{i, j\} \in g$ indicates that i and j are linked in the network g; otherwise $\{i, j\} \notin g$. Links are undirected, if i has a link with j then j also is linked with i. We denote the link $\{i, j\}$ also with ij. Let $g + ij$ denote the network obtained by adding the link ij to the existing network g and let $g - ij$ denote the network obtained by deleting the link ij from the existing network. We define g^{ij} as the adjacent network obtained by either adding or deleting a link in g. Thus,

$$g^{ij} = \begin{cases} g + ij, & \text{if } ij \notin g \\ g - ij, & \text{if } ij \in g \end{cases}$$

The utility function vector $u : G(n) \to \mathbb{R}^n$ models the overall benefit net of costs of the actors in a network, where $G(n)$ is the set of all possible networks with n actors. We represent the utility of actor i in network g by $u_i(g)$. The network stability concept we start from is proposed by Jackson and Wolinsky (1996). A network g is *myopically pairwise* stable if

1. $\forall ij \in g$, $u_i(g) \geq u_i(g - ij)$ and $u_j(g) \geq u_j(g - ij)$
2. $\forall ij \notin g$, if $u_i(g + ij) > u_i(g)$ then $u_j(g + ij) < u_j(g)$

In words, a network is myopically pairwise stable if no actor wants to severe a link and no pair of actors wants to add a link. The first part of the definition captures the idea that a link can only remain in a network if both actors want to have this link. The second part captures the idea that a link cannot be added to the network if only one of the actors in a dyad wants to add that link. We added the qualification "myopic" to this definition, because stability is completely based on the direct consequences of a relational change. The addition allows us to distinguish it from farsighted pairwise stability defined below.[4]

To address efficiency, one could consider Pareto efficiency, but the disadvantage is that there often exist many Pareto incomparable states. Alternatively one can consider efficiency based on the sum of utilities of all actors.

[4]There are some other limitations to the concept of myopic pairwise stability addressed for instance by Buskens and Van de Rijt (2008) and Jackson (2008). First, the concept only considers deviations on a single link at a time. It is not possible that a player severs several links simultaneously. Second, it considers only deviations by at most a pair of actors. There are models that allow for coalition-wise deviations, and there are models of multiple link deviations at a time that strengthen the weak notion of myopic pairwise stability (Jackson and Van den Nouweland, 2005; Buskens and Van de Rijt, 2008). Besides several extension of myopic pairwise stability, there are also different stability resp. equilibrium notions such as pairwise Nash stability (for a discussion see e.g. Bloch and Jackson, 2006)

This aggregate measure is common in the literature (see e.g. Jackson, 2008), however, requires interpersonal comparison of utility. Next to this sum of utilities, we assess efficiency by investigating the extent to which actors are able to avoid the inefficient complete network as we show below.

2.2.2 The utility function: the co-author model

The method developed in this chapter can be applied to any utility function based on a network structure as defined above. In the following, we use the co-author model by Jackson and Wolinsky (1996) to illustrate our formalization of limited farsightedness. In the co-author model, the utility function is based on a setting in which researchers collaborate with each other on research papers. Actors prefer to have many direct links with neighbors who only have few links. The fewer links an actor has, the more time he can spend on each link separately. Actors are thus in competition with others' indirect links (Jackson, 2008). Denote the degree of actor i, which is the number of links of actor i, as n_i. Then formally, the utility for actor i in the co-author model is given by

$$u_i(g) = \sum_{j:ij \in g} \left[\frac{1}{n_i} + \frac{1}{n_j} + \frac{1}{n_i n_j} \right].$$

The formalization implies that actors distribute time equally over their links. The last fraction of the equation captures the synergy between the two researchers; if the actors spend more time on each others' project they generate more synergy. An actor's utility only depends on the actors' own degree and the degree of his neighbors. The model produces negative externalities, because if actor i creates a link to actor j, this reduces the utility of the actors actor i was already related to as well as the actors actor j was already related to. The co-author model also implies a tension between efficiency and stability, because the gains of the actors who create a new link are mostly less than the losses of the other actors. Still, immediate network gains of creating links imply individual short-term incentives that lead to an inefficient network in the long run. For a broader discussion on this "tension" between stability and efficiency see Jackson (2008); Buechel and Hellmann (2012). Jackson and Wolinsky (1996) show that in the co-author model the efficient network structure consists of pairs of actors only linked to each other and that myopically pairwise stable networks contain more links and, as a consequence, are inefficient. Buechel and Hellmann (2012) generalize this result, showing that utility models that produce negative externalities in general lead to overconnected networks. In the co-author model, the network formation process with myopic actors almost exclusively leads to the inefficient complete network.

To illustrate that there might be other stable networks under non-myopic behavior, consider the following example. Figure 2.1 shows a sequence of three adjacent networks with four actors. The utilities, indicated by the numbers next to the nodes, are taken from the co-author model. Arrows that lead from one network to another show the direction of the formation process when actors make myopic decisions.

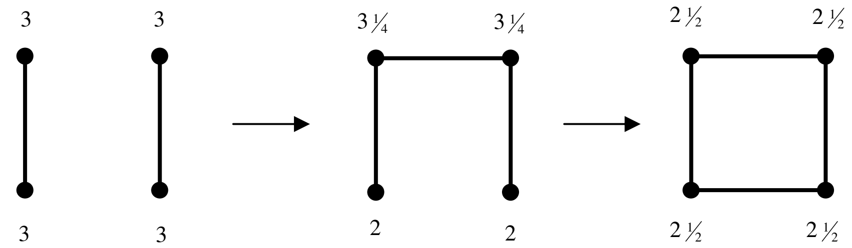


Figure 2.1: Improving path assuming myopic decision-making

If the (efficient) network on the left is the starting network, adding the link in the network in the middle is a myopic best response for two actors, because their utility raises by 0.25 points. In the subsequent step, the other two actors also form a link between them and they all reach the network on the right where everybody receives a payoff of 2.5. Compared to the starting network, all actors are worse off. This illustrates the tension between efficient and stable networks (assuming myopic best response behavior) as shown by Jackson and Wolinsky (1996). Let us now consider actors who are looking ahead. Farsighted actors anticipate the reactions of others and themselves and are able to foresee how the process might evolve. If the two actors who add the first link in the example above anticipate the reaction of the other two actors, they would prefer to stay in the first network

2.2.3 Farsighted actors and network stability

The general idea we introduce is that farsighted actors anticipate the network formation process that arises through altering the network structure by themselves and others. Farsighted actors compare the payoff they get from the current network g to an anticipated network g'. We assume that actors ignore the payoff of intermediate steps since they perceive these states as transient states in which they expect to stay only a negligible amount of time. Intermediate network steps are not considered in the utility function of actors.[5] The set of networks g' that they consider to be relevant depends on the number of steps they look ahead in the network formation process. To formalize this idea we need the concept of a *myopic improving path* (Jackson and Watts, 2002).

Following the definition of Jackson and Watts (2002), a myopic improving path from a network g to a network $g' \neq g$ is a finite sequence of networks $g_1, g_2, \ldots, g_K$ with $g_1 = g$ and $g_K = g'$ such that, for every $k \in \{1, 2, \ldots, K-1\}$, either

1. $g_{k+1} = g_k - ij$ for some ij such that $u_i(g_k - ij) > u_i(g_k)$ or $u_j(g_k - ij) > u_j(g_k)$, or
2. $g_{k+1} = g_k + ij$ for some ij such that $u_i(g_k + ij) > u_i(g_k)$ and $u_j(g_k + ij) \geq u_j(g_k)$.

An improving path (see figure 2.1) is a sequence of adjacent networks that can emerge when individuals create or break links based on the improvement the resulting network offers relative to the current one. Each network differs from the previous network by exactly one link. We say that an improving path is a sequence of adjacent networks with the property that g^{ij} "defeats" its predecessor g for actor i and j, which we denote by $g \prec g^{ij}$.

From the definition of myopic pairwise stability, it immediately follows that a network is myopically pairwise stable if there is no myopic improving

[5] An example with a discounted stream of payoffs for intermediate steps is found in Dutta et al. (2005)

path from network g to any other network g'. To establish myopic pairwise stability one needs only to consider one other network g' for comparison with the current network g. In this setting actors only need to know whether adding or severing a link is immediately beneficial.[6]

To extend the concept of myopic pairwise stability to a stability concept based on farsightedness, we need to consider longer sequences of networks. *A farsighted improving path* (Herings et al., 2009; Jackson, 2008) from a network g to a network $g' \neq g$ is defined as a finite sequence of networks $g_1, g_2, \ldots, g_K$ with $g_1 = g$ and $g_K = g'$ such that, for every $k \in \{1, 2, \ldots, K-1\}$, either

1. $g_{k+1} = g_k - ij$ for some ij such that $u_i(g_K) > u_i(g_k)$ or $u_j(g_K) > u_j(g_k)$, or

2. $g_{k+1} = g_k + ij$ for some ij such that $u_i(g_K) > u_i(g_k)$ and $u_j(g_K) \geq u_j(g_k)$.

Thus, two actors who evaluate an existing or non-existing link between each other change this link if they are better off in the anticipated network g_K at the end of a path of arbitrary length. Jackson (2008) defines the concept of *farsighted pairwise stability*: a network g is farsightedly pairwise stable if there is no farsighted improving path from network g to some network g' such that each pair of consecutive networks along the sequence are adjacent. The idea of a farsighted improving path captures the notion that the actors anticipate all further changes along the path and only compare the final network to the current one, thus neglecting intermediate network utilities (Jackson, 2008). This definition of farsightedness assumes perfect farsightedness of actors. Thus, if actors follow an improving path they would not do this unless they anticipate that the endpoint is justified as the resting point of the process. The existence problem is solved by Page et al. (2005); Bhattacharya (2006); Barrientos (2005); Herings et al. (2009) applying the concept of the largest consistent set (LCS) by Chwe (1994) in networks. This solution concept can make predictions for stable networks when actors are farsighted. The LCS defines a set of networks, such that every farsighted improving path that leaves

[6] Jackson and Watts (2002) show that the improving paths do not always converge to a myopic pairwise stable network, but that they might also cycle through a sequence of networks that are repeatedly visited without an option to leave that cycle.

the set has an end point that is again in the set. Therefore, all networks in the LCS can function as resting point.

Meanwhile there exist several different set-based solution concepts. For a good overview of recent papers and a discussion on different approaches of (perfect) farsightedness models see Herings et al. (2009, 2010). Still, all these solution concepts have some common limitations. First, they often do not provide clear cut predictions, because many networks might be within stable sets and the selection problem of multiple predictions arises. Second, the assumption that actors look many steps ahead, certainly in somewhat larger networks, seems less plausible. Third, the farsighted stability concepts mentioned above largely ignore the process of network formation. E.g., although there might be a farsighted improving path from one network to another, depending on the utility function of the network, it might be plausible that along the way some actors have an incentive to deviate from this specific improving path and aim for another network.

We address these three limitations, by developing a stability concept assuming *limitedly* farsighted actors. First, we limit farsightedness by defining an improving path that only considers a limited sequence of adjacent networks, Thus, a sequence of networks not of arbitrary length, as in the definition of farsighted improving paths above, but with an appointed length. The myopic improving path is a special case in which only sequences of length 2 are considered and can, therefore, also be called the one-step improving path. We generalize this idea by formalizing the K-step improving path: A *K-step improving path* from network g_1 to a network $g_{K'+1} \neq g_1$ is a sequence of at most $K+1$ networks $g_1, g_2, \ldots, g_{K'+1}$ such that for every $k \in \{1, 2, \ldots, K'+1\}$, either

1. $g_{k+1} = g_k - ij$ for some ij such that $u_i(g_{K'+1}) > u_i(g_k)$ or $u_j(g_{K'+1}) > u_j(g_k)$, or

2. $g_{k+1} = g_k + ij$ for some ij such that $u_i(g_{K'+1}) > u_i(g_k)$ and $u_j(g_{K'+1}) \geq u_j(g_k)$.

Some remarks are needed to clarify this definition. First, it should be clear that if $K = 1$, this is precisely the definition of a myopic improvement path.

Second, the definition differs from the farsighted improving path in the sense that the maximal number of changes in the network that is considered in the improving path is K and *not any arbitrary* number. Third, we need to distinguish K' and K in this definition to allow also for shorter improving paths. Imagine that we consider two-step improving paths, but at some occasion only a myopic improvement is possible after which no further myopic improvement is possible. Then, we still expect actors who might look two steps ahead to implement this myopic improvement. Fourth, realize that the last change in a K-step improving path is a simple myopic improvement. Similarly, if $K > 2$, the last two steps in the K-step improving path correspond with steps in a two-step improving paths. In other words, the decision of actors to change the first link in a K-step improving path can be understood as if these actors assume that the subsequent actors will follow at most a $K-1$-step improving path, and so on. In this way, our formalization directly links to other decision-making models in which actors are modeled as if they believe to think ahead one step more than their partners in the interaction. See, for example, the related assumptions formulated in Stahl and Wilson (1995) on player's models of other players or in the cognitive hierarchy model by Camerer et al. (2004). In these models, it is also assumed that every actor believes he understands the game better than all the other actors. This inconsistency between own and assumed other behavior is consistent with psychological evidence of persistent overconfidence about relative skills in many different domains (e.g. Camerer and Lovallo, 1999) and can be proven to be an evolutionary stable strategy (Johnson and Fowler, 2011). In line with this, if we assume actors who think two steps ahead ($K = 2$) it implies that every actor believes that the other actors are thinking $K - 1 = 1$ step ahead, therefore playing myopic best response. In that sense, actors who think two steps ahead play *anticipatory* best responses.

We use the concept of a K-step improving path to also define K-step pairwise stability. The idea is that actors look K steps ahead in the network and based on that evaluate whether changing relations might improve their utility. Note that also the K-step improving path implies that links are created if both actors want the link, but that links can be severed unilaterally. The problem is that although actors might see a particular improving path that indeed might improve their position, there might be other improving paths from intermediate networks that deteriorate their position. Why should actors who implement subsequent changes follow the improving path that the actors who made the initial change might have had in mind? After actors who considered a two-step improving path have changed a relation, there are probably many possible myopic improvements for the other actors. Some of these improvements might be on an improving path considered from the situation of the initial actors, but some subsequent improvements, might also be detrimental for the initial actors. (Of course, if we considered the deletion of links, this argumentation only needs to apply to one initial actor.)

Therefore, we need to formalize in addition, how actors weight improving paths that might follow their change, but which are not necessarily improving paths from the actor's perspective who made the initial change. We consider three alternative decision rules to resolve this issue. Note that also with respect to these decision rules we assume homogeneity among the actors to determine stable networks later on. Thus, the stability notions below will be based on the assumption that all actors are to the same extent limitedly farsighted and follow the same decision rules.

Before we can introduce the decision rules, we need to formalize the set of possible paths an actor might consider when anticipating at most K changes in the network. We formalize this in a recursive manner. First we need to define the set of target networks, which is the set of networks an actor i in network g who thinks K steps ahead considers as possible end points after changing a relation with actor j: $M_g^K(ij)$. In addition, we introduce notation for the utility that an actor i assigns to this set of possible target networks, i.e., the utility that i expects from changing the relation with j: $U_i^K(g^{ij})$. For example, if $K = 1$ (myopic actors), then $M_g^1(ij) = \{g^{ij}\}$ and $U_i^1(g^{ij}) = u_i(g^{ij})$. We can already determine the utility that i assigns to this set of networks, because the set contains only one network in case of myopic improvements. We specify this utility further below.

Analogously to the definition of g^{ij} defeating g for myopic improvements we can now also define that g^{ij} defeats g for K-step improvements if in case of adding a link: $U_i^K(g^{ij}) > u_i(g)$ and $U_j^K(g^{ij}) \geq u_j(g)$; and in case of removing a link $U_i^K(g^{ij}) > u_i(g)$ or $U_j^K(g^{ij}) > u_j(g)$. We denote this as $g \prec_K g^{ij}$.

Subsequently, we can define the relevant set of networks to be considered by actors who look two steps ahead:

$$M_g^2(i_1j_1) = \begin{cases} \bigcup_{\substack{i_2,j_2 \neq i_1,j_1 \\ g^{i_1,j_1} \prec_1 g^{i_1j_1,i_2j_2}}} M^1_{g^{i_1j_1}}(i_2j_2), & \text{if there is a } i_2, j_2 \text{ such that} \\ & g^{i_1j_1} \prec_1 g^{i_1j_1,i_2j_2} \\ g^{i_1j_1}, & \text{otherwise.} \end{cases}$$

This is the set of all myopic improvements after the link i_1, j_1 would be changed. If there are no myopic changes anticipated, then only direct myopic improvements are considered. Furthermore, we can define for actors who look three steps ahead:

$$M_g^3(i_1j_1) = \bigcup_{\substack{i_2,j_2 \neq i_1,j_1 \\ g^{i_1j_1} \prec_2 g^{i_1j_1,i_2j_2}}} M^2_{g^{i_1j_1}}(i_2j_2 \leftarrow i_1j_1).$$

Here $M^2_{g^{i_1j_1}}(i_2j_2 \leftarrow i_1j_1)$ is the relevant set of networks to be considered by actors who look two steps ahead from $g^{i_1j_1}$ and consider changing $i_2, j_2 \neq i_1, j_1$. The notation is slightly different because the myopic improvement that these actors consider beyond $g^{i_1j_1,i_2j_2}$ should not include changing i_1j_1 again.

And more generally we can write:

$$M_g^K(i_1j_1) = \bigcup_{\substack{i_2,j_2 \neq i_1,j_1 \\ g^{i_1j_1} \prec_{K-1} g^{i_1j_1,i_2j_2}}} M^{K-1}_{g^{i_1j_1}}(i_kj_k \leftarrow i_{k-1}j_{k-1} \leftarrow ... \leftarrow i_1j_1)$$

The complexity of notation is due to the assumption that actors can consider shorter path lengths while anticipating future outcomes. For example, actors who look K-steps ahead might only consider a myopic improvement, assuming that there are no subsequent linking changes. A step-by-step description of this formation process can be found in Section 2.4 where the simulation model is presented.

Because the decision of the actors in the network involves strategic uncertainty about which subsequent path of changes in the network will be chosen, this decision resembles a strategic decision-making situation that involves risk. Consider a process in which in each round one pair of actors is chosen randomly to evaluate a link. This implies that there are well-defined probabilities about how the network will evolve given what actors assume about how others evaluate links. We present three different decision rules for actors in such situations that are well known for decisions under risk (see Von Neumann and Morgenstern, 1944; Luce and Raiffa, 1958). These decision rules specify the value actors assign to the set of possible network positions they might reach in K steps.

1. *The maximax decision rule.* Actors focus completely on the best case for this decision rule. Actors' utility in the current networks is compared to the maximum utility possible in all networks that are considered as endpoints. In terms of improving paths, this implies that if a change is on some K-step improving path for the initiating actors, they implement this change. We formalize that by assuming that the utility that an actor i derives from changing a link ij in network g equals his maximal possible value in the networks under consideration:

$$\mathrm{MMAX}_i^K(g^{ij}) = \max_{h \in M_g^K(ij)} u_i(h).$$

2. *The maximin decision rule.* Actors evaluate the situation looking at the worst case. The utility for a specific change is now completely based on the worst situation among all the networks that are relevant to consider:

$$\mathrm{MMIN}_i^K(g^{ij}) = \min_{h \in M_g^K(ij)} u_i(h).$$

3. *The decision rule based on the "principle of insufficient reason" (PIR).* Here, actors consider all networks that might be reached equally likely and calculate the *mean* of all possible utilities. It is not possible to give a closed formula for the general K-step case. The utility of a change is formalized as the expected utility based on all possible networks that

might be reached in two or three steps, which clarifies how the PIR decision rule works:

$$\mathrm{PIR}_i^2(g^{ij}) = \frac{\sum_{h \in M_g^2(ij)} u_i(h)}{|M_g^2(ij)|}.$$

The calculation is more complex for the three-step procedure:

$$\mathrm{PIR}_i^3(g^{ij}) = \frac{\sum_{\substack{kl \neq ij \\ g^{ij} \prec_2 g^{ij,kl}}} \frac{\sum_{h \in M^2_{g^{ij}}(kl \leftarrow ij)} u_i(h)}{|M^2_{g^{ij}}(kl \leftarrow ij)|}}{|\{kl \neq ij | g^{ij} \prec_2 g^{ij,kl}\}|},$$

where the vertical lines indicate the cardinality of the sets. The formalization implies that at every next level of thinking each possible change is considered equally likely.

These decision rules model individual risk preferences in their most extreme appearances (see Luce and Raiffa, 1958). Actors who consider a change are uncertain which pair of actors is picked in the subsequent round(s) and are therefore uncertain which path the formation process follows. We interpret the maximin decision rule as a way of modeling extreme risk aversion, the PIR decision rule as risk neutrality and the maximax decision rule as extremely risk seeking behavior. In the vast literature on decision-making involving strategic risk, not much is known about how individual risk preferences affect decisions in complex strategic situations like network formation. We start with these simplified forms of modeling risk preferences to investigate how sensitive the predictions are to varying risk preferences.

Consequently, three risk-related decision rules for limitedly farsighted behavior are analyzed in how predictions differ. We assume that for each decision rule actors are homogeneous, so there are either only risk-averse, only risk-neutral, or only risk-seeking actors. Note that the sets $M_g^K(ij)$ in the definitions above also depend on the chosen decision rule.

Clearly, the three decision rules that we defined might lead to different sets of stable networks. Still, we can now define straightforwardly K-step stability.

A network g is *K-step pairwise stable* if for a given specification of the utility function U^K from a given set of foreseeable networks $M_g^K(ij)$ there is no pair of actors i and j such that $(g \prec_K g^{ij})$.

Some remarks are appropriate related to this definition of K-step pairwise stability. First, the ordering of networks is not complete. If actors move from network g to g^{ij}, they might want to move back again after the change, because they overlook a different set of networks after the move. Given the utility functions it is clear that the set of MMAX K-step pairwise stable networks is a subset of the PIR K-step stable networks, which is again a subset of a the MMIN K-step stable networks. The reason is that if actors do not anticipate *any* network in which they might be better off by changing a link (MMAX), they certainly do not see any improvements if they apply stricter rules on when they want to change as PIR or, even stricter, MMIN.

2.3 Farsightedness in the co-author model

Figure 2.2 shows the metanetwork (as introduced by Willer, 2007) representing all non-isomorphic network structures with $n = 4$ and utilities given by the co-author model. The arrows in the metanetwork of networks represent possible transitions from one to the other network if actors would be myopic. From this metanetwork, it can be inferred that network K, the complete network, is the myopically pairwise stable network, because that is the only network without outward pointing arrows. We now describe the predictions when actors are looking ahead.

2.3.1 Looking two steps ahead

To identify the stable networks when actors look two steps ahead, we can also use the metanetwork for myopic improvements. Actors who look two steps ahead place themselves in the shoes of the other actors, assuming these actors are myopic. They follow two arrows in the metanetwork anticipating subsequent changes. For example, the two actors at the top of network B who consider moving from B to C realize that they eventually might end up in network E, F, or G. Now there are two more networks that can be stable. First, the circle network (I) is stable under the maximin, PIR, and maximax decision rule. This can be seen as follows. Actors who look two steps ahead expect that if they would move to network J, the process would continue to network K. This is also the only network to be considered from network J. In network K, the two actors who initiated the change from I to J are both worse off compared to network I. Therefore, actors who look two steps ahead do not want to move from network I to J. The only other change that has to be considered from network I is the path through network G to H. In this case, again, both actors who initiated the change from I to G are worse off in network H. The efficient two-dyads network (D) is stable only under the maximin and PIR decision rules. The most crucial change to be considered is whether two actors would like to connect to network G. Looking forward, they then expect that they will reach network I or H. In network I, they would both earn 2.5, while in network H, one of them will earn 2.25 and one will earn 3.67. This is not attractive under the maximin and the PIR decision rule, because the worst that can happen is that one earns $2.25 < 3$. Also the average of these three outcomes is below 3. However, because the best outcome is $3.67 > 3$, the actors do want to move to network G under the maximax decision rule. The complete network (K) remains stable for all three decision rules, because removing a relation can only bring them back to network K taking myopic subsequent improvements into account.

In a similar way, one could investigate, for each of the three decision rules, from which network actors who look two steps ahead are willing to move. Based on that one could also draw the metanetwork for actors looking two steps ahead. This metanetwork would immediately reveal the stable networks as the networks without outgoing links.

2.3.2 Looking three steps ahead

If actors look three steps ahead, the metanetwork is not a convenient instrument anymore to check for stable networks. One would need two metanetworks, one for myopic actors and one for actors looking two steps ahead. Combining these two metanetworks, the anticipated changes after a change by an actor who looks three steps ahead, can be investigated. This, however, would be a tedious and error-prone job that can better be done by a computer program developed to systematically check all these steps. Therefore, we continue by describing the computer program used to check the stability of networks for the different types of decision rules explained above and to simulate the dynamic process in the network that ultimately converges to a stable network for actors looking two and three steps ahead.

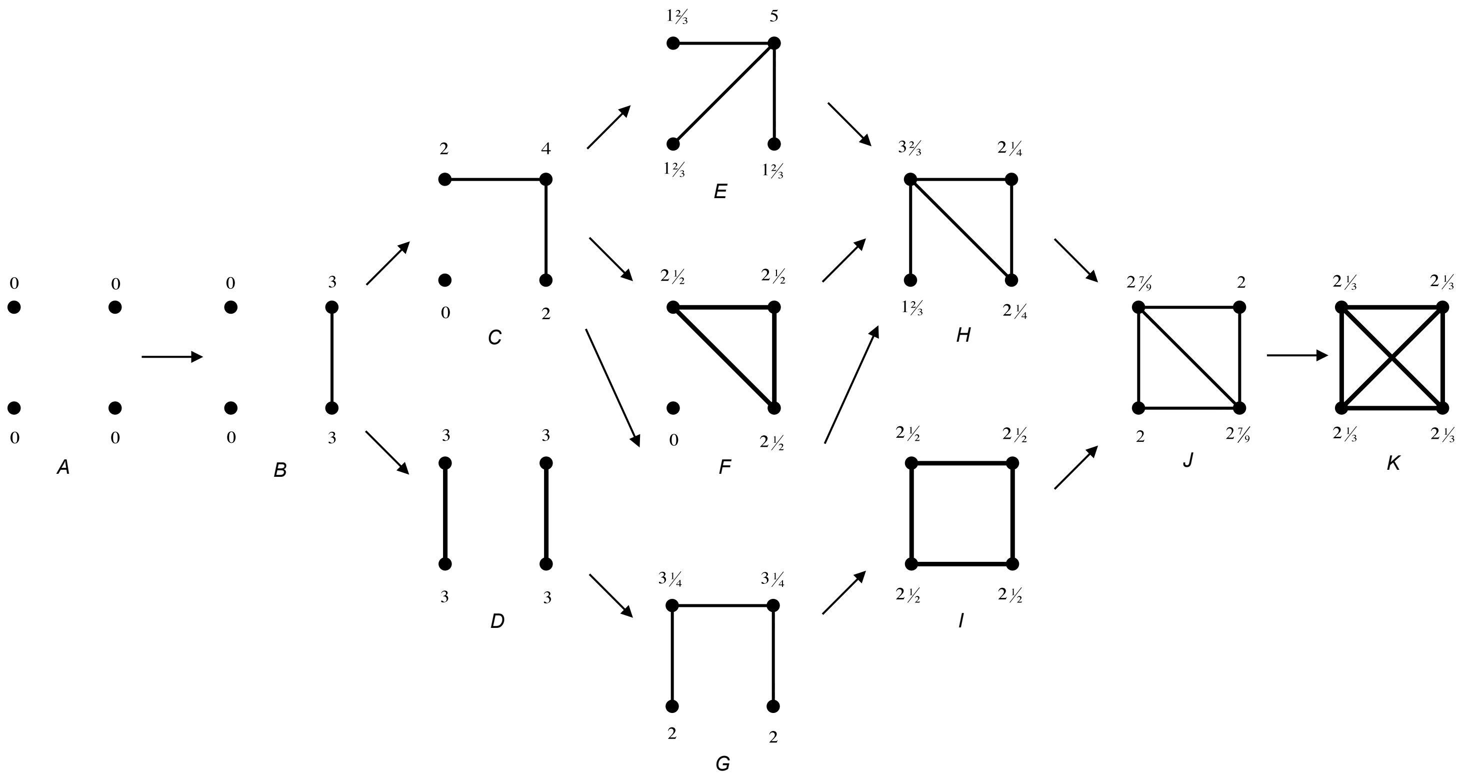


Figure 2.2: Co-author model with $n = 4$, all non-isomorph networks

2.4 Simulation

There are two reasons why we use simulations to continue the stability analyses of the network formation models introduced above. First, we would like to consider networks with more than 4 actors. Second, we would like to estimate the likelihood that a specific stable network is reached in situations with more than one stable network.

In section 2.3, we identified the stable networks for four-actor networks in the co-author model when actors look two steps ahead. Even for this simple case, we neither proved that the networks we claimed to be stable are the only stable one's, nor did we explain for all possible deviations from the stable networks that they indeed were not attractive for actors who look two steps ahead. The simulation provides us with the opportunity to check for every possible network with sizes from 3-8 (these are 13,595 non-isomorphic networks, see also Buskens and Van de Rijt, 2008) to identify whether they are stable for the different decision rules specified. In addition, the simulation provides a possibility to follow the network updating process from a non-stable network to a stable network.

The simulation method takes the following steps:

1. Start with some network g.
2. Randomly pick a pair of actors $\{i, j\}$ (every pair with equal probability) to check whether they want to change their link.
3. If i and j do want to change the link ij, change the link and return to step 2 for the new network.
4. If i and j do not want to change the link ij, randomly choose another pair of actors until you find two actors that do want to change their link. Change this link and return with the new network to step 2.
5. If there does not exist any pair of actors anymore who want to change their link, the program ends and the final network is a stable network.

What happens in step 2 of the process described above depends on the stability concept under consideration. It might be that the process we describe above does not converge and that the updating of links continues to cycle through a series of networks. This did not occur in any of our simulation.

When we consider the case of myopic actors, then step 2 is simply checking whether both actors are better off if they consider creating a link and whether one of the two is better off if they consider removing a link. When we consider actors who look two steps ahead, however, step 2 of the simulation process becomes more complicated and consists of the following sub-steps:

2a. In the current network g, if the link ij exists, remove ij; otherwise, create ij to reach network g^{ij}.

2b. For all pairs of actors k and l that are not equal to the pair i and j, consider whether network $g^{ij,kl}$ is a myopic improvement over g^{ij} for actors k and l and, thus, whether myopic actors k and l would like to change their link.

2c. If k and l indeed would like to change, store the payoffs that i and j obtain in network $g^{ij,kl}$.

2d. Take the minimum, the mean, or the maximum of all the payoffs for i stored in step 2c, depending on whether the MMIN, PIR, or MMAX decision rule is considered. Do the same for j. In case $ij \notin g$, if the resulting utility of moving to g^{ij} for both i and j is larger than what they earn in g, add the link ij; in case $ij \in g$, if the resulting utility of moving to g^{ij} for either i or j is larger than what they earn in g, remove the link ij. If there are no k and l who want to change in g^{ij}, i and j change from g to g^{ij} if this is a myopic improvement for them.

The implementation of the version of farsightedness where actors look three steps ahead looks similar, but still requires further explanation because of the payoffs that need to be stored in the process:

2a. In the current network g, if the link ij exists, remove ij; otherwise, create ij to reach network g^{ij}.

2b. For all pairs of actors k and l that are not equal to the pair i and j, consider whether network $g^{ij,kl}$ is a two-step ahead improvement over g^{ij} for actors k and l and, thus, whether actors k and l who look two steps ahead would like to change their link.

2c. If k and l indeed would like to change, store the minimum, mean, or maximum payoff (depending on the chosen decision rule) for i of all the networks that are myopic improvements from network $g^{ij,kl}$, excluding changing ij and kl back. Do the same for j. If there are no myopic improvements possible from network $g^{ij,kl}$, but k and l still want to change to $g^{ij,kl}$, store i's and j's payoffs of network $g^{ij,kl}$. Repeat step 2c for all pairs k and l that are not i and j.

2d. Take the minimum, the mean, or the maximum of all the payoffs for i stored in step 2c, depending on the decision rule to be applied. Do the same for j. In case $ij \notin g$, if the resulting utility of moving to g^{ij} for both i and j is larger than what they earn in g, add the link ij; in case $ij \in g$, if the resulting utility of moving to g^{ij} for either i or j is larger than what they earn in g, remove the link ij. If there are no k and l, who want to change in g^{ij}, i and j change from g to g^{ij} if this is a myopic improvement for them.

Because we start in every possible network, we are sure that we determine also every possible stable network for each condition. When we start in a stable network the process immediately stops and because we also save the number of iterations until convergence, it is straightforward to check which network structures are stable.

Because the order of pairs of actors that can evaluate their link is randomly determined, it does not need to be the case that if we start in a given network the process always converges to the same stable network. Therefore, we start the simulation five times from each starting network to determine the likelihood that a specific stable network is reached, based on that we start an equal number of times in every possible non-isomorphic starting network.

2.5 Results

In this section, we present the results of our simulations. We investigate *which* networks are stable when actors are limitedly farsighted, looking two and three steps ahead, and compare these to predictions for myopic actors. Thereafter, we consider the question how likely it is that certain networks emerge.

2.5.1 Stable networks

Table 2.1 summarizes the number of stable networks under the different stability concepts for each network size. The maximin decision rule produces very high numbers of stable networks. The numbers increase drastically with network size. The maximax decision rule shows the other extreme and has only very few stable networks. This pattern is even clearer when actors look three steps ahead. The reason is that if actors look further ahead, for the maximin decision rule it becomes more and more likely that an actor finds an alternative network in which he is worse off and, therefore, does not want to change. For the maximax decision rule, the opposite happens. Actors almost always find an alternative network in which they would be better off if they look enough steps ahead and, therefore, they hardly ever stop changing the network. Because these two decision rules focus purely on the worst- or best-case scenario, a decision can be based on very unlikely events in a large set of alternative outcomes. Therefore, we argue that the PIR decision rule offers the best interpretable results, as it does not produce such extreme results. Realize that from the simulation, it is clear that, under the maximin decision rule, there should be at least as many stable network as under the PIR decision rule, and that, under the PIR decision rule, there should be at least as many stable networks as under the maximax decision rule. The reason is that the conditions under which actors want to change are most restrictive for the maximin decision rule, less restrictive for the PIR decision rule, and least restrictive for the maximax decision rule.

The complete network is stable for $n = 3$ for all levels of farsightedness and all decision rules. Additionally, we observe a single dyad with one isolated actor as a stable network for actors looking two and three steps ahead, for each decision rule. In this case, the two connected actors (each obtaining a utility of 3) are excluding the single actor such that they will not agree to form a link with him because of the threat of ending worse off in the completely connected network (which brings them a utility of only 2.5).

Table 2.1: Number of stable networks

	$n = 3$	$n = 4$	$n = 5$	$n = 6$	$n = 7$	$n = 8$
myopic (one-step)	1	1	1	2	2	2
two-step						
maximin	2	3	7	14	45	153
PIR	2	3	2	2	3	4
maximax	2	2	1	1	2	2
three-step						
maximin	2	4	7	29	137	981
PIR	2	4	6	6	5	7
maximax	2	2	1	1	1	1

The stable networks for $n = 4$ were already reported in section 2.3. The efficient network of dyads is stable for the maximin and PIR decision rule, but not for the maximax decision rule. We also find the circle network and the complete network stable under all of the three decision rules and levels of farsightedness.

Remember that for myopic actors the complete network is the only stable network for $n \leq 5$. For $n \geq 6$, there is one additional stable network for myopic actors that consists of a single dyad and completely connected component (from here on labeled as "dyad+com"). These network structures are also among the stable network predictions when actors look two and three steps ahead. For the maximax decision rule and when actors look three steps ahead, the complete network is the only prediction for $n > 4$. For larger networks, under the maximin and PIR decision rule, the complete network also remains a stable network, but there is a number of other stable networks as well. The more frequent network structures that are stable in the farsightedness models for $n = 5$ are shown in figure 2.3. We discuss these networks in more detail in the following sections where we analyze the likelihood of the emergence of specific networks.

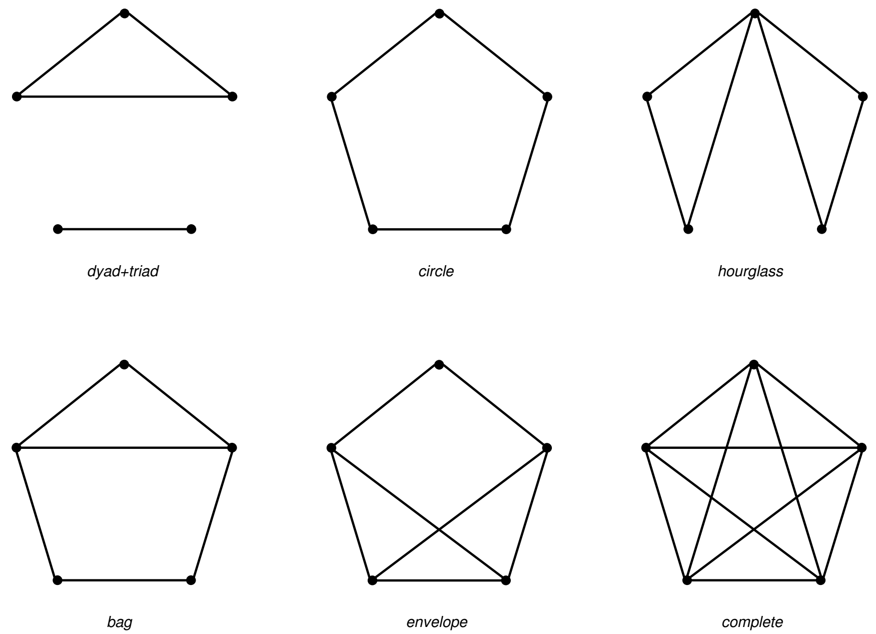


Figure 2.3: Stable networks for $n = 5$

2.5.2 The likelihood of the emergence of networks

Looking two steps ahead

We now analyze the likelihood of specific networks to emerge. Table 2.2 summarizes the results of the dynamic procedure for all networks from size 3 to 8. The numbers in the rows report the percentage of the simulations runs that converged to a certain network structure. Starting five times from all non-isomorph networks.[7] We display these percentages for the *complete* network, because it is the most common structure we observe, and also for the so-called *dyads* networks, because these are the most efficient structures. Efficient networks consist of either only dyads for even-sized networks or dyads plus a single triad for uneven-sized networks. The row *"other"* (as shown in

[7] We realize that the precise likelihoods depend on the fact that we use every non-isomorphic network only once, while it might make sense to use a weight for the results of each network relative to the number of isomorphisms that exists for each non-isomorphic network. We decided not to introduce this complication, because the main conclusion are not driven by the exact percentages that each stable network emerges.

table 2.2) reports important networks that also emerged frequently (e.g. the label (dyad+com) means that this network consists of one single dyad plus one completely connected component). We further report the average number of *iteration* steps (i.e. link changes) it takes until convergence.

In the upper block of the table the results of the myopia predictions are listed (*myopic*), followed by the three different decision rules for actors who are looking two steps ahead, referred to as *maximin, PIR, maximax*.

For actors looking two steps ahead, we make the following general observations: under all decision rules the complete network is the most frequently emerging network. However, in smaller networks, for limitedly farsighted actors, efficient networks emerge in approximately half of the cases. And the larger the network size, the more likely it is that the complete network emerges.

We further describe the detailed results for all decision rules.

Under the *maximin* decision rule, stable networks emerge that are not the inefficient complete network, for smaller networks ($n = 3$ and $n = 4$) and in half of the cases. For $n = 4$, efficient dyads and the circle network emerge in 27% and 24% of cases. For $n = 5$, the process runs towards the complete network in 55% of all cases, dyadic networks emerge only in 14% (the efficient dyad+triad network in 6% and the dyads+iso network in 8% of cases), the circle network in 11% of cases. For larger networks ($n \geq 6$), the likelihood that efficient networks evolve, becomes very small (3%, 1% and almost 0% for sizes from 6 to 8) and the complete network appears more often.

Under the *PIR* decision rule, the complete network emerges for $n = 4$ in more than half (55%) of the cases. For a circle and a two-dyad network, the likelihood is 33% and 12%. For $n > 4$, the complete network appears in most cases (in 89% for $n = 5$ to more than 98% of cases for networks $n = 7$ and $n = 8$). For $n \geq 7$, the “other” network has the same structure as in the myopia model, namely a network with a single dyad and one completely interconnected component. However, this network was never reached from any other initial network.

Under the *maximax* decision rule, the circle network is more likely to appear than the complete network (75%) for $n = 4$. However the complete network emerges in 100% of cases for $n = 5$ and $n = 6$. For $n > 6$, the

Table 2.2: Proportions emergence of stable networks: myopic and looking two steps ahead

	$n = 3$	$n = 4$	$n = 5$	$n = 6$	$n = 7$	$n = 8$
myopic (one-step)						
complete	1.0	1.0	1.0	.99	.99	.99
dyads	–	–	–	–	–	–
other	–	–	–	(dyad+com) .01	(dyad+com) .01	(dyad+com) .01
no. of iterations (std. dev.)	1.5(1.1)	3(1.7)	5(2.1)	7.4(2.7)	10(2.9)	14(3.1)
maximin two-step						
complete	.50	.49	.55	.64	.75	.83
dyads	.50	.27	.14	.03	.00	.00
other	–	(circle) .24	(circle) .12	(dyad+com) .08	(dyad+com) .05	(dyad+com) .03
no. of iterations (std. dev.)	.5(.5)	1.4(1.1)	2.5(2.0)	4.7(2.9)	7.8(3.9)	12(4.5)
PIR two-step						
complete	.50	.51	.89	.93	.98	.98
dyads	.50	.11	.11	.00	–	–
other	–	(circle) .38	–	(dyad+com) .07	(dyad+com) .02	(dyad+com) .02
no. of iterations (std. dev.)	.5(.5)	1.8(1.6)	4.3(2.2)	7.0(2.8)	11(5.2)	14(3.4)
maximax two-step						
complete	.50	.25	1.0	1.0	.99	.99
dyads	.50	–	–	–	–	–
other	–	(circle) .75	–	–	(dyad+com) .01	(dyad+com) .01
no. of iterations (std. dev.)	.5(.5)	2.4(2.2)	9.8(6.9)	36(28)	114(97)	468(438)
no. starting networks	4	11	34	156	1,044	12,346

[a] See figure 2.3 and the text for a explanation of "other" networks.

dyad+com network emerges in only 1% of all simulation cases.

When actors look two steps ahead, there is no state in which the process is cycling. Under the risk seeking decision rule (maximax) to reach a stable network state, the number of link changes is the highest. Actors constantly change the network to achieve a network position that they assume is more beneficial (note the average number of iteration steps).

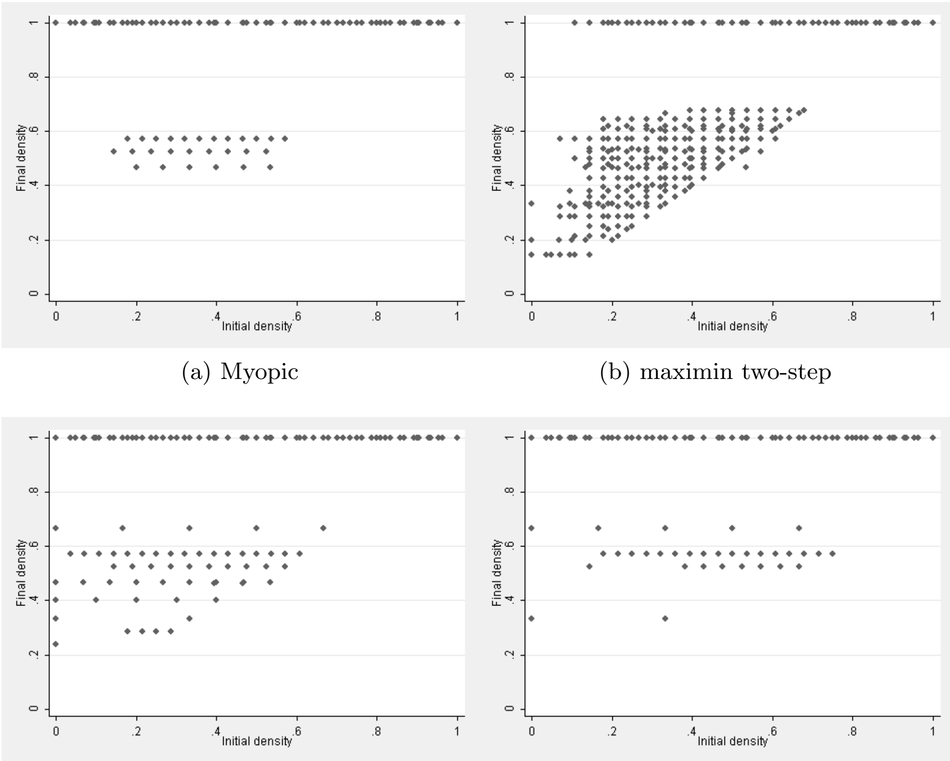
The scatter plots in figure 2.4 reports the formation processes where density[8] of the initial network (on the x-axis) is plotted against the density of the converged network (on the y-axis).[9] All repetitions over all network sizes are displayed. Most formation processes stabilize in the inefficient complete network (density equal to 1). Therefore most points are located on the upper part of the graph. In figure 2.4a, the points lying on the three horizontal lines in the middle are the dyad+com networks that are stable for networks of size 6 to 8. In figure 2.4b, networks that are indicated by points lying on the diagonal, represent cases where the initial network is also the final network. Most stable networks lie above this diagonal, indicating that the networks become more dense until convergence. Note (e.g. in figure 2.4b) that if the initial network is already quiet dense (around .7) then the formation processes always stabilize in the inefficient complete network. Formation processes in which the final network is less dense than the initial network are infrequent, since in most situations there are only few incentives for actors to delete links, even when actors look ahead (these cases are the points lying below the diagonal). This appears more often under the maximax decision rule, where actors foresee more networks in which they are better off and therefore tend to delete more links.

Looking three steps ahead

The detailed results for actors who look three steps ahead are shown in table 2.3. In general we observe a similar pattern as for actors who look two steps

[8]The proportion of links in a network relative to the maximal number possible links.

[9]In the co-author model network density is related to efficiency as described above. However the density measure better shows how adding links is the driving force of formation processes in the co-author model. The corresponding efficiency tables are shown in appendix A.2



(a) Myopic (b) maximin two-step

(c) PIR two-step (d) maximax two-step

Figure 2.4: Initial network density versus final network density, myopic and two-step

ahead, but now the pattern becomes sharper: Still with increasing network size, converged networks tend to become overconnected and, therefore, inefficient. Although the effect of network size is less severe than compared to when actors look two steps ahead. For example, under the PIR decision rule, actors who look three steps ahead will not end up in completely connected networks as often as when looking two steps ahead (for $n = 5$ and $n = 6$ in only around 30% of cases the complete network is stable). In more detail, for $n = 3$ the results remain unchanged as compared to actors who look two steps ahead. Under the maximin decision rule the complete network is often not the final network of the process (it is highest for $n = 4$ with 31% of cases). There are many stable networks when actors use the minimax decision rule. Now looking three steps ahead actors foresee even more network positions where they might end up worse off. Therefore, most processes stop after very few link changes (the number of iteration steps with actors who look three steps ahead is lower than with actors who look two steps ahead). For $n = 4$, one additional network emerges, the network with a triad and an isolated actor (triad+iso) (18% of cases). This is possible because all actors within the triad fear that they might end up worse off after connecting to the isolated actor (looking three steps ahead actors foresee the formation process untill the complete network). For $n = 5$ in 27% the complete network emerges, in 9.4% of cases the efficient dyad+triad network and the two dyads with an isolated actor in 8.8% of cases. Other networks that emerge frequently are the bag network with 23%, and the hour glass in 17% (see figure 2.3). For $n = 6$, the complete network emerges in 16.3% of cases, but in only 2.6% of formation processes actors remain in the efficient dyad structure. Most cases stabilize in the dyad+com network. For $n = 7$, the network that emerges most often has one actor with five connections, four actors with four, one with three and one with two connections ($5^1 4^4 3^1 2^1$) (see appendix A.1). For $n = 7$ and $n = 8$, efficient dyads are only stable when they are the starting network configuration.

Under the PIR decision rule, the triad+iso network emerges in 29% of cases for $n = 4$. The circle and efficient network emerge in 27% of all cases. The complete network emerges in 16% of cases. For $n = 5$, the complete network emerges in 26.5% of cases, the dyad+triad network in 8.8%, and the dyads+iso network in 6.5% of cases. Other converged networks for $n = 5$ are the "envelope" (see figure 2.3) in 22.9% of cases and the circle network (5.9% of cases). For $n = 6$, the complete network appears in 32.4% of cases, the network that emerges most often is an almost completely connected network where three links are missing (the octahedron, see appendix A.1). Efficient dyads only emerge when the process also starts in this network. For $n = 7$ and $n = 8$ the complete network emerges in most cases. Efficient networks are unlikely and emerge in less than 1% of cases.

Under the maximax decision rule, there are three converged networks for $n = 4$. The circle network emerges in 60%, the complete network in 15%

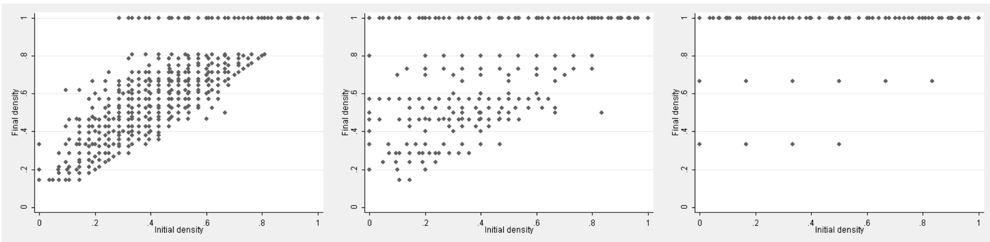
Table 2.3: Emergence of stable networks: looking three steps ahead

	$n=3$	$n=4$	$n=5$	$n=6$	$n=7$	$n=8$
maximin three-step						
complete	.50	.31	.27	.16	.09	.22
dyads	.50	.27	.18	.02	.01	.00
other	–	(triad+iso) .18	(bag) .23	(dyad+com) .26	($5^1 4^4 3^1 2^1$) .10	(dyad+com) .01
no. of iterations (std. dev.)	.5(.5)	1(0.9)	2.0(2.5)	5.3(8.5)	3.7(4.7)	5.7(10)
PIR three-step						
complete	.50	.16	.27	.32	.97	.97
dyads	.50	.27	.01	.00	.01	.00
other	–	(triad+iso) .29	(bag) .29	(octah.) .37	(dyad+com) .02	(dyad+com) .02
no. of iterations (std. dev.)	.5(.5)	1.8(2.9)	11(28)	37(71)	206(209)	461(456)
maximax three-step						
complete	.50	.15	1.0	1.0	1.0	1.0
dyads	.50	.25	–	–	–	–
other	–	(circle) .60	–	–	–	–
no. of iterations (std. dev.)	.5(.5)	8.2(8.9)	n.a.	n.a.	n.a.	n.a.
no. starting networks	4	11	34	156	1,044	12,346

[a] See figure 2.3, Appendix A.1, and the text for a explanation of "other" networks.

and the dyad in 25% of cases. For $n > 4$, there is only one stable network, namely the complete network. This can be explained because from every other network actors who use the maximax decision rule anticipate a network position in which they are better off than in their current position. Note the high number of link changes in this procedure.

Additionally, we observe cycles in the maximin decision rule for $n = 8$. In 11.2% of the simulation runs the process did not converge to some network. By looking at the starting networks that always end up in non-convergence, we identify the networks that are part of cycles. In our simulations there were 547 different cases of starting networks that always lead to a cycle. Of the networks that are part of cycles, 96% can be described by six different networks structures. These, however, do not have any appealing structural properties we could detect.



(a) maximin three-step (b) PIR three-step (c) maximax three-step

Figure 2.5: Initial network density versus final network density, three-step

For actors who look three steps ahead, the scatter plots between initial network density and final network density show similar patterns as compared to the plots for actors who look two steps ahead. There are more formation processes where the initial network density is higher than the density of the stable network (points below the diagonal). Also note that under the maximin and PIR decision rule the initial network density can be higher (around .8) before all networks stabilize in the complete network (compared to the version of actors looking two steps ahead where density is around .7. Note the gap in figures 2.4b and 2.5a). For the PIR decision rule, looking three steps ahead implies more networks that stabilize in intermediate density levels than compared to the two-steps version.

2.6 Conclusion and discussion

Theoretical arguments and empirical results have questioned the commonly used assumption of myopic behavior in network formation models. We develop a model in which actors make their decisions in a limitedly farsighted manner, to analyze how this affects the emergence and efficiency of networks. In the model, actors anticipate subsequent decisions of other actors when making their own decisions. Changing the microfoundations of the network formation model implies new predictions at the macro-level in the sense that different networks are predicted to be stable than for myopic behavior.

The main finding is that in *smaller* networks, where limitedly farsighted actors are able to oversee the formation process, it is possible to overcome the tension between efficiency and stability, while this is impossible for myopic actors. However, limitedly farsighted actors cannot fully overcome this tension in larger networks; as the network size increases they still end up in suboptimal situations. Increasing the level of farsightedness to three steps helps to overcome the tension between efficiency and stability in some more cases but also here, as network size increases, actors end up in inefficient structures, predominantly the complete network.

Experimental results for the co-author model show that the emergence of efficient networks, as predicted by the limited farsightedness model, is possible when subjects play this game in the laboratory (see Van Dolder and Buskens, 2008). The experimental evidence is hard to reconcile with myopic behavior and may be consistent with limited farsightedness assumptions. On the one hand, some phenomena, e.g., deviations from game-theoretic predictions we observe in experiments or real life situations, can often be better explained assuming some form of limited rationality. On the other hand, experimental researchers claim that their results can be explained by assuming subjects use more sophisticated strategies, and that myopic best response behavior might be a too simple form of modeling bounded rationality (Callander and Plott, 2005; Van Dolder and Buskens, 2008; Corten and Buskens, 2010). With the means of simulation techniques, we were able to predict possible network outcomes when actors are limitedly farsighted for networks from size 3 to 8.

Additional assumptions about how actors evaluate uncertain network outcomes were needed when assuming limited farsightedness in a dynamic formation process. Risk preferences can have a big impact on the formation process and on predictions of stable networks. Risk-averse actors prefer other network changes than risk-neutral or risk-seeking actors. The formation process itself differs in terms of convergence time, i.e., the number of link changes needed to reach a stable state. Risk-seeking actors take far more link changes to get to a stable state. Also they are more likely to move to intermediary and temporarily less beneficial network positions to strive for a perceived better outcome. This might explain some seemingly irrational behavior often observed in experiments. In models of strategic network formation the influence of risk preferences so far seems neglected.[10] Looking at the different predictions, risk preferences seem to be a rather important factor. In a dynamic approach, where actors are indifferent on where the process might evolve, it is inevitable to discuss actors' evaluation of future outcomes in terms of risk preference and how this might influence actors' decisions. Because we only considered very extreme forms of risk-averse and risk-seeking preferences, we could show that risk preferences matter, but we neglected weaker forms of risk averse and risk seeking preferences that might be more realistic in analyzing network formation behavior in empirical applications. More research will be needed to shed light on that topic.

Future research might look as follows: first, other ways in which actors derive utility from networks should be used to study how limited farsightedness affects network formation in different settings (e.g. the connections model, see Jackson and Wolinsky, 1996). Second, experiments on network formation should be conducted to test the model. Third, risk preferences and also heterogeneity of actors should be included into theoretical models to study their effects in more detail. Individual level differences (heterogeneity) is an important factor within network formation.[11] Heterogeneity in our approach

[10] We are only aware of one working paper by Kovářík and Van der Leij (2010)

[11] Fowler et al. (2009) could explain a large amount of variance within network character-

can be understood in two ways: first, heterogeneity regarding farsightedness (some actors might look further ahead than others), and second, heterogeneity in terms of risk preferences. It is of interest to investigate both cases of heterogeneity and how they might influence predictions of stable networks. The simulations in this chapter only covered networks of size 3 to 8. Applying the model to larger networks would be another extension where the impact of limitedly farsighted actors on network formation can be investigated. Possibly, actors interact limitedly farsighted within their local network but interact myopically with more distant actors in the network.

istics such as in-degree through individual differences in genes.

Chapter 3

Strategic Formation of Networks to Obtain Information When Actors Are Limitedly Farsighted*

3.1 Introduction

Information is an important resource in today's society that is often passed on and obtained within social networks. People receive important information through their social network, or they occupy positions within a network that are beneficial (Granovetter, 1973; Burt, 1992). From empirical research, we know that actors are aware of the network structure they are embedded in (Krackhardt, 1987) and that actors realize that certain network positions are beneficial. It is therefore argued that actors will choose their relations to optimize their benefits (Burt, 1992; Flap, 2002) and that people will strategically invest in their social relations. Strategic networking behavior has become an important explanatory mechanism to study phenomena like co-authorship among researchers, collaborations among firms, alliances among

*This chapter was written in collaboration with Vincent Buskens and Stephanie Rosenkranz, with Dominik Morbitzer being the first author.

political agents, or friendship (Goyal et al., 2006; Bojanowski et al., 2012; Jackson, 2008).

To understand the complex structures of real-world social networks we need to analyze how and why networks form, how networks affect certain outcomes of individuals and how networks evolve over time. Research regarding social networks focuses on these complex and intertwined aspects. Formal theory building can help to answer these questions (Coleman, 1990). However, these macro-micro-macro models often rely on unrealistic and problematic assumptions, e.g. about how actors make decisions. These assumptions need to be carefully investigated (Raub et al., 2011). We refer to such micro-level assumptions about individual behavior as the microfoundations of the model.

Theories mainly from economics model social network formation using game-theoretical tools. So far, the models lack well-established microfoundations and also produce unrealistic results that do not resemble empirically observed networks (Jackson and Wolinsky, 1996; Bala and Goyal, 2000; Raub et al., 2011). In their seminal paper, Jackson and Wolinsky (1996) model payoffs of individuals as a function of the network, and then examine individual incentives to form networks. They established the notion of pairwise stability. A network is considered pairwise stable if no actor wants to delete a link and no pair of actors want to add a link. Later, Jackson and Watts (2002) extended the static analysis and considered network formation as a dynamic process in which pairs of actors sequentially decide whether to change their relations or not. One main assumption of these dynamic models of network formation is the so-called myopic best response behavior. Actors make their networking decisions myopically, meaning that they only look at their immediate gains and neglect subsequent network changes that might occur. However, predictions of these models fail in experimental tests. Researchers often interpret these deviations as signs of anticipatory, i.e., farsighted behavior, such that individuals seem to take subsequent network changes into account while deciding with whom to connect (Pantz, 2006; Berninghaus et al., 2012; Van Dolder and Buskens, 2008; Corten, 2009). Of course, there are alternative ways of explaining the observed deviations from the "myopia" model. One can argue that subjects do not only act selfishly but also take the outcome of other actors into account (Corten, 2009; Van Dolder and Buskens, 2008). However, experimental research suggests that social preferences might not improve explanation in network formation (Van Dolder and Buskens, 2008). Following the argumentation that deviations might be due to farsightedness of actors, researchers address the rationality assumptions in the models (Herings et al., 2009; Pantz, 2006; Morbitzer et al., 2011).

In chapter 2 we set up a model where it is assumed that actors are farsighted but only in a limited way. Given experimental evidence from related fields in behavioral game theory we know that people look ahead but often not more than two or three steps (see Camerer, 2003). Beauty contest games are used to analyze to what extent people do reason ahead when thinking strategically. Foreseeing reactions in network situations is different and more complex compared to games such as the beauty contest game. Therefore, we started with a simple model of farsightedness, namely looking two and three steps ahead as compared to looking one step ahead.

In chapter 2 we applied the model using the utility function of the coauthor model by Jackson and Wolinsky (1996). Given myopic best response it is predicted that actors end up in the complete and inefficient network, thus creating a tension between stability and efficiency. Using computer simulations, we were able to show that actors who look ahead can overcome this dilemma and can also end up in more efficient network structures. However, as the network becomes larger the myopia model and the model of limited farsightedness give similar predictions. As the network becomes bigger, the complexity increases and limitedly farsighted actors are no longer capable to anticipate what might happen in the long run.

In this chapter we apply the assumption of limited farsightedness to two additional utility functions: We use the connections model by Jackson and Wolinsky (1996), as well as the utility function used by Buskens and Van de Rijt (2008) as a conceptualization of Burt's constraint measure (1992) to see how limited farsightedness affects network formation in different contexts. Both utility functions model information as a resource that can be obtained through social networks. Jackson & Wolinsky's (1996) connections model captures the idea that being connected to others is beneficial. There is a spillover effect of valuable information from indirect connections in a network, having close relations comes with a cost (e.g. time or effort). Thus, the model relies on three parameters, the benefits of direct and indirect relations, and the costs of direct relations. Buskens and Van de Rijt's (2008) utility function models Burt's (1992) idea of structural holes. It captures the idea that actors who fill intermediate positions between otherwise not connected (groups of) actors can benefit by brokering the flow of information (or other resources). These intermediate positions are the so-called structural holes. While creating relations in the connections model is about obtaining as much information as possible, also via not directly connected others, in the structural holes model, there is competition for unique and valuable information. The two utility functions model different incentives to create or break links. This leads to different implications for the network formation process, both at the actor level, as actors make different linking decisions based on different expected utilities, as well as at the network level, where different utility functions imply different efficient networks.

We study which networks are predicted to emerge in these two different settings in which obtaining information is important. How do these networks differ depending on whether redundant information is problematic and how do they differ depending on the assumed level of farsightedness of the actors? We study network differences in terms of efficiency, inequality, and density of networks.

The remainder of the chapter is organized as follows. In section 3.2, the model of network formation is described. In section 3.3, we present the utility functions of network formation. In section 3.4, the results are reported. In section 3.5, we conclude with a discussion of the results.

3.2 Model

In this section we describe the basic notation and assumptions of the model of network formation. For a more detailed version of the network formation model with limited farsightedness see Morbitzer et al. (2011). We present the formation process in terms of the computer simulations that are used to predict the stable networks.

The set $N = \{1, \dots, n\}$ is the set of nodes representing actors. A network g indicates the actors in N that are connected via a link. Formally, g is a set of unordered pairs of actors $\{i, j\}$. For any pair i and j, $\{i, j\} \in g$ indicates that i and j are linked in the network g; otherwise $\{i, j\} \notin g$. Links are undirected, if i has a link with j then j also is linked with i. We denote the link $\{i, j\}$ also with ij. Let $g + ij$ denote the network obtained by adding the link ij to the existing network g and let $g - ij$ denote the network obtained by deleting the link ij from the existing network. We define g^{ij} as the adjacent network obtained by either adding or deleting a link in g.[1]

The utility function vector $u : G(n) \to \mathbb{R}^n$ models the overall benefit net of costs of the actors in a network, where $G(n)$ is the set of all possible networks with n actors. We represent the utility of actor i in network g by $u_i(g)$. The stability concept we start from is pairwise stability as proposed by Jackson and Wolinsky (1996). A network g is *myopically pairwise* stable if

1. $\forall ij \in g$, $u_i(g) \geq u_i(g - ij)$ and $u_j(g) \geq u_j(g - ij)$
2. $\forall ij \notin g$, if $u_i(g + ij) > u_i(g)$ then $u_j(g + ij) < u_j(g)$

In words, a network is myopically pairwise stable if no actor wants to severe a link and no pair of actors want to add a link based on immediate payoff changes.

We now present the dynamic network formation model in terms of the computer algorithm that we used to simulate the process. With the help of the computer simulations we can check stability for every possible network with sizes 3 to 8 actors. We implemented the formation process for actors who are myopic, thus look one step ahead and *limitedly farsighted* actors, who look two and three steps ahead in the same way as in Morbitzer et al. (2011).

The simulation method takes the following steps:

1. Start with some network g.
2. Randomly pick a pair of actors $\{i, j\}$ (every pair with equal probability) and check whether they want to change their link.

[1] We use this notion for practical reasons when introducing the model of limited farsightedness.

3. If i and j do want to change the link ij, change the link and return to step 2 for the new network.
4. If i and j do not want to change the link ij, randomly choose another pair of actors until you find two actors that do want to change their link. Change this link and return with the new network to step 2.
5. If there does not exist any pair of actors anymore who want to change their link, the program ends and the final network is a stable network.

The outcome of step 2 of the process described above depends on how actors' incentives are modeled (the utility functions) and on their degree of farsightedness. Note that it might be that the process we describe above does not converge and that the updating of links continues to cycle through a series of networks.

When we consider the case of myopic actors, then step 2 is simply checking whether both actors are better off if they consider creating a link and whether one of the two is better off if they consider removing a link as described in the pairwise stability notion above. In the limited farsightedness notion of chapter 2, it is assumed that limitedly farsighted actors consider reactions of others as if these others are one step less farsighted than the focal actor. This idea is similar to models on level-k-thinking or cognitive hierarchy theory (see e.g. Stahl and Wilson, 1995; Camerer et al., 2004). The idea implies an inconsistency of own behavior and perceived behavior of others and is in line with psychological evidence on overconfidence (e.g. Camerer and Lovallo, 1999). Also note that networks that are "in between" an assumed future network state are not considered in the utility calculations: Only the expected utility of the future network(s) is compared with the current utility. We assume that actors do not take these "in between" states into account since they consider these states only as transition points towards a future network. When we consider actors who look two steps ahead step 2 of the simulation process becomes, thus, more complicated and consists of the following sub-steps:

2a. In the current network g, if the link ij exists, remove ij; otherwise, create ij to reach network g^{ij}.

2b. For all pairs of actors k and l that are not equal to the pair i and j, consider whether network $g^{ij,kl}$ is a myopic improvement over g^{ij} for actors k and l and, thus, whether myopic actors k and l would like to change their link in network g^{ij}.

2c. If k and l indeed would like to change, store the payoffs that i and j obtain in network $g^{ij,kl}$.

2d. Take the mean of all the payoffs for i stored in step 2c. Do the same for j. In case $ij \notin g$, if the resulting utility of moving to g^{ij} for both i and j is larger than what they earn in g, add the link ij; in case $ij \in g$, if the resulting utility of moving to g^{ij} for either i or j is larger than what they earn in g, remove the link ij. If there are no k and l who want to change in g^{ij}, i and j change from g to g^{ij} if this is a myopic improvement for them.[2]

The implementation of the version of farsightedness where actors look three steps ahead looks similar, but still requires further explanation because of the payoffs that need to be stored in the process:

2a. In the current network g, if the link ij exists, remove ij; otherwise, create ij to reach network g^{ij}.

2b. For all pairs of actors k and l that are not equal to the pair i and j, consider whether network $g^{ij,kl}$ is a two-step ahead improvement over g^{ij} for actors k and l and, thus, whether actors k and l who look two steps ahead would like to change their link.

2c. If k and l indeed would like to change, store the mean payoff for i of all the networks that are myopic improvements from network $g^{ij,kl}$, excluding changing ij and kl back. Do the same for j. If there are no myopic improvements possible from network $g^{ij,kl}$, but k and l still want to change to $g^{ij,kl}$, store i's and j's payoffs of network $g^{ij,kl}$. Repeat step 2c for all pairs k and l that are not i and j.

[2]Morbitzer et al. (2011) analyzed other scenarios in which actors differently weight possible future payoffs.

2d. Take the the mean of all the payoffs for i stored in step 2c. Do the same for j. In case $ij \notin g$, if the resulting utility of moving to g^{ij} for both i and j is larger than what they earn in g, add the link ij; in case $ij \in g$, if the resulting utility of moving to g^{ij} for either i or j is larger than what they earn in g, remove the link ij. If there are no k and l, who want to change in g^{ij}, i and j change from g to g^{ij} if this is a myopic improvement for them.

Furthermore we define some notation for the most important and common stable networks we find. A bipartite network is a network in which actors can be divided in two groups such that there are no links within these groups. The complete bipartite network K_{n_1,n_2} is the bipartite network in which all the possible links between actors in two groups, which have sizes n_1, n_2, are present. A balanced bipartite network is a bipartite network such that the difference between the number of actors in the largest group and the number of actors in the smallest group is at most 1 (see figure 3.6a for an example of a complete bipartite network). Another special case of a complete bipartite network is the so-called n_2-*star* network, where one of the two groups consists of one single actor (K_{1,n_2}). Furthermore, we present some networks according to the degree of the actors as $N_{{k_1}^{l_1},\ldots,{k_n}^{l_n}}$, where k indicates the degrees of actors and l is the number of actors in the network with that degree.

Stable networks will also be analyzed in terms of their efficiency, equality and density. Efficiency will be the sum of all utilities of actors within a network, divided by the highest possible sum of payoffs in a network.[3] This utilitarian notion is not unproblematic but common in the literature (see e.g. Jackson, 2008). Furthermore, inequality is measured as the standard deviation of all utilities in a network, thus a low value indicates equality, a high value indicates inequality. Finally, density of the network will be defined as the number of links in a network divided by the maximal possible number of links.

[3]More precisely, we calculate efficiency as: efficiency $= \frac{\sum_i u_i(g)}{max \sum_i u_i(g)}$

3.3 Utility functions

In this section we introduce the utility functions we use in the simulations to study how farsightedness affects the emergence of networks.

3.3.1 Connections model

The connections model of Jackson and Wolinsky (1996) is well known in the literature on strategic network formation. Links in this model offer actors a benefit, for instance in terms of receiving information. But links are also costly (e.g. time or effort it takes to maintain a relation). In the connections model, actors also benefit from indirect links. However, the benefit of indirect links deteriorates with the distance of the relationship. A friend of a friend is indirectly still beneficial but less valuable than a direct benefit from a direct friend. In the symmetric connections model, the benefits fall off exponentially with the distance. The payoff is given by:

$$u_i(g) = \sum_{j \neq i} \delta^{t(ij)} - \sum_{j:ij \in g} c$$

where $t(ij)$ is the shortest path length between i and j and δ $(0 < \delta < 1)$ is the payoff i gets from being connected to j and let $c \geq 0$ be the costs for maintaining a link. The connections model satisfies positive externalities such that links created by other actors are beneficial for the focal actor. Buechel and Hellmann (2012) generalize an important result of the connections model: situations characterized by positive externalities create networks that are "under-connected" (i.e. networks having too few connections to be efficient structures).[4]

In the connections model efficient networks[5] can be described as:

1. the complete network, if $(c < \delta - \delta^2)$,
2. the star network if $(\delta - \delta^2 < c < \delta + ((n-2)/2)\delta^2)$,

[4] On the other hand, situations of negative externalities create networks that are 'over-connected', i.e. too dense to be efficient. An example is the co-author model by Jackson and Wolinsky (1996).

[5] A network g is efficient relative to a profile of utility functions $(u_1, ..., u_n)$ if $\sum_i u_i(g) \geq \sum_i u_i(g')$ for all $g' \in G(n)$.

3. and the empty network if $(\delta + (n-2)/2)\delta^2 < c)$.

The second important proposition for this utility model concerns pairwise stable networks and states the following:[6]

1. A pairwise stable network has at most one (non-empty) component.
2. For $c < \delta - \delta^2$ the unique stable network is *complete*.
3. For $\delta - \delta^2 < c < \delta$ the *star* encompassing all actors is pairwise stable, but not necessarily the unique stable network.
4. For $\delta < c$ any pairwise stable network which is non-empty is such that each actor has at least two links and thus is inefficient.

For high and low link costs, the efficient networks overlap with the pairwise stable networks. For intermediate cost levels, disparities between efficiency and pairwise stable networks occur. There are cases when pairwise stable networks tend to be Pareto inefficient (see also Jackson, 2008).

Hummon (2000) investigates an agent-based simulation of a dynamic network formation process under the utility of the connections model and found several architectures of stable networks that were not covered by the analytical results of Jackson and Wolinsky (1996). These stable networks were observed in the intermediate regions of the cost-benefit space, here pairwise stable networks do not always coincide with the efficient star structure (Hummon, 2000).

To maintain feasibility in terms of the simulations we use a truncated version of the connections model, for which the above mentioned propositions also hold (see Jackson and Wolinsky, 1996).[7] In the truncated version only an actor j that is at most at a distance d (here with $d = 2$) is beneficial to actor i. Distance is defined as the shortest path between two actors. We set $\delta = 0.5$ and let the cost level run between .2 and .69 to capture (mainly) the intermediary and higher cost levels as described in the second set of propositions.

Figure 3.1 shows an exemplary formation process in the connections model with $\delta = 0.5$ and $c = .45$ when actors are myopic. In the first three networks, one pair of actors always benefits from creating a link between them. In

[6] For proofs of these propositions see Jackson and Wolinsky (1996).

[7] The simulations for actors who look three steps ahead took about three weeks to check for all networks of the sizes mentioned.

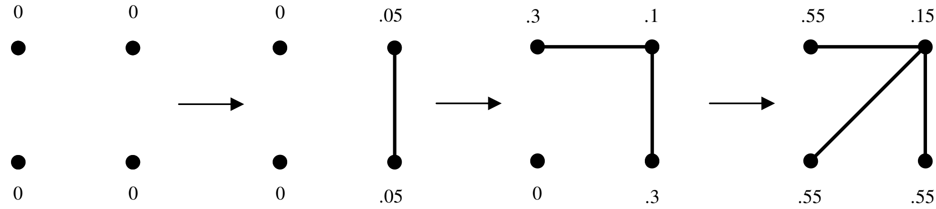


Figure 3.1: Possible formation in the connections model with myopic actors (numbers indicate actors' utility in the network)

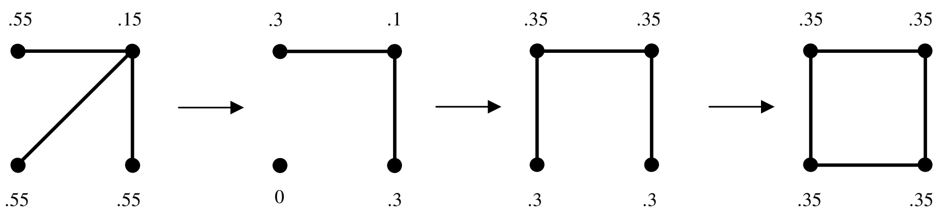


Figure 3.2: Possible formation in the connections model with limitedly far-sighted actors (numbers indicate actors' utility in the network)

the network on the right, the efficient star network, the process stops. Here no pair of actors can benefit by adding a link, and no actor can benefit by cutting a link. The star is the efficient network structure in the connections model. However, it distributes payoff unequal over actors, since the star actor has the highest costs. Figure 3.2 shows the network formation process when actors are limitedly farsighted and look two steps ahead. In the star network on the left, the star actor (top right) will cut a link because he foresees the possibility to be better off in a (line) network, that can follow the initial cut of the link. The formation process with limitedly farsighted actors converges to the $K_{2,2}$ (circle) network. Note that the circle network is (next to the star network) also myopically stable in this example. For limitedly farsighted actors, only the circle network is stable. The circle network is less efficient than the star network, it however distributes payoff equally over the actors. The example illustrates that (limited) farsightedness does not necessarily lead to more efficient network structures, but it might reduce inequality.

3.3.2 Structural holes

Buskens and Van den Rijt's 2008 model is based on the idea that actors try to improve their network position by entering "Structural Holes" as proposed by Burt (1992). Structural holes are positions in a social network where there is the opportunity to connect otherwise not connected groups of people. Connecting different groups gives an individual the potential of brokering information flows between these groups to his or her benefit. Burt's study of managers in a large electronics company shows that occupying structural holes is correlated with higher compensation, more positive performance evaluations, promotions, and good ideas (Burt, 2004). Burt introduced a measure to quantify the benefits from filling structural holes. In the network formation model by Buskens and Van de Rijt (2008), actors are striving for these advantageous positions based on Burt's so-called constraint measure:

$$constraint_i = \sum_{j \neq i}(p_{ij} + \sum_{k \neq i, k \neq j} p_{ik}p_{kj})^2$$

where p_{ij} is the proportion of time that i invests in contact j. It is assumed that actors are distributing their time equally over their contacts. Therefore, if i is connected to j $p_{ij} = 1/d_i$ and d_i is i's degree. Actor i's utility is a decreasing function of the constraint measure and is:

$$u_i(g) = -constraint_i(g)$$

Burt's constraint measure lies between 0 and 9/8. The constraint measure has a value 0 for isolates. Buskens and Van de Rijt (2008) argue that this value is not plausible as it implies isolates are least constrained and therefore define the value 2 for isolates (see Buskens and Van de Rijt, 2008). A higher score on the constraint measure means that structural opportunities are more constrained and therefore network benefits are lower. In the structural holes model in some situations, for instance when two actors with whom an actors is connected "close a triad", decisions can impose negative externalities on others. Figure 3.4 shows an example case: in the star network on the left, two peripheral actors benefit from creating a link. This closes a triad with the two actors and the star actor. The star actors suffers by this creation of the link as it decreases his payoff (the actor loses the potential of brokering information between the two other actors).

Using the same simulation techniques as described here for myopic actors, Buskens and Van de Rijt (2008) find that the dominant stable network structures that emerge are complete bipartite networks and most often balanced complete bipartite networks. Balanced complete bipartite networks distribute benefits evenly among actors, so in a setting where everybody wants to enter structural holes, nobody can maintain such a position in the long run, thus confirming formally Burt's speculation.[8]

Figure 3.3 shows a possible formation process in the structural holes model when actors are myopic. In the first three networks, one pair of actors always benefits creating a link between them. In the network on the right, the star

[8]Assuming farsightedness in the context of structural holes seems plausible. Strategically behaving actors might achieve a better network position if they anticipate what other (strategically behaving) actors might do, while changing relationships. The question, whether actors who are more farsighted achieve better network positions arises, but it will not be answered here, because we assume homogeneous actors.

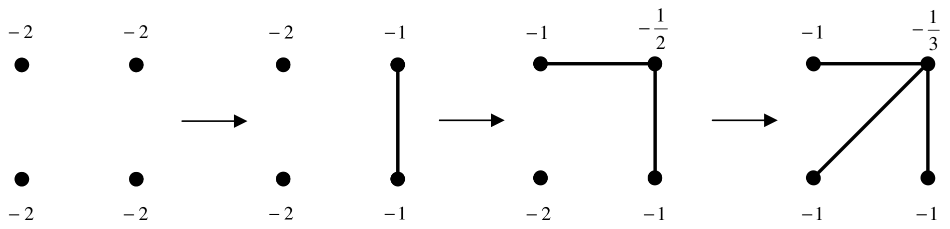


Figure 3.3: Possible formation in the structural holes model with myopic actors (numbers indicate actors' utility in the network)

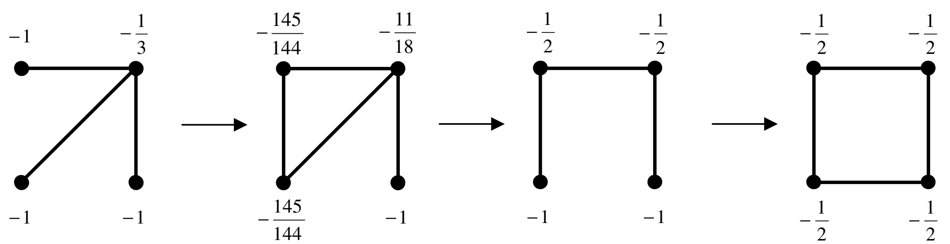


Figure 3.4: Possible formation in the structural holes model with limitedly farsighted actors (numbers indicate actors' utility in the network)

network, the process stops. Here no pair of actors can benefit from adding a link, and no actor can benefit from cutting a link. In the structural holes model, the star network is not the efficient network structure. Figure 3.4 shows the network formation process when actors are limitedly farsighted and look two steps ahead. In the star network on the left, two of the peripheral actors will create a link because they foresee the possibility to be better off in the line network that might follow the initial creation of the link (they anticipate two possible network positions, either the middle position where they earn $-.5$ or the peripheral position where they earn -1, thus an expected utility of $-.75$). Note that limitedly farsighted actors accept to be worse off after building a link (as can be seen in the second network) when they anticipate to be better off in the end. The formation process with limitedly farsighted actors converges in the circle network. Note that the circle network is (next to the star network) also myopically stable in this example. For limitedly farsighted actors only the circle network is stable. In the structural holes model, this is the efficient network structure. Also note that in this example there is no conflict between efficiency and inequality. In the structural holes model, the complete balanced bipartite networks are efficient and equal.

3.4 Results

In the following section, we report the results of the simulation model. Since we adopted a dynamic process we cannot only determine which network structures are stable but also which are the most likely network structures to emerge. Simulation runs started in each of 13,595 non-isomorphic networks of sizes 3-8. Networks that are formed, after each of the simulation processes (as described in section 3.2) stops, can be considered stable. If after 100,000 link changes no stable network is reached, the process stops. All starting networks were enumerated five times (for the connections model starting networks were enumerated five times for eight cost levels). This results in 67,975 cases for each level of farsightedness, in total 203,925 cases for the structural holes model and eight times more for the connections model because we use eight different cost levels (1,631,400 cases). Below we study the effects of farsightedness on specific characteristics of emerging networks. Significant differences do not have an interpretation in the classical sense, because the simulation data cannot be interpreted as a random sample of a given population. Also, due to the very high number of cases, small differences easily become statistically significant. To measure the "importance" of specific effects, we look at the effect sizes[9] to analyze differences between levels of farsightedness in terms of efficiency, inequality, and density of the stable networks.

3.4.1 Connections model

In the connections model, predictions about stable networks highly depend on the cost level. We therefore simulated the formation processes around the cost levels, that are mentioned in the second set of propositions for $\delta = .5$ (see Jackson and Wolinsky, 1996). Eight different cost levels were used in the simulation, ranging from .2 to .69. The cost level was increased in steps of .07. Therefore, the precise cost levels used were .2, .27, .34, .41, .48, .55, .62, .69.

A *low cost* level of .2 captures the first part of the second set of propositions, where $c < \delta - \delta^2 = .25$. The *medium cost* range between .27 and .48 covers the second part (where $.25 = \delta - \delta^2 < c < \delta = .5$). The *high cost* range between .55 and .69 covers the third part (where $c > \delta = 0.5$). We collapse the results according to the cost level ranges we find in the propositions on stable networks, thus we report the most common and important networks that emerge at a low cost level .2, a medium cost level between .27 and .48, and a high cost level between .55 and .69.

In all cases and under all levels of farsightedness the complete network is the only stable outcome for low costs. It only emerges at this specific cost level. At other cost levels, we mostly find multiple stable networks. Network structures also differ between levels of farsightedness. We analyze these networks in terms of efficiency, inequality, and density of stable networks. Effects in the tables below indicate differences comparing the two limited farsightedness models with the myopia model.

[9] The effect size is measured with η^2, which can be interpreted as the proportion of the total variance that is attributed to an effect.

With limitedly farsighted actors, not every simulation process converges to a stable network (after 10,000 iterations a non-converged process is most likely stuck in a cycle and the process is stopped. Table B.1 in the appendix shows the percentages of non-converged formation processes). We included the networks that are part of cycles for the analysis on efficiency, inequality and density. We argue that cycle networks are also part of the outcome of the formation process and therefore an important result when considering differences in networks characteristics between the levels of farsightedness (see appendix B.1 for more information on the occurrence of cycle networks and how we included them in the analysis).

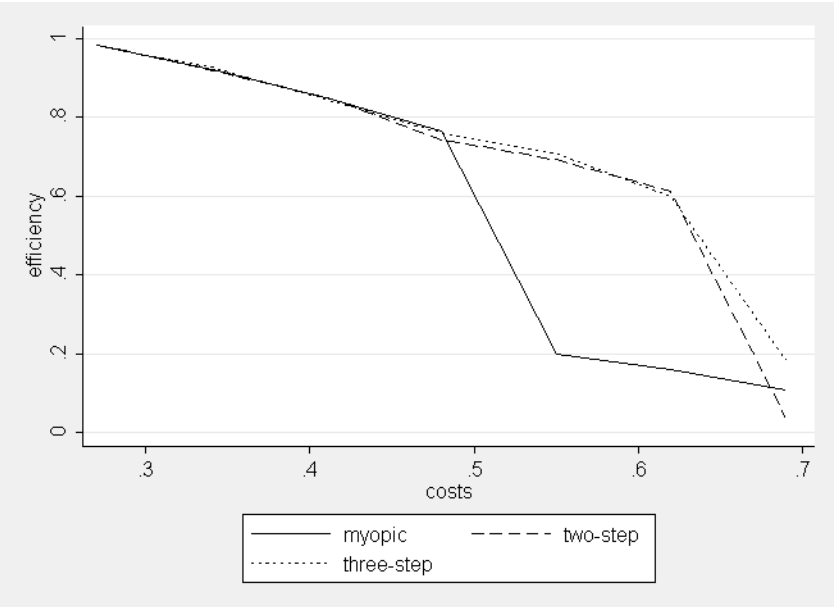


Figure 3.5: Efficiency of networks by cost level, connections model

Comparing the stable networks over the different cost levels shows that for *high cost* levels there are big differences in nearly all analyzed characteristics between the myopic and the two farsightedness scenarios (see figure 3.5 and also tables 3.1-3.3). In the high cost range, the empty network emerges in most cases and under all sizes. Networks with higher costs tend to be severely under-connected and, therefore, inefficient (see Buechel and Hellmann, 2012).

The empty network emerges less often when actors are limitedly farsighted. In general, this implies that, for all network sizes, networks are more efficient when actors look two or three steps ahead. Figure 3.5 plots efficiency of networks against cost levels. Efficiency decreases with costs. In the range where $\delta - \delta^2 < c < \delta$, there is a drop of efficiency when actors are myopic. However, when actors look ahead, this drop is observed at higher cost ($c = .69$). Also note that since the empty network distributes payoffs equally, this implies an increase in inequality in most cases with limitedly farsighted actors compared with myopic actors (see table 3.2). Except for $n = 8$, networks are more equal when actors look two or three steps ahead (the 5-actor circle with three remaining isolates is often stable when actors are myopic; this network distributes payoffs unequally). Since actors who look two or three steps ahead are more likely to remain connected for higher cost levels, density is significantly higher (see table 3.3). So for higher cost levels, the problem of under-connected networks is less severe when actors look more steps ahead. Therefore, networks are more efficient.

Comparing stable networks at *medium costs* is more complicated, since there is no clear overall pattern that can be observed. Regarding efficiency and inequality, we see mostly small effects, often in opposing directions. There are, however, large effects for actors looking three steps ahead compared to myopic actors for density: emerging networks are less dense for all network sizes if actors look three steps ahead. Also for actors looking two steps ahead, networks are less dense, but only when $n \geq 6$ (see table 3.3). Overall, different network structures emerge between levels of farsightedness. In terms of the mentioned network characteristics, the differences between emerging networks are better explained with costs than with levels of farsightedness.[10] For medium cost levels, we give description of emerging networks for size $n = 6$ and $n = 8$, to illustrate how they relate to the observed differences in network characteristics. Detailed results in terms of network characteristics are shown in tables 3.1-3.3, the description of the most frequently emerging networks for all network sizes can be found in appendix B.2.

[10] Regression models explaining efficiency, inequality, and density show that the level of farsightedness accounts for 2%-5% of explained variance, while costs explain 60%-90%.

Table 3.1: Efficiency of stable networks

	$n=3$	$n=4$	$n=5$	$n=6$	$n=7$	$n=8$
Connections model, medium costs						
myopic	1(0)	.907(.09)	.888(.09)	.883(.09)	.882(.08)	.880(.08)
two-step	.610(.41)***	.868(.10)*	.881(.09)	.828(.11)*	.820(.14)*	.880(.09)
three-step	.425(.25)***	.860(.12)*	.932(.06)*	.738(.18)***	.773(.20)**	.890(.08)
Connections model, high costs						
myopic	0(0)	0(0)	.057(.13)	.082(.10)	.117(.11)	.160(.11)
two-step	0(0)	.135(.22)**	.314(.28)**	.269(.20)***	.357(.27)***	.458(.30)***
three-step	0(0)	.045(.25)	.292(.36)**	.294(.18)***	.335(.26)**	.515(.24)***
Structural holes						
myopic	—	1.17(.29)	1.03(.06)	1.10(.16)	1.11(.10)	1.10(.13)
two-step	—	1(0)***	1(0)***	1.01(.05)***	1(.03)***	1.04(.09)***
three-step	—	1(0)***	1(0)***	1.02(.08)***	1(.02)***	1.03(.05)***

[a]Standard deviation in parentheses; asterisk indicates a small effect with $\eta^2 = .01$; double asterisk indicates a medium effect with $\eta^2 = .06$. triple asterisk indicates a large effect with $\eta^2 = .14$ comparing the myopia model with each of the farsightedness models.

Table 3.2: Inequality of stable networks

	$n = 3$	$n = 4$	$n = 5$	$n = 6$	$n = 7$	$n = 8$
Connections model, medium costs						
myopic	.072(.05)	.037(.05)	.071(.06)	.074(.06)	.086(.06)	.083(.07)
two-step	.072(.05)	0(0)**	.048(.03)*	.107(.06)*	.108(.08)*	.018(.03)***
three-step	.059(.04)*	.042(.05)	.013(.02)***	.157(.06)***	.115(.09)*	.014(.02)***
Connections model, high costs						
myopic	0(0)	0(0)	.000(.00)	.022(.03)	.054(.04)	.094(.06)
two-step	0(0)	.001(.01)*	.015(.03)*	.093(.07)***	.063(.05)	.037(.3)***
three-step	0(0)	.018(.03)***	.036(.06)**	.074(.06)**	.094(.06)**	.043(.02)***
Structural holes						
myopic	—	.085(.15)	.075(.04)	.031(.05)	.056(.01)	.025(.03)
two-step	—	0(0)***	.091(0)***	.004(.02)***	.045(.01)***	.013(.02)**
three-step	—	0(0)***	.091(0)***	.005(.02)***	.045(.01)***	.013(.03)**

[a]Standard deviation in parentheses; asterisk indicates a small effect with $\eta^2 = .01$; double asterisk indicates a medium effect with $\eta^2 = .06$. triple asterisk indicates a large effect with $\eta^2 = .14$ comparing the myopia model with each of the farsightedness models.

Table 3.3: Density of stable networks

	$n=3$	$n=4$	$n=5$	$n=6$	$n=7$	$n=8$
Connections model, medium costs						
myopic	.667(0)	.619(.05)	.562(.05)	.512(.04)	.474(.03)	.448(.02)
two-step	.5(.17)***	.667(0)**	.575(.02)*	.493(.05)*	.446(.05)**	.430(.02)**
three-step	.383(.08)***	.565(.08)**	.483(.02)***	.405(.03)***	.404(.06)***	.433(.01)***
Connections model, high costs						
myopic	0(0)	0(0)	.047(.10)	.083(.09)	.116(.09)	.141(.07)
two-step	0(0)	.123(.02)**	.231(.20)***	.218(.14)***	.228(.17)**	.245(.16)**
three-step	0(0)	.124(.17)**	.236(.20)***	.258(.14)***	.248(.13)***	.281(.12)***
Structural holes						
myopic	—	.624(.07)	.582(.04)	.571(0.6)	.520(.05)	.535(.05)
two-step	—	.667(0)***	0.6(0)***	.597(.01)***	.571(.01)***	.555(.03)**
three-step	—	.667(0)***	0.6(0)***	.596(.02)***	.571(.01)***	.564(.01)***

[a] Standard deviation in parentheses; asterisk indicates a small effect with $\eta^2 = .01$; double asterisk indicates a medium effect with $\eta^2 = .06$. triple asterisk indicates a large effect with $\eta^2 = .14$ comparing the myopia model with each of the farsightedness models.

For $n = 6$, there are large effects when actors look three steps ahead, compared to myopic actors: networks are less efficient, more unequal and less dense. The network on figure B.1c is stable in most cases when actors are myopic. Most cases converge to the network with a 5-actor circle and one isolate actor when actors look three steps ahead. This network is less efficient, less dense, and more unequal. Also likely to emerge at costs $c = .34$ is the 5-star network. The two bipartite $K_{3,3}$ (22%) and $K_{2,4}$ (29%) networks are the two most likely emerging networks when actors look two steps ahead. This results in differences with only small effect sizes between myopic actors and actors who look two steps ahead.

For $n = 8$, emerging networks show no differences in efficiency. However, networks are more equal and less dense when actors look ahead (see table 3.1 - 3.3). The networks in figure B.1e and B.1f are myopically stable in most cases (18% and 14%). At medium costs and with actors who look two steps ahead, the most likely networks are the cube, and the $K_{2,6}$ network. For actors who look three steps ahead, the wheel network (see figure B.1b) emerges in most cases. The most likely networks to emerge for the limited farsightedness scenarios, the cube and the wheel network distribute payoffs equally, and are also less dense than the myopically stable networks.

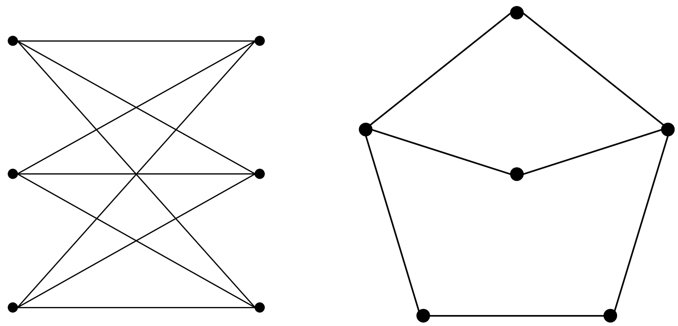
In the connections model, limitedly farsighted actors build different networks as compared to myopic actors. With increasing costs, stable networks become under-connected and therefore inefficient. Limitedly farsighted actors can prevent the increasing inefficiency to higher cost levels, as they stay more connected than myopic actors. For medium cost levels differences between stable networks in terms of the analyzed network characteristics can better be explained with the networks that emerge at specific cost levels and specific network size than with the level of farsightedness.

3.4.2 Structural holes

We replicated the results for $3 \leq n \leq 8$ from Buskens and Van de Rijt (2008) for the class of myopically pairwise stable networks. Negligible differences occur because of the randomness involved in the simulation process (see section 3.2).

In terms of efficiency, inequality and density there are significant differences between myopic actors and actors who are limitedly farsighted. Stable networks become more efficient (note that efficiency calculated with the constraint measure indicates high efficiency if equal or close to 1 and lower efficiency for values higher than 1), more equal and more dense (see tables 3.1-3.3). This result occurs because the likelihood increases that complete balanced bipartite networks will emerge when actors look further ahead. Complete balanced bipartite networks are efficient, egalitarian and rather dense (see Buskens and Van de Rijt, 2008). The detailed results for myopic actors are best described in Buskens and Van de Rijt (2008). Table 3.3 shows the most likely emerging networks in the structural holes model. The general pattern is that in most cases complete balanced bipartite networks emerge. For networks size 3 to 5, complete bipartite networks emerge in over 80% of cases. These networks are still the most likely (with over 60%) for network size 6 to 8. However, there are also a number of other networks that might emerge. The likelihood of other stable networks to emerge increases slightly with network size. For $n = 3$, there is one stable network, the 2-star network, when actors are myopic. When actors limitedly farsighted, the process cycles, alternating between the complete and the 2-star network. There is always an actor who wants to cut a link in the complete network, and always a pair of actors that wants to build a link in the 2-star network. When actors are myopic there are two stable for $n = 4$, the $K_{2,2}$, i.e. the circle network, and the 3-star network. Only the circle network emerges with actors who look two or three steps ahead. Also for $n = 5$, there are two stable network with myopic actors, the $K_{2,3}$ and the circle network. With limitedly farsighted actors only the $K_{2,3}$ is stable.

We find four stable networks for $n = 6$ when actors are myopic, the $K_{3,3}$ that emerges in 69%, the $K_{2,4}$, the bag (see figure 3.6b), and the $K_{2,2,2}$ in fewer cases. When actors make limitedly farsighted decisions, there are only two stable network, the $K_{3,3}$ and the $K_{2,4}$. For $n = 7$ and myopic actors, there are three stable networks, the $K_{3,4}$ that emerges in 53% of cases, the $N_{2^1,3^6}$ (one actor with two links and six with three links) in 45%, and the $K_{2,5}$ that emerges in only 2% of cases. Only two networks are stable with limitedly farsighted actors, the $K_{3,4}$ that emerges in almost all cases and the $K_{2,5}$ that



(a) $K_{3,3}$ (b) bag

Figure 3.6: Some important stable networks

emerges in very few cases. Ten networks are stable for $n = 8$ and myopic actors, the $K_{4,4}$, the $N_{3^6,4^2}$, the $K_{3,5}$, and the wheel network (see figure B.1b) are the most likely networks. There are six more stable networks, however, they only appear very infrequently. With actors who look two steps ahead, there are four stable networks. The most likely network is the $K_{4,4}$, that emerges in 77% of cases; the $K_{3,5}$ and the $N_{3^6,4^2}$ emerge in 12% and 11% of cases. The $K_{2,6}$ is very infrequent and emerges in only 10 out of 61,730 cases. There are only three stable networks for actors who look three steps ahead, in most cases the $K_{4,4}$ and the $K_{3,5}$ emerge (in 81% and 19% respectively), and the $K_{2,6}$ in only very few cases.

3.5 Conclusion and discussion

Social networks can be beneficial for several reasons. In this chapter, we compared networks that are built when actors are myopic with networks that are built when actors are limitedly farsighted. The two utility functions that were used model information as a valuable resource for actors. Predictions on emerging networks change when actors are more farsighted.

In the connections model, the most striking pattern we observe is that un-

Table 3.4: Emergence of networks, structural holes model

	$n=3$	$n=4$	$n=5$	$n=6$	$n=7$	$n=8$
myopic						
complete bipartite ($K_{\lfloor n/2\rfloor\lceil n/2\rceil}$)	1.0	.84	.81	.69	.53	.61
($K_{\lfloor n-2/2\rfloor\lceil n+2/2\rceil}$)	–	.16	–	.13	.02	.12
other	–	–	.19 (circle)	.15 (bag)	.45 ($2^1, 3^6$)	.12 ($3^6, 4^2$)
convergence	1.0	1.0	1.0	1.0	1.0	1.0
no. of iterations (std. dev.)	1(.73)	1.9(1.3)	3.2(1.9)	4.8(2.4)	6.8(2.9)	9.6(3.5)
no. emerging networks	1	2	2	4	3	10
two-step						
complete bipartite ($K_{\lfloor n/2\rfloor\lceil n/2\rceil}$)	–	1.0	1.0	.97	.99	.77
($K_{\lfloor n-2/2\rfloor\lceil n+2/2\rceil}$)	–	–	–	.03	.00	.12
other	–	–	–	–	–	.11 ($3^6, 4^2$)
convergence	0	1.0	1.0	1.0	1.0	1.0
no. of iterations (std. dev.)	–	3.5(2.8)	12(10)	10(5.7)	15(7.3)	17(6.8)
no. emerging networks	–	1	1	2	2	4
three-step						
complete bipartite ($K_{\lfloor n/2\rfloor\lceil n/2\rceil}$)	–	1.0	1.0	.95	.99	.81
($K_{\lfloor n-2/2\rfloor\lceil n+2/2\rceil}$)	–	–	–	.05	.00	.19
other	–	–	–	–	–	.00 ($K_{2,6}$)
convergence	0	1.0	1.0	1.0	1.0	1.0
no. of iterations (std. dev.)	–	5.2(5)	13(9.3)	16(11)	21(11)	27(12)
no. emerging networks	–	1	1	2	2	3
no. starting networks	4	11	34	156	1044	12346

der high costs of links, limitedly farsighted actors can overcome the problem of under-connectedness. Under limited farsightedness, stable networks with high link costs are denser and therefore more efficient. The differences in network characteristics in medium cost levels are not directly related to the level of farsightedness. However, different network structures can emerge. Looking at the differences in emerging networks in the case of the structural holes model, the pattern is more clear. Already in the myopia model there is a strong tendency towards the efficient complete balanced bipartite network architecture to emerge. When increasing the level of farsightedness, this pattern becomes even stronger: we observe a higher likelihood of these efficient networks to emerge. Less frequently emerging networks that are stable and inefficient when actors are myopic become unstable under limited farsightedness.

To sum up: the connections model is associated with positive externalities and creates the problem of under-connectedness (see Buechel and Hellmann, 2012, for details). Compared to myopic actors, limitedly farsighted actors can overcome this tension between stability and efficiency for higher cost levels. At higher costs, limitedly farsighted actors build significantly more dense, and therefore more efficient networks. Also, in the structural holes model, limitedly farsighted actors build more efficient networks, as the likelihood of complete bipartite networks to emerge increases with the level of farsightedness. Other than the connections model, the co-author model is associated with negative externalities and creates the problem of over-connectedness. In chapter 2 we analyzed that limitedly farsighted actors can, depending on the network size, overcome the dilemma of efficiency and stability in the co-author model (Jackson and Wolinsky, 1996).

Another interesting observation is the high likelihood of bipartite networks to emerge in the connections model (which is the highest when actors look two steps ahead). So comparing the connections model and the structural holes model, both contexts favor a similar kind of network architecture, as opposed to star like structures in e.g. Bala and Goyal (2000).

Limited farsightedness affects the emergence of stable networks. The effect is different in different contexts. Empirical research is necessary to study whether the assumptions of limited farsightedness lead to better predictions for the network formation outcome. Not only is it important to see whether farsightedness is an alternative solution for network formation games, and in that sense a superior decision rule than the myopic notion of pairwise stability, but also to study which specific micro-behavior assumption applies best in a specific context.

Building models of farsightedness in network formation is a complex task. To set up such models, additional assumptions are necessary. In the approach of Morbitzer et al. (2011) problems like behavioral inconsistency arise, or issues such as how actors weigh anticipated network outcomes (see discussion ibid.). More theoretical and experimental testing of such models will be necessary to address these issues.

Chapter 4

Limited Farsightedness in Network Formation Experiments*

4.1 Introduction

Theoretical and empirical research demonstrates how networks affect social and economic life. Given that social relationships can be beneficial, actors have incentives to strategically invest in relations that yield the highest benefits (Flap, 2004). Partnerships of firms, professional relationships and also friendships are examples where people strategically connect with each other and thereby form networks. However, how do people decide with whom to connect in such complex social environments? It is far from trivial to determine how different individual decision-making rules affect the formation of networks and how these structures feed back to subsequent linking decision of individuals.

The benefits of individual linking decisions are not only contingent on actors' own behavior, but also on the behaviors of other actors in the network. The extent to which actors are farsighted and thus able to anticipate linking

*This chapter was written in collaboration with Vincent Buskens, Heiko Rauhut and Stephanie Rosenkranz, with Dominik Morbitzer being first author.

decisions of other network members may affect their success in making beneficial connections. Consider a scientist who is looking for a co-author for a joint project. It is reasonable to connect with a co-author who has few other co-authors so that this co-author can concentrate on the joint project with the focal scientist. If, however, many other scientists simultaneously decide to connect with the same co-author, this co-author will have relatively little time for each project. If actors foresee the linking decisions of other network members, they can connect with a different, less connected co-author and profit from a more beneficial collaboration.

The optimal number of links of interaction partners differs in various social situations. Regarding co-authors, it may be beneficial to connect with scientists with few connections. In contrast, when students are looking for jobs after graduation, it may be beneficial for them to connect with people having as many links as possible. After all, every link may provide information about an interesting open position. Thus, connecting with highly connected people may yield better information to find a job (Granovetter, 1973) as has been modeled for example in the connections model by Jackson and Wolinsky (1996), where it is beneficial to be connected to highly connected individuals. However, being a "star", i.e., being directly connected to many others, requires to maintain many relationships. Therefore, farsighted actors prevent becoming a star themselves and rather connect to a star so that they can use the information without the costs of maintaining too many links. The two situations described above correspond with two well-known models for how networks generate utility for actors, namely, the co-author and the connections model (Jackson and Wolinsky, 1996).

Interestingly, both the co-author and the connections model have social dilemma type features as they create a tension between stability and efficiency of networks. In the co-author model, actors try to exploit others' work by having many links to sparely connected co-authors who do the main bulk of the work. These links often have negative externalities for other actors in the network. In the connections model, on the contrary, links of actors impose positive externalities on others. As a consequence, actors can try to exploit others' links by receiving information without sharing the costs of maintaining the links. Different capabilities of actors to foresee these inherent dynamics can create variation in micro-level behavior of actors and, consequently, substantially different macro-level outcomes in terms of network structures.

In this chapter, computer simulations and behavioral experiments are used in parallel to analyze and test the complex and dynamic network formation process at the macro level through micro-level decision-making. The computer simulations predict that farsightedness is a crucial micro-level variable in explaining the emergence of different network structures. If actors are sufficiently farsighted, they can overcome the tension between stability and efficiency of networks. In the co-author model, more farsighted actors tend to build less links and form more efficient networks. In the connections model, more farsighted actors tend to generate more often the more egalitarian circle network than the unbalanced star network (see also chapters 2 and 3).

In this chapter, the simulation results are tested using experiments in which actors can add and cut links over time. These experiments are conducted using the utility functions from both the co-author and connections model. In addition, we use the beauty contest game, which measures levels of cognitive reasoning, as a proxy for farsightedness of subjects (Nagel, 1999). The experimental results indicate that people behave limitedly farsighted under certain circumstances. As a consequence on the macro-level, especially in the co-author model, more efficient networks emerge. Therefore, our model can explain why a significant proportion of people avoids the "network trap" and connects to less people than myopic actors would do. This farsighted behavior enhances their efficiency in sharing their work or receiving new information.

The research program of studying the dynamics of network formation is an application of micro-macro links in sociology (Raub et al., 2011; Coleman, 1990). Actors who make myopic individual decisions generate substantially different networks compared to actors who make farsighted individual decision-making. In this chapter we show how changing micro-level assumptions about actors' ability to look ahead affects predictions for macro-level outcomes of the network formation process, while the experiments provide some evidence for the new predictions. The combination of agent-based simulations using different micro-level assumptions and laboratory experiments in which actors actually build and cut network links allows for a novel and precise investigation of micro-macro links in networks.

The remainder of the chapter is organized as follows. In section 4.2, theoretical and empirical research on network formation is reviewed. In section 4.3, the theoretical predictions are derived by computer simulations. In section 4.4, the experimental design is described and in section 4.5, the empirical results are reported and compared to the simulation scenarios. Section 4.6. concludes and provides a discussion.

4.2 Previous theoretical and experimental research on network formation

Research on network dynamics applies game-theoretic tools to analyze how networks are formed through individual changes of the network structure. In what we call *pure network formation models*, it is assumed that actors derive utility from their network position and try to maximize their expected utility through their linking choices.

Following the seminal model of Jackson and Wolinsky (1996), Watts (2001) considers network formation as a dynamic process in which pairs of actors decide sequentially on whether to change the relation between them. A network is considered stable when no pair of actors jointly wants to create a link and no actor wants to delete a link anymore. This notion is based on the so-called myopic best response assumption. The *myopia model* has the implication that actors neglect subsequent decisions of other actors and only look at their own immediate gain (Watts, 2001; Jackson and Watts, 2002).

However, the assumption of myopic decision-making is problematic and often criticized. Laboratory experiments show that there is a discrepancy between theoretical predictions of the myopia model and empirical behavior. These deviations may be explained by the fact that people are to some extent farsighted in their decision-making (Pantz, 2006; Corten, 2009; Van Dolder and Buskens, 2008). In particular, if actors are well informed about the properties of their network and the costs and benefits of building and cutting links, they may well be farsighted in their strategic network formation behavior (Jackson, 2008).

Different models of farsightedness in network formation have recently been developed by Dutta et al. (2005), Page et al. (2005), or Herings et al. (2009). Farsighted actors realize that changing the network can lead to further changes from other actors or themselves. Therefore, they anticipate subsequent network changes when making their linking decision. However, most models on farsightedness in network formation consider *perfect farsightedness*. This rather extreme assumption considers actors who are able to foresee the complete formation process when evaluating their network changes.

So far, there has been a limited amount of empirical research on the microfoundations of behavior in network formation. Pantz (2006) is one of the few to study network formation focusing on micro-level behavior. The author conducted experiments where subjects played a network game similar to the connections model (Jackson and Wolinsky, 1996). Predictions of myopic best response behavior and perfectly rational, farsighted Nash behavior were compared. However, neither of the two models predicted the behavioral data well. This study suggested that people act more sophisticated than pure myopic players, but less sophisticated than perfectly farsighted players. Thus, limited farsightedness in network formation seems a plausible assumption trying to understand network formation processes. To the best of our knowledge, only Berninghaus et al. (2012) and Morbitzer et al. (2011) develop theoretical models of *limitedly* farsighted actors. These models of limited or perfect farsightedness demonstrate that different assumptions about the extent of myopic or farsighted decision-making at the individual level have serious consequences on the emerging networks and their stability (e.g., Herings et al., 2009; Morbitzer et al., 2011). In contrast to the view that macro-level behavior may be robust to many individual-level modifications (Coleman, 1986; Becker, 1976), this shows how different microfoundations have indeed non-trivial implications on macro-level outcomes (cf. Schelling, 1978; Raub et al., 2011). In this chapter we apply the myopia model and the model of limited farsightedness to a particular experimental setting and test the implications with the experiment.

4.3 Network formation with myopic and limitedly farsighted actors

In the following section, we first describe the theoretical model that defines the network formation process and how actors make their network decisions when they are myopic and limitedly farsighted. We present the formation process in terms of the computer simulations that are used to predict the stable networks.

4.3.1 Simulation model of network formation

Here we describe the basic notations and characteristics of the model of network formation. For a more detailed version of the network formation model with limited farsightedness see chapter 2.

The set $N = \{1, \ldots, n\}$ is the set of nodes representing actors. A network g indicates the pairs of actors in N that are connected via a link. Formally, g is a set of unordered pairs of actors $\{i, j\}$. For any pair i and j, $\{i, j\} \in g$ indicates that i and j are linked in the network g; otherwise $\{i, j\} \notin g$. Links are undirected, if i has a link with j, then j is also linked with i. We denote the link $\{i, j\}$ also with ij. Let $g + ij$ denote the network obtained by adding the link ij to the existing network g and let $g - ij$ be the network obtained by deleting the link ij from the existing network. We define g^{ij} as the adjacent network obtained by either adding or deleting link ij in g.

The utility function vector $u : G(n) \to \mathbb{R}^n$ models the overall benefit net of costs of the actors in a network, where $G(n)$ is the set of all possible networks with n actors. We represent the utility of actor i in network g by $u_i(g)$. The stability concept we start from is pairwise stability as proposed by Jackson and Wolinsky (1996). A network g is *myopically pairwise* stable if

1. $\forall ij \in g$, $u_i(g) \geq u_i(g - ij)$ and $u_j(g) \geq u_j(g - ij)$
2. $\forall ij \notin g$, if $u_i(g + ij) > u_i(g)$ then $u_j(g + ij) < u_j(g)$

In words, a network is myopically pairwise stable if no pair of actors jointly wants to add a link and no actor wants to severe a link unilaterally.

We now present the dynamic network formation model in terms of the computer algorithm that we used to simulate the process. With the help of the computer simulations we can check the stability of networks. We implemented the formation process for actors who are myopic, thus look one step ahead, and *limitedly farsighted* actors, who look two steps ahead in the same way as in chapter 2.

The simulation method takes the following steps:

1. Start with some network g. Here g is the empty network.
2. Randomly pick a pair of actors $\{i, j\}$ (every pair with equal probability) and check whether they want to change their link.
3. If i and j do want to change the link ij, change the link and return to step 2 for the new network.
4. If i and j do not want to change the link ij, randomly choose another pair of actors until you find two actors that do want to change their link. Change this link and return with the new network to step 2.
5. If there does not exist any pair of actors anymore who want to change their link, the program ends and the final network is a stable network.

What happens in step 2 of the process described above depends on whether actors look one or two steps ahead. Note that it might be that the process we describe above does not converge and that the updating of links continues to cycle through a series of networks.

When we consider the case of myopic actors, then step 2 is simply checking whether both actors are better off if they consider creating a link and whether one of the two is better off if they consider removing a link. When we consider actors who look two steps ahead, however, step 2 of the simulation process becomes more complicated and consists of the following sub-steps:

2a. In the current network g, if the link ij exists, remove ij; otherwise, create ij to reach network g^{ij}.

2b. For all pairs of actors k and l that are not equal to the pair i and j, consider whether network $g^{ij,kl}$ is a myopic improvement over g^{ij} for actors k and l and, thus, whether myopic actors k and l would like to change their link in network g^{ij}.

2c. If k and l indeed would like to change, store the payoffs that i and j obtain in network $g^{ij,kl}$.

2d. Take the mean of all the payoffs for i stored in step 2c. Do the same for j. In case $ij \notin g$, if the resulting utility of moving to g^{ij} for both i and j is larger than their utility in g, add the link ij; in case $ij \in g$, if the resulting utility of moving to g^{ij} for either i or j is larger than their utility in g, remove the link ij. If there are no k and l who want to change in g^{ij}, i and j change from g to g^{ij} if this is a myopic improvement for them.

Note that we assume that limitedly farsighted actors consider reactions of others as if others are one step less farsighted than they themselves are. Actors who think two steps ahead assume that other actors think one step ahead, i.e. are myopic. This inconsistency of own behavior and the assumption on behavior of others is in line with psychological evidence on overconfidence (e.g., Camerer and Lovallo, 1999). Also, note that networks that are "in between" an assumed future network state are not considered in the utility calculations. Only the expected utility of the future network(s) is compared with the current utility. We assume that actors do not take these in between states into account since they consider these states only as transition points towards a future network. The explained simulation implies that a network is two-step pairwise stable if considering the expected utilities no pair of actors want to change their links.

4.3.2 Utility functions and simulation results

In pure network formation models, utility is a function of the network itself. Network benefits might be determined quite differently depending on the context. To capture this, different utility functions can be created. Farsighted behavior can also affect the formation process differently in different contexts (see Herings et al., 2009; Morbitzer et al., 2011).

We use two models of network formation, namely, the co-author and the connections model by Jackson and Wolinsky (1996). We choose these two models because they capture two different mechanisms that might drive network formation as described in the introduction. Also they are well-known in the literature, which enhances comparability of the farsightedness model. Most importantly, using two models allows comparing different predictions of the myopia and the limited farsightedness model. The two utility functions capture how negative (co-author model) and positive externalities (connections model) can affect network formation.

The connections model

In the connections model, actors receive a benefit from connections they have, dependent on the distance between actors in the network (imagine a network that is used by actors to receive valuable information). Having a link to someone else is costly because of the time and effort that has to be invested to maintain the relation. The benefit of connections deteriorates with the distance between actors because it is harder to receive information from people that are further away. Deterioration is represented by a factor δ that lies between 0 and 1 and indicates the benefit from a direct relationship and is raised to higher powers for more distant relationships. In the connections model the benefits fall off exponentially with the distance. The payoff is given by

$$u_i(g) = \sum_{j \neq i} \delta^{t(ij)} - \sum_{j:ij \in g} c,$$

where $t(ij)$ is the shortest path length between i and j and δ is the payoff i gets from being connected to j. Let $c \geq 0$ be the costs for maintaining a link. The connections model satisfies positive externalities as creating new links benefits actors' neighbors, thus friends of friends are beneficial for one's own payoff. For the experiment we set up a *truncated* version of the connections model where there are only two kinds of benefits: from direct connections (friends) and from connections at distance two (friends of friends) in order to keep payoff calculations for the subjects simpler. We set $\delta = .5$ and the cost level at $c = .45$. Very high and very low cost levels lead to trivial predictions: with high costs no one connects and with very low costs everybody in the network connects with everybody. The more interesting predictions occur in intermediate cost levels where there are disparities between efficient and pairwise stable networks. In the connections model, efficient networks (sum of all utilities) take only three forms; the complete network, if costs are low ($c < \delta - \delta^2$), the star network with middle range costs ($\delta - \delta^2 < c < \delta + ((n-2)/2)\delta^2$), and the empty network if costs are high ($\delta + ((n-2)/2)\delta^2 < c$) (see Jackson and Wolinsky, 1996, for proofs and more detail). Since in the experiment $\delta - \delta^2 < c < \delta + \delta^2$ and $n = 4$, the efficient network is the star network.

Figure 4.1 shows the so-called "metanetwork" for myopic actors with $\delta = .5$ and $c = .45$. The metanetwork shows all non-isomorphic networks with four actors, while the arrows between the networks indicate how the network formation process is expected to develop for myopic actors. Networks with no arrows pointing outwards indicate stable networks, in this case myopically pairwise stable networks in the connections model. As can be seen, there are two stable networks in figure 4.1: the star network, which is also the efficient network, and the circle network.

When there are multiple stable networks, the metanetwork allows us also to make macro-level predictions about the likelihood of a stable network to emerge. Starting from the empty network (as in the experiment), the formation path will end in either one of the two networks described above. From the empty network, the process always moves to the dyad network. From this network, the process can either go to the 3-line or the dyads network. One can infer by investigating all paths and the likelihoods of these paths, which depend on the number of isomorphisms of the different networks, that the circle network emerges with probability 13/18. So emergence of the circle network is more likely than of the star network, if we assume that the process starts at the empty network and follows in a deterministic manner our model. Figure 4.2 shows the metanetwork when changing the assumption of myopic actors to the assumption that all actors look two steps ahead. While the star network is no longer stable, the circle turns out to be the only stable structure applying limited farsightedness.

To generalize our predictions, we use computer simulations. By letting the formation process run many times from the empty network to convergence, we can for both our utility functions and for myopic actors as well as for actors who look two steps ahead calculate the likelihood that they end up in a specific network. In addition, it is relatively straightforward to add some decision noise to these simulations and infer how predictions change if actors sometimes do not exactly follow the deterministic process described above. Such deviations are also likely in an experimental context. We adopt noise in the simulations by including an error term in the utility calculations. The error term has the form of a normally distributed variable, with a mean of 0 and a specified standard deviation (noise level in tables 4.1 and 4.2). This implies that if utilities of two networks are more similar, actors are more likely not to move towards the optimal network. We can calculate the likelihoods of networks to which the process converges. For every scenario, we run 1000 repetitions, always starting the simulations from the empty network, as this was also the starting network in the experiment. Table 4.2 shows the predicted likelihoods of emergence to the most important networks for each scenario. Sometimes networks exist at the end of the simulation steps that are not stable in the deterministic process. With noise, no network is strictly stable, because due to large mistakes actors can move away from any network again. Therefore, the simulation process can result in many different networks. In particular, the 4-line network is often the final network because the payoffs in the 4-line and circle network are very similar and its position in the metanetwork is between the empty and the two stable networks.

Qualitatively, the *main prediction* that follows from these analyses is that in case actors are myopic, the circle network may emerge, but also a substantial number of star networks. If actors look two steps ahead no star networks emerge. Our model does not only provide predictions for the macro-level outcomes of the model, but also for the expected changes in the networks actors want during the network formation process. We can give for every network position for every actor the expected behavior. Figures 4.1 and 4.2 show these expected choices for each actor. We explain the notation based on the 4-line network in figure 4.1. Next to every actor, there might be symbols representing the individual “desire” about a link change. In the 4-line network, we see that there is an ordinary link between the two top actors. This indicates that indeed both want to have this link. However, when we look at the two links on the left and the right going down to the bottom actors, two lines (||) are drawn through this link next to the top actors as well as next to the bottom actors. This implies that in this network, all actors actually do want to remove these links. In addition, the two bottom actors have small lines next two them (– –) towards each other and towards the top actor to whom they are not connected. This indicates that although they do not have these links, they would be willing to make these connections. Considering these intentions, it is also clear that the process can move from the 4-line network to the 3-line or the circle network. The process cannot go to the kite network, because the top actors in the line are not willing to connect with the bottom actor they are not yet connected to. In a similar way, all possible changes can be seen in the other networks in the metanetwork. These micro-level predictions will be used to determine which model predicts behavior better at the micro level: a model that assumes every actor to be myopic or a model that assumes every actor to be limitedly farsighted.

Table 4.1: Simulation results connections model

	Noise level			
	0	0.02	0.05	0.1
Myopic	**73.9% (circle)** **26.1% (star)**	**75.1% (circle)** **24% (star)** 0.9% (4-line)	**57.6% (circle)** **23.7% (star)** 18.2% (4-line) 0.5% (3-line)	**32.1% (circle)** **21.7% (star)** 41.6% (4-line) 4.5% (3-line)
Two-step	**100% (circle)**	**100% (circle)**	**100% (circle)**	**93% (circle)** 3.5% (4-line) 3.5% (3-line)

In bold: stable networks for the deterministic case.

Investigating the micro-level behavior, it can be seen why the efficient star network is unstable if actors look two steps ahead. The peripheral actors are all satisfied in the star network, but the star actor foresees network positions where he is better off. Star actors are "sponsoring" indirect links for other actors. This makes the network efficient but it creates unequal payoffs. Limitedly farsighted stars will therefore cut the links to all peripheral actors to achieve a network position where payoffs are higher.

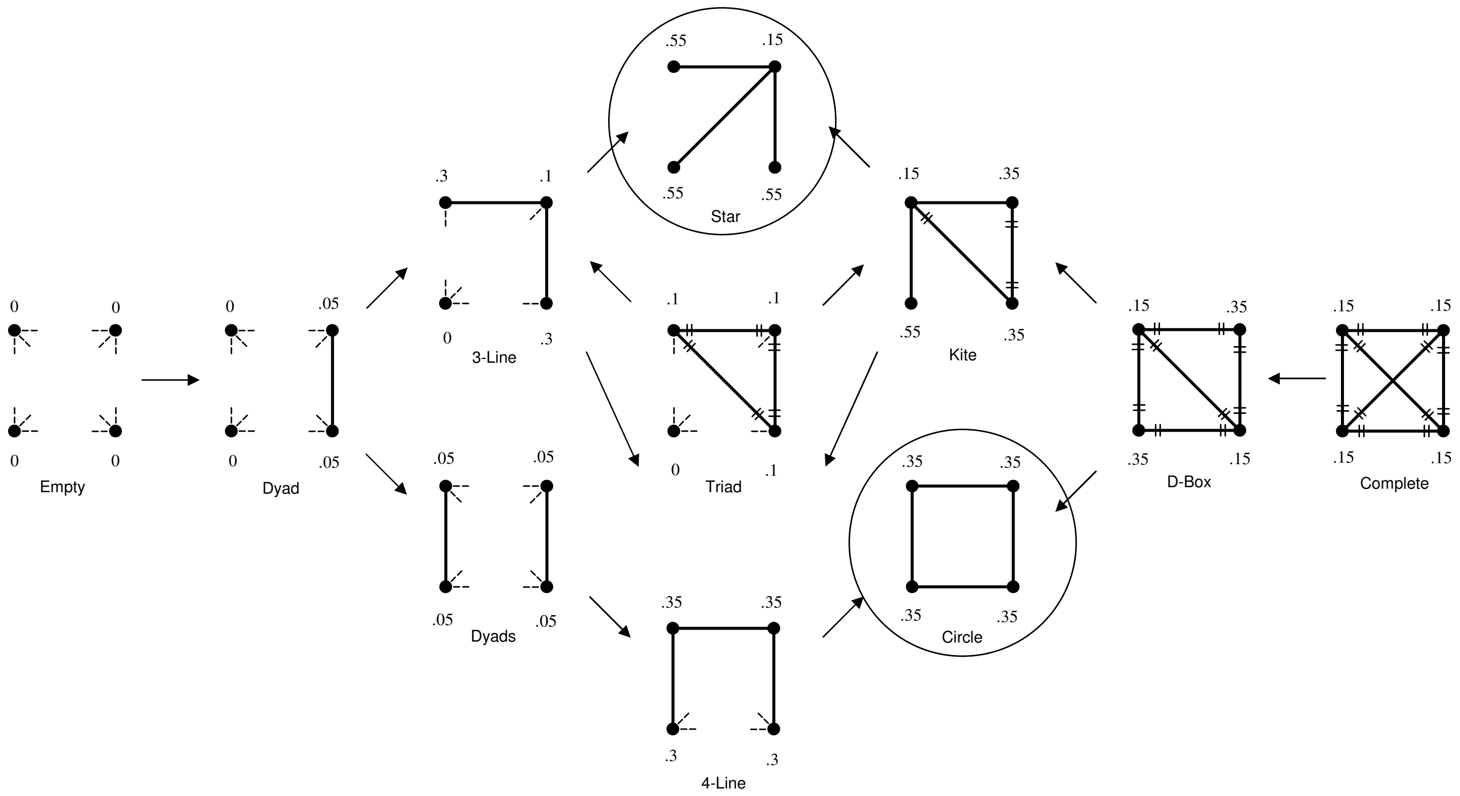


Figure 4.1: Connections model with $n = 4$, all non-isomorph networks, myopic network formation.
(||) indicates actors prefer to remove these links; (– –) indicates actors prefer to create these links. Large circles indicate stable networks. Numbers indicate utilities in that network position.

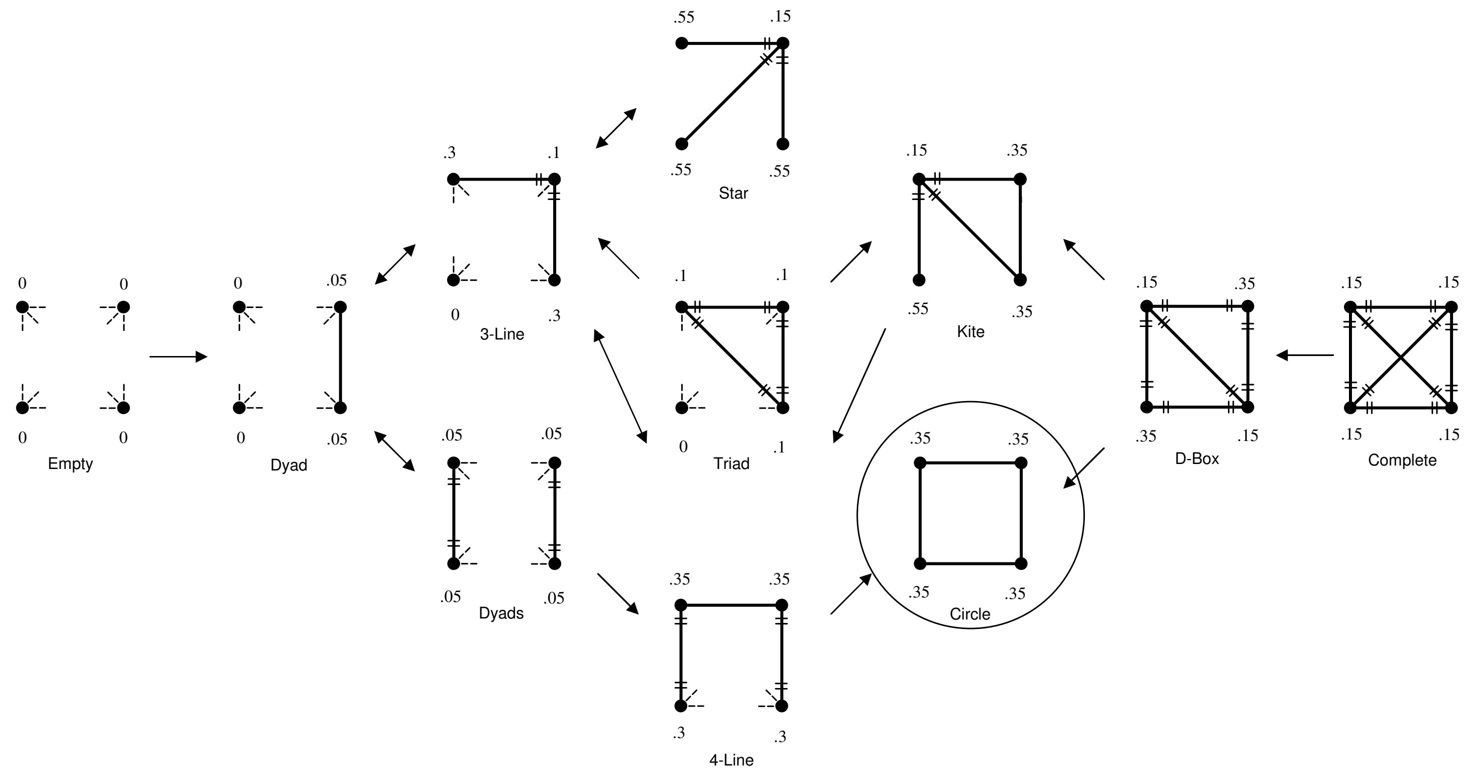


Figure 4.2: Connections model with $n = 4$, all non-isomorph networks, limitedly farsighted network formation. (||) indicates actors prefer to remove these links; (– –) indicates actors prefer to create these links. Large circles indicate stable networks. Numbers indicate utilities in that network position.

The co-author model

The co-author model captures the idea of actors receiving benefits from a network of, e.g., researchers working together on projects. The time an actor spends on a project is inversely related to the number of projects he or she is working on, i.e., time is equally distributed among the projects. Researchers benefit from working on many projects, however, they prefer that their co-authors have only few other projects. The co-author model creates negative externalities, such that actors creating links will thereby decrease their neighbor's payoffs (as they have less time to put in the project with this neighbor). Formally, the payoff for actor i in the co-author model is given by

$$u_i(g) = \sum_{j:ij\in g} \left[\frac{1}{n_i} + \frac{1}{n_j} + \frac{1}{n_i n_j} \right]$$

where n_i is the degree of an actor i and n_j the degree of a neighbor j.

Figure 4.3 shows the metanetwork when actors are myopic. The complete network is the only stable network. Myopic actors keep adding links until they reach the completely connected network, because in every network at least two actors have an immediate benefit from creating a link between each other. Driven by these short-term incentives, myopic actors end up in a Pareto-suboptimal network. The efficient network structures in the co-author model consists of networks where pairs of actors remain unconnected from other actors (dyads network). This creates a tension between stability and efficiency.

If we assume that actors look two steps ahead, we obtain different predictions for stable networks than when assuming myopic actors. Figure 4.4 shows the metanetwork of the formation process when actors are limitedly farsighted. Again the arrows show the direction of the formation process, the networks where no arrows are pointing outwards indicate the two-step farsighted pairwise stable networks. Next to the complete network, we see two additional stable networks, the dyads network and the circle network.

Running similar simulations as for the connections model, we obtain the predictions for emerging networks as shown in table 4.2 (note that the noise levels are higher than for the connections model, because of the utility dif-

Table 4.2: Simulation results co-author model

	Noise level			
	0	0.1	0.2	0.4
Myopic	**100% (com.)**	**100% (com.)**	**94.5% (com.)** 0.1% (circle) 5.4% (d-box)	**62.3% (com.)** 2.7% (circle) 28.5% (d-box) 5.7% (kite)
Two-step	**26.7% (com.)** **53.3% (circle)** **16.7% (dyads)**	**31.3% (com.)** **52.3% (circle)** **14.4% (dyads)** 2% (kite)	**34.2% (com.)** **50.2% (circle)** **8% (dyads)** 5% (kite)	**17.4% (com.)** **41.9% (circle)** **4.2% (dyads)** 24.3% (4-line)

In bold: stable networks for the deterministic case.

ferences in the co-author model between respective networks are larger than in the connections model). The co-author model provides a more distinctive prediction for the different assumptions on how actors make decisions. Myopic actors will create the complete network, actors who look two steps ahead create the circle, dyads, or the complete network.

Qualitatively, we can make the following *prediction*: if actors are myopic, the complete network is the only stable network, but if actors look two steps ahead, next to the complete network, the dyads and the circle network are also likely to emerge.

Figures 4.3 and 4.4 also provide indications for the predicted behavior at the micro level using the same notation as in figures 4.1 and 4.2. The predictions of the different models will be analyzed based on the experiment explained in the following section.

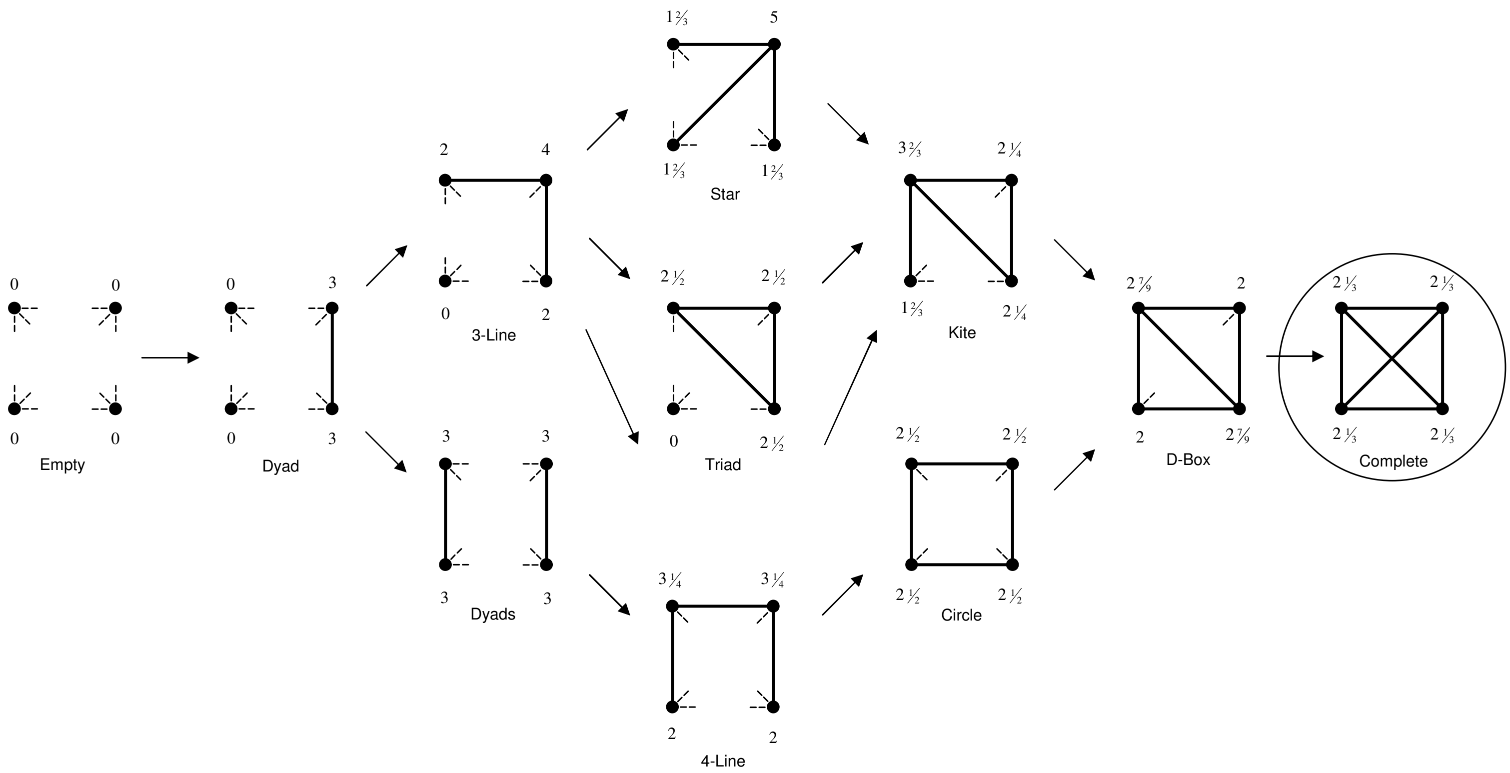


Figure 4.3: Co-author model with $n = 4$, all non-isomorph networks, myopic network formation.
(||) indicates actors prefer to remove these links; (−−) indicates actors prefer to create these links. Large circles indicate stable networks. Numbers indicate utilities in that network position.

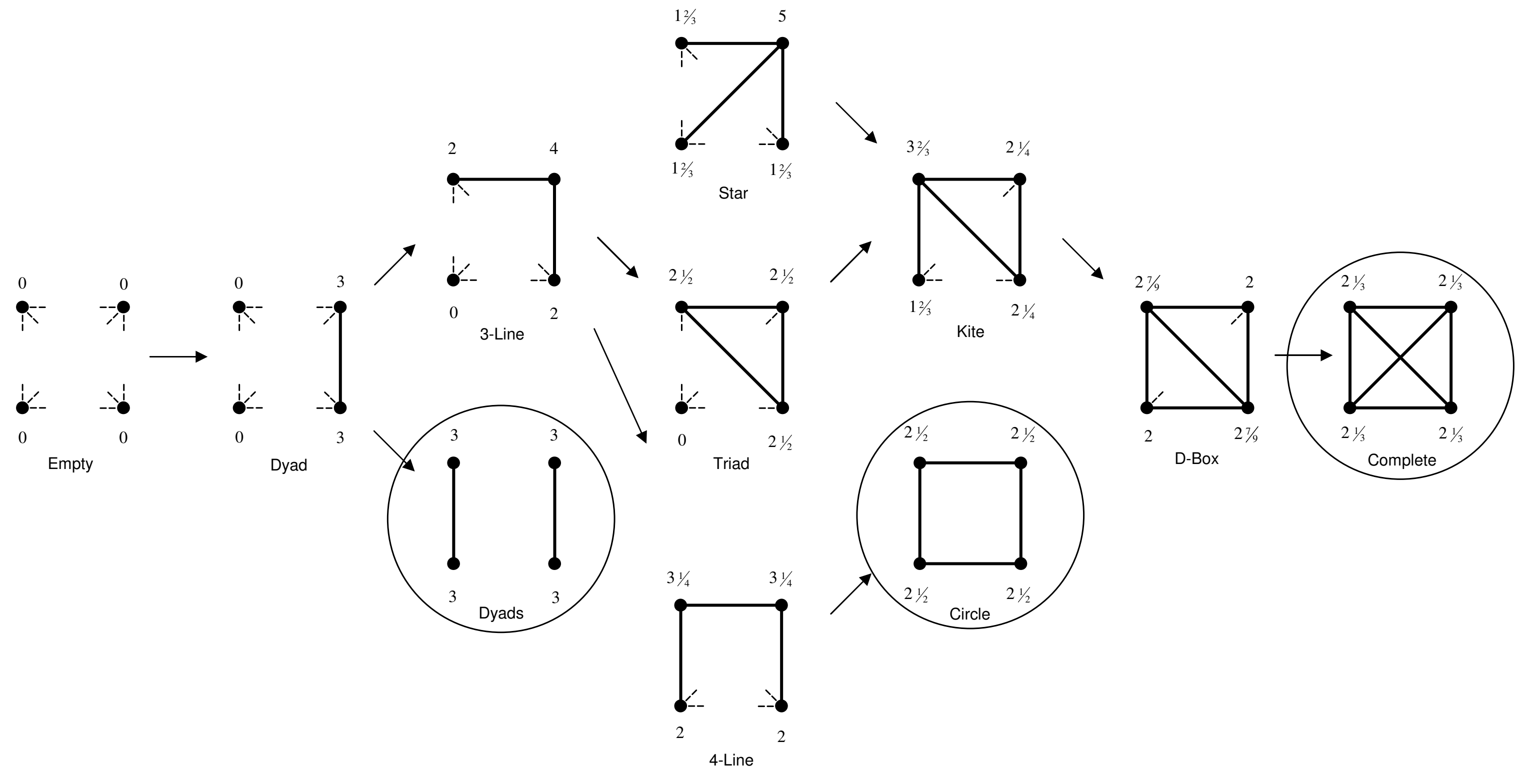


Figure 4.4: Co-author model with $n = 4$, all non-isomorph networks, limitedly farsighted network formation. (||) indicates actors prefer to remove these links; (– –) indicates actors prefer to create these links. Large circles indicate stable networks. Numbers indicate utilities in that network position.

4.4 Experimental design

We conducted a computerized experiment in which subjects interacted in a network formation game. The experiment took place in February 2011 at the ELSE Lab at Utrecht University; z-Tree (Fischbacher, 2007) was used for programming. Instructions and screen texts were available in Dutch and English (see appendix C.1). The experiment involved nine sessions with 136 subjects, 89% of whom were students. Students had backgrounds from various fields of study, mostly sociology, economics, and psychology. Out of all subjects, 65% were female and the average age was 23 years. Subjects played the network formation game in groups of four. A session in the experiment consisted of two treatments. Subjects participated in both treatments. One treatment consisted of payoffs according to the co-author model and the other of payoffs according to the connections model. The order of treatments was varied between sessions and instructions were handed out to subjects at the start of each treatment. In each treatment, subjects played two rounds with the same utility function. One round consisted of one network formation process by four subjects. At the beginning of each treatment subjects played a trial round to get familiar with the network game. After every round, subjects were randomly reshuffled into new groups to ensure anonymity.

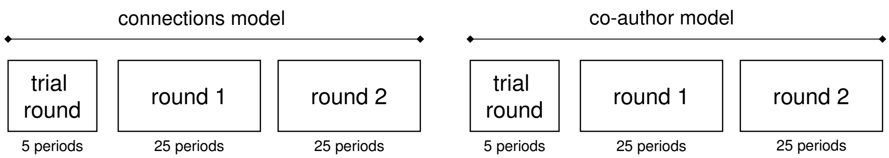


Figure 4.5: Example set-up of a session

One round consisted of 25 discrete periods. Trial rounds had five periods (see figure 4.5). In all rounds, the empty network was the starting network. In each period, all subjects in the network could choose which relation to change. Subjects where represented as circles on the screen and they were able to choose relations to other subjects in their own group. The blue circles

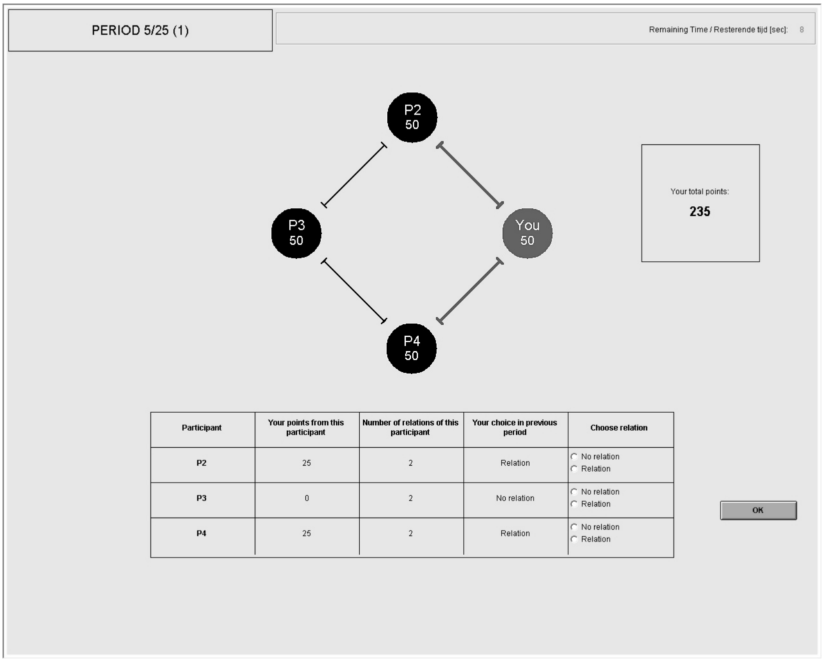


Figure 4.6: Screenshot of the network formation experiment

referred to ego and black circles to other group members. As can be seen in figure 4.6, subjects saw a graph of the current network on the screen. For each relation, they could indicate by radio-buttons whether or not to link to this actor in the subsequent period. Subjects had 30 seconds to make their decisions. If no decision was made, the decision from the previous period was applied. If there was no decision in the first period, "no link" was used as a default decision. After each period, the computer checked which network changes were requested by the subjects, i.e., which existing relations were requested to be removed by one of the subjects involved and which non-existent relations were requested to be built by both actors involved. Then, the computer randomly chose *one* of these requested changes to be implemented in each group. In the subsequent period, subjects where informed about the new network structure and about the new payoff for their network position on screen. Subjects received a sheet of paper on which all non-isomorphic networks with four actors were shown including the payoffs connected to the different network positions (see figures in appendix C.1).[1] Subjects received monetary payments for their network position in each period.[2] Points were transfered into Euros at a rate of 300 to 1. Complete instructions are given in appendix C.1.

Permitting only one link change per period by a randomized protocol, out of all intended link changes per group, is a novel approach that has not been carried out in previous experiments. Most experiments used a discrete time protocol, allowing subjects to change their entire set of linking choices (e.g. Falk and Kosfeld, 2012; Berninghaus et al., 2012; Callander and Plott, 2005; Goeree et al., 2009). Changing one link at a time keeps the formation process clearly arranged, as some researchers observed that subjects had coordination problems when deciding on the whole set of linking choices in discrete time (see Berninghaus et al., 2012; Callander and Plott, 2005). Even more importantly, this technique allows to record all three linking decisions in each period by all subjects in their respective network positions. These choices can be considered as individual linking decisions. If all links can change simultaneously, we would need to analyze the changes from one network to a new network in which more than one relation changes at a time. This is also not consistent with our theoretical model. Our approach resembles the strategy method (Selten, 1967; Rauhut and Winter, 2010; Brandts and Charness, 2011) in which decisions are requested for all events that might happen in the subsequent stage of the game while only one of these events actually materializes.

After the networking game, we let subjects play the beauty contest game (Nagel, 1999). The beauty contest game is a game to capture the ability of iterated reasoning. In the beauty contest game, subjects have to state a number in the range between 0 and 100. The subject who chooses the number closest to p times (here $p = 0.5$) the average number stated by all participants wins the lot. The game was carried out three times to see how subjects adapt their strategies. In the questionnaire that followed afterwards we measured subjects' risk preferences using the Sensation Seeking Scala V (Zuckerman, 1994) as well as with the Holt & Laury gambles (e.g. Holt and Laury, 2002).

[1]Note that payoffs were multiplied by 200 for the connections model and by 20 for the co-author model to make calculations easier for subjects.

[2]Hoyer et al. (2012) and Mantovani et al. (2011) present an alternative approach where subjects only receive payoffs for their final network.

4.5 Results

The result section begins with the analysis at the macro (group) level. After that, we report the analysis of micro-level (individual) behavior of subjects.

4.5.1 Macro-level results

To analyze the predictions of the myopia and limited farsightedness model we look which network structures are formed by subjects on the group level. In each group, four subjects interacted with each other for 25 periods. We refer to that as a *formation process*. In total, there are 136 formation processes (68 for each utility function). To analyze the data, we define stability "empirically" as a network that emerges at least three periods in a row (see also Callander and Plott, 2005; Burger and Buskens, 2009). We refer to these networks as the *emerged networks*. The percentage of formation processes in which at least once a network emerges is 71.3% (97 out of 136). We observe differences between rounds, as well as between treatment orders within sessions: In the second round and second treatment, there are more formation processes with emerged networks (see table 4.3). Coordinating on a stable network is apparently easier in the connections model, as the percentage formation processes with emerged networks is higher (83.8% versus 58.8%).[3]

Table 4.3: Numbers and percentages of formation processes with observed emerged networks

Utility	Round 1	Round 2	Treatment 1	Treatment 2	Total
Conn.	70.6% (24/34)	97.1% (33/34)	77.8% (28/36)	90.6% (29/32)	83.8% (57/68)
Co-aut.	55.8% (19/34)	61.7% (21/34)	53.1% (17/32)	63.8% (23/36)	58.8% (40/68)
Total	63.3% (43/68)	79.4% (54/68)	66.2% (45/68)	76.5% (52/68)	71.3% (97/136)

[3]The comparison between the two treatments is problematic, as coordination problems can also be related to the different number of possible stable networks in the two utility functions. In the connections model, two stable networks for the myopic case, one with two-step farsighted actors. In the co-author model, one stable network for the myopic case, three with two-step farsighted actors.

We analyze the emerged networks in terms of their frequency and average length. In total, we find 158 emerged networks (in 136 formation processes), 91 in the connections model, 67 in the co-author model. In some rounds multiple networks emerge. Table 4.4 shows the analysis for the connections model. The circle network occurs most often with an average length of 11.0 periods and a maximum of 22 periods. The 4-line network emerges frequently, however, this network has a much shorter average length with 4.1 periods (and a maximum of 10 periods). The myopically stable star network emerges in only 5 sequences with an average length of 7.4 periods and a maximum of 13 periods. Four of these five sequences had the same subject as the star. This subject volunteered to be the star for 13 periods and 10 periods in each of the two formation processes. If we neglect this one subject (who might indeed be strictly myopic or very altruistic), the results are better described with the predictions of the model when actors look two steps ahead (including some noise). With myopic actors the star network is expected to emerge rather frequently, with limitedly farsighted actors this network is not stable. Predictions with limitedly farsighted actors predict the circle network to emerge most likely (the 4-line and 3-line networks are predicted including some noise).

Table 4.4: Sequences of emerged networks, connections model

network	avg. length	max. length	emerged networks
circle	11.0(7.3)	22	51.6%(47/91)
star	7.4(4.2)	13	5.5%(5/91)
4-line	4.1(1.4)	10	37.4%(34/91)
3-line	3.2(0.4)	4	5.5%(5/91)

Table 4.5 shows the results for the emerged networks in the co-author model. Looking at all 67 sequences of emerged networks, the dyads network emerges 21 times, with an average length of 9.2 periods and a maximum length of 24 periods (see table 4.5). In two cases the network was stable for the entire formation process after emergence. The average length of periods in which the complete network emerges is lower with around 4.8 and a maximum number of 12 periods. However, the number of emerged networks is the same. The circle network emerges in only few cases with an average length of 3.7 periods. The

kite, d-box, and 4-line networks emerge in only few cases with a low average length.

Table 4.5: Sequences of emerged networks, co-author model

network	avg. length	max. length	emerged networks
dyads	9.2(7.1)	24	31.3% (21/67)
complete	4.8(2.5)	12	31.3% (21/67)
circle	3.7(1.1)	5	4.5% (3/67)
kite	3.3(0.5)	4	9.0% (6/67)
d-box	3.3(0.5)	4	11.9% (8/67)
4-line	3.1(0.4)	4	11.9% (8/67)

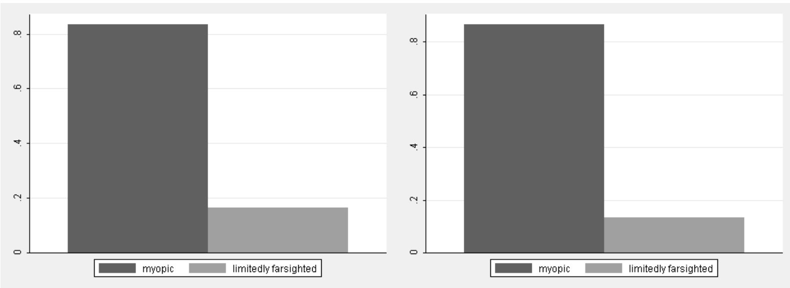
The predictions from the myopia model can be rejected, as the number of emerged networks that are *not* the complete network is high. The model of limited farsightedness predicts the dyads, circle and complete network to be stable. The dyads and the complete network are the most frequent networks we observe in this treatment. The simulation model predicts a high likelihood of the circle network to emerge, this cannot be confirmed by our data.[4] We also ran simulations where actors look three steps ahead; then the dyads network is the only stable network when starting from the empty network. Still, in the experiment, we observe a high number of the complete networks, indicating that actors sometimes end up in the network trap, which is also likely when actors are limitedly farsighted.

All empirically emerged networks for both utility functions were predicted by the simulation models. Interestingly, the most frequently emerged networks were the ones predicted by the deterministic simulation models. The model of limited farsightedness predicts the emerged networks quite accurately in terms of the set of stable networks. The likelihoods of specific networks to emerge (also when including noise) cannot be confirmed by the data.

[4] In a previous version of the experiment that was conducted in the SocioLab at ETH Zürich we observed very similar results. The circle network emerged most often in the connections model, the star network never emerged. In the co-author model, however, the circle network emerged most often, followed by the dyads and the complete network. The Zürich experiment was set up slightly different, rounds only consisted of 15 periods and there was no forced ending of the decision periods.

4.5.2 Micro-level results

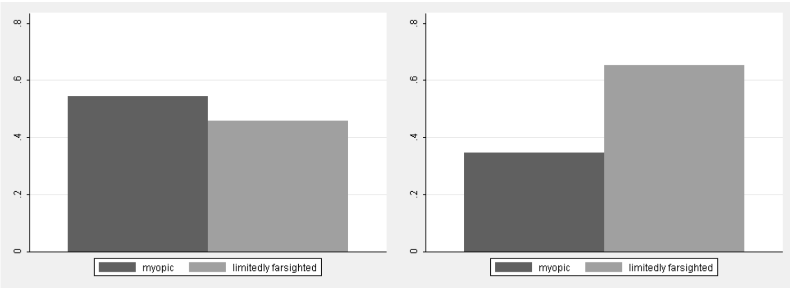
In the experiment, subjects could indicate to build or cut links to other group members. In total, there are 40800 linking decisions (136 subjects $\times$ 4 rounds $\times$ 25 periods $\times$ 3 decisions). The theoretical models describe behavior for every linking decision, allowing to compare the data with the myopia and the model of limited farsightedness. Decisions can be classified as distinctly myopic or limitedly farsighted, ambiguously myopic and limitedly farsighted, or as neither myopic nor limitedly farsighted. Of all decisions made in the experiment, 79.11% were in accordance with the myopia model, 74.7% were in accordance with the model of limited farsightedness.



(a) treatment 1 (b) treatment 2

Figure 4.7: Percentages of myopic or two-step farsighted choices for decisions in which these can be distinguished, connections model

The following analysis focuses on decisions which can be distinctly classified as myopic or farsighted. Figures 4.7 and 4.8 show the percentages of myopic and farsighted decisions for the two treatments, split by treatment order. In the connections model, a clear majority of subjects make myopic linking decisions. Also in the co-author model, subjects often act myopically. However, when the treatment is played second, subjects act more farsighted. Note that the difference between the two utility functions is also likely to be related to the different sets of stable networks. In the connections model, the most frequently emerged network, the circle network, is myopically and limited farsightedly stable. In the co-author model, the most frequently emerged network, the dyads network, is only stable when actors look two steps ahead.[5]



(a) treatment 1 (b) treatment 2

Figure 4.8: Percentages of myopic or two-step farsighted choices for decisions in which these can be distinguished, co-author model

To investigate farsighted behavior in more detail, we run a multi-level logistic regression on whether or not a decision was in line with two-step farsightedness. We take into account that decisions are nested within subjects, which are nested in groups, which are nested in sessions. Since the session level did not add explanation, it was excluded from the final analysis as presented below.

For every linking decision, given the current state of the link (present or not), subjects can either indicate to want to have the link or not. The dependent variable measures whether subjects make this decision according to limitedly farsighted behavior (coded with 1) or myopic best response behavior (coded with 0). This gives us 5741 decisions (2660 in the connections model, 3081 in the co-author model.[6]

As independent variables we include the expected utility change if the status of the link would be changed, according to myopic and according to limitedly farsighted decision-making. Using these utility calculations we can

[5]Note that there is a qualitative difference between two-step farsighted decisions in the two treatments: in the co-author model farsighted actors indicate to not create a link, despite an immediate gain, in order to avoid a farsighted loss. In the connections model, farsighted actors indicate to remove an existing link, despite an immediate loss, in order to achieve a farsighted gain.

[6]Compare figures 4.1 with 4.2 and figures 4.3 with 4.4 to see which networks and which network positions are involved in these decisions.

analyze whether subjects decisions are driven either by myopic or by limitedly farsighted expected utility calculations, by both, or by none of these calculations. Negative values of these variables indicate an expected loss, positive values indicate an expected gain. To control for learning effects we add the period, period squared, the round and the order of treatments. Furthermore, we calculate the level of farsightedness of subjects, i.e. the steps of reasoning subjects applied in the beauty contest game. We calculated the level of reasoning k with the following formula:

$$k = \frac{ln(^{b}/_{100p})}{ln(p)}$$

where 100 is the highest number that can be chosen, p is the factor (here $p = 1/2$), and b is the number chosen by the subject in the beauty contest game. This results in a measure between -1 and 6. For example, for $b > 50$ the measure is negative, subjects who choose the number 50 are defined as thinking 0 steps ahead, subjects who chose 25 think 1 step ahead, etc. The interpretation here is: imagine others do not think ahead, they choose on average 50. The winning number in that case equals 25. The measure is not defined for subjects who choose the number 0. Choosing the number 1 results in 5.64 thinking steps. We therefore defined choosing the number 0 as thinking 6 steps ahead. On average, subjects think approximately two steps ahead (see table 4.6), which is a common finding in beauty contest game experiments (see Camerer, 2003, for a survey on beauty contest game experiments).

Table 4.6: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
Limited farsighted decision	0.39	0.488	0	1
Expected utility (myopic)	0.108	0.25	-0.3	0.950
Expected utility (limitedly farsighted)	-0.093	0.204	-0.5	0.2
Period	12.626	7.127	2	25
Second round	0.486	0.5	0	1
Second treatment	0.569	0.495	0	1
Co-author	0.537	0.499	0	1
BCG	1.933	1.484	-0.604	6
Male	0.331	0.471	0	1

Table 4.7: Random intercept logistic regression on farsighted decision making

	Limited farsighted decision	
Expected utility (myopic)	0.147	(0.330)
Expected utility (limitedly farsighted)	2.388 ***	(0.518)
Period	0.080 ***	(0.027)
Period squared	−0.004 ***	(0.001)
Second round	−0.242	(0.203)
Second treatment	0.263	(0.206)
Co-author	1.925 ***	(0.316)
BCG	−0.239 **	(0.098)
BCG*Co-author	0.554 ***	(0.075)
Male	−0.718 **	(0.279)
Constant	−2.232 ***	(0.338)
Var. (subject)	1.004	(0.095)
Var. (group)	1.343 ***	(0.109)
Observations	5741	
Log lik.	−2491.282	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.7 shows the result of the model.[7] The myopically expected utility change is not significant, however the two-step farsightedly utility calculation has a positive and highly significant effect. A higher farsightedly expected utility increases the chance that subjects act farsightedly. The result indicates that subjects make their expected utility calculation in a two-step farsighted manner rather than myopically.

The period in which the decision was made has a strong positive effect on farsighted decision-making. The quadratic effect of period is negative and highly significant. This indicates that subjects are more likely to act farsighted with increasing playing period. However, the effect decreases over time. We observe no significant effects of the round and treatment order.

[7]We also ran models where we controlled for risk aversion, measured as the sum of risk averse choices in the Holt & Laury lottery. In the Holt & Laury lottery subjects have to choose between a sure payment and a gamble. We neglected inconsistent behavior of subjects when they switched back and forth between choices and only added up the number of risk averse choices (see also Holt and Laury, 2002). We observed no significant effects.

There is a strong and positive effect of the co-author treatment. Playing the co-author model, subjects are more likely to make farsighted decisions. We observe a negative main effect of the beauty contest game measure (BCG in the table 4.7). However, there is a strong positive interaction effect between the level of farsightedness in the beauty contest game and the co-author model. In the connections model, subjects who score high on the beauty contest game measure are less likely to make farsighted decisions. In the co-author model, this effect is positive: subjects who score higher are more likely to act farsightedly. To explain these contrasting effects, we have to analyze in which networks and which network positions these decision points occur. In the connections model, most decision points can be found in the 3-line, 4-line and dyads network (see figures 4.1 and 4.2). All decisions where we can differentiate between farsighted and myopic behavior are decisions about removing links to achieve an anticipated benefit as a peripheral actor in the star network. This position yields the highest payoff in the connections model. In the model of limited farsightedness actors assume that other actors make subsequent decisions myopically, leading the formation process from the mentioned networks to the star network. Additionally, the star network is only stable when the star actor is myopic. Subjects in the experiment seem to anticipate that the star actor will not want to remain in this position, therefore making the star network undesirable, as the peripheral position cannot be maintained. The beauty contest game measures two different concepts, subjects' level of farsightedness and subjects' beliefs about farsightedness of others. The negative effect in the connections model seems to be related to that: higher level reasoning subjects anticipate that the star network is unstable because the star actor is *not* myopic. So what we classify and observe as myopic behavior might indeed be farsighted behavior. This problem of classifying decisions as myopic or farsighted is not problematic in the co-author model: myopic decisions are only about adding links for an immediate gain. So farsighted behavior can only be described as decisions where actors do not add links.[8]

[8]Deleting a link is never consistent with farsighted behavior in the model of limited farsightedness. Although, in dense networks, we often observe deletion of links by subjects to leave the network trap.

4.6 Conclusion and discussion

Most models of strategic network formation assume myopic decision-making. This assumption has been criticized with theoretical arguments and empirical results suggest that subjects use limitedly farsighted strategies when making network decisions (Jackson, 2008; Pantz, 2006). In this chapter, we experimentally investigated whether subjects' network decisions are myopic or limitedly farsighted. Using computer simulations we predicted network formation when actors are myopic, thus look one step ahead, and when actors look two steps ahead. The connections model and the co-author model were used as utility functions.

The experimental macro-level results show that the model of limited farsightedness predicts the macro-level outcomes better than the myopia model of network formation. In the connections model, subjects hardly build the efficient star network and end up most often in the circle network. In the co-author model, subjects are able to avoid the "network trap" and end up most often in the efficient dyads network.

We furthermore analyzed individual decision-making. The beauty contest game measure has different effects in both treatments. Subjects who apply more steps of iterated reasoning are more likely to behave farsightedly in the co-author model and are less likely to behave farsightedly in the connections model. The negative effect in the connections model is related to two assumptions made in the model of limited farsightedness: assuming that actors make decisions believing that other actors think one step less ahead, creates an inconsistency problem as all subjects are limitedly farsighted themselves but consider all others to be myopic. Furthermore, the anticipated future networks for which limitedly farsighted actors compare utilities are assumed to be resting points of the formation process.

In the connections model, the efficient star network is stable when the star actor is myopic. Limitedly farsighted actors want to be in the periphery in the star network, assuming that others are myopic. The behavior of subjects in the experiment suggests that subjects anticipate that the star network is not stable as the star actor would cut links assuming that he is limitedly farsighted. To analyze individual behavior, we only looked at decisions that can be classified as either myopic or limitedly farsighted. In some of these decisions limitedly farsighted actors want to change links to end up in the periphery in the star network. To a large degree, subjects in the experiment do not want to make these decisions. What we then consider in the connections model as myopic, and therefore not limitedly farsighted, behavior might indeed often be another form of anticipatory, i.e., farsighted behavior. Although we are able to better predict macro-level outcomes with the model of limited farsightedness, the inconsistency issue in the model of limited farsightedness creates problems when explaining micro-level behavior. Future models of perfect or limited farsightedness have to take such issues into account. Besides further investigating the appropriate level of farsightedness, researchers also have to further investigate how farsightedness is related to beliefs about others' level of farsightedness.

The example of the star network in the connections model also points out that heterogeneity of groups in terms of the level of farsightedness might be of importance to explain our results. So far, we only make predictions for homogeneous groups of actors: all actors are either myopic or limitedly farsighted. Consider two examples. In the connections model, the efficient star network is only unstable if all actors are farsighted. To make the star network stable, only one single myopic actor is required. The network formation process converges to the star network as soon as all farsighted actors are in peripheral positions. In the co-author model, at least two farsighted actors are necessary to remain in the efficient dyads network. Imagine a situation with two strictly myopic actors. Then both actors would want to build a link between each other and therefore would destabilize the dyads network. If these two myopic actors are in the same dyad and two farsighted actors in the other dyad, the dyads network is stable, since link creation is only possible with mutual consent. If, however, the two myopic actors are separately connected with two farsighted actors, then the myopic actors would build a link between them and make the dyads network unstable.

So naturally further questions arise: how do different distributions of the level of farsightedness of actors affect the emergence of networks? How is farsightedness distributed in a population? Simulation models that study the effects of heterogeneity and further experimental research are necessary to solve these open research questions. In chapter 5 we make a first step in this direction, by investigating in more detail the composition of groups of subjects in the experiment.

Chapter 5

Classifying Individuals in Levels of Farsightedness*

5.1 Introduction

Building and cutting network links is a strategic process. In recent years, game-theoretic tools have been used to develop models of network formation, in which actors strategically decide with whom to connect. Most dynamic models adopt a form of bounded rationality as an individual-level behavioral theory, namely, myopic best response behavior (see Jackson, 2008, for a overview): it is assumed that actors neglect subsequent decisions of other actors and only consider the immediate gain of their decisions. This crucial assumption has often been criticized and in recent years alternative models have been developed that vary the level of farsightedness (see e.g. Pantz, 2006; Herings et al., 2009; Morbitzer et al., 2011). There is also experimental evidence that suggests that neither the myopic nor the perfect farsightedness assumption predicts actual behavior of subjects well, thus promoting a form of *limited* farsightedness (see Pantz, 2006). Limited farsightedness in network formation as an alternative behavioral model has been studied so far by Berninghaus et al. (2012) and Morbitzer et al. (2011). Morbitzer et al. (2011) present a network formation model, incorporating ideas of level-k-reasoning and Cogni-

*This chapter is single-authored.

tive hierarchy models (Stahl and Wilson, 1995; Camerer et al., 2004). Actors look two or three steps ahead, and therefore, are limitedly farsighted. Assuming that actors look two or three steps ahead leads to new predictions on stable networks.

Furthermore, experimental research suggests that subjects differ in terms of their ability to look ahead (see chapter 4). In social (i.e. interdependent) decision-making experiments, researchers often observe different types of actors, classifiable by certain characteristics, as for instance, their social value orientation (see e.g. Aksoy and Weesie, 2012). In this chapter we focus on heterogeneity among subjects regarding their abilities to look ahead.

Discovering such heterogeneity is an important research task: including heterogeneity among actors into models of strategic network formation might lead to more heterogeneous networks that better resemble empirically observed networks (Galeotti et al., 2006). A problem with theoretically modeling heterogeneity in terms of the level of farsightedness is that the predictions depend on the proportion of myopic and farsighted actors in the population (see also the discussion in chapter 4). In this chapter, we investigate the observed proportion of myopic and limitedly farsighted actors in an experimental situation. This empirical analysis can further help to fine tune simulation models. Next to the proportions of myopic and limitedly farsighted subjects, we want to investigate how many classes of actors concerning levels of farsightedness there are, and whether these classes are better described with "pure" types of actors or with types of actors that also "mix" levels of farsightedness when making network decisions. Here, we mean by "pure" that actors always act according to the same level of farsightedness and by "mixed" that actors differ in level of farsightedness depending on the decision. Related to this, we investigate whether farsightedness is an individual trait, or whether farsightedness is context dependent. We want to predict class membership with an independent measure of subjects' ability to look ahead. We use results from a beauty contest game as a proxy for subjects' level of farsightedness to predict class membership.

To classify individuals we use data on decisions of subjects who participated in a network formation experiment. Actors can indicate a linking change if they prefer such a change. Theoretical predictions on what subjects prefer depend on how far actors look ahead. Therefore, we are able to match linking decisions of the subjects to levels of farsightedness. In chapter 4 we studied in which situations subjects are more likely to act limitedly farsighted assuming all actors use the same decision model. Results show that subjects' network decisions can indeed be partially predicted by the model of limited farsightedness.

In this chapter, Latent Class Models (LCM) are used to classify subjects, based on their linking decisions. Latent class models use categorical latent variables to represent subpopulations where population membership is not known but is inferred from the data (McCutcheon, 1987; Vermunt, 2003). With probit regression models, we predict linking changes of subjects, using decision models for actors who look one, two, and three steps ahead. Thereby, we classify subjects into classes characterized by different levels of farsightedness. In the same model, we also predict class membership with the ability of iterated reasoning, as measured with a beauty contest game (Nagel, 1999).

The remainder of the chapter is organized as follows. In section 5.2, decision-making of myopic and farsighted actors is described. In section 5.3, we present the decision-making situation in the experiment. In section 5.4, the statistical model is described. In section 5.5, the empirical results are reported. In section 5.6, we conclude with a discussion of the results.

5.2 Myopic and limitedly farsighted decision-making

We start with describing how actors make network decisions according to the myopia model and the model of limited farsightedness. After that, we discuss payoff functions used in the experiment. Furthermore, we describe the decision-making situation in the experiment.

In so-called pure network formation models, utility is a function of the network itself. The set $N = \{1, \ldots, n\}$ is the set of nodes representing actors. A network g indicates the actors in N that are connected via a link. Formally, g is a set of unordered pairs of actors $\{i, j\}$. For any pair i and j, $\{i, j\} \in g$ indicates that i and j are linked in the network g; otherwise $\{i, j\} \notin g$. Links are undirected: if i has a link with j, then j also is linked with i. We denote the link $\{i, j\}$ also with ij. We define g^{ij} as the adjacent network obtained by either adding or deleting a link in g. Depending on a certain position in a network g, actor i receives a utility $u_i(g)$. Actors have the means to alter the network, i.e. they can choose with whom they want to have a link or not. Actors link in order to maximize their benefit. In the commonly used notion of pairwise stability, a link ij is created if two actors i and j benefit from creating a link between each other and a link ij is deleted if one actor benefits from removing this link. If no such linking change is possible in a network, the network is pairwise stable.

Myopic actors calculate utilities considering only the immediate change in utility, if the status of a link is changed. Myopic actors want to change a link if the expected utility change is larger or equal than 0, thus $u_i(g^{ij}) \geq u_i(g)$. Actors want to keep the current status of the link if the utility change is less than 0, thus $u_i(g^{ij}) < u_i(g)$.

Limitedly farsighted actors calculate expected utilities differently. Actors who look two steps ahead anticipate *myopic* linking changes from other actors k and l, after the link ij under evaluation would be changed.[1] If the other actors would myopically change links in the subsequent network g^{ij}, actors who look two steps ahead evaluate the utility they would have in such a future network $g^{ij,kl}$. If there is more than one future network $g^{ij,kl}$ (because several subsequent linking changes can occur in g^{ij}), the mean utility of all future networks is taken as the expected utility and then compared to the current utility.[2] If the expected utility change is larger or equal to 0, actors want to change the status of the link ij. If it is negative, they want to keep the current status of the link. If there are no anticipated subsequent network changes from other actors, actors who look two steps ahead consider a myopic linking change and then want a linking change in the same manner as described for myopic actors. Note, actors who look two steps ahead assume that other actors look one step less ahead than they themselves do (looking one step ahead is myopic

[1]Other actors include actors that are not involved in the link under evaluation.

[2]The procedure of taking the mean value of all possible values is often referred to as the Principle of Insufficient Reason (see Luce and Raiffa, 1958; Morbitzer et al., 2011).

behavior as described above).[3]

The expected utility calculations for actors who look three steps ahead look similar to those for actors who look two steps ahead. Actors who look three steps ahead anticipate linking changes from other actors such that they assume others to look two steps ahead. After the link under evaluation ij would be changed, actors check if in the subsequent network g^{ij} other actors k and l want to change the status of links when they look two steps ahead as described above. If they want to change, actors then check if there are myopic changes in $g^{ij,kl}$. After evaluating such events, they take the mean of all possible future network utilities, depending on the number of subsequent changes. If the expected utility change is larger or equal to 0, actors want a linking change. If the expected utility change is negative, actors want to keep the current status of the link ij.

For more details and discussions on the theoretical model see chapter 2.

5.3 Set-up of the experiment

We conducted a computerized experiment in which subjects interacted in a network formation game. The experiment took place in February 2011 at the ELSE Lab at Utrecht University; z-Tree (Fischbacher, 2007) was used for programming. Instructions and screen text were available in Dutch and English. The experiment involved nine sessions with 136 subjects, 89% of whom were students. Students had backgrounds from various fields of study, most of which from sociology, economics, and psychology. Out of all subjects, 65% were female and the average age was 23 years. Subjects played a network formation game in groups of four. A session in the experiment consisted of two treatments. In one treatment payoffs were given by the connections model, in the other treatment, payoffs were given by the co-author model (Jackson and Wolinsky, 1996). We only give a short intuition on the payoff functions. In the context of the analysis presented here, detailed discussions on stability

[3]This "inconsistency" of own behavior and beliefs about others behavior, is in line with findings from psychological research on overconfidence (see also Camerer and Lovallo, 1999).

and efficiency of networks are not necessary (see Jackson and Wolinsky, 1996; Jackson, 2008, for a broader discussion).

In the truncated version of the *connections model*, which we adopted in the experiment, it is assumed that actors receive benefits from direct and indirect relations (relations via one intermediate). The connections model satisfies positive externalities as creating new links benefits your neighbors. Thus, relations to friends of friends are beneficial for one's own payoff. The payoffs in the connections model are given by

$$u_i(g) = 200 \times \Big(\sum_{j:ij \in g} (\delta - c) + \sum_{k:ij \in g, jk \in g, ik \notin g} \delta^2 \Big)$$

where c is the cost of maintaining a direct relation, δ is the payoff actor i gets from being directly connected to another actor and δ^2 the payoff from being connected via an intermediate. We set $\delta = .5$ and the cost level at $c = .45$.[4]

In the *co-author model*, actors receive benefits only from being directly connected to other actors. The benefit from a link depends on the number of links, i.e. the degrees of the actors i and j involved in the link. The payoffs for actor i in the co-author model are given by

$$u_i(g) = 20 \times \sum_{j:ij \in g} \left[\frac{1}{n_i} + \frac{1}{n_j} + \frac{1}{n_i n_j} \right]$$

where n_i is the degree of actor i and n_j the degree of neighbor j. The co-author model creates negative externalities, such that actors creating links will thereby decrease existing neighbors' payoffs.

All subjects participated in both treatments. The order of treatments was varied between sessions and instructions were handed out to subjects at the start of each treatment. In each treatment, subjects played two rounds with the same payoff function. One round consisted of one network formation process by four subjects. At the beginning of each treatment subjects played a trial round to get familiar with the network game. After every round, subjects were randomly reshuffled into new groups to ensure anonymity.

[4]We chose this specific cost range because here the set of stable networks differs when actors are myopic as compared to when actors are limitedly farsighted.

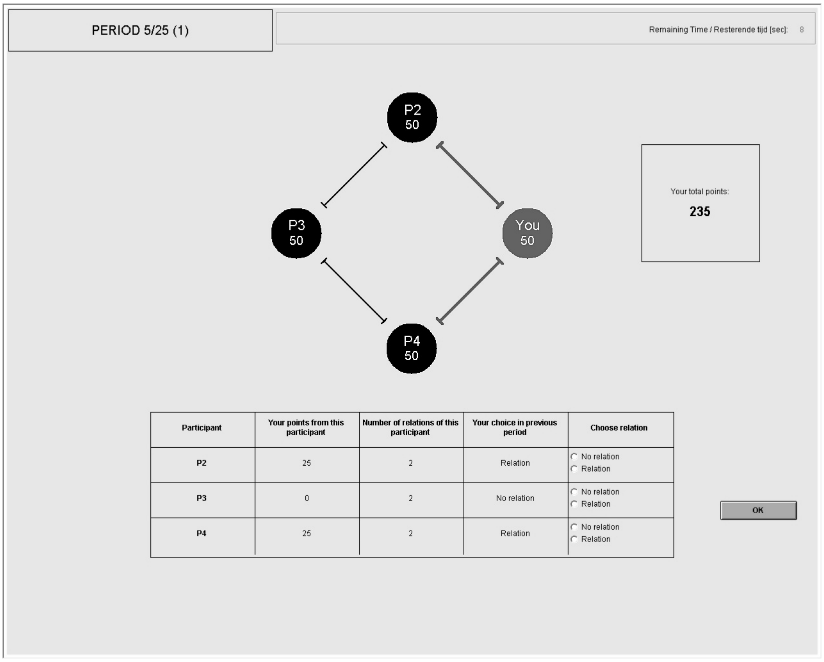


Figure 5.1: Screenshot of the network formation experiment

One round consisted of 25 discrete periods. Trial rounds had five periods. In each period, all subjects in the network could choose which relation to change. Subjects where represented as circles on the screen and they were able to choose relations to other subjects in their own group. Blue circles referred to ego and black circles to other group members. As can be seen in figure 5.1, subjects saw a graph of the current network on the screen. For each relation, they could indicate by radio-buttons whether or not to link to this actor in the subsequent period. Subjects had 30 seconds to make their decisions. If no decision was made, the decision from the previous period was applied. If there was no decision in the first period, "no link" was used as a default decision. After each period, the computer checked which network changes were requested by the subjects, i.e., which existing relations were requested to be removed by one of the subjects involved and which non-existent relations were requested to be built by both actors involved. Then, the computer randomly chose one of these requested changes to be implemented in each group. In the subsequent period, subjects where informed about the new network structure and about the new payoff for their network position on screen. Subjects received a sheet of paper on which all non-isomorphic networks with four actors were shown including the payoffs connected to the different network positions. Subjects received monetary payments for their network position after each period. Points were converted into Euros at a rate of 300 to 1.

Permitting only one link change per period by a randomized protocol, out of all intended link changes per group, is a novel approach that has not been carried out in previous experiments.[5] This technique allows to record all three linking decisions in each period by all subjects in their respective network positions. We consider the linking choice per period as individual linking decisions. That means we assume that subjects make the payoff calculations for every link independently. Our approach resembles the strategy method (Selten, 1967) in which decisions are requested for all events that might happen in the subsequent stage of the game while only one of these events actually materializes.

After the networking game, we let subjects play the beauty contest game (Nagel, 1999). The beauty contest game is a game to capture the ability of iterated reasoning. In the beauty contest game, subjects have to state a number in the range between 0 and 100. The subject who chooses the number closest to $\frac{1}{2}$ times the average number guessed by all participants wins the lot.[6] In the questionnaire that followed afterwards, we measured subjects'

[5]Most experiments used a discrete time protocol, allowing subjects to change their entire set of linking choices (e.g. Falk and Kosfeld, 2012; Berninghaus et al., 2012; Callander and Plott, 2005; Goeree et al., 2009).

[6]We calculate the level of reasoning z of subjects with the following formula:

$$z = \frac{ln({}^{b}/_{100*\frac{1}{2}})}{ln(\frac{1}{2})}$$

where 100 is the highest number that can be chosen, and b is the number chosen by the subject in the beauty contest game. This results in a measure between -1 and 6. For example, for $b > 50$ the measure is negative, subjects who choose the number 50 are defined as reasoning 0 steps ahead, subjects who chose 25 reason 1 step ahead, etc. The interpretations is: imagine others do not reason ahead, but choose randomly, they choose on average 50. The winning number in that case equals 25. The measure is not well defined for subjects who choose the number 0. Choosing the number 1 results in 5.65 steps of reasoning. We therefore defined choosing the number 0 as reasoning 6 steps ahead.

risk preferences using the Sensation Seeking Scale V (Zuckerman, 1994) as well as with Holt & Laury lotteries (e.g. Holt and Laury, 2002).

5.4 The statistical model

We apply a so-called multi-level mixture model, where we take into account that decisions are nested within individuals (see Vermunt, 2003), using Mplus (Muthén and Muthén, 1998-2010). Figure 5.2 shows the graph for the mixture model for the basic three-class solution. In the figure, rectangles represent observed outcomes. The circle represents the categorical latent variable that will define the class an actor belongs to. The arrows represent regression relationships. We use a probit regression on outcome variable y whether actors want to change a link or not, and a multinomial logit regression on latent classes c. The dashed arrows from c to the arrows from x variables to y, indicate that the slope in the regression of y on x is allowed to vary across the classes c. In the following, we describe the overall model in three parts: the latent class model that determines class membership, the multinomial logit model on latent class membership, and, for each class, the probit model on y, the linking decisions of the individuals.

We start by describing the latent class model. Let Y_{ij} denote the j-th decision of the n decisions of subject i. The latent class variable is denoted by L_i, a particular latent class by c, and the number of latent classes by C.

The probability structure defining a simple LCM can be expressed as follows:

$$\begin{aligned} P(Y_{i1} = y_{i1}...Y_{in} = y_{in}) &= \sum_{c=1}^{C} P(L_i = c) P(Y_{i1} = y_{i1}...Y_{in} = y_{in} | L_i = c) \\ &= \sum_{c=1}^{C} P(L_i = c) \prod_{j=1}^{n} P(Y_{ij} = y_{ij} | L_i = c) \end{aligned} \tag{5.1}$$

The probability of observing responses Y_i, $P(Y_{i1} = y_{i1}...Y_{in} = y_{in})$, is a weighted average of class-specific probabilities $P(Y_{i1} = y_{i1}...Y_{in} = y_{in}|L_i = c)$.

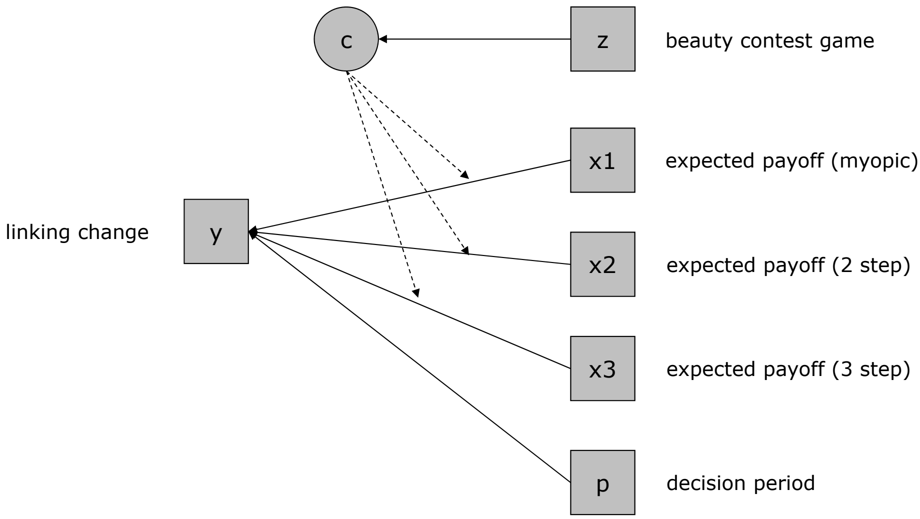


Figure 5.2: The pure three-class solution

The weight $P(L_i = c)$ is the probability that person i belongs to latent class c, also called unconditional probabilities. As can be seen from the second line, the responses of a subject are independent conditional on the latent class that the subject belongs to. The term $P(Y_{ij} = y_{ij}|L_i = c)$ is the probability of observing response y_{ij} given that the person concerned belongs to latent class c. These conditional response probabilities are used to name the latent classes. Probabilities for class membership are calculated via Bayesian estimations (see Asparouhov and Muthén, 2010).

Furthermore, we perform a multinomial logit regression on class membership (the top arrow in figure 5.2). The model can be expressed as follows:

$$Pr(L_i = c) = \frac{\exp(\alpha_c + \beta_c Z_i)}{\sum_{j=1}^{C} \exp(\alpha_j + \beta_j Z_i)} \qquad j = 1, \ldots, C, \tag{5.2}$$

where α_j, β_j are the parameters to be estimated, $\alpha_1 = \beta_1 = 0$ for identification, and Z_i is the score from the beauty contest as described above.

For each class, we perform probit regressions on the observed dependent variable y_{ij}, which measures whether subjects indicate a change on a linking decision ($y_{ij} = 1$ if "change", $y_{ij} = 0$ if "no change"). In each of the two treatments, each of the two rounds played consisted of 25 periods in which 136 subjects had to make three linking decisions. This gives us $n = 150$ linking decisions per subject per treatment. The independent variables $x1$, $x2$, $x3$ are the expected payoff changes for a linking change, calculated for actors who are myopic ($x1$), for actors who look two steps ahead ($x2$), and for actors who look three steps ahead ($x3$). The variable p controls for the playing period in which the decision was made (see figure 5.2). We included p as a control, as we expect less linking changes in later periods.[7] The probit model can be expressed as follows:

$$P(Y_{ij} = y_{ij} | L_i = c) = \Phi(\alpha_c + \beta_c X_{ijc} + \beta p), \tag{5.3}$$

where α_c is the cutoff point for each class, and X_{ijc} can include the explanatory variables $x1$, $x2$, $x3$ for Y_{ij} per class .

We are then able to "prescribe" classes by defining, for each class, the independent variables in the probit regression. The idea is that subjects belonging to a specific class make the expected payoff calculations according to the respective level of farsightedness. If we define a class, only using one predictor variable, we assume that actors in this class only look ahead as described in the expected payoff calculation of the predictor variable. We refer to these classes as *pure* classes. By defining multiple independent variables for a class, we assume that in such a class, actors "use" different levels of farsightedness. We refer to these classes as *mixed* classes. The rationale behind estimating the mixed classes is to test whether the pure models give a reasonable fit to the data. If the mixed classes fit the data considerably better than the pure class models, the fit of the pure class models is problematic. A non-zero cutoff point α_c can be interpreted as the "tendency" to change (when positive) or resist changing links (when negative).

We will specify the probit model for two exemplifying cases, the pure three-class model, and the mixed two-class model. For the pure three-class model

[7]Groups tend to coordinate towards some network, where no subject wants to change links anymore.

(see also figure 5.2), we define three classes $c1$, $c2$, and $c3$. For each class we predict linking changes with one of the expected utility calculations $x1$, $x2$, and $x3$ and the period p_j the decision was made. The decision period does not depend on classes c. The classes are formally defined as follows:

$$c1 : P(Y_{ij} = y_{ij}|L_i = c1) = \Phi(\alpha_{c1} + \beta_{c1} x1_{ijc1} + \beta p_j),$$
$$c2 : P(Y_{ij} = y_{ij}|L_i = c2) = \Phi(\alpha_{c2} + \beta_{c2} x2_{ijc2} + \beta p_j),$$
$$c3 : P(Y_{ij} = y_{ij}|L_i = c3) = \Phi(\alpha_{c3} + \beta_{c3} x3_{ijc3} + \beta p_j).$$

The formula for $c1$ shows that choices of actors who are placed in the class $c1$ are only determined by the payoff change for myopic actors $x1$ and the period p.

In the mixed two-class model, we predict linking changes for classes $c1$ and $c2$ with all three expected utility calculations $x1$, $x2$, and $x3$. The classes are formally defined as follows:

$$c1 : P(Y_{ij} = y_{ij}|L_i = c1) = \Phi(\alpha_{c1} + \beta_{1c1} x1_{ijc1} + \beta_{2c1} x2_{ijc1} + \beta_{3c1} x3_{ijc1} + \beta p_j),$$
$$c2 : P(Y_{ij} = y_{ij}|L_i = c2) = \Phi(\alpha_{c1} + \beta_{1c2} x1_{ijc1} + \beta_{2c2} x2_{ijc1} + \beta_{3c2} x3_{ijc1} + \beta p_j).$$

Here the first formula indicates that choices of actors in the class $c1$ can be affected by the payoff changes $x1$, $x2$, and $x3$, as well as the period p.

Multi-level mixture models are calculated in Mplus using maximum likelihood estimation (Muthén and Muthén, 1998-2010). A problem with mixture models is that there often exist multiple maxima of the likelihood. To avoid the problem that a local solution has been reached, we increased the number of random starting values in all models to ensure that we find the global maximum. In all models, the same optimum was reached multiple times and therefore the best loglikelihood value was replicated multiple times for a trustworthy solution.

5.5 Results

For every model that we run, we get results for the three parts of the model, as described in equations 5.1 - 5.3. Results for the latent classes consist of the average latent class probabilities for the most likely latent class membership, and the class proportions based on the most likely class membership. First, the average latent class probabilities for most likely latent class membership are very high in all models (.98 on average), i.e., there is hardly any doubt in which class a subject is assigned to, given the results of the model. Second, in subsection 5.5.1 we report the results for the probit regression on linking changes for every model in more detail. The effects of the variables used in equation 5.3 describe the behavior of the class. Note that the control effect of the decision period p does not depend on the class c and is the same over each class. In all models, the playing period has a significant negative effect on linking change y. The effect is very stable between different models and lies around -0.03 in the connections model, and around -0.02 in the co-author model. With increasing periods, subjects are less likely to indicate a linking change. Third, in subsection 5.5.2 we report the results of the multinomial logit model on class membership (equation 5.2). Theoretically, we cannot expect to find differences between the two treatments of the experiment. However, we empirically did observe differences in behavior. Therefore, we show the results separated by the treatments.

5.5.1 Latent classes

We analyze class composition, i.e. how many subjects are likely to be in which class, and how subjects look ahead in this class. We first describe the solutions for the connections model. To assess the model fit we report the Bayesian Information Criterion (BIC) and the loglikelihood. According to Nylund et al. (2007), BIC is the best performing information criterion that is used to determine the best model and from that what the optimal number of classes to distinguish is.

Connections model

Table 5.1 shows the results for *pure classes* in the connections model. The three columns on the left, describe the classes and which independent variables are included per class. The two columns on the right, report the BIC and the loglikelihood. For each class, we show which x-predictor was used in the probit regression model to define the class. In the same column, we report the cutoff point α, the effects on the dependent variable y and below that the proportion of subjects assigned to the class.

We start with the simplest models and then steadily build up the number of classes. Models 1, 2, and 3 are one-class solutions, i.e. we assume that everybody is the same in his ability of looking ahead. These models assume homogeneous populations. We run three models for each level of farsightedness, represented by $x1$, $x2$, and $x3$. Of the first three models, model 2, where it is assumed that actors look two steps ahead, shows the best model fit, as indicated by a lower BIC value and a higher loglikelihood value (closer to 0). Assuming that populations are homogeneous, the model where actors look two or three steps ahead describes behavior of subjects better than assuming myopic behavior.

To describe the behavior of each class, we analyze the effects of the independent variables $x1$, $x2$, and $x3$. The coefficients β from the probit regression depend on σ, the standard deviation of the decision noise of the model, with $\frac{\beta}{\sigma}x$. Larger effects between classes then indicate that behavior of subjects in such a class can be better explained with the independent variable(s). In models 1 and 2, we see for $x1$, and $x2$ respectively a positive significant effect on y. The higher the expected utility change, the more likely is a linking change. Surprisingly, in model 3, we observe a negative effect for the class of actors who look three steps ahead. A higher expected utility change decreases the likelihood to change a link. The effect can be explained via the high occurrence of linking decisions of subjects in the circle network (23% of all decisions occur within this network). In this network myopic actors and actors who look two steps ahead have no incentive to change any links, i.e., $x1$ and $x2$ are negative for all decisions in that network. Actors who look three steps ahead have an incentive to change links in that network, as the expected utility change $x3$ is positive. Because most subjects in the experiment do not want to change links in the circle network, we observe a negative effect for $x3$. Although model 3 fits the data almost as well as model 2, this is not because of theoretical arguments that actors look three steps ahead.

Table 5.1: Latent class models, pure classes, connections model

Model	Classes			Model fit	
	$c1$	$c2$	$c3$	BIC	-LL
1.	$(\alpha)x1$ (0.54) 1.75 100%	–	–	23049.893	-11500.138
2.	$(\alpha)x2$ (1.12) 3.01 100%	–	–	22819.880	-11385.132
3.	$(\alpha)x3$ (-0.76) -2.92 100%	–	–	22823.286	-11387.266
4.	$(\alpha)x1$ (0.22) 1.78 55%	$(\alpha)x2$ (2.52) 6.03 45%	–	20730.516	-10330.526
5.	$(\alpha)x2$ (2.23) 5.43 57%	$(\alpha)x3$ (-0.75) -1.68 43%	–	20971.188	-10450.863
6.	$(\alpha)x1$ (0.51) 2.40 39%	$(\alpha)x2$ (2.60) 6.12 42%	$(\alpha)x3$ (-1.55) -3.38 19%	20410.987	-10150.915

Cells under $c1$, $c2$, and $c3$ include: first, the cutoff point α plus independent variables $x1$, $x2$, and/or $x3$ of the probit models per class; second, the effects β_c of these independent variables on y; and third, the class proportions based on the most likely class membership of subjects.

The model fit improves significantly for the two-class solutions, as presented in models 4 and 5. In model 4, we define a class of myopic actors and a class of actors who look two steps ahead. In model 5, we define a class of actors who look two steps ahead and a class of actors who look three steps ahead. Model 4, has the better model fit of the two-class solutions. For model 4, 55% of the subjects are assigned to the class of myopic actors and 45% to the class of actors who look two steps ahead. In model 5, 57% are assigned to the class of actors who look two steps ahead and 43% to the class with actors who look three steps ahead.

The model fit again improves in the three-class solution presented in model 6. Here, we impose a class with myopic actors, a class with actors who look two steps ahead, and a class with actors who look three steps ahead. Overall, we see that the model fit improves when we increase the number of classes. Suggesting that behavior of subjects is better described when we assume heterogeneity among subjects. The biggest increase occurs going from the one-class solutions to the two-class solution. In model 6, most subjects are assigned to the classes with myopic actors and actors who look two steps ahead, each about 40%. 20% of subjects are classified as actors who look three steps ahead. Additionally, models 5 and 6 again have a negative effect for $x3$ indicating that this effect is caused by something else than looking three steps ahead.

Table 5.2 reports the results for *mixed classes* in the connections model. For every class, we now use all three levels of farsightedness $x1$, $x2$, and $x3$ to predict linking changes. The second line in the columns show the respective effects of $x1$, $x2$, and $x3$ on the dependent variable y. Below that, we again report the proportion of subjects assigned to each class. Also with the mixed class solutions, increasing the number of classes significantly increases the model fit.

Behavior of subjects assigned to the mixed classes can be described via the effects of the three x-variables on y. In the one-class solution of model 7, $x1$ and $x2$ have a positive and significant effect on the linking change y, $x3$ has a significant negative effect. In this model, we assume that subjects are homogeneous, but behavior is better described with multiple levels of farsightedness. The strongest positive effect is found with $x1$. Myopic behavior

Table 5.2: Latent class models, mixed classes, connections model

Model	Classes				Model fit	
	$c1$	$c2$	$c3$	$c4$	BIC	-LL
7.	$(\alpha)x1, x2, x3$ (-0.53) (2.64, 0.70, -4.45) 100 %				21351.520	-10641.029
8.	$(\alpha)x1, x2, x3$ (-0.58) (3.67, 1.79, -5.30) 52%	$(\alpha)x1, x2, x3$ (n.s.) (2.08, n.s., -2.73) 48%			19732.011	-9811.428
9.	$(\alpha)x1, x2, x3$ (n.s.) (3.81, 1.96, -5.58) 44%	$(\alpha)x1, x2, x3$ (-1.67) (2.18, n.s., -2.17) 40%	$x1, x2, x3$ (n.s.) (2.43, -0.70, -4.49) 16%		19526.665	-9678.985
10.	$(\alpha)x1, x2, x3$ (-0.34) (3.66, 2.25, -5.61) 38%	$(\alpha)x1, x2, x3$ (0.72) (3.07, n.s., -3.42) 35%	$(\alpha)x1, x2, x3$ (n.s.) (3.36, -1.59, -1.59) 9%	$(\alpha)x1, x2, x3$ (-2.6) (1.17, n.s., n.s.) 18%	19410.654	-9591.209

Cells under $c1$, $c2$, and $c3$ include: first, the cutoff point α plus independent variables $x1$, $x2$, and/or $x3$ of the probit models per class; second, the effects β_c of these independent variables on y; and third, the class proportions based on the most likely class membership of subjects.

describes linking decisions of subjects best, however, looking two steps ahead also predicts linking changes of subjects. The negative effect of $x3$ is likely to be related to arguments we described for the effect in the pure class solution.

In the two-class solution of model 8, 52% of subjects are assigned to the class $c1$ which has a similar pattern to the class described in model 7. In class $c2$, the effect of $x1$ is positive and significant, $x2$ is not significant, and $x3$ is negative and significant. Model 9 shows the mixed three-class solution. Most subjects are assigned to classes $c1$ and $c2$, which are similar to the classes described in model 8. We observe a third class $c3$, where 16% of subjects are assigned to. In $c3$, the effect of $x1$ is positive, and for $x2$ and $x3$ the effects are negative. The four-class solution presented in model 10, classes $c1$, $c2$, and $c3$ are similar as the classes described in model 9. The majority of subjects are assigned to the first two classes (74%). In class $c4$, only the effect of $x1$ is positive and significant. Around 18% of subjects are assigned to this class.

In the pure class models, the cutoff points α indicate a tendency to change links for classes with $x1$ and $x2$. Classes with $x3$ show a tendency to resist changing links. In the mixed class models, if classes show an effect, then mostly a negative effect, i.e. a tendency to resist changing ties.

In the connections model, the class where most subjects are assigned to show predominantly myopic behavior. All mixed classes have positive significant effects for $x1$. However, looking two steps ahead also adds to the explanation of linking behavior of subjects in one class. Although increasing the number of mixed classes in the connections model increases the model fit significantly, we argue that model 8 is sufficient to describe groups of subjects in terms of their linking choices, implying that about half of the subjects act myopic and the other half acts sometimes myopic and sometimes look two steps ahead.

Comparing the 3-class pure solution and the 3-class mixed solution, we see that the model fit is significantly better for the mixed class solution. This indicates that the pure class models fit the data poorly and, thus, that the assumption that specific subjects have a given level of farsightedness is violated.

Co-author model

Table 5.3 shows the results for the *pure-class* solutions in the co-author model. The model fit increases with number of classes. Of the one-class solutions in models 11, 12, and 13, model 12, when actors look two steps ahead, has the best model fit. In the co-author model, assuming homogeneous subjects, the model where actors look two steps ahead, describes behavior of subjects best.

Of the two-class solutions, model 15 performs better than model 14. Model 15 assumes that there are two classes of limitedly farsighted actors, looking two and three steps ahead with about half of them looking two steps ahead and the other half looking three steps ahead. Note that this is different in the connections model, where most subjects are assigned in classes with assumed myopic behavior. In models 14 and 16, around 20% of subjects are assigned to the "myopia" class. In all pure-class solutions we observe positive effects of the x-variables.

Table 5.4 reports the results for *mixed-class* solutions in the co-author model. The model fit increases with number of classes. The highest increase occurs between the one-class and the two-class solution.

In the mixed one-class solution, we observe a negative effect of $x1$, and positive effects for $x2$ and $x3$. The negative effect of $x1$ seems to be related to the high occurrence of decisions in the dyad network, where only myopic actors have an incentive to change links. However, most subjects in this network do not indicate linking changes. The effect of $x2$ is slightly larger than that of $x3$, indicating that both levels of limitedly farsighted behavior seem relevant. In the mixed two-class solution in model 18, the first class shows a similar pattern as described in the one-class solution. In both classes limitedly farsighted behavior explains behavior better. In class $c2$, the effect of $x3$ is larger as the effect of $x2$, as compared to class $c1$. In model 19, we find two very similar classes $c1$ and $c2$ that have a negative effect of $x1$, a strong and positive effect of $x2$ and small and positive effect of $x3$. The third class reports a negative effect of $x1$, the effect of $x2$ is not significant, and the effect of $x3$ is positive and significant: a class, where subjects mainly look three steps ahead. In model 20, there are three very similar classes $c1$, $c2$, and $c3$ with a negative effect of $x1$, a positive effect $x2$ and smaller but also positive effect of $x3$. Class

Table 5.3: Latent class models, pure classes, co-author model

Model	Classes			Model fit	
	$c1$	$c2$	$c3$	BIC	-LL
11.	$(\alpha)x1$ (0.93) 0.33 100%	–	–	23716.149	-11833.266
12.	$(\alpha)x2$ (2.36) 0.93 100%	–	–	22732.487	-11341.435
13.	$(\alpha)x3$ (3.71) 1.53 100%	–	–	22823.286	-11386.835
14.	$(\alpha)x1$ (0.88) 0.09 20%	$(\alpha)x2$ (3.15) 1.31 80%	–	21402.219	-10666.378
15.	$(\alpha)x2$ (4.90) 2.01 48%	$(\alpha)x3$ (2.76) 1.08 52%	–	21159.515	-10545.026
16.	$(\alpha)x1$ (1.10) 0.14 21%	$(\alpha)x2$ (4.77) 1.94 49%	$(\alpha)x3$ (2.96) 1.32 30%	20735.044	-10312.944

Cells under $c1$, $c2$, and $c3$ include: first, the cutoff point α plus independent variables $x1$, $x2$, and/or $x3$ of the probit models per class; second, the effects β_c of these independent variables on y; and third, the class proportions based on the most likely class membership of subjects.

Table 5.4: Latent class models, mixed classes, co-author model

Model	Classes				Model fit	
	$c1$	$c2$	$c3$	$c4$	BIC	-LL
17.	$(\alpha)x1, x2, x3$ (4.48) (-0.62, 1.75, 0.70) 100 %				22007.749	-10969.143
18.	$(\alpha)x1, x2, x3$ (5.40) (-0.74, 2.48, 0.54) 77%	$(\alpha)x1, x2, x3$ (4.31) (-0.58, 0.80, 1.36) 23%			20500.926	-10195.885
19.	$(\alpha)x1, x2, x3$ (8.17) (-0.90, 3.96, 0.41) 33%	$(\alpha)x1, x2, x3$ (4.01) (-0.58, 1.65, 0.59) 52%	$(\alpha)x1, x2, x3$ (5.27) (-0.72, n.s., 2.01) 15%		20074.480	-9952.892
20.	$(\alpha)x1, x2, x3$ (3.96) (-0.69, 1.99, 0.48) 21%	$(\alpha)x1, x2, x3$ (8.27) (-0.93, 4.00, 0.44) 32%	$(\alpha)x1, x2, x3$ (4.09) (-0.53, 1.47, 0.66) 37%	$(\alpha)x1, x2, x3$ (5.84) (-0.70, n.s., 2.31) 10%	19410.654	-9591.209

Cells under $c1$, $c2$, and $c3$ include: first, the cutoff point α plus independent variables $x1$, $x2$, and/or $x3$ of the probit models per class; second, the effects β_c of these independent variables on y; and third, the class proportions based on the most likely class membership of subjects.

$c4$ has negative effect of $x1$, the effect of $x2$ is not significant, and $x3$ has a large positive effect.

In the co-author model, the cutoff points α is positive, thus, indicating a tendency to change links in all models.

Most of the mixed classes show a dominant effect of one of the x variables. In the connections model, in the mixed class models, the effect sizes are comparably equal. Thus, in the co-author model, pure types of actors seem to work rather well. Although the model fit of mixed classes is still better with two or more classes, the improvement is less dramatic than for the connections model.

Although increasing the number of classes for the mixed classes also increases the model fit, the classes of the three-class and four-class solutions seem very similar in terms of the ascribed behavior. The mixed two-class solution of model 18 seems to offer the best interpretable result, with one class of actors that predominantly look two steps ahead, and a smaller class with actors that predominantly look three steps ahead.

5.5.2 Predicting class membership

In this subsection, the outcomes of the multinomial logit regression on class membership are reported. We expect to find a relationship between the score of the beauty contest game and the latent classes subjects are assigned to. Subjects that apply more steps of iterated reasoning are expected to be in classes that are more farsighted. Finding such a relationship would suggest that farsightedness is, at least to some degree, a personal trait. If this holds, then we also expect that subjects are placed in the same classes, in both games. As reported above, this is not the case as behavior differs between treatments. In the following, we discuss the results only for the models we argued to be the best interpretable models. We chose the pure three-class solution and the best interpretable solutions of the mixed two-class models respectively.

Table 5.5 reports the results of the multinomial logit model for the connections model. In the pure three-class solution of model 6, we have three classes $c1$, $c2$, and $c3$ to which subjects can be assigned. In the table we report the effects of the beauty contest choice measured by z, comparing all possible alternative outcomes. For the pure-class solution, we only find a weak significant difference between classes $c2$ and $c3$. Thus, the likelihood to be a member of class $c2$ increases with an increasing z, in comparison to class $c3$. Other comparisons show no significant differences between classes. For the mixed-class solution we find a significant effect. Subjects who score higher on z are more likely to be assigned to class $c1$. In class $c1$, behavior of subjects can also be predicted with limitedly farsighted behavior, as the effect of $x2$ is positive and significant in $c1$ (see table 5.2), while $c2$ is the class with myopic actors. Thus, the beauty contest choices predict to some extent farsighted choices in the connections model.

As can be seen in table 5.6 there are no significant effects in the co-author model. Class membership in the co-author model cannot be predicted with the steps of reasoning subjects applied in the beauty contest game.

Table 5.5: Multinomial logit model on latent class membership, connections model

	Pure-class solution, model 6			Mixed-class solution, model 8
	$c1$ vs. $c2$	$c1$ vs $c3$	$c2$ vs. $c3$	$c1$ vs. $c2$
z	-0.146	0.335	0.481*	-0.361**
intercept	-0.253	0.203	-0.050	0.598*

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.6: Multinomial logit model on latent class membership, co-author model

	Pure-class solution, model 16			Mixed-class solution, model 18
	$c1$ vs. $c2$	$c1$ vs $c3$	$c2$ vs. $c3$	$c1$ vs. $c2$
z	0.160	2.99	0.138	-0.141
intercept	-1.266**	-1.017**	0.250	1.471**

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Overall, we do not find much support that class membership can be predicted with the measure from the beauty contest game. The only weakly significant effect that we observe can be found in the mixed-class solution in the connections model. In the co-author model, where we can distinguish better between myopic and farsighted behavior than in the connections model (see discussion in chapter 4), we do not find any effects.[8] In previous analyses of the experimental data, we observed some effects of the beauty contest game measure, predicting the likelihood to act limitedly farsighted (see chapter 4). In the statistical analysis presented in this chapter, we find only a weak relationship between performance in the beauty contest game and the level of farsightedness in the network formation game.

5.6 Conclusion and discussion

We classified subjects by different levels of farsightedness, based on subjects' decisions in a network formation experiment. We investigated whether subjects are homogeneous or whether subjects are heterogeneous when making linking decisions. Furthermore, we investigated which level of farsightedness described linking decisions best, and whether subjects applied different levels of farsightedness when making their decisions. Also, we investigated whether behavior of actors differs in different contexts of network formation. Results can be summarized as follows: First, subjects are not homogeneous when making linking decisions in network formation. Models with one-class solutions, i.e. assuming that actors are homogeneous, perform worse than solutions with multiple classes. The model fit increases significantly when we increase the number of classes. Second, we observe that subjects' behavior is better described with types of actors that "mix" levels of farsightedness. Only very few actors are "pure" types of actors. Third, farsightedness is context dependent. In the connections model, most subjects are assigned to classes where myopic behavior is the dominant factor to predict linking decisions. In the co-author model, most subjects are assigned to classes where limited farsightedness is the dominant factor to predict linking decisions.

The fact that the mixed class models fit the data considerably better than the pure class models provides a challenge for the interpretation of how sub-

[8] We also analyzed the other solutions but hardly found any effects of the beauty contest game measure.

jects make decisions in the experiment. At least, it is unlikely that subjects can be classified in types according to the farsightedness as specified in our model. The strict interpretation of the mixed models would be that they combine possible resulting networks thinking two steps ahead and possible resulting networks thinking three steps ahead in one decision. We find this interpretation problematic, because it suggests that one subject combines different decision models within one decision. A more plausible interpretation might be that subjects sometimes think two steps ahead and at other times think three steps ahead. For example, if the decision problem is easier, subjects are more likely to think three steps ahead or if they are more experienced, subjects are more likely to think three steps ahead. However, the last interpretation does not correspond with the specification of the latent classes in our models. Such an interpretation would need a much more complex specification of classes that also depends on contextual factors. Future models might incorporate and further develop these ideas.

Furthermore, we predicted class membership with the beauty contest game measure. We used choice in the beauty contest game as a proxy for the level of farsightedness. We expected to find a positive relation between choices indicating more steps of iterated reasoning in the beauty contest game and the ability to look ahead in the network formation game. In the statistical analysis presented in this chapter, we find mixed evidence on such a relationship. In chapter 4 we analyzed under which conditions subjects where more likely to make limitedly farsighted decisions as compared to myopic decisions. Results show a positive effect of the beauty contest measure in the co-author model and a negative effect in the connections model. Surprisingly, in the analysis presented in this chapter, we only found effects in the connections model such that subjects that score higher in the beauty contest game measure are more likely to be assigned in classes where decisions are better explained with limitedly farsighted behavior. Still, given the mixed empirical results, in both chapters, we observe some weak evidence that there is a relationship between the ability of iterated reasoning and farsighted behavior in network formation. This result suggests that farsightedness and the ability of iterated reasoning can, to some small degree, be interpreted as personal traits. Furthermore, the beauty contest game measures not only subjects' ability to look ahead, but also subjects' beliefs on others' abilities to look ahead. For instance, very farsighted individuals still might choose comparably high numbers in the beauty contest game, because they believe others are not capable to think far ahead. Both concepts, subjects level of farsightedness and subjects beliefs about the farsightedness of others, cannot be differentiated with the beauty contest game measure. This might be an additional explanation why we do not find a clear relationship between the latent classes and the beauty contest game measure.

With the statistical analysis we analyzed the heterogeneity of individuals in terms of their level of farsightedness in network formation. Future theoretical models could include the results of this exploratory analysis to fine tune models of network formation. However, given the difficult interpretation of behavior in the connections model (see chapter 4 for a detailed discussion), also more theoretical work on alternative models of limited farsightedness is needed.

Appendix A

Appendix Chapter 2

A.1 Stable networks

Figure shows infrequently emerging networks for when actors look three steps ahead.

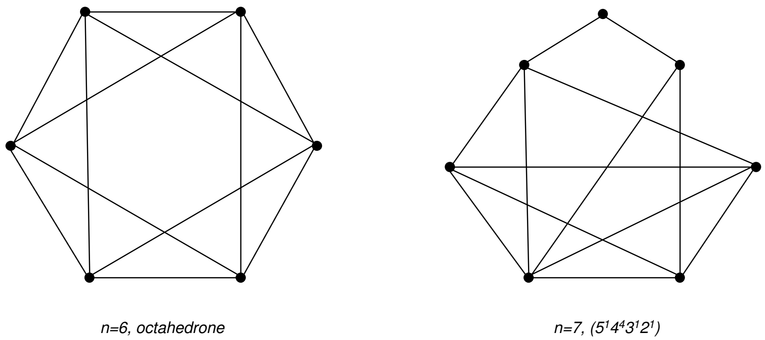
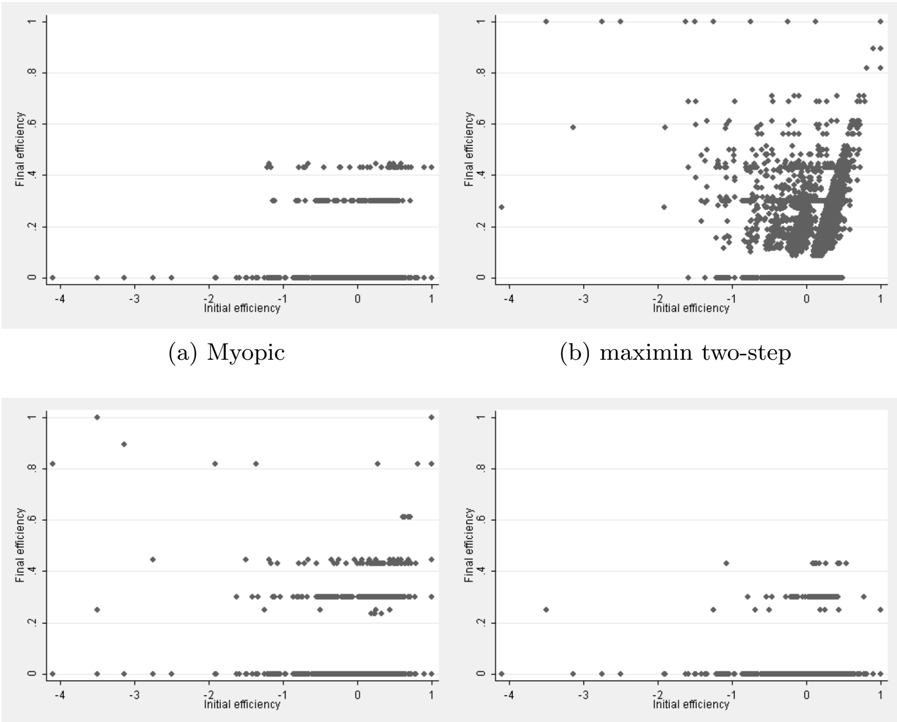


Figure A.1: Stable networks for actors looking three steps ahead, $n = 6$ and $n = 7$

A.2 Network efficiency

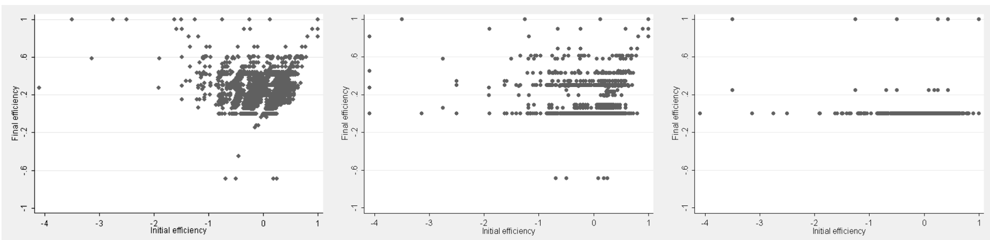
Figures A.2 and A.3 show the relationship between the efficiency of the initial networks and the final network of the formation process.



(a) Myopic (b) maximin two-step

(c) PIR two-step (d) maximax two-step

Figure A.2: Initial network efficiency versus final network efficiency for $n = 3$ through 8, co-author model with actors who look two steps ahead



(a) maximin three-step (b) PIR three-step (c) maximax three-step

Figure A.3: Initial network efficiency versus final network efficiency for $n = 3$ through 8, co-author model with actors who look three steps ahead

Appendix B

Appendix Chapter 3

B.1 Convergence of networks

There are cycles in which actors can get stuck. The smallest cycle is, for instance, at $n = 3$ and consists of the dyad and triad network. For networks size $n > 5$, the cycles are more difficult to describe as they consist of many networks. Once a group of actors enter a cycle they cannot leave the cycle anymore. Still, starting from the same network, the process can convergence if actors take a different path towards a stable state. Almost all non-convergence occurs in intermediary cost levels between .27 and .48 when actors look two steps ahead. The percentages of formation processes that are not converging is even higher with actors who look three steps ahead. Here, non-convergence occurs in a cost range between .27 and .62 (see table B.1). By including the non-converged simulation runs we basically draw a sample of networks out of the set of networks that are part of cycles.

B.2 Stable networks

For $n = 3$ and medium costs, the efficient 2-star network is the stable network when actors are myopic. There is no convergence in this cost range when actors look two or three steps ahead. The process will not converge as the star actor in the 2-star network will delete a link (to get rid of the star position)

Table B.1: Convergence in the connections model

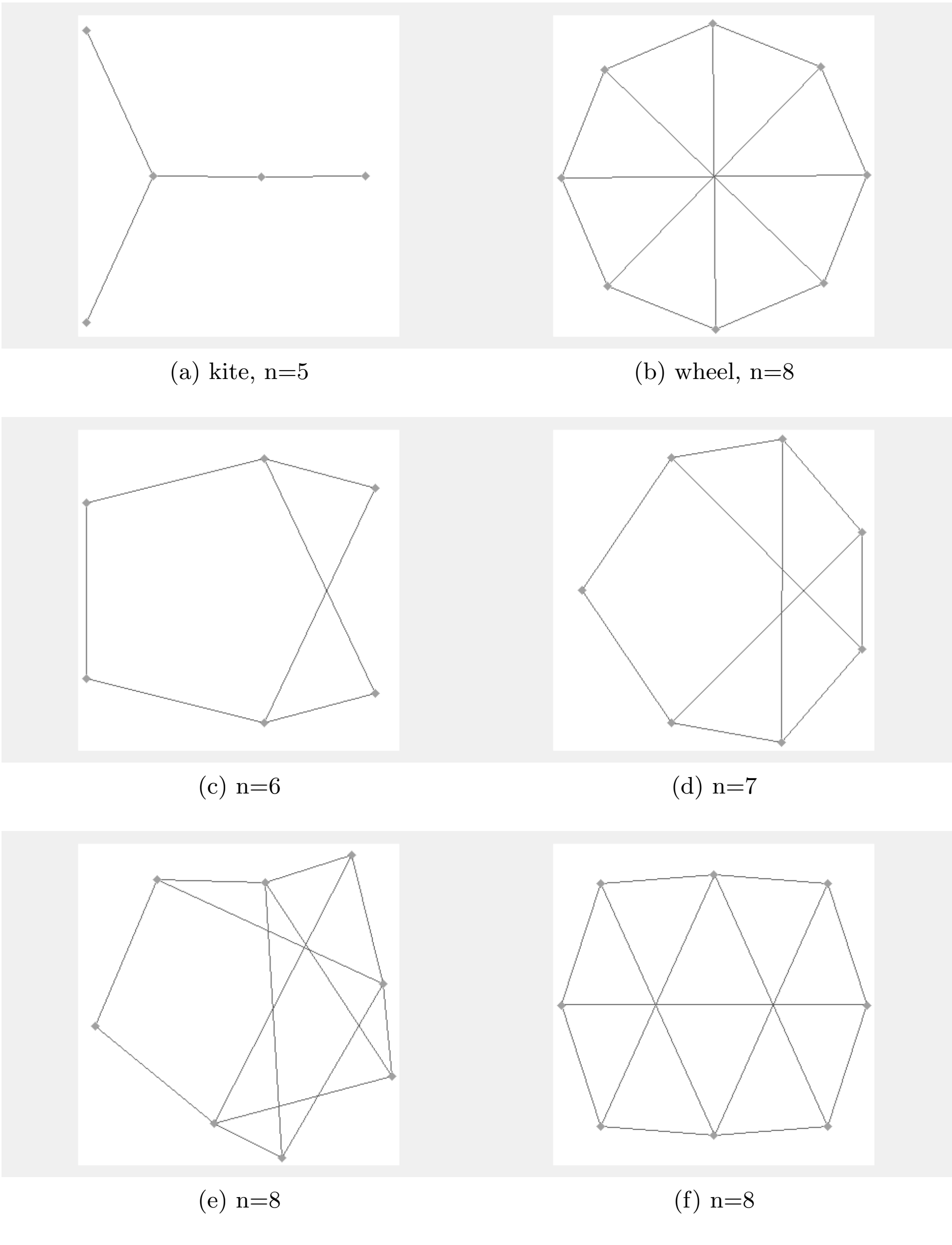
	$n = 3$	$n = 4$	$n = 5$	$n = 6$	$n = 7$	$n = 8$
medium costs between .27 and .48						
myopic	1.0	1.0	1.0	1.0	1.0	1.0
two-step	0	1.0	1.0	.51	.61	.93
three-step	0	.30	.99	.38	.49	.99
high costs between .55 and .69						
myopic	1.0	1.0	1.0	1.0	1.0	1.0
two-step	1.0	1.0	1.0	1.0	.99	1.0
three-step	1.0	.51	.70	1.0	.66	.99

and in the single dyad network, two actors will build a link again as they assume that they benefit from it. Therefore, efficiency and density are higher when actors are myopic (see tables 3.1 and 3.3).

For $n = 4$, we find two myopically stable networks, the circle ($K_{2,2}$) network (that emerges in 71% of cases) and the efficient 3-star network (in all other cases). When actors look two steps ahead (and at cost levels between .27 and .55) only the circle network is stable. The star network is not stable anymore (the star actor who has the lowest payoff wants to get rid of this position by cutting links; see figure 3.2). The efficient 3-star network is the only emerging network when actors look three steps ahead and cost are between .27 and .34. This results in a small effect for efficiency, which is lower for actors who look two steps ahead. Density is higher in the circle network than in the star network. For inequality, this effect is the other way around (see tables 3.1 – 3.3).

For $n = 5$, the $K_{2,3}$ network, the circle network and the 4-star are stable when actors are myopic. The $K_{2,3}$ network emerges in most cases (with 69%). The circle network emerges in 20% of cases. When actors look three steps ahead, there are two stable networks: the star network, and in a cost range from .27 to .69 the kite network (see figure B.1a). The kite network distributes payoffs rather equal, while being less dense than the $K_{2,3}$ network. When actors look two steps ahead, the $K_{2,3}$ network emerges most often (56%). Therefore, inequality and density are lower when actors look three steps ahead than when actors are myopic (see tables 3.2 and 3.3).

For $n = 7$, most of the frequent networks distribute payoffs rather equally and we observe only small differences between myopic actors and limitedly farsighted actors (see table 3.2). Emerging networks, when actors are limitedly farsighted, are less dense, and therefore less efficient. The effect sizes are large when actors look three steps ahead compared to myopic actors. The networks on figure B.1d (28%) and the bipartite $K_{3,4}$ (13%) network are likely to emerge when actors are myopic. For actors who look two steps ahead, the two most likely networks to appear are the two bipartite networks, $K_{3,4}$ (29%) and $K_{2,5}$ (22%). The star network is stable, however, emerges very infrequent when actors look three steps ahead and costs are low ($c = .34$). The most likely network to emerge in cost levels between .27 and .34 is shown on figure B.1d. Both of these networks are less dense than the bipartite networks that emerge when actors are looking less steps ahead. This leads to a negative (medium) effect of farsightedness on efficiency.



(a) kite, n=5

(b) wheel, n=8

(c) n=6

(d) n=7

(e) n=8

(f) n=8

Figure B.1: Frequently emerging network structures, connections model

Appendix C

Appendix Chapters 4 and 5

C.1 Instructions for the experiment

Below, you find the exact instructions for the experiment used in chapter 4 and 5.

Instructions

You are participating in a sociological experiment. Please read the following instructions carefully. These instructions state everything you need to know in order to participate in the experiment, and they are identical for all participants in the experiment. If you have any questions, please raise your hand. One of the experimenters will approach you in order to answer your question. You can earn money by means of earning points during the experiment. The number of points that you earn depends on your own choices, and the choices of other participants. At the end of the experiment, the total number of points that you earn during the experiment will be exchanged at an exchange rate of:

300 points = 1 EUR

The money you earn will be paid out anonymously and in cash at the end of the experiment. The other participants will not see what you earn. Further instructions on this will follow below and on the computer screen. During the experiment you are not allowed to communicate with other participants and you are not allowed to use your cell phone. Also, you may only use the functions of the PC than those that are necessary for the experiment.

Overview of the experiment

The experiment consists of two different scenarios. In each scenario, you will play for two times 25 periods. After that you will be asked to participate in some short additional decision making situations and finally to fill in a questionnaire. You find information and an explanation of the different scenarios and the decision making situations in this instruction. During the two scenarios, you will play in groups of four persons. Every group is formed by the computer system at random among all participants. After every 25 playing periods, you will be assigned to new randomly chosen other participants in your group. In the two scenarios, you and the other three participants in your group will be represented on the screen by circles. The blue circle represents you. Also the positions on the screen are randomly assigned.

In the two scenarios, you can earn points by creating relations to other participants in your group. In each period you can decide with whom you wish to have a relation. In figure 1 below you see the decision screen. Underneath the circles that represent you and the other participants in your group you see a table. In this table you choose the relations you want to have with other participants.

Each period lasts at most 30 seconds. During these 30 seconds you choose with which other participant you would like to have a relation and subsequently you click the OK button. If you have **not** made your choices **and** clicked OK within these 30 seconds, your decisions from the previous period will remain valid. If you do not enter a choice in the first period, then three times ‘no relation’ is selected.

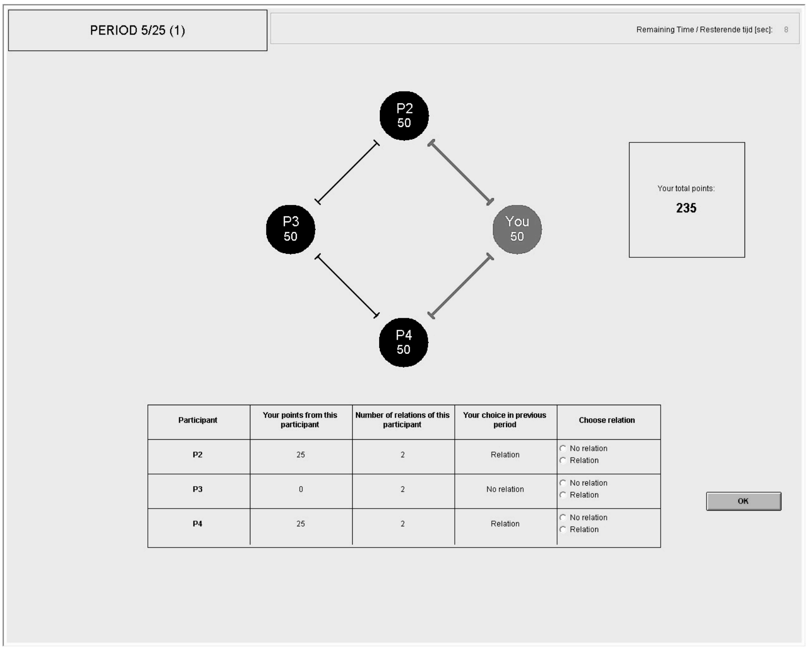


Figure 1: Decision screen

After all participants have indicated which relations they want to have or the 30 seconds have passed, the computer will randomly change **one** relation among all the desired relation changes as indicated by the participants in your group.
A relation can only be created if **both** participants in a relation indicate that they want to have a relation with each other. A relation can be removed if **one** of the participants in this relation indicates that he or she does not want the relation anymore.

In figure 2 you see an example of how the relations in your group might change. In the left part of figure 2, imagine you indicated that you want to have a relation with participant P2 and P4, but not with P3. At the same time P2 indicated a relation with P3 and you, but not with P4. P3 indicated a relation with P2 and P4, but not with you. And P4 indicated only a relation with P3. After these choices, the computer investigates which relations the group wants to change. In this case two changes are possible. The relation between you and P4 might be removed because P4 indicated 'no relation' with you. Alternatively, the relation between P2 and P3 can be created because both P2 and P3 indicated to want to have the relation. The computer now randomly chooses one of these two changes. Therefore, your group will be in one of the situations on the right side of figure 2 after this period.

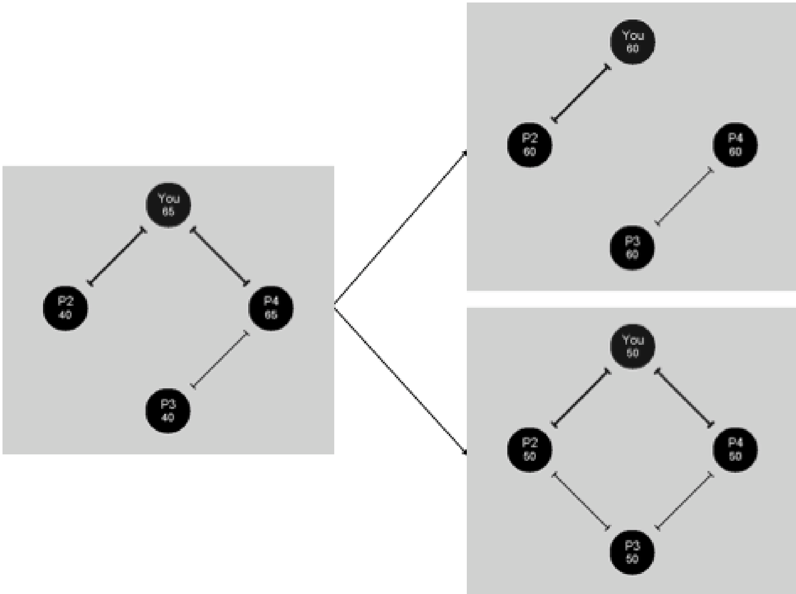


Figure 2: Example of possible relation changes

If a desired change is not established then you can try again in the next period. In the following period you will be informed which relation was changed. Depending on the particular scenario, you earn a certain amount of points in each period as a result of the relations that you have. The earnings you have received so far are displayed in a box on the right of your screen. The earnings of yourself and the other participants in the current situation are shown in the circles. On the following pages it is explained how the earnings in the first scenario are determined.

Scenario 1

Below, it is explained how the number of points that you earn in this scenario depends on the relations you create. Read this carefully and try to understand the situation. Do not worry if you find it difficult to grasp the situation based on the description below. On the next page, two examples are shown including calculation of points earned. Next to this, you will play a trial round in which you can gain experience with the scenario while your choices do not have any financial consequences.

The number of points that you can earn in this scenario depends on two factors: 1) the number of relations that you have; 2) the number of relations the participants have to whom you are connected.

The table below shows how you can calculate the points you receive for every relation you have. The columns indicate the number of relations you have and the rows indicate the number of relations the participant to whom you are connected have.

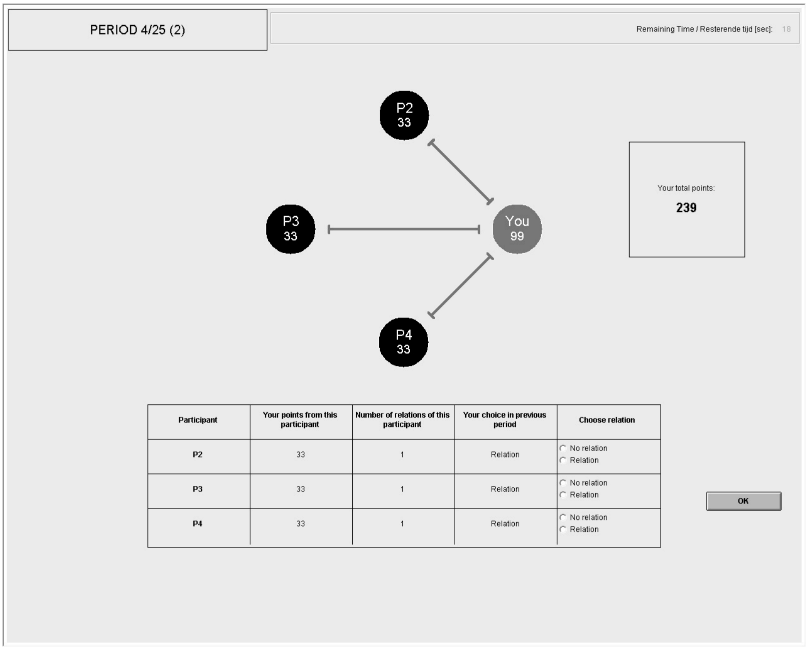
Number of relations you have

Number of relations that a participant has to whom you are connected

	1	**2**	**3**
1	**60**	**40**	**33**
2	**40**	**25**	**20**
3	**33**	**20**	**15**

An important principle that is clearly observable in the table is that a relation to a participant returns more points if the other participant has fewer relations. Using the table above, you can calculate your total number of points and calculate how this changes if you change a relation.

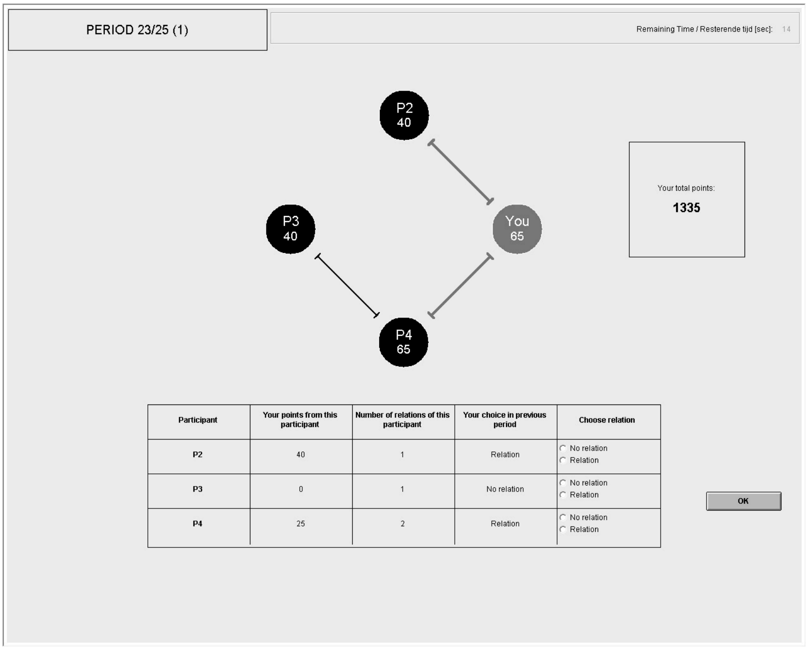
Example 1



You have three relations to others who only have one relation. In the table you can see that if you have three relations and you are connected with someone having one relation that you earn 33 points for this relation. You therefore earn in total in this example 3 × 33 = 99 points.

The other participants each have one relation with you having three relations. They earn 1 × 33 = 33 points.

Example 2



You and P4 each have two relations, one relation with another participant who has two relations and one relation with someone who has only one relation. You and P4 earn 40 + 25 = 65 points each. The participants P2 and P3 who each have one relation to someone who has two relations earn 40 points.

On the following page you see every possible position you can have in the group and the points you earn in each position. Keep this paper sheet next to you during the scenario.
Before the scenario really starts, there are 5 trial periods in which you can practice with this scenario. In these trial periods you cannot earn points. After the trial periods, the "real" periods start in which you can earn points. You play two times 25 periods in this scenario. In the top left corner of the screen you can see in which period you are. The example above shows a period 23 of the second series of 25 periods. After 25 periods you will be matched with new other participants.

Scenario 2

Below, it is explained how the number of points that you earn in this scenario depends on the relations you create. Read this carefully and try to understand the situation. Do not worry if you find it difficult to grasp the situation based on the description below. On the next page, two examples are shown including calculation of points earned. Next to this, you will play a trial round in which you can gain experience with the scenario while your choices do not have any financial consequences.

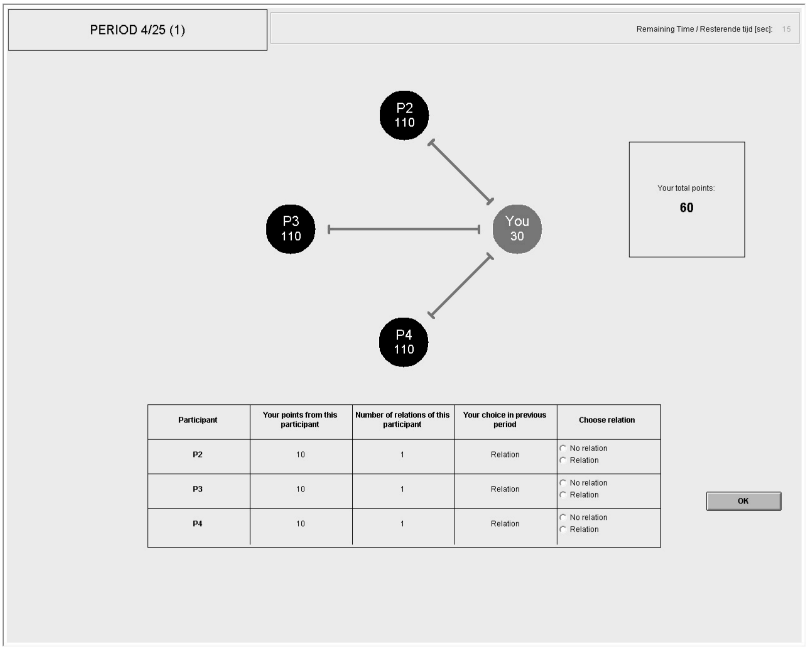
The number of points that you can earn in this scenario depends on two factors: 1) the number of relations that you have; 2) the benefits from participants to whom you are not directly but indirectly connected indirectly through another participant.

You receive 10 points for each direct relation. You receive 50 point for each participant with whom you do **not** have a relation, but are connected to through another participant. It is important to note that for each other participant you can only earn points once.

The total number of points that someone earns in a period can thus be written as follows:

10 × the number of direct relations +
50 × the number of participants to whom you are only connected indirectly through another participant

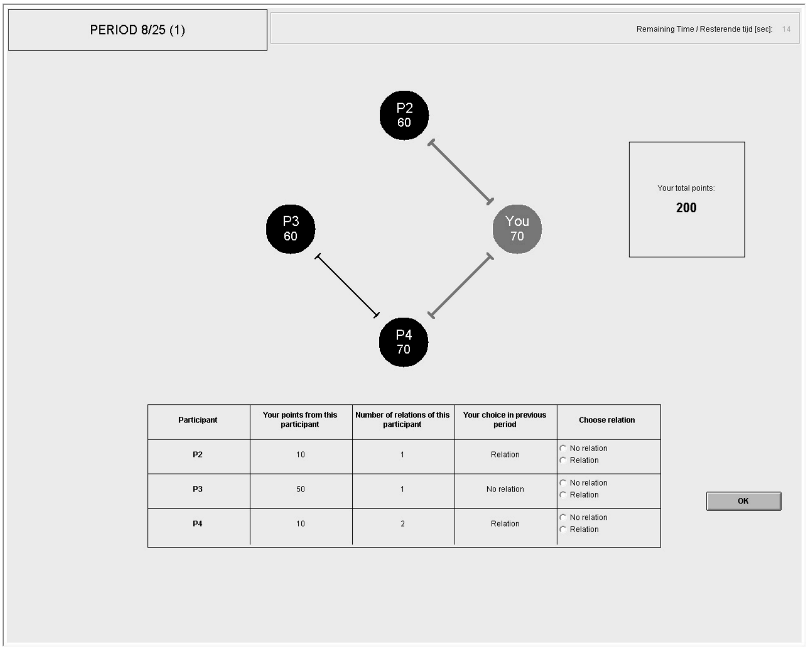
Example 1



You have three direct relations and you are with no one connected in an indirect way. You therefore earn 3 × 10 = 30 points.

The other participants each have one direct relation with you and are via you indirectly connected with the two other participants. They earn 1 × 10 + 2 × 50 = 110 points.

Example 2



You and P4 have two direct relations and one indirect connection. You therefore earn
$2 \times 10 + 1 \times 50 = 70$ points each.

The participants P2 and P3 have one direct relation (with you and P4, respectively) and they are indirectly connected with one other participant (with P4 and you, respectively). Therefore they earn $1 \times 10 + 1 \times 50 = 60$ points.

On the following page you see every possible position you can have in the group and the points you earn in each position. Keep this paper next to you during the scenario.

Before the scenario really starts, there are 5 trial periods in which you can practice with this scenario. In these trial periods you cannot earn points. After the trial periods, the “real” periods start in which you can earn points. You play two times 25 periods in this scenario. In the top left corner of the screen you can see in which period you are. The example above shows a period 23 of the second series of 25 periods. After 25 periods you will be matched with new other participants.

Additional game

You will now play an additional game. Again, you can earn points depending on the decisions you and the other participants make. These points will be added to your earnings in the previous games. You will still receive 1 EUR for 250 points.

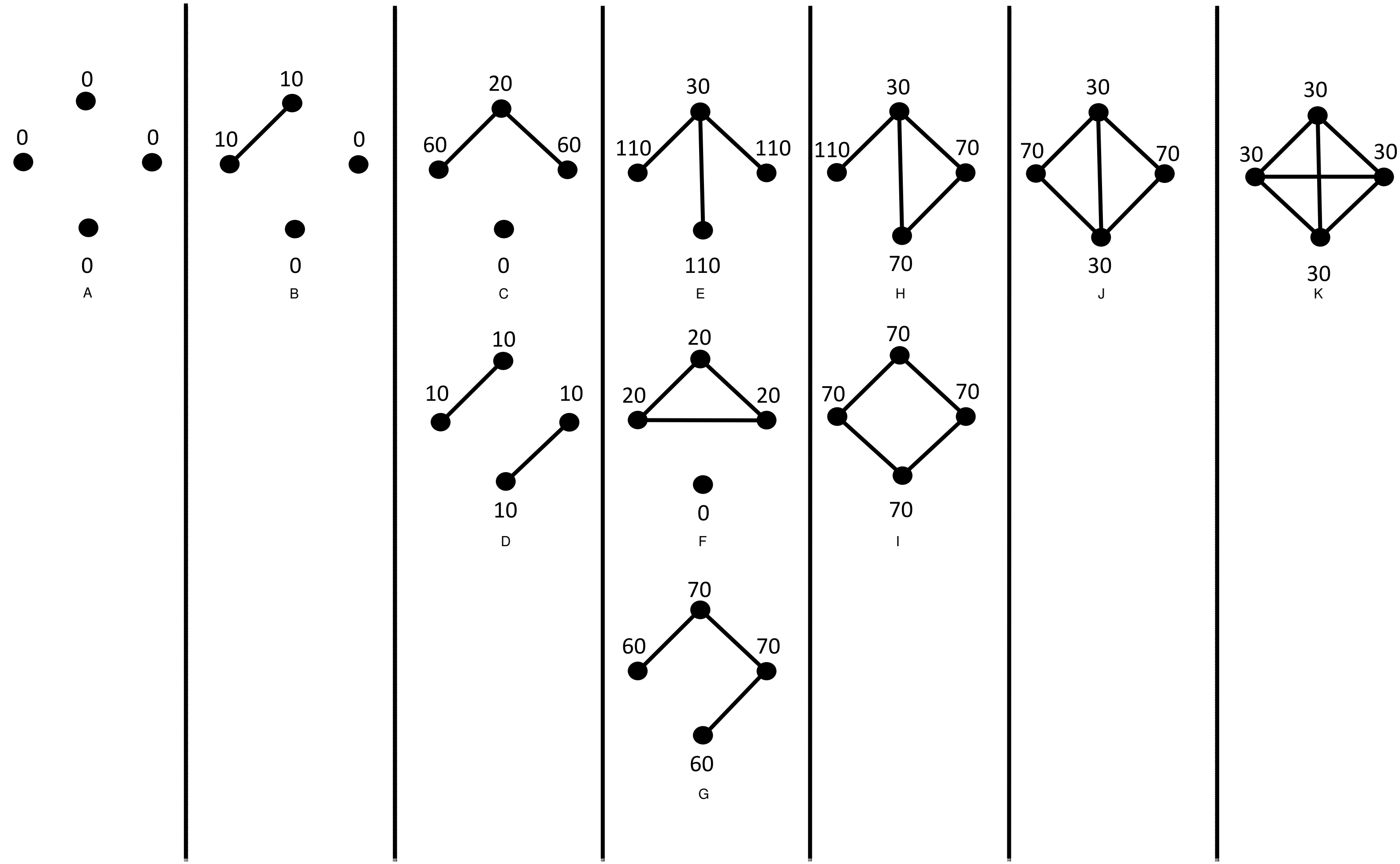
You will now play with every participant of the experiment simultaneously. In this game, all participants in this room simultaneously choose a number between 0 and 100 (0 and 100 are also allowed). The other participants will not know during or after the game which number you have chosen. After everybody picked a number, the average of the numbers that have been chosen by all participants will be calculated. *The participant who has chosen the number closest to half of the average of all participants will receive 400 points*.

For example, in a group of three people imagine that one chooses 25, one 50, and one 75. We first calculate the average: $\frac{25+50+75}{3}=\frac{150}{3}=50$. Now we take half of the average which is 25. So the participant who chose 25 receives the 400 points. When multiple participants are equally close to half the average, the 400 points will be randomly assigned to one of these participants. All other participants will not receive any points. You will play this game three times in a row.

After the additional game is finished there will be a questionnaire. Please take your time to fill in this questionnaire. Meanwhile we will count the money you earned. Please remain seated until you have received your money and signed your receipt.

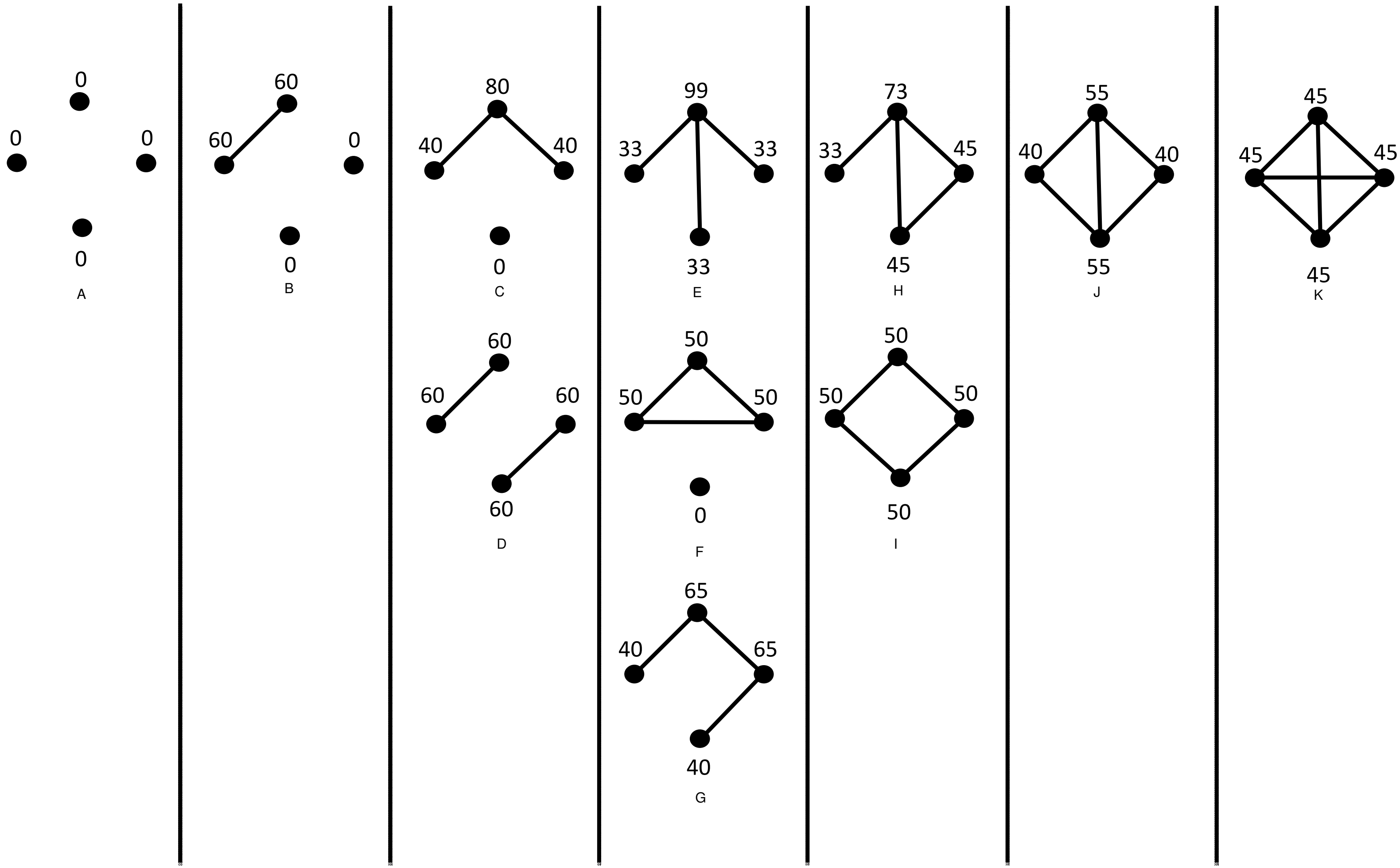
Points earned for a given position within the group:

(Groups on screen look different)



Points earned for a given position within the group:

(Groups on screen look different)



References

Aksoy, Ozan and Jeroen Weesie. 2012. "Beliefs about the Social Orientations of Others: A Parametric Test of the Triangle, False Consensus, and Cone Hypotheses." *Journal of Experimental Social Psychology* 48:45–54.

Asparouhov, Tihomir and Bengt Muthén. 2010. "Bayesian Analysis of Latent Variable Models Using Mplus." *Unpublished Work: www. statmodel. com/download/BayesAdvantages18. pdf* .

Aumann, Robert J. 1995. "Backward Induction and Common Knowledge of Rationality." *Games and Economic Behavior* 8:6–19.

Bala, Venkatesh and Sanjeev Goyal. 2000. "A Noncooperative Model of Network Formation." *Econometrica* 68:1181–1229.

Barrientos, Jorge Hugo. 2005. "Stable and Farsighted Set of Networks." *Lecturas de Economia* pp. 191–205.

Becker, Gary S. 1976. *The Economic Approach to Human Behavior*. Chicago: University of Chicago Press.

Berger, Roger and Rupert Hammer. 2007. "Die doppelte Kontingenz von Elfmeterschüssen: Eine empirische Analyse." *Soziale Welt* 58:397–418.

Berninghaus, Siegfried K., Karl-Martin Ehrhart, and Marion Ott. 2012. "Forward-Looking Behavior in Hawk-Dove Games in Endogenous Networks: Experimental Evidence." *Games and Economic Behavior* 75:35–52.

Bhattacharya, Anindya. 2006. “Stable and Efficient Networks with Farsighted Players: The Largest Consistent Set.” Technical report, Mimeo, University of York.

Bloch, Francis and Matthew O. Jackson. 2006. “Definitions of Equilibrium in Network Formation Games.” *International Journal of Game Theory* 34:305–318.

Bojanowski, Michal, Rense Corten, and Bastian Westbrock. 2012. “The Structure and Dynamics of the Global Network of Inter-Firm R&D Partnerships 1989-2002.” *Journal of Technology Transfer* 37:967–987.

Brandts, Jordi and Gary Charness. 2011. “The Strategy Versus the Direct-Response Method: A First Survey of Experimental Comparisons.” *Experimental Economics* 14:375–398.

Buechel, Berno and Tim Hellmann. 2012. “Under-connected and Over-connected Networks: The Role of Externalities in Strategic Network Formation.” *Review of Economic Design* 16:71–87.

Burger, Martijn J. and Vincent Buskens. 2009. “Social Context and Network Formation: An Experimental Study.” *Social Networks* 31:63–75.

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

Burt, Ronald S. 2004. “Structural Holes and Good Ideas.” *American Journal of Sociology* 110:349–399.

Buskens, Vincent and Arnout Van de Rijt. 2008. “Dynamics of Networks if Everyone Strives for Structural Holes.” *American Journal of Sociology* 114:371–407.

Callander, Steven and Charles R. Plott. 2005. “Principles of Network Development and Evolution: An Experimental Study.” *Journal of Public Economics* 89:1469–1495.

Camerer, Colin F. 2003. *Behavioral Game Theory: Experiments in Strategic Interaction*. Princeton, NJ: Princeton University Press.

Camerer, Colin F. and Ernst Fehr. 2006. "When Does Economic Man Dominate Social Behavior?" *Science* 311:47–52.

Camerer, Colin F., Teck-Hua Ho, and Juin-Kuan Chong. 2004. "A Cognitive Hierarchy Model of Games." *Quarterly Journal of Economics* 119:861–898.

Camerer, Colin F. and Dan Lovallo. 1999. "Overconfidence and Excess Entry: An Experimental Approach." *American Economic Review* 89:306–318.

Cederman, Lars-Erik. 2005. "Computational Models of Social Forms: Advancing Generative Process Theory." *American Journal of Sociology* 110:864–893.

Chwe, Michael S.K. 1994. "Farsighted Coalition Stability." *Journal of Economic Theory* 63:299–325.

Coleman, James S. 1986. "Psychological Structure and Social Structure in Economic Models." *Journal of Business* 59:365–369.

Coleman, James S. 1990. *Foundations of Social Theory*. Cambridge, MA: Harvard University Press.

Corten, Rense. 2009. *Co-evolution of Social Networks and Behavior in Social Dilemmas: Theoretical and Empirical Perspectives*. Ph.D. thesis, ICS, Utrecht University.

Corten, Rense and Vincent Buskens. 2010. "Co-evolution of Conventions and Networks: An Experimental Study." *Social Networks* 32:4–15.

Costa-Gomes, Miguel, Vincent P. Crawford, and Bruno Broseta. 2001. "Cognition and Behavior in Normal-Form Games: An Experimental Study." *Econometrica* 69:1193–1235.

De Graaf, Nan Dirk and Henk D. Flap. 1988. "With a Little Help from My Friends: Social Resources as an Explanation of Occupational Status and

Income in West Germany, the Netherlands, and the United States." *Social Forces* 67:452–472.

Diekmann, Andreas. 2008. "Soziologie und Ökonomie: Der Beitrag experimenteller Wirtschaftsforschung zur Sozialtheorie." *Kölner Zeitschrift für Soziologie und Sozialpsychologie* 60:528–550.

Dutta, Bhaskar, Sayantan Ghosal, and Debraj Ray. 2005. "Farsighted Network Formation." *Journal of Economic Theory* 122:143–164.

Epstein, Joshua M. 2007. *Generative Social Science: Studies in Agent-based Computational Modeling*. Princeton, NJ: Princeton University Press.

Falk, Armin and Michael Kosfeld. 2012. "It's All about Connections: Evidence on Network Formation." *Review of Network Economics* 11:2.

Fischbacher, Urs. 2007. "z-Tree: Zurich Toolbox for Ready-made Economic Experiments." *Experimental Economics* 10:171–178.

Flache, Andreas and Michael Macy. 2006. "Bottom-up Modelle sozialer Dynamiken. Agentenbasierte Computermodellierung und methodologischer Individualismus." *Kölner Zeitschrift für Soziologie und Sozialpsychologie, Sonderheft 44/2004 "Methoden der Sozialforschung"* pp. 536–559.

Flap, Henk. 2002. "No Man Is An Island: The Research Programme of a Social Capital Theory." In *Conventions and Structures in Economic Organization*, pp. 29–59. Northampton, MA: Edward Elgar.

Flap, Henk. 2004. "Creation and Returns of Social Capital." In *Creation and Returns of Social Capital: A New Research Program*, edited by Henk Flap and Beate Völker, pp. 3–23. New York, NY: Routledge.

Fowler, James H., Christopher T. Dawes, and Nicholas A. Christakis. 2009. "Model of Genetic Variation in Human Social Networks." *Proceedings of the National Academy of Sciences* 106:1720–1724.

Galeotti, Andrea, Sanjeev Goyal, and Jurjen Kamphorst. 2006. "Network Formation with Heterogeneous Players." *Games and Economic Behavior* 54:353–372.

Goeree, Jacob K., Arno Riedl, and Aljaz Ule. 2009. "In Search of Stars: Network Formation Among Heterogeneous Agents." *Games and Economic Behavior* 67:445–466.

Goyal, Sanjeev. 2007. *Connections: An Introduction to the Economics of Networks*. Princeton, NJ: Princeton University Press.

Goyal, Sanjeev., Marco J. Van Der Leij, and Jose Luis Moraga-González. 2006. "Economics: An Emerging Small World." *Journal of Political Economy* 114:403–412.

Granovetter, Mark S. 1973. "The Strength of Weak Ties." *American Journal of Sociology* 78:1360–1380.

Gulati, Ranjay. 1995. "Social Structure and Alliance Formation Patterns: A Longitudinal Analysis." *Administrative Science Quarterly* 40:619–652.

Herings, P. Jean-Jaques., Ana Mauleon, and Vincent Vannetelbosch. 2009. "Farsightedly Stable Networks." *Games and Economic Behavior* 67:526–541.

Herings, P. Jean-Jaques., Ana Mauleon, and Vincent Vannetelbosch. 2010. "Coalition Formation Among Farsighted Agents." *Games* 1:286–298.

Holt, Charles A. and Susan K. Laury. 2002. "Risk Aversion and Incentive Effects." *American Economic Review* 92:1644–1655.

Hoyer, Britta, Stephanie Rosenkranz, and Kris de Jaegher. 2012. "Network Disruption and the Common Enemy Effect - An Experiment." *Working Paper* .

Hummon, Norman P. 2000. "Utility and Dynamic Social Networks." *Social Networks* 22:221–249.

Jackson, Matthew O. 2003. "A Survey of Models of Network Formation: Stability and Efficiency." Mimeo.

Jackson, Matthew O. 2008. *Social and Economic Networks.* Princeton, NJ: Princeton University Press.

Jackson, Matthew O. and Brian W. Rogers. 2007. "Meeting Strangers and Friends of Friends: How Random Are Social Networks?" *American Economic Review* 97:890–915.

Jackson, Matthew O. and Anne Van den Nouweland. 2005. "Strongly Stable Networks." *Games and Economic Behaviour* 51:420–444.

Jackson, Matthew O. and Alison Watts. 2002. "The Evolution of Social and Economic Networks." *Journal of Economic Theory* 106:265–295.

Jackson, Matthew O. and Asher Wolinsky. 1996. "A Strategic Model of Social and Economic Networks." *Journal of Economic Theory* 71:44–74.

Johnson, Dominic D.P. and James H. Fowler. 2011. "The Evolution of Overconfidence." *Nature* 477:317–320.

Kovářík, Jaromr and Marco J. Van der Leij. 2010. "Risk Aversion and Networks: Microfoundations for Network Formation." Working Paper.

Krackhardt, David. 1987. "Cognitive Social Structures." *Social Networks* 9:109–134.

Luce, R. Duncan and Howard Raiffa. 1958. *Games and Decisions. Introduction and Critical Survey*. New York, NY: Wiley.

Mantovani, Marco, Georg Kirchsteiger, Ana Mauleon Echeverria, and Vincent Vannetelbosch. 2011. "Myopic or Farsighted? An Experiment on Network Formation." *FEEM Working Paper No. 45.2011* .

McCutcheon, Allan L. 1987. *Latent Class Analysis*, volume 64. Beverly Hills, CA: Sage.

McKelvey, Richard D. and Thomas R. Palfrey. 1992. "An Experimental Study of the Centipede Game." *Econometrica* 60:803–836.

Morbitzer, Dominik, Vincent Buskens, Stephanie Rosenkranz, and Werner Raub. 2011. "How Farsightedness Affects Network Formation." ISCORE Discussion paper. Utrecht University.

Mouw, Ted. 2003. “Social Capital and Finding a Job: Do Contacts Matter?” *American Sociological Review* 68:868–898.

Muthén, Linda K. and Bengt O. Muthén. 1998-2010. *Mplus' Users Guide, 6th edn.* Los Angeles, CA: Muthén and Muthén.

Nagel, Rosemarie. 1999. “A Survey on Experimental Beauty-contest Games: Bounded Rationality and Learning.” In *Games and Human Behavior: Essays in Honor of Amnon Rapoport*, edited by David V. Budescu, Ido Erev, and Rami Zwick. Mahwah, NJ: Lawrence Erlbaum.

Nylund, Karen L., Tihomir Asparouhov, and Bengt O. Muthén. 2007. “Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture Modeling: A Monte Carlo Simulation Study.” *Structural Equation Modeling* 14:535–569.

Page, Frank H. Jr., Myrna H. Wooders, and Samir Kamat. 2005. “Networks and Farsighted Stability.” *Journal of Economic Theory* 120:257–269.

Palacios-Huerta, Ignacio and Oscar Volij. 2008. “Experientia Docet: Professionals Play Minimax in Laboratory Experiments.” *Econometrica* 76:71–115.

Palacios-Huerta, Ignacio and Oscar Volij. 2009. “Field Centipedes.” *The American Economic Review* 99:1619–1635.

Pantz, Katinka. 2006. *The Strategic Formation of Social Networks: Experimental Evidence*. Aachen: Shaker Verlag.

Raub, Werner, Vincent Buskens, and Marcel A.L.M. Van Assen. 2011. “Micro-Macro Links and Microfoundations in Sociology.” *Journal of Mathematical Sociology. Special Issue: Micro-Macro Links and Microfoundations* 35:1–25.

Raub, Werner and Chris Snijders. 1997. “Gains, Losses, and Cooperation in Social Dilemmas and Collective Action: The Effects of Risk Preferences.” *Journal of Mathematical Sociology* 22:263–302.

Rauhut, Heiko and Fabian Winter. 2010. “A Sociological Perspective on Measuring Social Norms by Means of Strategy Method Experiments.” *Social Science Research* 39:1181–1194.

Rosenthal, Robert W. 1981. “Games of Perfect Information, Predatory Pricing and the Chain-Store Paradox.” *Journal of Economic Theory* 25:92–100.

Rubinstein, Ariel. 1998. *Modeling Bounded Rationality*. Cambridge, MA: MIT Press.

Schelling, Thomas C. 1978. *Micromotives and Macrobehavior*. New York: Norton.

Selten, Reinhard. 1967. “Die Strategiemethode zur Erforschung des eingeschränkt rationalen Verhaltens im Rahmen eines Oligopolexperiments.” In *Beiträge zur Experimentellen Wirtschaftsforschung*, edited by H. Sauerman. Tübingen: J.C.B. Mohr (Paul Siebeck).

Snijders, Tom A. B. 2001. “The Statistical Evaluation of Social Network Dynamics.” *Sociological Methodology* 31:361–395.

Stahl, Dale O. and Paul W. Wilson. 1995. “On Players’ Models of Other Players: Theory and Experimental Evidence.” *Games and Economic Behavior* 10:218–254.

Stuart, Toby E. 1998. “Network Positions and Propensities to Collaborate: An Investigation of Strategic Alliance Formation in a High-Technology Industry.” *Administrative Science Quarterly* 43:668–698.

Uzzi, Brian. 2008. “A Social Network’s Changing Statistical Properties and the Quality of Human Innovation.” *Journal of Physics A-Mathematical and Theoretical* 41:224023.

Van de Bunt, Gerhard G., Marijtje A.J. Van Duijn, and Tom A.B. Snijders. 1999. “Friendship Networks Through Time: An Actor-oriented Dynamic Statistical Network Model.” *Computational & Mathematical Organization Theory* 5:167–192.

Van Dolder, Dennie and Vincent Buskens. 2008. "Individual Choices in Dynamic Networks: The Role of Efficiency and Equality." ISCORE Discussion paper. Utrecht University.

Van Duijn, Marijtje A.J., Evelien P.H. Zeggelink, Mark Huisman, Frans N. Stokman, and Frans W. Wasseur. 2003. "Evolution of Sociology Freshmen Into a Friendship Network." *Journal of Mathematical Sociology* 27:153–191.

Vega-Redondo, Fernando. 2007. *Complex Social Networks*. Cambridge, MA: Cambridge University Press.

Vermunt, Jeroen K. 2003. "Multilevel Latent Class Models." *Sociological Methodology* 33:213–239.

Von Neumann, John and Oskar Morgenstern. 1944. *Theories of Games and Economic Behavior*. Princeton, NJ: Princeton University Press.

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

Weesie, Jeroen, Chris Snijders, and Vincent Buskens. 2009. "The Rationale of Rationality." *Rationality and Society* 21:249–277.

Willer, Rob. 2007. "The Role of Metanetworks in Network Evolution." *Journal of Mathematical Sociology* 31:101–119.

Zuckerman, Marvin. 1994. *Behavioral Expressions and Biosocial Bases of Sensation Seeking*. Cambridge, MA: Cambridge University Press.

Samenvatting

Beperkt vooruitdenken bij netwerkformatie

Omdat sociale relaties nuttig kunnen zijn, hebben actoren een motivatie om strategisch te investeren in hun relaties (Flap, 2004). De positie die actoren in een netwerk van sociale relaties innemen, kan hun uitkomsten beïnvloeden (Burt, 1992; Uzzi, 2008). Gegeven dat netwerkposities van belang zijn, en gegeven dat actoren tot op zekere hoogte de relatiestructuur tussen alle actoren kunnen overzien, is het aannemelijk dat ze zich in een gunstige netwerkposities proberen te manoeuvreren (Krackhardt, 1987; Burt, 1992). Beslissingen van actoren in netwerken hebben niet alleen een effect op hun eigen positie en uitkomsten, maar deze beslissingen hebben ook een effect op de posities en dus de uitkomsten van anderen in het netwerk. Vaak wordt verondersteld dat actoren in dergelijke complexe en dynamische netwerksituaties bij het nemen van een beslissing de daaropvolgende beslissingen van andere actoren verwaarlozen. Dit kortzichtig handelen wordt aangeduid als 'myopic best response' gedrag (myopic betekent *bijziend*). Modellen met standaard rationaliteitsaannames veronderstellen daarentegen dat actoren perfect rationeel zijn en daarmee ook perfect vooruitziend: zij zijn in staat om alle mogelijke reacties van anderen te voorzien in een complexe omgeving zoals dynamische netwerken. Die assumptie lijkt echter onrealistisch, aangezien mensen waarschijnlijk niet in staat zijn om dergelijke complexe cognitieve taken uit te voeren. Bestaat er een realistischere tussenweg? Indien actoren niet slechts naar de onmiddellijke baten kijken, maar in hun beslissingen ook *in beperkte mate* anticiperen op de reacties van anderen, kan dit al gevolgen hebben voor de vorming van sociale netwerken. Jackson (2008) betoogt dat actoren meer op de toekomst anticiperen als ze een goed beeld hebben van de context en de motieven van andere actoren bij het aangaan of verbreken van sociale relaties. Daarom is het de moeite waard om te onderzoeken hoe individueel gedrag, afhankelijk van het vooruitdenkend vermogen van actoren, de formatie van sociale netwerken beïnvloedt.

De laatste jaren zijn speltheoretische middelen ontwikkeld om de mogelijke uitkomsten van netwerkformatie te analyseren. Speltheorie beschrijft situaties waarin rationele actoren strategische beslissingen nemen waarbij hun eigen resultaat ook afhankelijk is van de beslissingen van andere actoren, en vice versa. Er wordt aangenomen dat de actoren rekening houden met deze onderlinge afhankelijkheid. In speltheoretische termen: uitgaande van doelgericht handelen, maximaliseert elke actor zijn eigen nut, gegeven de strategieën van de andere actoren. Tevens wordt verondersteld dat alle actoren weten dat alle actoren rationeel zijn, alle actoren zijn ook van deze veronderstelling op de hoogte, en alle actoren weten weer dat alle actoren van deze veronderstelling op de hoogte zijn, enzovoort ad infinitum (zie bijvoorbeeld Aumann, 1995). In situaties waarin actoren zijn ingebed in netwerken, moet bovendien verondersteld worden dat actoren de structurele component van netwerken meenemen in hun beslissing, teneinde zichzelf in een optimale positie in het netwerk te manoeuvreren. Pas de laatste jaren wordt onderzocht hoe en waarom specifieke netwerkstructuren tot stand komen als de actoren hun netwerkpositie kunnen veranderen (Goyal, 2007; Vega-Redondo, 2007; Jackson, 2008). Dergelijke modellen over strategische netwerkvorming gaan er vanuit dat actoren 'nut' ontlenen aan netwerken en van netwerkeffecten. Actoren hebben de mogelijkheid om zelf te kiezen met wie zij een relatie willen onderhouden. Op deze manier wordt een sociaal netwerk niet beschouwd als een exogeen bepaalde structuur, maar als een endogeen *gevolg* van de beslissingen van actoren die verbindingen kunnen aangaan, onderhouden of verbreken met anderen (Jackson and Wolinsky, 1996; Bala and Goyal, 2000). In zogenoemde *pure* netwerkformatiemodellen ontlenen actoren alleen 'nut' aan hun specifieke posities binnen het netwerk. De 'nutsfunctie van het netwerkformatieproces' is de vooraf gedefinieerde wijze waarop de netwerkstructuur de uitkomst van een actor bepaalt. Het is mogelijk dat het aangaan en verbreken van verbindingen gebeurt op basis van bepaalde regels, zoals over welke verbindingen actoren wel en niet kunnen veranderen of over de volgorde waarin actoren hun beslissingen nemen. Om een voorbeeld te geven, in modellen zoals beschreven in Bala and Goyal (2000) wordt het gehele netwerk in één keer gevormd (en wordt netwerkformatie dus als een 'one-shot game' weergegeven). In andere modellen, waaronder de modellen beschreven in dit proefschrift, creëren of verbreken actoren hun sociale relaties één voor één in een dynamisch proces (Jackson and Watts, 2002). Deze laatste benadering lijkt beter geschikt voor het modelleren van netwerkformatieprocessen, aangezien dergelijke beslissingen in de praktijk ook eerder een sequentieel dan simultaan karakter hebben. Een netwerk wordt als stabiel beschouwd wanneer er geen enkel paar van actoren hun relatie meer wil veranderen. In dergelijke dynamische modellen wordt vaak aangenomen dat actoren kortzichtige (bovengenoemde 'myopic best response') beslissingen nemen. Kortzichtige actoren kijken slechts één stap vooruit en overwegen alleen of ze beter af zijn direct na het toevoegen of verbreken van een relatie. Hiermee veronachtzamen zij echter de mogelijke toekomstige acties van de andere actoren. Het maken of verbreken van een relatie zou namelijk kunnen leiden tot maken of verbreken van een relatie door een andere actor in de toekomst, wat op zijn beurt weer effect kan hebben op de uitkomst van de eerste actor. In de realiteit zijn actoren waarschijnlijk niet zo kortzichtig als de standaard speltheoretische netwerkformatiemodellen veronderstellen. Het lijkt meer aannemelijk dat actoren een complexere heuristiek gebruiken om te bepalen welke banden ze willen veranderen: actoren gebruiken wellicht verder vooruitdenkende strategieën die rekening houden met de latere beslissingen van anderen.

In de literatuur over netwerkformatie wordt een aantal uitbreidingen van de veronderstelling van kortzichtigheid beschreven. Het eerste alternatief gaat naar het andere uiterste en veronderstelt dat actoren perfect vooruitdenkend zijn (Page et al., 2005; Dutta et al., 2005; Herings et al., 2009; Pantz, 2006). Dit houdt in dat de actoren stap voor stap hun sociale relaties aangaan en verbreken terwijl zij volledig anticiperen op alle veranderingen in het gehele netwerk totdat een bepaald 'eind' netwerk bereikt is. Een dergelijke opeenvolging van netwerkveranderingen totdat het uiteindelijke netwerk bereikt is, is natuurlijk alleen haalbaar indien *alle* actoren hun positie in het uiteindelijke netwerk prefereren boven hun netwerkpositie op het moment dat ze de verandering bewerkstelligen (immers, waarom zou men *nu* een relatie aangaan of verbreken als dat in het *uiteindelijke* netwerk minder resultaat oplevert dan de huidige positie?). Zoals eerder betoogd, is de aanname van 'perfect vooruitdenken' onrealistisch bij de toenemende complexiteit van grotere netwerken. Bovendien verschaffen de bestaande modellen met perfect vooruitdenkende actoren geen duidelijke voorspellingen voor willekeurige netwerken, maar vooral algemene stellingen over de voorwaarden voor netwerkstabiliteit aangevuld met enkele voorbeelden voor specifieke nutsfuncties.

Naast de theoretische argumenten om netwerkformatiemodellen met vooruitdenkende actoren te ontwikkelen, blijkt uit experimenteel onderzoek dat modellen met kortzichtige actoren empirisch waargenomen uitkomsten niet altijd goed voorspellen (Callander and Plott, 2005; Pantz, 2006; Berninghaus et al., 2012; Van Dolder and Buskens, 2008; Corten and Buskens, 2010). Het zou kunnen zijn dat het verschil tussen de voorspelling en de empirie kan worden verklaard door een bepaalde mate van anticiperend gedrag van de actoren te veronderstellen. Bovendien suggereren de resultaten van Pantz (2006) en Berninghaus et al. (2012) dat actoren volledig kortzichtig noch perfect vooruitziend handelen: kortom, ze suggereren beperkt vooruitdenken van de actoren.

Aanpak en resultaten

Theoretisch model: hoofdstukken 2 en 3

In hoofdstuk 2 ontwikkelen we een theoretisch model van netwerkformatie waarbij actoren beperkt vooruitdenken. Puttend uit ideeën van 'level-k-thinking theory' (Stahl and Wilson, 1995) gaan wij ervan uit dat elke actor anticipeert op de volgende acties van alle andere actoren, *waarbij de actor aanneemt dat de anderen één stap minder vooruitdenken dan hijzelf.* Actoren die bijvoorbeeld zelf twee netwerkformatiestappen vooruitdenken, veronderstellen dat andere actoren slechts één stap vooruitdenken. We nemen dus aan dat actoren zich niet realiseren dat anderen mogelijk precies even ver vooruitdenken als zij zelf. Door gebruik te maken van computersimulaties worden de stabiele netwerkstructuren afgeleid die het meest waarschijnlijk zijn om te ontstaan onder de veronderstelling dat de actoren één, twee, of drie stappen vooruitdenken. In elke stap van het dynamische formatieproces kunnen twee (willekeurig gekozen) actoren besluiten om een relatie aan te gaan, te verbreken of te behouden. Omdat het onzeker is welke veranderingen in het netwerk volgen op een dergelijke beslissing, zijn extra veronderstellingen nodig over hoe actoren beslissingen nemen onder onzekerheid. Wij passen deze ideeën als eerste toe op het co-auteur model van Jackson and Wolinsky (1996). Dit netwerkformatiemodel impliceert een spanningsveld tussen stabiliteit en efficiëntie wanneer actoren kortzichtig handelen. De computersimulaties laten zien dat kortzichtige actoren eindigen in een netwerk dat te veel verbindingen heeft en daardoor inefficiënt is. Actoren die beperkt vooruitdenken, lukt het wel om in een efficiënt netwerk te eindigen, maar alleen als het netwerk klein is. Bij grotere netwerken eindigen zowel kortzichtige als vooruitdenkende actoren in dezelfde stabiele, inefficiïte netwerken. Dit hoofdstuk laat hiermee zien dat het veranderen van de microgrondslagen van het netwerkformatiemodel leidt tot nieuwe gevolgen op macro-niveau: andere netwerken worden als evenwicht voorspeld.

In hoofdstuk 3 wordt het netwerkformatiemodel met beperkt vooruitdenken zoals ontwikkeld in hoofdstuk 2 toegepast op twee andere contexten: het 'connections' model van Jackson and Wolinsky (1996) en het 'structural holes' model van Buskens and Van de Rijt (2008). Beide modellen richten zich op het verkrijgen van informatie: informatie is een belangrijke hulpbron die vaak wordt doorgegeven en verkregen binnen sociale netwerken. Jackson en Wolinsky's (1996) connections model geeft uitdrukking aan het idee dat het hebben van verbindingen met anderen bevorderlijk is. Actoren ontlenen niet alleen waardevolle informatie aan de actoren in hun netwerk met wie ze direct, maar ook met wie ze indirect verbonden zijn, terwijl alleen aan het aangaan en onderhouden van directe relaties kosten zijn verbonden (bijvoorbeeld tijd of inspanning). Buskens en Van de Rijt's (2008) model geeft daarentegen uitdrukking aan Burt's (1992) idee van structurele gaten: actoren die twee anders niet-verbonden groepen met elkaar verbinden, kunnen profiteren van hun unieke netwerkpositie. Zij vormen de brug tussen zogenoemde structurele gaten in het totale netwerk en kunnen zodoende optreden als poortwachter voor de stroom van informatie. Computersimulaties laten zien dat kortzichtige actoren in het connections' model eindigen in te weinig verbonden, en dus inefficiënte, netwerken. Wanneer de kosten van verbindingen toenemen, neemt de efficiëntie van het netwerk af. Als actoren in beperkte mate vooruit kunnen denken, bouwen zij efficiëntere netwerken bij hoge verbindingskosten dan kortzichtige actoren. In het 'structural holes' model eindigen kortzichtige actoren meestal wel in efficiënte netwerken. Echter, als actoren twee of drie stappen vooruit kunnen denken, neemt de waarschijnlijkheid van het bouwen van efficiënte netwerken nog verder toe.

Experimentele studies: hoofdstukken 4 en 5

In hoofdstuk 4 wordt experimenteel onderzocht of proefpersonen kortzichtige beslissingen nemen of dat hun netwerk beslissingen meer in overeenstemming zijn met een beperkt vooruitziende blik. De proefpersonen spelen een netwerkformatiespel in groepjes van vier, waarbij zowel de nutsfunctie van het 'connections' model als het 'co-auteur' model een conditie vormen. De proefpersonen beslissen sequentieel of en met wie zij een relatie aan willen gaan in hun groep. Het 'beauty contest' spel wordt gebruikt om het iteratief denkvermogen van proefpersonen te meten, als proxy voor hun vooruitdenkend vermogen. De resultaten laten zien dat het model met beperkt vooruitdenkende actoren de uitkomsten op het macroniveau beter voorspelt dan een model met kortzichtige actoren. Een meerderheid van de netwerken die ontstaan in beide condities worden behoorlijk accuraat voorspeld door het model met beperkt vooruitdenken. In het geval dat er meerdere stabiele netwerken zijn, kan met het simulatiemodel voorspeld worden welk specifieke netwerk het meest waarschijnlijk is om te ontstaan. Deze voorspellingen worden echter niet ondersteund door de experimentele data. Op het micro-niveau nemen we zowel kortzichtig als vooruitdenkend gedrag waar. We hebben de netwerkkeuzes geanalyseerd waarvoor het mogelijk is om vast te stellen of proefpersonen kortzichtig of vooruitdenkend gedrag vertonen. We vinden dat proefpersonen met een hoger iteratief denkvermogen, zoals gemeten met het 'beauty contest' spel, zich vaker vooruitdenkend gedragen in het 'co-auteur model', maar *minder* vaak in het ‘connections’ model. Dit resultaat hangt echter sterk af van de specifieke aannames die worden gemaakt bij het modelleren van ‘beperkt vooruitdenken’. Zo hangt wat wij als een vooruitdenkende beslissing classificeren af van de aanname dat beperkt vooruitdenkende actoren veronderstellen dat alle andere actoren minder vooruitdenkend zijn. De tegengestelde resultaten in het ‘co-auteur’ en ‘connections’ model kunnen worden teruggevoerd tot de verschillende implicaties die deze aanname heeft. Als we een iets andere aanname hanteren, namelijk dat vooruitdenkende actoren lijken te veronderstellen dat anderen ook vooruitdenkend zijn, dan heeft dit belangrijke gevolgen voor het classificeren van de individuele beslissingen. We beargumenteren dat het vaak geobserveerde kortzichtig handelen in het ’connections’ model dan eigenlijk goed verenigbaar zou kunnen zijn met vooruitdenkend gedrag.

In hoofdstuk 5 worden de proefpersonen ingedeeld in verschillende typen op basis van hun vooruitdenkend vermogen bij het maken van keuzes in het netwerkformatie-experiment. De eerdere experimentele resultaten suggereren immers dat proefpersonen verschillen in termen van hun vermogen om vooruit te kijken. Latente klasse modellen, waarbij vanuit de data categorische latente variabelen worden afgeleid die subpopulaties voorstellen, worden gebruikt om deze heterogeniteit te identificeren. In dit hoofdstuk onderzoeken wij de proportie van de proefpersonen in het laboratorium die kortzichtig en die vooruitdenkend zijn. Verder onderzoeken we of het vermogen om vooruit te denken een persoonlijke eigenschap van het individu is, of afhankelijk is van de context. We analyseren of het individuele gedrag het beste beschreven kan worden aan de hand van ‘pure’ typen (proefpersonen die óf één óf twee óf drie stappen vooruitdenken), of aan de hand van gemengde’ typen (proefpersonen die kunnen wisselen in het aantal stappen dat zij vooruitdenken). Resultaten laten zien dat proefpersonen verschillen in hun vermogen om vooruit te kijken. Daarnaast blijkt het vermogen om vooruit te kijken context afhankelijk te zijn: het aantal stappen dat proefpersonen vooruitdenken verschilt per conditie in het experiment. We observeren dan ook dat de beslissingen van de proefpersonen bij netwerkformatie beter worden beschreven door een indeling van proefpersonen op basis van gemengde typen dan op basis van pure typen.

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Curriculum Vitae

Dominik Morbitzer (1980) was born in Ludwigsburg, Germany. He graduated from the Hans-Grüninger-Gymnasium in Markgröningen in 2000. Between 2001 and 2007, he studied Sociology, Computer Science and Art and Media Science at the University of Konstanz. In January 2008 he received a Magister Artium degree in Sociology from the University of Konstanz. In September 2008, he became a PhD student at the Interuniversity Center for Social Science Theory and Methodology (ICS) in Utrecht, where he completed this dissertation. In 2010, he spent a research period at the Chair of Sociology, in particular of Modeling and Simulation at the ETH Zürich. As of April 2013 he works as a consultant in Munich.

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