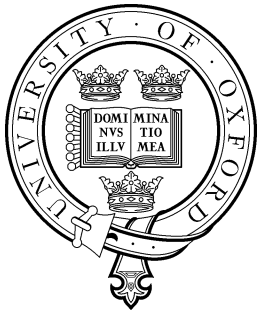
The Emergence of Multiple Status Systems in Adolescent Communities

A multiplex network theory of group formation



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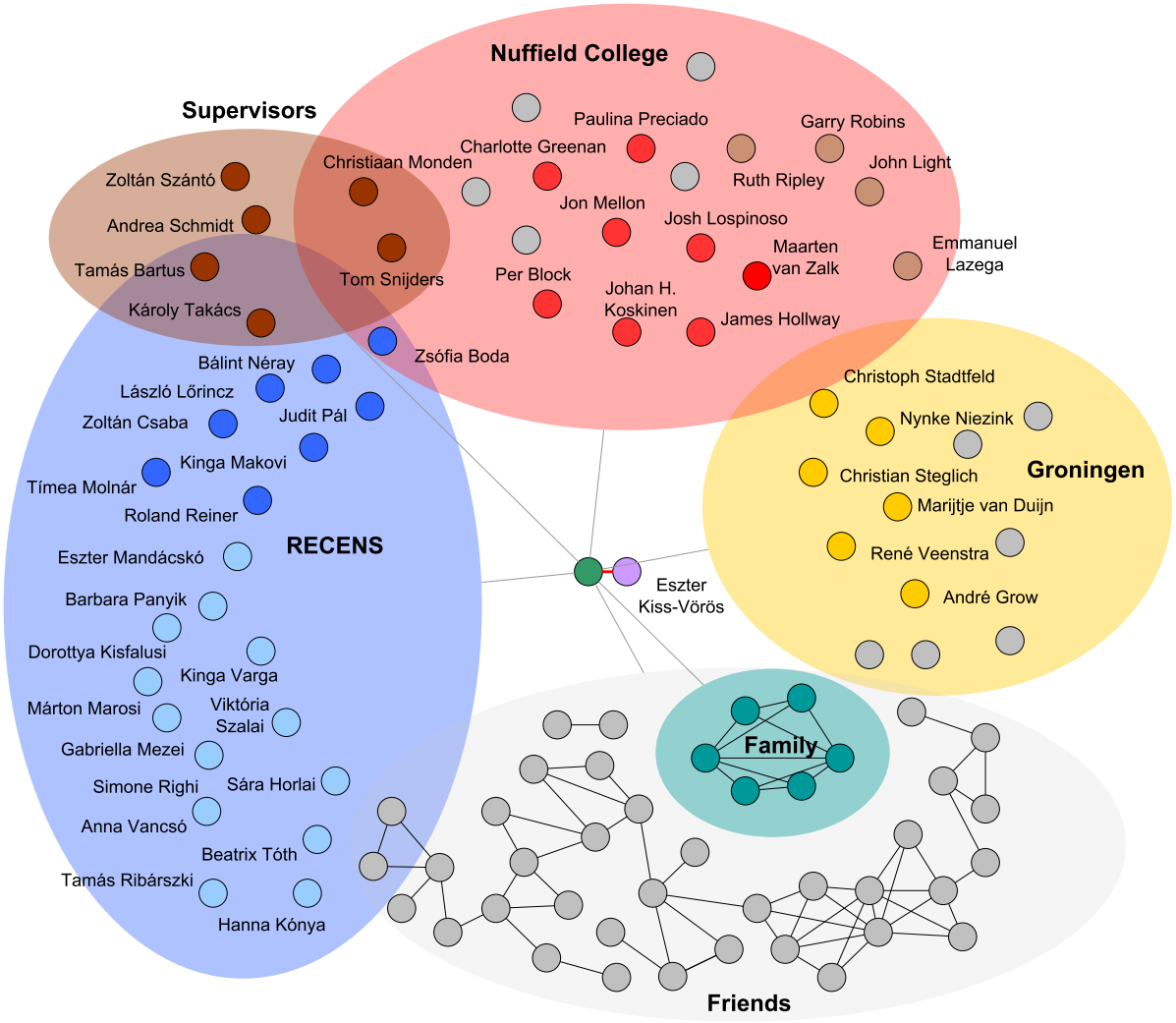
To my friends.
It's about you, after all.

Acknowledgements



For the support, care, and fun... and work: I thank you all. – A.V.

Abstract

How do informal groups emerge in adolescent communities? What distinguishes a group from just a set of students? Who will end up together in a group and who will be left out? Why are there more groups in some classrooms and fewer in others? What determines whether these groups overlap in their members or they are completely segregated, perhaps antagonistic?

While a huge body of research in sociology and social psychology focuses on these questions, an integrated approach that is able to answer all of them is yet to be developed. Without realizing that these five issues are interrelated, we cannot hope to understand how groups influence individuals and how they shape our communities.

This thesis proposes an integrative theory of informal group formation in communities. Based on the tradition of Social Network Analysis, it develops a framework in which interpersonal relations and reputations are formed through a process called informal status production. Groups emerge from this micro-process by the alignment of positive relations and agreement in peer-perceptions between actors.

The main micro-mechanisms predicted by the theory are tested on a unique longitudinal network dataset from school classrooms. To this end, a new empirical procedure was developed, by which a few aggregated networks can be constructed from tens of relational items. This allows the analysis of rich network data with several relational dimensions.

The empirical studies of multiplex network dynamics confirm that there are strong interdependencies between friendships and perceptions. Students who agree about their peers tend to become friends, but more so when they hold a minority opinion in the class. This contributes to group formation. Friends also influence each other's perceptions, but we manage to show that the presence of groups around them interferes with this process by moderating the influence of individual peers.

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Chapter 1

Introduction

Groups enable and oblige us. Without them, people would not be able to satisfy most of their material, social, and emotional needs, such as the need for safety, affection, approval, or status (Kadushin, 2012; Ormel, Lindenberg, Steverink, and Verbrugge, 1999; Baumeister and Leary, 1995). In return, however, groups influence and constrain the behavior of their members: they develop social norms and enforce them by various sanctions (e.g. Coleman, 1994). This double nature explains why groups are so ubiquitous in society and so central in the lives of individuals.

The fact that groups exist embedded in social systems has important sociological implications. First, some groups may develop norms and promote behaviors which go against the general values of society or the aims of a specific social institution. For the former case, criminal organizations or extremist groups stand as well-known examples; for the latter, it is enough to think about oppositional school cultures (Willis, 1977) or emergent norms for low performance at the workplace (Roethlisberger and Dickson, 1939, Homans, 1950). But, protestant groups and their "notorious" work ethic in the 17th century were also undermining the values of traditional society at the time, according to Weber (1905).

Second, the emergence of multiple groups within a community, such as in a school or workplace, can be a source of severe social conflicts (e.g. Sherif, Harvey, White, Hood, Sherif, et al., 1961). This is especially likely (but not limited to the case) when the values of the groups are incongruous. However, not only differences in norms related to certain behaviors or activities can be the roots of inter-group conflict. Groups may vary in their status systems, their collectively shared ideas about who deserves respect and approval in the community and who does not. If we place this next to the tendency of groups to favor their own members over the out-group (see e.g. Tajfel and Turner, 1979), it is apparent that conflicting status systems can lead

to conflicts between groups. Therefore, studying the emergence of multiple groups is essential for understanding the social structure of communities.

When thinking about groups in society, one might first associate to formal, relatively stable formations, such as sport teams, big political parties, or lawyer guilds. In reality, however, most of the groups we encounter day by day are dynamic and rather unstable entities. Just think about your friendship groups, your division or office at your workplace, your hobby volleyball team, the people with whom you organize play time for kids in need, your civil activist organization, and so on. Being a group is more than just signing work contracts, paying membership fees, having the same profession, or going to the same workplace every day.

Groups require constant upkeep which is provided by a series of social and psychological mechanisms. These include processes that facilitate decision making related to group goals, that generate positive affections between members, that help the resolution of conflicts, and so on. The main point is that the *informal* social processes are the ones which ensure that members feel connected to a group and continue to contribute to the achievement of collective goals. If the informal mechanisms do not work adequately, groups can quickly disintegrate. Consequently, to understand the effects of groups on individuals and communities, we have to focus our attention to the social processes by which they emerge, function, and dissolve.

1.1 Group puzzles

In line with their importance for individual and social outcomes, understanding how groups emerge is a key topic for the social sciences. However, all disciplines involved seem to leave some questions related to group formation unanswered. In general, sociological studies often emphasize the importance of social categories (class, ethnicity, gender, etc.) for group formation (Merton, 1968; McPherson, Smith-Lovin, and Cook, 2001). In this approach, however, the question remains why not all people with the same characteristics automatically act as a group (see e.g. Elster, 1989; Olson, 2009).

Social psychologists have long been aware of this issue, and they elaborated on the cognitive-perceptual processes required for the activation of group identities (e.g. Tajfel and Turner, 1979; Turner, 1991). It is not always clear, however, how the theoretical and experimental results apply to complex, real-life situations in which people may be members of multiple groups and subject to multiple sources of influence over an extended period of time.

The research tradition of Social Network Analysis focuses exactly on studying the structure of real-life communities over longer periods. Various empirical definitions for groups have been developed in this research stream. However, most of these concepts are useful for "detecting" groups in a community based on a single network of relations, for example friendship (e.g. Freeman, 1992; Katz, Lazer, Arrow, and Contractor, 2004). By conceptualizing group structure just as one characteristic of a social network derived from a single graph, this approach does not take into account the various other dimensions found relevant for group formation, like interpersonal perceptions or different identities.

How do groups form? What are the characteristics that distinguish groups from a set of actors? How are group boundaries drawn? Why are there many groups in some communities but only a few in others? What determines whether multiple groups are overlapping or segregated in a given setting? It seems that there is no single disciplinary approach which can provide answers to all of these questions. We argue that the key to finding an appropriate framework which may explain the relevant consequences of group formation is focusing on the informal social mechanisms through which groups emerge.

1.2 Groups and status hierarchies

There are two main bases for social differentiation in informal settings: groups and status. As it is discussed in detail in this thesis, we have good reasons to believe that the formation of groups and status systems in communities occur in parallel. Even more than that, they can actually be thought of as two outcomes of the same social process. Accordingly, we argue that by studying how status develops in informal contexts we may be able to identify the key mechanisms behind group formation.

Studies of status hierarchies often do not pay a lot of attention to group formation (e.g. Gould, 2002; Martin, 2009). In cases when the two phenomena are examined jointly, the focus is typically on status differences between the groups (e.g. Schmader, Major, Eccleston, and McCoy, 2001). Some results, however, highlight that group dynamics and status dynamics are closely intertwined (e.g. Adler and Adler, 1995; Eder, 1985).

How can we study status and groups from the same theoretical perspective? What is common in the two phenomena? It seems that they both affect the goal achievement of individuals (see Lindenberg, 1997). On the one hand, being a member of a group alters how fellow group members treat us, at the very least. Over that,

group membership often influences how much individuals of the in-group are willing to consider and contribute to the goals of out-group peers, and vice versa. On the other hand, having high or low status in a community has an effect on how much cooperation a person can expect from his or her peers.

The impact of status on individual goal achievement becomes even more apparent when we consider that it is not only a hierarchical concept. Social roles are also integral parts of ones status (Linton, 1936). They capture a horizontal dimension of the phenomenon: status is not only about being above or below someone, but also about being different. Some people may be good at resolving conflicts in their community and some at helping others with, say, mathematical problems. These two roles are quite different in content, yet the amount of social recognition that comes with them may be identical, depending on how the two activities are valued in the community (cf. Coleman, 1960).

In this thesis, it is assumed that individuals in communities aim to achieve some set of goals (which can include simply the goal of feeling good). Because of this, they are motivated to interact with peers and to subsequently evaluate them in relation to the pursued goals. In reality, these evaluations are coupled with perceptions about characteristics, activities, or social roles of peers. This process is the assignment of status values to observable attributes. Communities may be quite different in how much status they assign to various attributes, but naturally the variation is constrained by the wide-spread beliefs and stereotypes in society (Ridgeway and Balkwell, 1997). In any case, we argue that the informal social mechanisms by which status is constantly (re)produced in a community, contribute to the emergence of groups.

1.3 A multiplex network approach to group formation

The thesis aims to develop a theory of group formation based on processes of status production. In doing so, we need to recognize that status in informal settings is both interpersonal and multi-dimensional. First, each member of a community develops their own views about the status of peers, and these status attributions do not necessarily coincide. In this sense, status is subjective and it is based on the perceptions individuals develop in the course of interactions with others. Thus, status in informal settings can be imagined as a social network in which individuals are connected by ties which represent the status they attribute to each of their peers.

Second, as mentioned above, many different individual characteristics, activities, and roles can function as the observable bases of a status attribution. This means that the status network of a community is multiplex in the sense that multiple types of perceptions can be considered as distinct forms of status. For a general example, a certain individual may find some of her peers smart, others helpful, yet others both smart and helpful. Each of the two types of perceptions will contribute to the status the given person attributes to her peers.

In sum, here we take an approach in which the system of status attributions is imagined as a multiplex network structure connecting the members of a community. Through various social processes, the ties in these networks change over time, and so does the status of individuals. The dynamics of the system can lead to network states in which the status attributions of some members of the community are aligned. This is an essential aspect of group formation. The aim of the thesis is to specify the network mechanisms that lead to the emergence of groups in communities.

1.4 Outline of the thesis

The thesis develops and tests a theory of group formation processes based on a framework of status production in informal communities. The text is organized into six main sections. Chapter 2 discusses the **'Theory and Research Questions'**: it provides a definition for the concept of groups which is used in the thesis, it outlines the conceptual framework of informal status production and, finally, sketches a theory for the emergence of groups. Three main research questions are derived from the theoretical arguments. Each of the questions are examined in one of the empirical studies of the thesis.

Chapter 3, describes the **'Data and Methods'** which are used in the analyses of the empirical chapters. First, the multiplex network panel dataset collected among Hungarian high-school students is introduced, and key descriptive statistics are reported about the two subsamples on which the three studies are based. Second, the statistical methods used in each empirical chapter are outlined: the multiplex network clustering procedure developed in Chapter 4 of this thesis, QAP tests for dyadic data structures, and the Stochastic Actor-oriented Model for network dynamics.

In the first empirical paper, **'Dimensions of peer-perceptions in school: Defining composite network measures'**, we propose and elaborate an empirical procedure for the cluster analysis of multiplex networks. By using this technique, we define three aggregated network measures from 21 peer-perception dimensions in

several classrooms. We show that the new measures may complement the more typical relational items, e.g. friendship and dislike, in studies of the dynamics of adolescent communities.

The second and third empirical chapters focus on comparing the newly constructed network items with friendship networks in the studied classrooms, in order to test certain predictions of the proposed theory. Chapter 5, **'Do friends think alike about their peers? The friendship–agreement link under heterogeneity in student characteristics'**, aims to establish the empirical relationship between peer-perceptions and friendships. The results show that, with substantial variations between classrooms, friends are typically more likely to agree in their positive and negative perceptions about others in the class than non-friends. This is more or less true also between students who are similar along important background variables.

The last empirical study in Chapter 6, titled **'Minority-agreement selection and the circles of influence: The co-evolution of friendships and perceptions in classrooms'**, applies Stochastic Actor-oriented Models to analyze the co-evolution of friendship and perception networks. The results provide some corroboration for the group formation theory formulated in Chatper 2, and they also lead to important hypotheses about selection and influence processes related to perceptions among students. In particular, we find that agreement in positive and negative perceptions contributes to the development of friendships, but especially in cases when two students agree against the majority of the classroom. Further, friends tend to influence each other's perceptions, but the context of the friendship groups they are embedded in moderates this effect.

Chapter 7 collects the **'Conclusions'** from the theoretical and empirical social research presented in this thesis. This final section provides a summary of the key contributions of the study, and highlights some limitations of the analyses, with future directions for development. Finally, an agenda for future research is presented for the further development of the ideas and models the current research could only start working on.

Chapter 2

Theory and Research Questions

Building on a diverse set of research from the disciplines of sociology, social psychology, and the tradition of Social Network Analysis, this chapter develops a theoretical framework of the elemental processes of informal social dynamics. After clarifying the basic concepts, we identify four types of mechanisms by which informal status is produced in the course of interactions between people. These mechanisms operate within individuals, in dyadic, triadic, or higher-order relational structures. It is argued here that informal status production is an essential social process which can be used to explain how groups emerge within communities. Accordingly, we propose a set of micro-level network mechanisms as part of a theory of group formation. Based on key predictions of the theory about the structure of interpersonal networks, we formulate three research questions to be investigated in the empirical chapters of the thesis.

2.1 Groups as subsets of a community

A clarifying discussion about the concept of community and group can be found in Merton's classic essay on reference group theory (see question 1.5 in Merton (1968), chapter XI). He identifies two dimensions of interdependence between people: whether they share common values and goals, and whether they interact with each other. A set of people who neither share common values nor interact, but have similar characteristics is labeled as a *social category*. According to Merton, people who have shared values and goals, but do not interact belong to a *community*. Finally, if both interactions and common values are present, people form a *group*.

The distinction between the three types is theoretically important, because each of them can serve as a reference group for people, however, in different situations. This idea is also present in Social Identity Theory, as social categorization can occur

based on social categories, communities, or groups (Tajfel and Turner, 1979). When explaining the spread of beliefs about status values, Status Construction Theory stresses the importance of interactions in task-oriented groups, but also provides a link between social categories and perceived task-relevant attributes (Ridgeway and Balkwell, 1997). Lastly, Self-categorization Theory and Social Comparison Theory, through their interest in influence processes, are more focused on groups as defined by Merton (Turner, 1991:155–160; Festinger, 1954).

Despite the enlightening categorization, one case seems to be missing from the typology. The difference between community and group in Merton's understanding is whether shared values and goals are paired with interactions or not. The stronger emphasis on values than interactions may be rooted in the functional approach of reference group theory and the other above mentioned theories: social and psychological processes are studied in relation to group goals which require a shared understanding of social situations and relations (values, norms) to be reached.

However, in principle it is also a possibility that a set of people regularly interact with one another (for example, because they spend much of their time in a shared space), yet do not have shared values or common goals. Of course, this would not mean that subsets of people in such social formations cannot have their distinctive goals and values. On the contrary, this case is theoretically interesting exactly because it allows the consideration of how group norms, values, and goals emerge from interactions between people who share a social setting. A specific mechanism related to these processes is studied in Status Construction Theory, but without accounting for the effects of beliefs on the pattern of interactions.

In order to complete Merton's classification, we need to distinguish between two types of communities. We may call a *value community* the already existing category, a set of people who share goals and values without interacting with each other. An example can be the community of professionals, e.g. masons, who work for the same end, have similar ideas and beliefs about their profession and how it should be conducted, have a sense of belonging to this community, but do not interact with each other on a regular basis.

The new category, *interaction community* (it could also be called a spatial community, where 'space' can be defined flexibly) refers to a set of people who do not have globally shared values or goals, but who interact with one another regularly. In summary, taking into account both interactions and shared values among people, we can derive four socially meaningful types of formations: social categories (no interaction, no shared values), value communities (no interaction, shared values), interaction

Table 2.1: The different concepts of reference group.

		Shared values and goals	
		No	Yes
Presence of interactions	No	Social category	Value community
	Yes	Interaction community	Group

communities (interactions, no shared values), and groups (interactions, shared values) – as presented in Table 2.1. From now on, we focus our attention to interaction communities (or simply communities for brevity) and groups.

In the present approach, a community is a set of people who have the opportunity to regularly interact with each other because they share a social setting (for instance spend time at the same location), but who do not have shared goals and values that can be the basis for collective action. Groups may exist within communities, containing a subset of its members who also have accepted, common values among themselves. Our inquiry is related to how these shared values develop within the community, which is equivalent to asking how groups emerge. Here we assume that the formation of groups is endogenous, a result of multiple social processes operating between people within the community. The aim of the theoretical work is to systematically identify the most important mechanisms related to group formation.

2.1.1 Informal interaction communities

As described so far, we investigate the formation of groups in the context of communities whose members share a social setting and so have the opportunity to interact with each other, but do not have collectively shared values or common goals. To be able to identify the generic endogenous social processes related to the emergence of groups that operate within these communities, it is necessary to abstract away from a set of characteristics of real-world interaction communities.

In most realistic social settings (at a workplace, for instance), interactions and relationships between individuals are affected by formal conditions, such as institutional hierarchies or externally determined collective goals. Studying how these factors influence or constrain spontaneous social interactions within a community is important in its own right, but it leaves us with the question of how things would have happened in the absence of the specific formal conditions. Therefore, to better

understand the endogenous processes of group formation, we shall assume momentarily that exogenous formal constraints do not exist and focus on communities that are purely informal.

The ideal type of an informal community is a community in which all social outcomes are results of endogenous mechanisms involving its members. The most important assumptions about the features of informal social settings are, therefore, the following:

- rules, norms, goals, and actions of the members are influenced solely by the sequence of interactions with other actors in the community and their consequences (this is the general definition of 'purely informal');
- there are no formal, globally acknowledged goals that are exogenous to this interaction process (theories about groups quite often assume such goals); this does not mean that individual actors cannot have goals, in fact they can have multiple goals as long as they are not formally imposed on them;
- there is no formal hierarchy in the community (no positions or formal power differences);
- the probability of interactions between community members are not affected by exogenous constraints, interactions are purely voluntary and depend on actor decisions; differences in interaction probabilities are still allowed if they emerge from endogenous processes;
- the content of interactions between members, what is happening when they meet, also depends only on the actors.

The only exogenous constraint on the ideal type of the informal community comes from the definition of interaction communities: members are required to spend a significant amount of time together, sharing the same social setting. This assumption is necessary to ensure equal meeting opportunities by default, the possibility of observing the behavior of other members even if one is not directly involved in an interaction, to allow for the endogenous evolution of norms and value systems (the ability to "act as a group"), and to make the community an important part of the social life of its members.

Naturally, purely informal communities are difficult, if at all possible, to find in real life. It is nonetheless useful to compare existing social settings to the ideal type

in order to see to what extent informal social processes may be altered by exogenous conditions.

There are a number of communities people usually become members of for a shorter or longer period of time, and which are close to being purely informal. For example, a school community or a classroom of children approaches many of the above mentioned criteria. Obvious deviations are a high level of academic achievement that usually appears here as a formally endorsed goal, or certain behaviors and norms which are enforced by teachers, parents, and the school, thus altering the goal structure and informal social activities of students. Still, thinking about one's school years, the constraints set by the different authorities still leave plenty of space for informal social interactions in school communities – and adolescents often seem to aim at minimizing the effects of these constraints.

Further, a workplace community can also get close to the ideal type of informal community, given there is room for relationships to develop voluntarily between colleagues, there are out-of-work activities organized for employees, or there is an opportunity for them to organize these events for themselves, and so on.

Of course, interactions at work-related social settings are strongly influenced by formal goals, and the formal evaluation of one's task-related achievement can have effects on his or her informal relationships or social standing in the community. Formal hierarchy is also a common feature of the workplace, which sets constraints on informal interactions and relationships, for instance in the form of rules or policies governing relations between employees and their superiors. Simply the fact that superiors have formal power over employees may alter their behavior in interactions compared to the case where this power is not present.

Despite the work-related constraints on social processes, there can still be ample opportunity for people in these social settings, especially those close to each other in the formal hierarchy, to interact freely and develop their own norms, values, and behavioral patterns. A classic sociological example showing the importance of informal community at the workplace is the Bank Wiring Room study discussed, among others, by Homans (1950).

A third example for an everyday-life community that is close to the purely informal type can be a hobby sports team. In this case, the absent shared goal criterion can be violated as good team performance in, say, amateur league games is definitely a common goal for such a community (its complete rejection even questions membership). This fact can strongly affect informal interactions and hierarchy: abilities, skills, performance, and showing willingness to sacrifice one's time and energy on

training to reach the common goal presumably have an influence on who is a valued member of the community.

However, in non-professional teams the identification with the performance goal may not be uniform, some members' primary goal in the community can be simply to do sports, feel good, or meet friends. The more a team has this "hobby character", the closer it is to a purely informal social setting with respect to goals and valued characteristics.

The line of examples could be continued indefinitely. What is important at the present point is that the different social settings or communities in which people take part can be more or less close to the ideal typical informal community. While the formal contextual conditions in which communities exist definitely alter the informal social processes operating between their members, it is still important to have a theoretical idea about how social mechanisms could unfold in the absence of these exogenous conditions.

In the following we explore some basic informal social processes, especially those that can be linked to group formation within communities. For this, however, we need to clarify what we mean by "group" and to set up a framework in which we can efficiently theorize about informal social processes.

2.1.2 Groups embedded in communities

After outlining the type of communities the present study focuses on, we now turn to discussing some characteristics of groups that distinguish them from communities. In our approach, a group is a social formation embedded in a(n informal interaction) community, involving a subset of the community members. As already noted, what differentiates a group from the rest of the community surrounding it is its members having shared goals and values.

Although we assume that every member of the community has the opportunity to interact with the other members (since the theoretical context of the group is an interaction community), this still allows groups to distinguish themselves from the rest of the community not just by sharing specific values and opinions, but also by interacting more frequently or in different ways among themselves than others in the community do.

The loose definition of the group naturally allows it to take various forms. The extent to which a group has shared values (or is perceived by non-members to have shared values) and the intensity of interactions between its members can vary. Whether group membership is salient may also depend on the contrast between value

similarities and cohesion within the group relative to the rest of the community, as reflected by the idea of "meta-contrast" in Self-categorization Theory (Turner, 1991).

The salient distinction between cliques and crowds in peer culture exemplifies the diversity of characteristics groups may hold. In the case of cliques a group becomes salient because its members have close relationships and frequently interact with each other, while in the case of crowds the group is mainly defined based on characteristic values or behaviors of its members (Brown, 1990) – although the latter case does not exclude the opportunity for more frequent interactions between crowd members (Urberg, Değirmencioğlu, Tolson, and Halliday-Scher, 1995).

Despite the large variety of social formations we may call groups, there is an important common feature that qualifies social formations as groups: they present a point of reference for actors, sometimes even for non-members, and therefore have an influence on behavior.

The extent to which groups have an effect on individual behavior depends on certain functional characteristics. The structure of interactions, the level of cohesion, closeness (Pearson and West, 2003), or integration (Adler and Adler, 1995), may be related to pressures towards conformity (Gavin and Furman, 1989) within the group. Given that conformity also leads to rejection of group members who deviate from shared values (Festinger, 1950), an agreement in the evaluation of others (shared perceptions) is also expected to emerge within groups with high conformity pressures.

Further, the strength of group boundaries, "permeability" (Gavin and Furman, 1989) or "exclusivity" (Adler and Adler, 1995), can greatly affect the interactions between group members and non-members. Finally, a vertical hierarchy, the presence of leaders within the group may also influence the group's control over the behavior of its members.

The presence of various forms of groups in communities can be related to the fact that groups are not static formations: they emerge, grow, shrink, break up, dissolve. This is due to the fact that the group is an endogenous phenomenon: it is emergent from the informal social processes operating within a community.

Accordingly, group boundaries which determine who is a member and who is not may not always be clear, either to the actors themselves or to outside observers. Differences in ideas about who belongs to a certain group and who does not may be connected to the different positions of actors within the community.

Some empirical work has identified three levels of group membership actors may hold: the group member, the peripheral, and the isolate (Henrich, Kuperminc, Sack,

Blatt, and Leadbeater, 2000; Pearson and Michell, 2000). For example, for a peripheral actor membership in a group may appear as a relevant, characteristic feature in his social life, while more central members of the same group or non-members might not see him as belonging to the group at all. This is again related to the concept of "meta-contrast" (Turner, 1991), as different social positions provide different "views" on the community structure and, therefore, actors can develop distinct notions about group boundaries. Finally, just as membership in a single group is not necessarily self-evident, actors can also be members of multiple groups at the same time.

What is behind the group boundary problem and multiple group membership in informal social settings? Are they simply results of different evaluations of actors about someone's social position? Are they related to the contrast effects on the perception of social position mentioned above? In the presented approach, we view these phenomena as emergent from a series of social events that trigger changes in interpersonal attributions and interaction probabilities between community members. Identifying the core processes related to group formation may help us explain the puzzles of group membership. Here we argue that developing shared perceptions about other members of the community through a series of interaction events is a key process related to group formation.

2.2 The community as a system of interdependences

Based on an exhaustive review of research on groups in sociology and social psychology, Lindenberg (1997) argues that we may understand "group" processes (in our definition: social processes within a community, which can also be related to group formation) as an interplay between three types of interdependencies between actors: structural, cognitive, and functional. Structural interdependence refers to the interactions between community members. Cognitive interdependence relates to actors interdependently evolving their perceptual ideas about the world, the community, its members and the social context. Lastly, functional interdependence captures the fact that group members depend on each other in achieving their personal or collective goals.

Lindenberg argues that the integration of the three interdependencies may help us in better explaining group processes. He goes on to state that a significant part of theorizing about groups in social psychology, especially in Social Identity Theory and Self-categorization Theory, sees the essence of the group being a "cognitively mediated functional interdependence" between its members, as they focus on the

connection between cognition (group identity, perceptions) and goal-related behavior. He also argues that Expectation States Theory (and we may add that its offspring, Status Construction Theory) achieves to link all three interdependencies: perceptions mediate the usefulness of actors for goal achievement in groups, and this process is embedded in interactions and meeting opportunities.

Although there is definitely a point in saying that theories about groups in the mentioned research traditions do not explicitly incorporate ideas about the structural interdependencies between actors, they do have implications for social interactions, as these are both the inputs for and the outcomes of cognitive-functional processes. In fact, the relevance of the schema of "cognitively mediated functional interdependence" comes from the fact that it explains how cognitive processes affect the behavior of actors, including their actions directed to others.

For example, Social Identity Theory seeks to explain, among other things, in-group preference and intergroup conflict which are certain aspects of the structure of interactions between actors. Social confirmation in Social Comparison Theory is based on the expression of opinions that naturally occurs in interaction situations. Opinion expression appears as an important step also in certain processes covered by reference group theory and Self-categorization Theory.

Therefore, it appears that instead of "cognitively mediated functional interdependence" we should talk about "cognitively and structurally mediated functional interdependence": the goals of actors determine their salient cognitions, these cognitions influence actions which in turn contribute to goals through goal achievement (Figure 2.2).

The presentation of the relations between the three interdependencies in Figure 2.2, however, still ignores the fact that goals, cognitions, and interactions co-evolve, and so it is not meaningful to focus on one of the interdependencies without taking into account the other two. The further clarification of the meaning of each interdependence leads to a more refined view on the interrelations of functional, cognitive, and structural dimensions of group processes.

First, functional interdependence means that people have goals and they need others to achieve them. How much goal achievement is possible depends on what others want, so on their goals. There is a clear value in thinking about functional interdependence on its own, as it was already shown by Thibaut and Kelley (1959), given goals are predefined. However, in reality people often need to find out what kind of goals others pursue, which they can do through interacting with them. That is, the interdependence of goals is only realized through interactions – in which cognitive

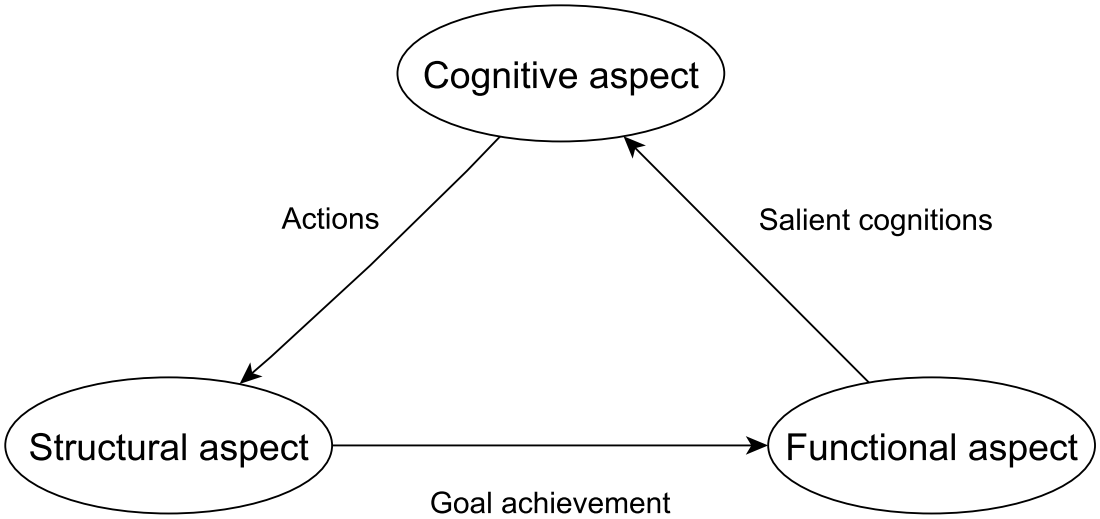

Figure 2.2: The model of cognitively and structurally mediated functional interdependencies.

processes also have a major role (perceptions about other people's goals). Ultimately, there is a cognitive feedback on the goals of actors: the cognitive processing of interactions reveals the possibilities for achieving certain goals, given the presence of others, and may alter the goals of individuals.

Second, structural interdependence can be simply put as what people do (act, communicate) depends on what others do. Again, to some extent it can be thought that these interdependencies between actors are self-containing, as in an actor's actions may alter the opportunities for actions taken by other people. Still, it can be argued that there must be a cognitive process that mediates between the actions of one actor and another – without such a mechanism we would have no clue about how actions are interdependent.

Furthermore, the motivation for action is provided by the goals of the actors. The question of which action should be taken in a given situation is answered by the combination of goals and ideas about actions that promote goal achievement. In other words, the explanation of intentional action (e.g. von Wright, 1971) requires reference to goals, perceptions, and actions at the same time.

Finally, cognitive interdependence refers to the phenomenon that what people think (about the world, each other or a situation) depends on what others think. As argued above, this interdependence cannot be separated from the structure of interactions which provide actors with information about the perceptions and goals that others have.

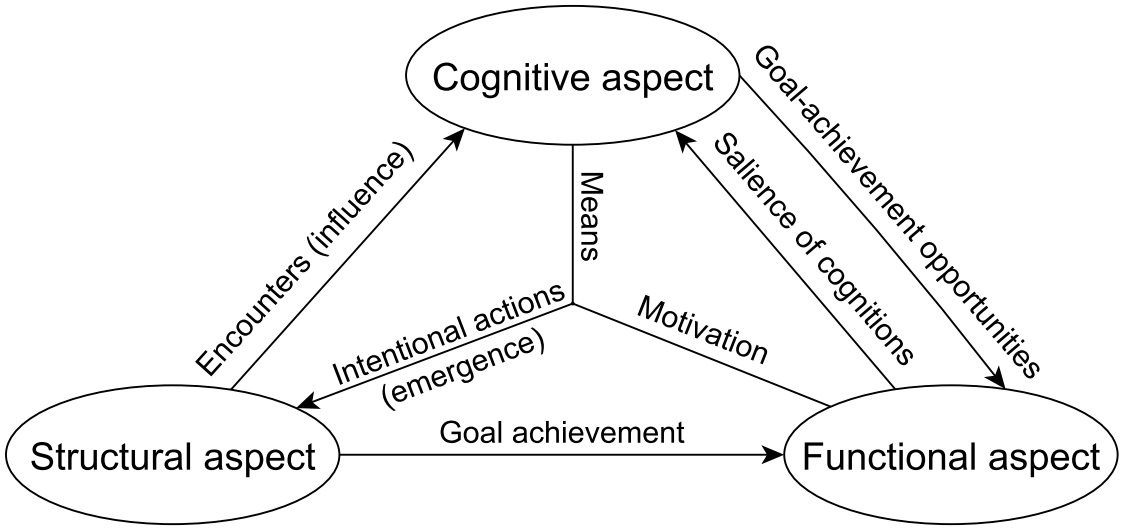

Figure 2.3: A more complete model of interdependencies in communities.

In summary, it can be argued that none of the three interdependencies can really operate on its own, without being mediated by the other two aspects of interdependence between actors. There is a dynamic interdependence between the interdependencies, but studying them separately or two at a time can easily obscure this. As a result, we may update the schema presented earlier as shown in Figure 2.3.

Within each actor, the functional and cognitive aspects interact: goals provide clues for selecting perceptions that are informative for goal achievement, and perceptions about others and the social situation provide the information about the opportunity for goal-achievement in a given setting. Goals provide the motivation for action, while cognition finds the means through which goals can be achieved. The combination of motivation and means leads to intentional action.

Goals and perceptions of an actor become emergent, observable to others through his or her actions. In case others do observe them, in some kind of social situation, an interaction or encounter, it can influence their perceptions (for instance, about the actor who just did something). As a consequence, functional and cognitive interdependence are generated through the mediation of interactions. Ultimately, the social actions of actors will contribute to their own and others' goal achievement. Here we argue that a theory that seeks to explain group processes should be able to accommodate the dynamic relations between the different interdependencies within communities.

2.2.1 The three building-blocks of social interdependence

From the above interpretation of interdependencies in communities it can be derived that the "building blocks", the units that represent each aspect of social processes have distinct characteristics. The functional aspect can be expressed in terms of the goals actors pursue, structure can be represented by relational events that occur between actors, and the cognitive aspect can be built up from relational states between them.

Accordingly, each aspect has its own "carrier", the smallest considered unit of analysis that expresses the given interdependence existing between the actors. Structural interdependence is carried by *interpersonal actions* (actions of an actor directed to another in interactions or encounters), cognitive interdependence by *interpersonal attributions* (the different perceptions actors have about the others), and functional interdependence by *status values* (the value or worth of actors for each other in achieving their goals).

The choice of the word "carrier" may seem odd at first when talking about attributions, status values, and social actions, but it represents the idea that interdependence is not something that simply exists between actors – it needs to be carried from one individual to another in order to have its effect on their behavior, to actually appear as interdependence.

In other words, the social forces that bind people together operate through the joint evolution of the qualities they attribute to each other, their ideas about the worth of these qualities for the achievement of their goals, and the interactions in which these ideas are expressed in social action.

On this point, we agree with Lindenberg's view that theories of social processes in groups (in our case: in communities) should aim at understanding the interdependencies of interdependencies (Lindenberg, 1997). In the present formulation, his proposition means the study of how interpersonal actions, interpersonal attributions, and status values are jointly generated, how they co-evolve in a community. Here we attempt to achieve this goal by building a theoretical framework of informal status production.

2.2.2 Forms of interpersonal attributions, status values, and interpersonal actions

In the previous section, we introduced the concepts of interpersonal attributions, status values, and interpersonal actions as the carriers of the three general aspects of interdependence that tie members of a community together. To bring these concepts

closer to empirical reality, still in the context of informal interaction communities, we distinguish between different types of attributions, status values, and actions.

The classification offered here is not meant to be complete or conclusive, at the present point it mainly serves the purpose of clearer understanding. It is to be noted that although we imply certain connections between the different types of attributions, status values, and actions, the correspondences between them are not exclusive in reality due to the fact that social situations are often multifunctional from the perspective of goal achievement of actors, as it will be treated in more detail in the following section.

The necessity of introducing distinct types of attributions, status values, and actions can be best shown through an example. Imagine a student, who we can call Ego, attending high school. Ego is not particularly good at maths which is nonetheless an important subject in the curriculum. He learned from bitter experience that getting bad grades in math adversely affects his opportunities for reaching important goals: his parents will be mad at him, his valuable free-time must be sacrificed to study more, and his teachers will judge his other activities in school in relation with his poor performance.

As a result, Ego realized that an effective way to get better grades in math and avoid these consequences is to rely on the help of his peers. But who should he turn to for help? He thinks that an other student in his class, Alter, is a smart person who has shown good skills in mathematics. This perception about Alter creates a potential that Alter might be of higher value for Ego in achieving his goal of better grades than others would be. This is only a potential, because Alter needs to actually help Ego for him to realize his goal, and it is not certain that she would. Despite this uncertainty, Ego needs to get better grades and the potential of Alter to act as a helper (due to her qualities) will encourage him to initiate an interaction with her.

Such an interaction, although instrumental for goal achievement, is primarily of an exploratory nature – Ego needs to find out whether Alter is actually willing to help him (e.g. by asking for only a little help from Alter or by casually bringing up the topic of math in conversation). The reaction of Alter to Ego's action will affect Ego's perceptions about Alter (she was nice and helpful or she was rude and dismissive), which may change her value for Ego in achieving better grades (increase or decrease in potential to help).

The story of Ego seeking help from Alter in math can also be told in a slightly different way. Either because Ego had a series of positive interactions with Alter or because he witnessed Alter helping others in math, he may think that Alter is in a

role of "the one who helps others with math problems". The attribution of the social role also generates a potential that Alter can be valuable for Ego's goal achievement, perhaps even more than the perception of mathematical skills did in the previous case.

Most importantly, however, the potential now is proven, the uncertainty of Alter's value for goal achievement is reduced, because she has already expressed willingness to help Ego or others in the past. This way, in the interactions between Ego and Alter the exploratory element becomes less important for Ego (in relation to the goal of better math grades), and his actions directed to Alter can be focused more on the purpose of the action: he may just simply approach Alter and directly ask her for the help he needs.

The story can still evolve further from here: in the course of repeated interactions, Ego may develop affection to Alter due to her high value for his goal achievement (which is intertwined with learning about additional traits, abilities, roles of Alter through the interactions). Affection may also be connected with a sense of Ego that Alter is in general of high value for him, which may bring an element of care into their interactions: Ego's actions towards the achievement of better grades can be suspended to allow more focus on Alter's goal achievement in the interaction.

Naturally, for such a relationship between Ego and Alter to develop, both parties' actions are crucial in the sequence of interactions. Although we concentrated on Ego, this note applies to the entire example. It should also be noted that above we focused on Ego's pursuit of a single goal (getting better grades in math) through his social interactions with Alter. While it is completely reasonable to think that very often multiple goals lie behind the social actions of people, we only turn to discuss this issue in the next section. Until then, it is sufficient to keep in mind that our example could be told in numerous different ways in which the interrelations between goals are taken into account. However, remaining simplistic with regards to the goal structure of Ego allowed us to demonstrate simply the qualitatively different forms interpersonal attributions, status values, and interpersonal actions may take.

Based on our example of seeking help, we can outline the types of attributions, status values, and actions that are distinguished in the present analysis (Table 2.4). Interpersonal attributions are considered to be perceptions of actors about traits, abilities, or skills of others, social roles actors may attribute to others, and feelings of affection towards others. *Trait perceptions* are thought to be constituted by multiple perceptual dimensions that represent whether an actor thinks that one of his peers

Table 2.4: Types of interpersonal attributions, status values, and interpersonal actions.

Interpersonal attributions	Status values	Interpersonal actions
perceptions of traits, abilities	potential	exploratory action
attribution of social roles	proven potential	purposive action
feeling of affection	general worth	caring action

possesses a certain trait, ability, or skill (e.g. being smart, being good at math, being nice or rude).

The attribution of a social role represents a set of expectations for the behavior of a peer in certain situations, where roles usually have some kind of collective function – this is an approach to roles that appears already in Linton's work (Linton, 1936). It is apparent from the previous example that social roles can be dyadic or collective: there is a difference in whether Ego expects to get help in math from Alter because he thinks Alter is "the one who always helps me with math problems" (*dyadic social role*) or "the one who always helps everyone in the class with math problems" (*collective social role*).

By *feelings of affection* we refer to sets of emotions that are linked to peers, such as comfort, liking, love, hate. We argue that the different types of interpersonal attributions influence social actions of actors only if they are coupled with values representing their usefulness, which may be positive or negative, for the achievement of the goals actors pursue in a situation.

The *usefulness of others* for goal achievement can be expressed in terms of status values, which again only affect social action in combination with interpersonal attributions. The overall status value of a peer to an actor is the aggregate of the usefulness of the peer in goal achievement as derived from the various interpersonal attributions the focal actor has to this peer. In this sense, status values place peers into a hierarchy based on their relations to goals: in a given situation, some may have a high value, others may have a low value for an actor's goal achievement.

Apart from this hierarchical component of status values, they can also take qualitatively different forms if we consider the uncertainty of goal achievement. A status value can be a *potential* if an actor thinks that a peer has the ability to help him reach his goal, but it cannot be guaranteed that the peer will do so. This may most often (but not exclusively) be the case with perceptions of traits or abilities.

The second form of status values can be called *proven potential* as in this case, the actor has some kind of proof (experience, observation) that the potentially useful

peer will actually help him (or not) to achieve his goal, and so the uncertainty related to goal achievement is reduced. Social roles (not exclusively but) in many cases may be the interpersonal attributions linked with proven potential.

Lastly, we can distinguish a third type of status values, which may be labeled as *general worth*. This form pertains to cases where an actor has such a high general certainty that a peer would help him achieve his goals that the actual potential of the peer related to the specific goal that is pursued becomes irrelevant. This type of status values may be related most closely (but not solely) to feelings of affection.

The combination of different interpersonal attributions and status values, while also affecting actors' propensity for social action, may lead to the emphasis of distinct motifs of action in social interactions. First, Newcomb (1961) thoroughly studied the role of "scanning" in interactions by which individuals get to know one another. Referring to a similar process, Leifer (1988) used the term *exploratory local action* for the strategic behavior of actors in interactions by which they aim to occupy high-status roles while avoiding to get locked into their low-status complementary roles. In his argument, actors take cautious, small steps of social action in order not to hand over the opportunity of taking a beneficial role to their interaction partners.

Although we do not assume strategic behavior on the part of actors, the ideas of exploratory action and "the acquaintance process" fit into the present framework: in interactions, actors are able to test the potential usefulness of peers for goal achievement, to validate or refute their beliefs about the connections between attributions and status values, and also to learn about earlier unknown traits, abilities, or skills of their partners. As a consequence, exploratory action is probably most important when trait and ability perceptions and potential motivate interpersonal action.

The second form of interpersonal action can be labeled as *purposive action*. The use of the term is motivated by Merton's classic essay, *The Unanticipated Consequences of Purposive Social Action* (Merton, 1936), in that this type of action is primarily focused on consequences, in our case the actual achievement of goals. When this aspect of interpersonal action receives high emphasis in an interaction, actions become solely directed toward goal achievement, just as in the second part of our example when Ego simply and directly asked Alter to help him. This highlights that the dominance of purposive action in a situation is most likely to lead to goal achievement when the partner's potential is proven, so probably in the cases when action is directed by social role attributions.

The third type of interpersonal action considered here may be called *caring action*. This represents an element of social action that focuses on the goal achievement of

the interaction partner instead of that of the actor. The emphasis on this form of action in an interaction can be viewed as most characteristic of actions motivated by feelings of affection and high general worth: an actor may temporarily suspend the pursuit of his on goals to assist a peer who is valuable to him in general, as a person. This process can consequently serve the function of the endowment of highly valuable relational partners.

Throughout this section, we implied that there are some direct correspondences between the types of interpersonal attributions, status values, and interpersonal actions which were introduced. For instance, we mentioned that exploratory action may be motivated by perceptions of traits and abilities together with a potential as a status value. Further, the example of seeking help at school depicted the three-three forms of attributions, status values, and actions in a hierarchical order, assuming for instance, that feelings of affection are in some respect at a higher level than perceptions of skills.

The suggested connections between the discussed concepts may hold to a certain extent. For example, it sounds sensible that a perception emerges easily, while the development of a role attribution or affection requires time and a sequence reinforcing interactions. However, at present we do not wish to formulate expectations about the interrelations between the presented notions. This is primarily because in reality these types do not appear on their own. As actors pursue several goals at once, a social situation can be relevant for them for many distinct reasons, and therefore the different types of attributions, status values, and actions can appear as a mixture in actual interactions. We briefly discuss this issue in the following section.

2.2.3 Goal structures and goal frames

The concept of individuals' goals is central to our theoretical framework. In the present approach, goals determine the status values that an actor links to specific perceptions, and also the salience of a set of perceptions in a given situation. The couplings of perceptions and status values can be imagined either as more stable cognitive structures, such as beliefs or stereotypes, or as ones that are likely to change from situation to situation as a result of the informal social processes discussed below. It is also important to emphasize that although we assume that individuals aim to reach various goals, these attempts are not necessarily conscious. In fact, as we elaborate in this section, goals are often complex cognitive structures themselves, which the actors may not directly or consciously use and control at all times.

There is a broad literature to rely on when thinking about the goals that people tend to pursue in social situations. In social psychology and sociology the commonly assumed general goals include, for example, self-evaluation (Festinger, 1954); identity verification (Burke, 2004); physical and social well-being (Ormel et al., 1999); or safety, effectiveness, and status (Kadushin, 2012). Instead of committing ourselves to one or more of these goal ideas, at the present point we are concerned only with goal structures, that is the connections between the different goals, and ideas about how people pursue their goals in actual social situations.

Ormel et al. (1999) present a hierarchical goal structure in which the universal goals of people are the achievement of physical and social well-being. These goals are reached, they argue, through the pursuit of second-order instrumental goals: comfort, stimulation, behavioral confirmation, affection, and status. The second-order goals in turn can be achieved by different activities, and the opportunities for engaging in goal-relevant activities depend on the resources available (see Ormel et al., 1999:67 for an overview). This work is relevant for us because it emphasizes the hierarchical nature of goals. We should always be aware that specific, lower-order goals may drive the actions of individuals in a given social situation, however, these situational goals often are instrumental for the achievement of the same higher-order goal (this is also related to the concept of goal chains – see e.g. Lindenberg, 1976).

The idea of goal frames (Lindenberg, 2008; Lindenberg, 1997) provides an additional element for understanding how goals are pursued by individuals in specific situations. The key aspect here is that social situations activate goal frames in which different goals become focal. The other goals, however, do not disappear, they are just pushed into the background, waiting for situational cues to activate them. For the present analysis, this means that the interpersonal attributions that do not have a status value in a given situation are still relevant, because they can take on a value anytime when the framing of the situation changes.

Finally, it is closely related to the structure of goals and goal frames that certain activities can be multifunctional for goal achievement Ormel et al. (1999), meaning that one activity can contribute to multiple goals. Similarly, social interactions and relations can also be multifunctional in some sense. In interactions where actors seek to achieve multiple goals, the associations between attributions and status values pertaining to each of the goals may become decoupled and new associations may be established.

For example, in the case of getting help in a math homework while also enjoying the company of the helper, which attribution has a higher status value: the fact that

the other is a good conversational partner or that he or she is helpful in solving the given problem? And isn't it possible that in the end both attributions will contribute to both the immediate social and problem-solving goals? Just as interactions can serve the achievement of multiple goals, relational partners can also be multifunctional. The fact that certain peers can contribute to the achievement of several goals of an actor will make them valuable for him or her in many different situations, and may ultimately have a high general worth for the focal actor. These multifunctional situations may underlie the development of intimate relationships, such as friendship.

2.3 The dynamics of the community: informal status production

So far, we have elaborated a conceptual framework in which interdependencies between members of a community are realized through interactions in which people perform different social actions. Their actions are directed to their peers and are motivated by the combination of interpersonal attributions and status values that they assign to each peer. Those attributions and corresponding status values are salient for an actor in a situation that are relevant for the achievement of his or her focal goals. From this framework, we can derive a simple and intuitive definition of informal status and we can also theorize about how status is produced in interactions between community members. Through informal status production, we aim to formulate hypotheses about processes that can be linked to group formation within the community.

2.3.1 What is informal status? Status attributions

The building block of informal status is an informal status attribution which is defined as a valued interpersonal attribution, or in other words, an interpersonal attribution with a status value. Dyadic informal status is then the aggregate of all status attributions from one actor to another. Finally, the informal status of an actor is the aggregate of his dyadic informal statuses over all of his peers. These definitions already tell about several characteristics of informal status.

First, status attributions motivate social actions: they provide the link between goals and actions related to goal-achievement. This also means that an interpersonal attribution that does not have a status value cannot be considered as a status attribution. For example, an actor can think that a certain peer in his community is an

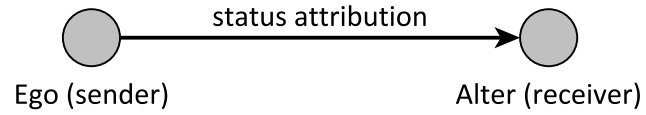

Figure 2.5: Network representation of a dyadic status attribution.

excellent athlete, but if this quality does not have any value for the achievement of his goals, it will not alter his interpersonal actions directed to this peer.

A good objection can be raised against this argument: in reality, people do tend to acknowledge the status of others even if they do not personally value the skill or activity which it is based on. This means accepting the high status of athletes when one is not at all interested in any sport activity, and acting according to this status attribution (e.g. behaving very politely with athletes). At the current point in the argument, we can reply to this objection that athletes may not be popular solely for being good at sports. It is easy to imagine that the role of athlete is associated with other attributions, such as being good looking, strong, cool, and some of these may have a value even for people who are not involved in sports. Thus, the status they attribute to good athletes is not a result of the acceptance of the values of others, but of some unconsidered although relevant elements in their attributions to athletes. The framework of informal status production will also provide some leads to how associations between different attributions can develop.

Second, informal status is essentially perceptual and subjective: it depends on what people attribute to their peers and the values they associate with these attributions. This does not place informal status at odds with other, more objective status definitions, such as control over scarce resources (e.g. Ormel et al., 1999), or positions (e.g. Martin, 2009; Gould, 2002), since a resource or a position can represent informal status if a) others attribute the control over the resource or the position to the actor (if they perceive the control), b) the resource or position in question has a value for others related to their own goals.

For condition a) to make sense we need to highlight that informal status is not primarily about what people can do, how they can use their power, if they have a high status (for which the perceptions of others may not be necessary). It is more about how much people can realize their goals from the social actions directed towards them which are motivated by their high status (their value for the goals of others in the form of specific attributions). In this framework of status, scarcity of a resource or a position can still mean an advantage in goal achievement for those who control it.

A third characteristic of informal status is that, above being something that originates in individuals, it is dyadic and has a sender, Ego, who attributes status to the receiver, Alter (as presented in Figure 2.5). Above the level of the dyad, the structure of the informal status system in the community can be represented by a network of dyadic status attributions directed from every actor to each of their peers. If we consider the several, context dependent attributions that give situational content to status attributions, the status system can be viewed as a set of multiplex networks.

2.3.2 The dynamics of informal status

It can be apparent from the discussion so far that in the present approach, informal status, defined as the aggregate of dyadic status attributions directed to an actor, is essentially a dynamic phenomenon. Although it makes sense to study the actions made possible by status at a given moment in time, every action taken by an actor has the potential to change his status – which can happen to the extent that the action affects the goal-related worth and interpersonal attributions directed to the actor by others. In addition, the view on informal status as a network of dyadic status attributions in a community points out some of the processes through which a status attribution from Ego to Alter may change.

An important source of changes in status attribution is the change of interpersonal attributions, that is, Ego's perceptions about Alter's traits and abilities, social roles, and the emotions of Ego related to Alter. This is so because Ego's perceptions about Alter in combination with Ego's goals define Alter's goal-related value to Ego, and thus Alter's dyadic status.

Interpersonal attributions can change through several channels. First of all, there may be cognitive processes operating in Ego that affect his or her perceptions, role attributions, or affections to Alter, without any apparent input from Alter or others. These processes can be related to the beliefs or stereotypes of Ego about the connections between different attributions. For example, if Ego finds Alter physically attractive and also thinks that attractive people are usually kind, he may start to think that Alter is a kind person – which may or may not be confirmed by his interactions with Alter, of course.

The second possible source of changes in Ego's attributions to Alter are the dyadic interactions between the two actors. This can occur in two basic ways: Ego may learn about Alter's traits, skills, roles that have been previously unknown to him, and Alter's actions directed to Ego may change. An example for the first case is when

colleagues while discussing work find out that they are both interested in watching football – this mutual perception may increase their value for each other in the achievement of their goals (they cannot only exchange advice about work but also discuss the latest results).

A simple example for Alter's behavior change is when Ego and Alter are friends, but Alter starts to hang out with other people, thereby neglecting Ego. In this case, the lack of willingness to participate in joint activities (perhaps teamed with shame and anger on the part of Ego after being dismissed as a friend) will make Alter less valuable for Ego's goal achievement, and thus decrease his status with Ego. (Note here that the cause behind Alter's behavior change can also be a change in the status he attributes to Ego, which is influenced by the same factors as discussed here.)

Another, third, process which can affect Ego's attributions to Alter is the observation of Alter's behavior and social actions without direct interaction. This can happen in encounters where some actors (including Ego) are bystanders who do not actively participate in the social situation. If Ego and Alter are classmates in school, and Alter has a funny comment in class, Ego may start to think that Alter is a fun person, which may have potential value for the achievement of Ego's goals.

Ego can also observe the interactions between Alter and other actors. If Alter is rude with someone and Ego witnesses it, it can lead to him thinking that Alter is not a nice person. Although both in the last two examples and in the previous case Ego's attributions changed due to learning something about Alter (where "learning" can also mean the confirmation of an already existing attribution), the key difference is that in the present examples, Alter's actions are not directed to Ego, the situation in which they take place is not dyadic.

The fourth process related to the changes in attributions can be relevant in situations where Ego interacts with actors (perhaps more than one) other than Alter. In these interactions, Ego's perceptions about Alter can be influenced by others. An illustrative example for this process is gossiping, where others in the situation may express opinions about Alter (who is absent), which may affect the attributions of Ego to him. The example highlights that influence can also occur in interactions between multiple actors (e.g. group discussions).

With regard to the mechanisms that operate in the situation, this case of attribution change is very similar to the previous in that Ego observes the relationship between some actor and Alter (or at least "half" of it if Alter is not present), which may affect his attributions to Alter. Yet the main difference is that in the encounters where influence can occur, we assume Ego can be prompted for a reaction by

the other actors in the situation. For example, after expressing a negative opinion of Alter, people can ask Ego if he agrees. This possibility means that Ego is not a bystander but an actual participant in these situations, which generates different pressures for opinion change.

Lastly, as a fifth option, Ego's attributions to Alter can be modified by changes related to Ego's goals. According to the idea of goal framing, the importance of different goals for Ego can change between situations. As different attributions may be relevant for achieving specific goals, it is possible that certain perceived characteristics of Alter are salient in a situation framed by one goal, but become irrelevant in another situation which focuses on the achievement of a different goal. This process probably causes short-term variations in Ego's attributions and, thereby, in Alter's status from Ego, because the first goal, for which Alter was valuable, may soon come to frame Ego's social actions again. A long-term effect on the salience of attributions, on the other hand, can be caused by a shift in Ego's goal structure, which can be related to certain goals gaining or losing significance for Ego.

Another effect on attributions to be mentioned here is the change in the associations between goals and attributions. It is possible that Ego's goal structure remains stable, but the attributions which he thinks are relevant for a given goal become different. This may happen either through learning (about which attributions are useful for achieving a goal) or due to the alteration of Ego's beliefs and stereotypes about the links (correlations) between different attributions. Finally, there can be multiple processes behind the changes in goals and goal–attribution associations: they may be modified due to experience, developmental trajectories, decreasing involvement in the community (or the presence of an alternative community), or unexpected life events.

To summarize, we showed that status dynamics driven by changes in interpersonal attributions (perceptions, role attributions, affection) from Ego to Alter can be caused by several social mechanisms. We identified five basic types of these processes, based on which we can say that Ego's status attribution to Alter can be affected by

1. cognitive processes in Ego that link different dimensions of interpersonal attributions and the goal-related value of these attributions,

2. the social actions of Alter in interactions with Ego,

3. Ego's observation of Alter's social actions as a bystander in social situations,

4. the influence of third actors revealing their opinion about Alter,

5. changes in Ego's goals.

All of the presented processes except for the exogenous changes in goals point to a key characteristic of status, namely, that it is constantly generated through a series different social mechanisms operating between the members of a community. Even in the case when only Ego's cognition is involved in status dynamics, his perceptions about Alter and, at least in part, his beliefs about the relevant attribution dimensions result from his participation in the social situations happening in the community.

Processes related to status creation, maintenance, and loss all occur in interactions and encounters, which are endogenous to the community, and in which members participate with the aim of achieving their goals, while simultaneously being in the roles of Ego, Alter, and the "Other". In this sense, status attributions are the results of a social production process.

Based on the idea that members of a community jointly participate in creating status attributions, we shall refer to the collection of social mechanisms related to the dynamics of status as informal status production. In the following, we further elaborate the most important endogenous mechanisms of informal status production and insert them into a single framework. As a foreword, it is important to emphasize, first, that status originates in the collection of dyadic perceptions, role attributions, and affections which in real settings can take different, context-specific forms. Therefore, an important aspect of informal status is that it is multidimensional (or multiplex) from this perspective.

Second, it also has to be noted that the existence of groups in a community can have a large impact on status production, as groups may alter opportunities for meetings between community members, for the observation of actions of others, and for influence. These effects can lead to the development of multiple status systems within the community, whereby the status attributions of group members become aligned and characteristically different from the status attributions of non-members. Due to the potential importance of groups in status production, we focus more closely in our discussion on the mechanisms that can be most closely associated with group formation processes.

2.4 Mechanisms of informal status production

As outlined above, informal status is multidimensional due to the fact that interpersonal attributions can take various forms depending on the social context. Important processes of informal status production take place when an element of interpersonal

attribution (a perception about a trait or ability, a role attributions, or a feeling of affection) appears, disappears, or when its corresponding status value is modified. These production processes operate through social interactions and encounters, hence status production involves all three carriers of interdependence in a community: social actions, interpersonal attributions, and status values.

Based on their dynamic interplay, we can sketch a few basic mechanisms of status dynamics. First we describe the processes operating at the lowest level, within Ego, and then step-by-step add dyadic and triadic/collective mechanisms, resulting in a model of informal status production which can be used as a framework for studying certain social phenomena, such as group formation.

2.4.1 I. Intrapersonal status production: self-influence and attribution salience

In our approach, an actor, Ego, is assumed to have goals which he or she aims to achieve and interpersonal attributions (perceptions, role attributions, affections) of several kinds to other actors, including Alter. For any specific goal, each attribution to Alter has a status value which provides Ego with a piece of information about Alter's potential usefulness for his goal achievement.

In a given situation, the combination of the important, focal goals and goal-relevant attributions determine Ego's evaluation of the value Alter for Ego's goal achievement, as shown in Figure 2.6. The set of Ego's valued attributions about Alter yield the dyadic status of Alter in the Ego-Alter relation. Ego's attributions to Alter can be affected by both Ego's goals and his evaluation of Alter's goal-related value, which represent two intrapersonal mechanisms of status production.

First, Ego's goals have an effect on his attributions to Alter in that they determine what kind of attributions are salient in a situation. Salient attributions are the ones relevant in the achievement of a given goal, that is, they have a positive or negative status value. When seeking to achieve his goal, Ego will consider his salient attributions to his peers. In other words, he will look for peers who in his opinion can help him reach his goal.

For example, if Ego is looking for help in his math homework, salient attributions are being good/bad at math, being helpful or not being helpful in general, and so on. If Ego's goals change, he may look for different attributes in Alter, and as a consequence, Alter's goal-related value will depend on the goal Ego is trying to achieve. It can also be noted, that Ego's attributions can have a feedback on his goals as in the attributes (e.g. skills, abilities) available in Alter carry information

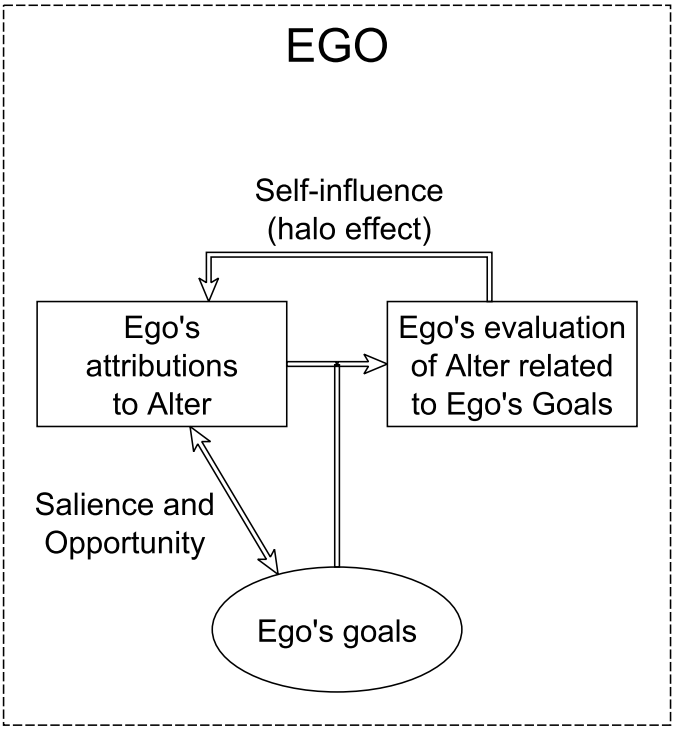

Figure 2.6: Informal status production I. Mechanisms within Ego.

about which goals are possible or most likely to be achieved by interaction with Alter – however, this effect is less important at the moment.

Second, apart from goals, Ego's evaluation of Alter's goal-related value can also modify his attributions to Alter. We label this process as self-influence, because Alter's value is something that is generated by Ego's goals and attributions in the first place. The consequences of self-influence cannot be fully understood without the multiplexity of interpersonal attributions. Since Alter's value originates in an attribution to Alter, self-influence can be understood as the mechanism that produces attributions from other attributions (Figure 2.7). The basis of this process can be provided by beliefs or stereotypes about certain connections between attributes.

A relevant example in the framework of Status Construction Theory is discussed in Ridgeway and Balkwell (1997) related to the emergence of gender stereotypes, where being a man becomes associated with an expectation of high task-related performance. Self-influence can be regarded as the process how such goal-related stereotypes are activated in situations: when Ego perceives that Alter is a man, he finds him valuable for the achievement of the given task; this positive value then activates other attributions that are connected to being valuable for the give task, such as good skills,

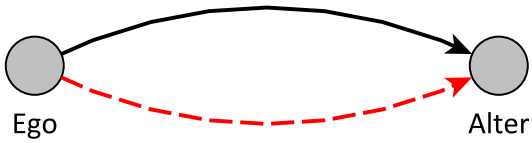

Figure 2.7: The production of an interpersonal attribution through self-influence.

abilities, and so on.

Self-influence is also analogous to the halo effect (named by Thorndike, 1920) known in psychology, the high within-respondent correlations between ratings of a person or object along different dimensions. The halo effect has two main substantive interpretations (Balzer and Sulsky, 1992): it may be caused by beliefs about the relations between rating dimensions, or by the fact that our general impression about someone affects our evaluation of his or her specific traits.

In the informal status production framework, the two halo effects actually become different examples of the same phenomenon. We already covered the first interpretation by the example about gender stereotypes, but instead of schemata we use goals and goal-relevant attributions to explain the connections between different attribution dimensions. The second interpretation can be rephrased along the same line: our general impression about someone is actually an evaluation of his or her worth, that is his goal-related value; if we think that someone is of high value for our goal, this impression will generate specific attributions that are also connected to being valuable for the achievement of the given goal.

The goal-related understanding of the halo effect is also backed by some experiments showing that people's affective response to an object is related to its perceived instrumental worth (Rosenberg, 1956). Therefore, it seems that the idea of the halo effect with a focus on goals and goal-related values is applicable to describe processes of self-influence in our framework.

2.4.2 II. Dyadic status production: interactions between Ego and Alter

Informal status is also produced in interactions between Ego and Alter. Ego's evaluation of Alter's value related to his goals determines the likelihood that Ego will direct a social action to Alter (e.g. initiate an interaction). The specific motivations of Ego's social actions have been discussed earlier.

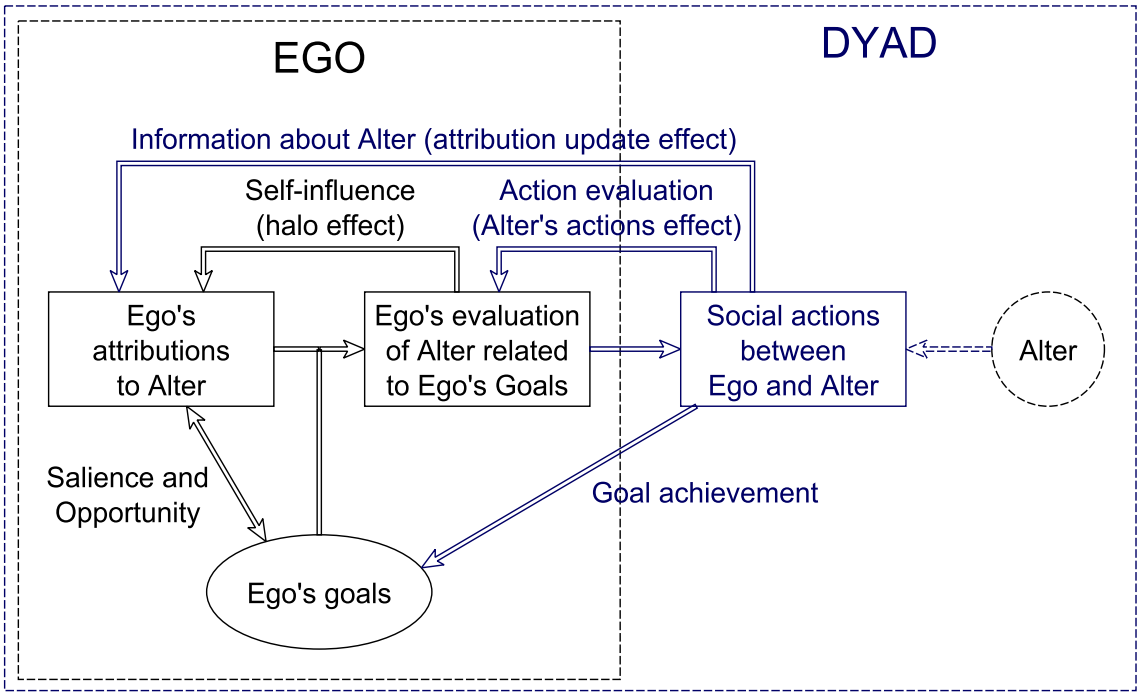

Figure 2.8: Informal status production II. Mechanisms within the dyad (Alter's perspective simplified).

The social actions between Ego and Alter can affect Ego's attributions to Alter in three ways (see Figure 2.8). First, the interaction can promote or obstruct Ego's goal achievement, and thus can restructure Ego's goals (for instance, when if a goal is achieved, another goal can be pursued). In the previous section, we described how the changes in Ego's goals can influence his attributions to Alter.

Second, along with goal achievement Alter's actions provide a feedback on his value for Ego: based on Alter's behavior in the interaction, his goal-related value is re-evaluated (increased, decreased, or left unchanged). This effect can provide fuel for self-influence as introduced previously.

We can find an interesting related example from a school context in Eder (1985). She describes that when girls who became popular abandoned their old friends and started to be dismissive with them in social situations (by not even returning their greetings), these old friends soon developed negative attributions towards the new popular girls (they started to see them as rude, stuck-up, ungrateful, and traitors). This example demonstrates clearly that if Alter does not "live up to the expectations" of Ego related to his goal-achievement, his goal-related value can decrease, which can in turn lead to the emergence negative attributions through self-influence.

Finally, in the course of an interaction, Ego can learn about Alter and develop new attributions and reinforce or dismiss old ones. This process can have far-reaching consequences when the new attribution is relevant for a goal of Ego which is not focal in the situation, but in general important for Ego – as it was the case with realizing common interest in football with a co-worker in work-related situation.

The three process mentioned here can easily be added to the framework of informal status production. If we consider that Alter in fact also acts as an ego in the situation, meaning that he has goals, attributions, and evaluations about Ego, the representation from Figure 2.8 can be further amended by viewing the processes discussed so far from Alter's point of view (presented in Figure 2.9).

2.4.3 III. Triadic status production: emergence and influence

The triad-level mechanisms are highly important in informal status production, because they provide the model for higher-order (collective- or group-level) social processes. When a third actor, let us call him Tertius, is added to the dyad, Ego becomes able to observe Alter's social actions without having to interact with him. (Ego can, of course, observe Alter doing non-social activities, e.g. pushups, without Tertius in the picture, but this is not important for us here.)

In their interactions, Alter and Tertius reveal their status attributions to each other (their reasons for interaction, whether they like each other, whether one asks a favor from the other, etc.) which can change Ego's perceptions Alter (and about Tertius as well, but let us focus on Alter).

The change in Ego's perceptions can occur in two ways. First, he can observe Alter's behavior in his interaction with Tertius, and learn about Alter's traits, abilities, just as previously described. The second process consists of two phases (as presented in Figure 2.10). The status attributions between Alter and Tertius, first, is revealed and perceived by Ego. This phase can be called *emergence*, because dyadic status attributions become visible to the onlookers, and in this sense collective. Ego's perception about the status attributions between Alter and Tertius are technically similar to the Cognitive Social Structures studied, among others, by Krackhardt (1987).

In the second phase of the process, Ego's perception about the status attribution between Alter and Tertius can *influence* Ego's status attribution to Alter (and Tertius) by interacting with Ego's goals, other perceptions about Alter, and Alter's value for Ego's goal achievement. It is important to stress that the state of Alter's status with Ego has a large impact on how this status can be influenced by the observation.

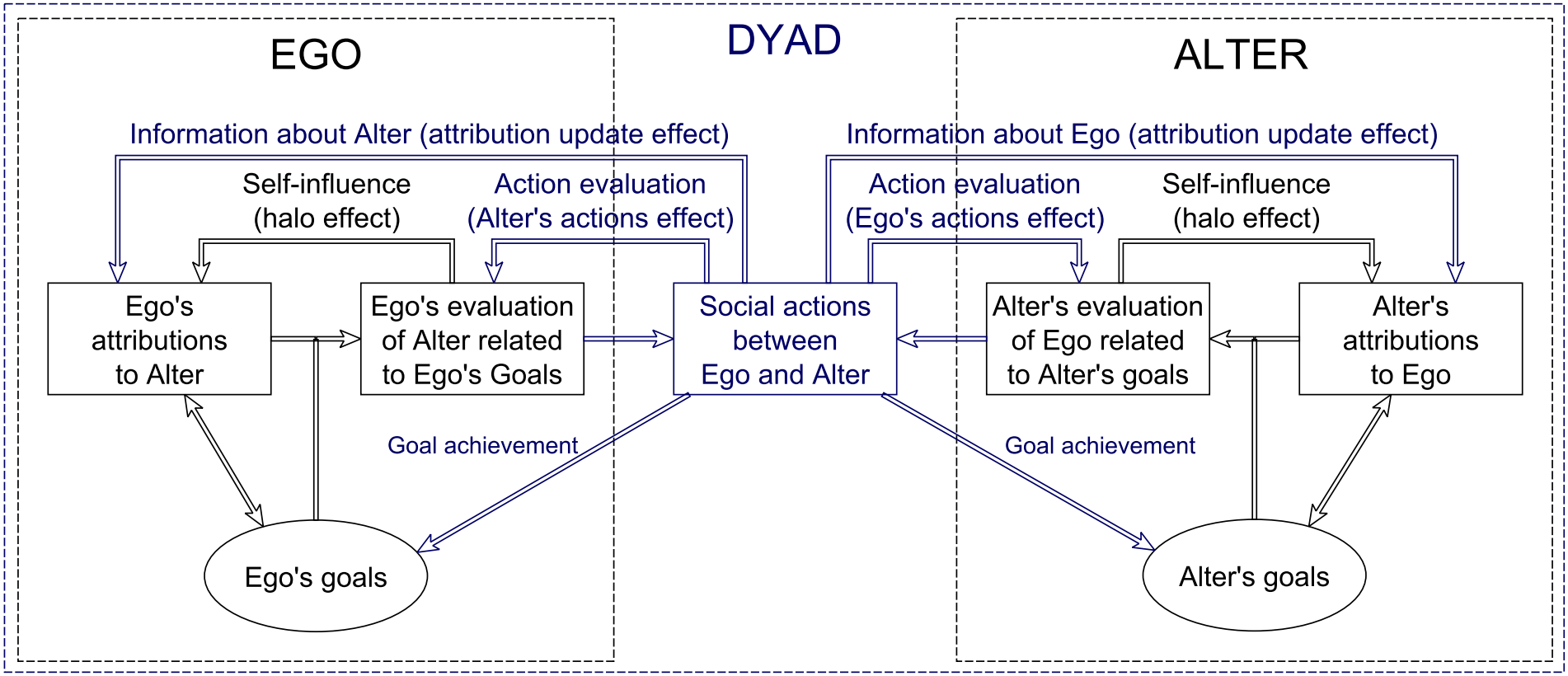

Figure 2.9: Informal status production III. Mechanisms within the dyad (Alter's perspective included).

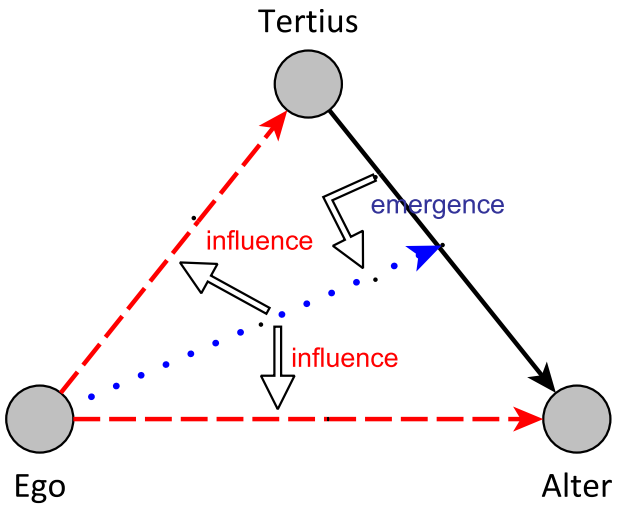

Figure 2.10: Emergence and influence effects in a triad.
(All ties represent status attributions.)

2.4.4 IV. Higher-order status production: collective and selective encounters

The processes that apply to triads can be generalized to situations with more than three actors. In the course of these encounters, actors can observe each others' status attributions to certain peers in the focus of attention, which can influence their perceptions about both the focal actors and the other bystanders. One way to imagine such situations is through events that spontaneously happen in the presence of some or all of the actors in a community. Such events can be called *collective encounters*.

A simple example for how emergence and influence effects operate in these situations is when in a classroom one of the students makes a funny comment about the class they are taking at the moment. The reactions of others to the comment can easily become visible: some will laugh loudly, some will not react, and some will be visibly horrified by the poor quality of the joke. As a result, each student's evaluation of the "funny" classmate (Alter), will be observable to others.

This situation induces two influence processes. First, the general reaction of the class can influence the reaction of individual students (e.g. those who start to laugh with a delay), and thereby their evaluation of Alter's action and the change in their status attribution to Alter will be affected.

Second, the situation can potentially influence also what different members of the classroom think about each other. For example, if there were only two students who

didn't find the comment funny, and if they observed each others' reaction to it, they might perceive each other as potentially valuable partners (who perhaps have similar humor). This can lead to interactions between them, which can develop into a durable relationship.

Collective encounters as introduced above may be regular events in certain communities, but they are not the only situations involving several actors that may be able to produce status attributions. Some encounters do not just happen when, somewhat randomly, one or more actors perform social actions publicly. There are also situations for which the participators are selected on purpose. These we can call *selective encounters*, as they involve only specific subsets of actors, mostly repeatedly.

An important example for a selective encounter that can produce informal status is gossiping in a group of friends. In these cases, people often talk about others who are not present. This can also be treated as revealing once status attributions, but to an absent Alter, which makes the situation very one-sided.

In addition, unlike in collective encounters where many actors are present, in selective encounters people can be more easily prompted to immediately react to the revealed status attribution. This gives a solid ground for influence on status attributions in these situations. If we add that open discussion about someone who is absent may be more likely to happen between actors who interact regularly and have a close relationship, it is clear that selective encounters potentially have an important role in the homogeneity of perceptions about peers in certain groups.

Collective and selective encounters, with the emergence and influence processes related to them can be further added to the model of informal status production, which now presents the most relevant social mechanisms responsible for the dynamics of status attributions in a single, common framework. The processes related to the level of the triad and above were added in Figure 2.11 in such a way that the routes of the production of Ego's status attribution to Alter and that of Alter to Ego could be traced.

The most important implications of the now complete model are the following. First, the goals of actors can be influenced by the perceived opportunities for goal achievement (as apparent from interpersonal attributions and perceptions), and by actually reaching goals, which can temporarily rearrange the goal structure.

Second, an important source of informal status, the different interpersonal attributions (perceptions, role attributions, affection), may be altered by three types of processes: by the cognitive interplay between the goal-related values of Alters and

attributions (halo effect), by the observation of others' behavior in interactions and in collective encounters, and by the influence of others in selective encounters.

Lastly, it cannot be overemphasized that social interactions, situations in which peers direct social action to an individual, have a key role in the goal achievement of actors. In the following, building on the presented framework we outline and theoretically motivate some social mechanisms by which the formation of groups within communities may become better understandable.

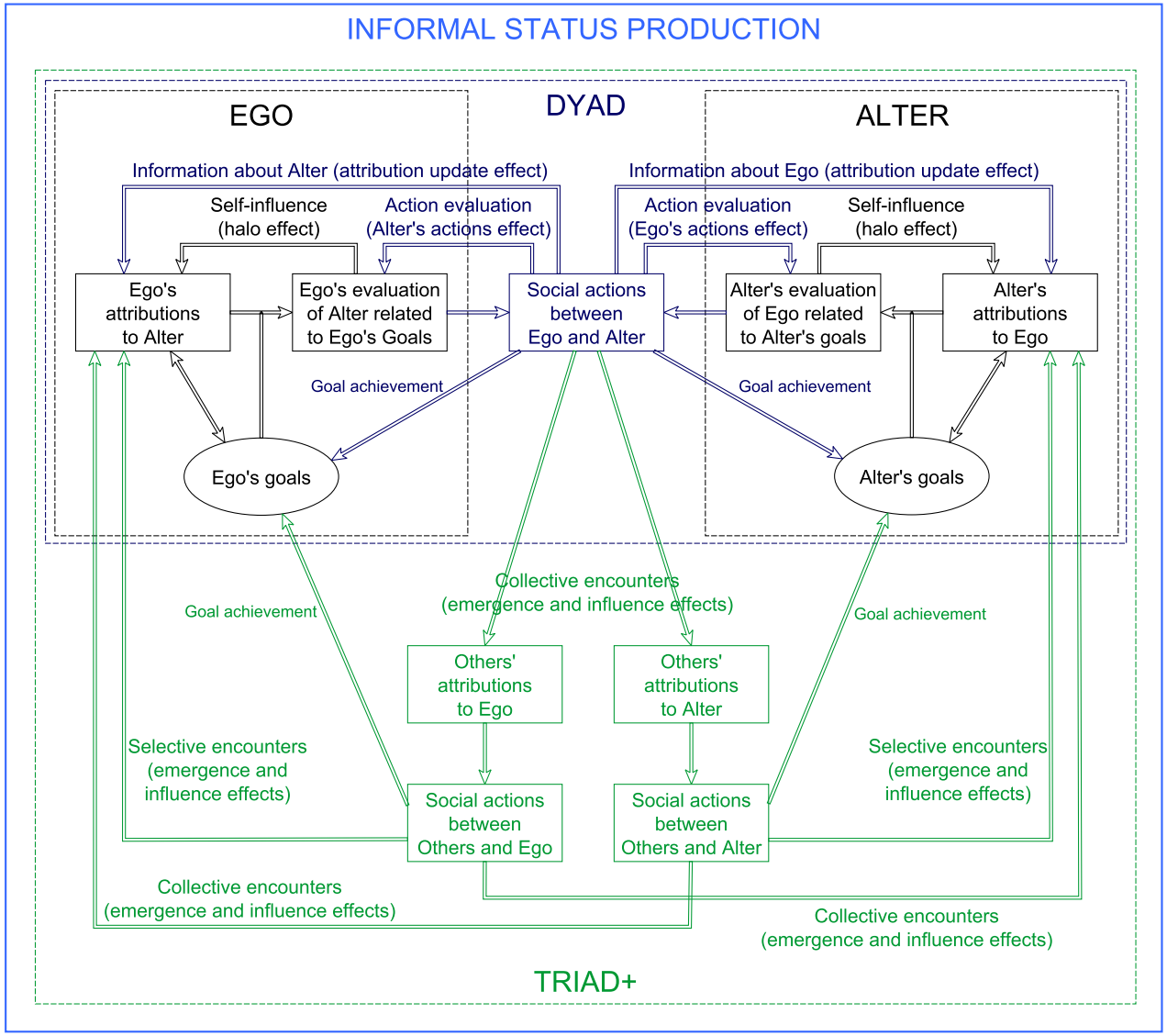

Figure 2.11: Informal status production IV. All discussed mechanisms.

2.5 A theory of group formation: the emergence of multiple status systems

The framework of informal status production elaborated so far points to certain social mechanisms that can be linked to the process of group formation in communities. Primarily, we focus on mechanisms that may bring about two of the distinguishing features of groups: the agreement of group members with regards to their interpersonal attributions to others in the community (shared attributions), and the presence of strong positive relationships that tie group members together (cohesion). This means that we are interested in processes that motivate social actions between actors who have similar attributions to their peers, and in those that may lead to the similarity in attributions of actors who interact. The key to understanding how such mechanisms may lead to the formation of multiple, overlapping groups (groups that share common members) is the multiplexity of status attributions.

It further follows from our approach that the presented theory describes the sufficient and necessary conditions for group formation in as much as the group is defined as a cohesive social unit with members having similar attributions (the definition used throughout the thesis).

We might say that the presence or absence of groups in a community is simply the outcome of the dyadic interactions between actors: each actor may have different status value for each other actor, which leads to the independent evolution of social relations and associations between attributions in dyads. Then, a group can be viewed as certain configurations in the structure of status attributions and social relationships between some actors as emergent from these dyadic processes.

While the role of dyadic interactions in group formation is not to be underestimated, we argue for the importance of triadic and higher-order mechanisms: in every community, encounters that involve three or more actors ensure that what happens in a dyad will have the potential to affect the status attributions and, as a result, the social actions of others directed to those involved in the encounter. Thereby, the collective production of informal status in encounters has a decisive role in group-formation processes.

2.5.1 Event–state links: the co-evolution of agreement and cohesion through social encounters

How can encounters generate agreement in status attributions and close social relations between actors? Social Comparison Theory (Festinger, 1954) argues, backed

up with experimental evidence, that in situations where what is right or wrong is ambiguous, people rely on social confirmation from others to ensure that their evaluations are correct. We may add that sufficient social confirmation can be gained by either adjusting one's evaluation of the situation (e.g. to the majority opinion) or by focusing on peers who have a similar evaluation to our own.

Applying this argument to our case, in encounters where status attributions to the actor(s) in the focus of attention are ambiguous (for example, as expressed by the opinion of whether a joke told was funny or bad), actors will be motivated to either change their attribution to the focal actor or to seek social confirmation from those peers who have attributions similar to theirs.

When is it likely that an ambiguous situation leads to changes in actors' status attributions, and when is it more probable that they will seek confirmation from actors with similar attributions? This question was already highlighted by Heider's balance theory, which originally focuses on this dilemma in the context of the dyad (Heider, 1946). We argue that conformity is more likely to happen in selective encounters and the search for similar peers in collective encounters. This is due to some key differences between the two types of encounters.

First, collective encounters are assumed to happen spontaneously (when an actor's social actions become visible to others), and so they may or may not contribute directly to the goal achievement of bystanders. On the contrary, selective encounters (the meeting of specific actors in the community) are more likely to be convened on purpose, and so they may be instruments for the goal achievement of the participants (e.g. by being involved in the business of a clique).

As a result, maintaining attributions that are in conflict with those of the others in a selective encounter jeopardizes goal achievement (argument with others, being expelled from the gang), and so actors may be more inclined to conform with the attributions of others. This is not the case in collective encounters, where one is able to keep his opinion and associate with similar peers (if there is any) to receive social confirmation.

The second main difference between selective and collective encounters, related to the previous point, is that maintaining an attribution in a conflicting situation is easier in the latter case. In collective encounters, the attention of onlookers focuses mainly on the focal actor(s) in the situation (e.g. the one who told the joke), and they are only concerned with the evaluation of the situation by others when this is in contradiction with their own evaluation.

The superficiality of actors in collective encounters makes it possible to withdraw or hide one's attribution to the focal actor if it is conflicting with that of the others. A good example for this is when hearing a horrible joke, one joins others in the laughter in order not to draw their attention to his conflicting opinion. Then social confirmation has to be sought from others who appeared to have a similar evaluation of the situation.

On the other side, selective encounters are difficult to withdraw from (goal achievement can be in progress), and so actors can be prompted by the others to react in some way to their attributions. In such a situation, pressures on changing one's attributions to conform with that of the others are larger.

2.5.2 Micro-mechanisms of group formation

Following from the previous argument, it can be hypothesized that after collective encounters actors will be likely to direct social actions to peers who showed similar attributions to the focal actor(s) in the situation in case there was ambiguity in the evaluations of actors. These actions may be initially exploratory, but in time can develop into a close relationship, for instance friendship – especially if the same actors often find that they can receive confirmation from each other. This leads to the formulation of the first micro-mechanism related to group formation.

> **Mechanism 1.** People who agree in their attributions to peers are likely to develop a close relationship.

In encounters of the selective type, actors are more susceptible to be influenced by the attributions of others to the focal actor, because these encounters most often happen between people who already have some kind of relationship established, like friendship. From this follows the second hypothesized process.

> **Mechanism 2.** People who have a close relationship are likely to influence each other and develop agreement in their attributions to peers.

Experimental evidence suggests that social confirmation has a decisive role in situations when someone's opinion confronts that of an entire group (Turner, 1991). Given that the person in minority is not alone, he or she is likely to hold on to the original evaluations. In our case, this finding implies that Mechanism 1 may have a different strength for each individual in a collective encounter. The strength of the mechanism depends on how much the focal actors attribution to a peer coincides with

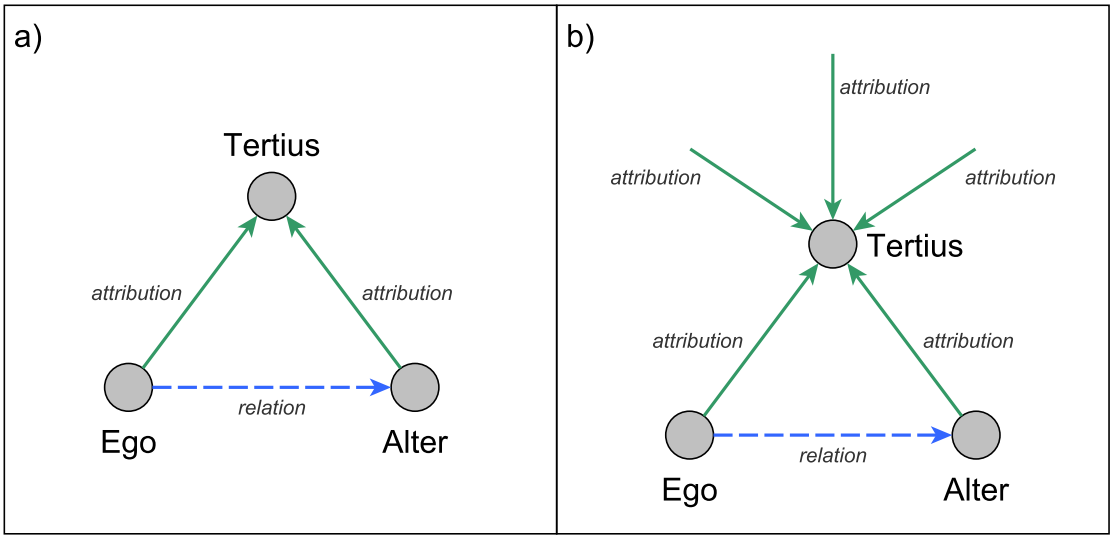

Figure 2.12: Group-formation mechanisms I.
Agreement generates close relations through collective encounters.

the general opinion of people in the same encounter: those who find themselves in the minority will feel a stronger need for social confirmation. Consequently, we can state the following hypothesis.

> **Mechanism 3.** Agreement in attributions between people contributes more to the development of a close relationship when it goes more against the general evaluation of the community.

If we imagine selective encounters as "invitation only" situations (such as in many cases of gossiping), it seems possible that sometimes actors invite friends to these events who are not friends themselves. However, once in the same situation these actors may also influence each others' attributions. This case is expressed by the fourth assumed mechanism of group formation.

> **Mechanism 4.** People influence each other's attribution more when they have more close peers in common.

The first two mechanisms establish the two-way dynamic links between attributions and relations in triads. The last two aim to generalize these processes to the group-level: they consider what happens in triads if they are embedded in different contexts. Further, mechanisms 1 and 3 describe peer-selection processes, that is, the social forces bringing people together based on the structure of interpersonal attributions in the community around them (Figure 2.12). Mechanisms 2 and 4 are influence

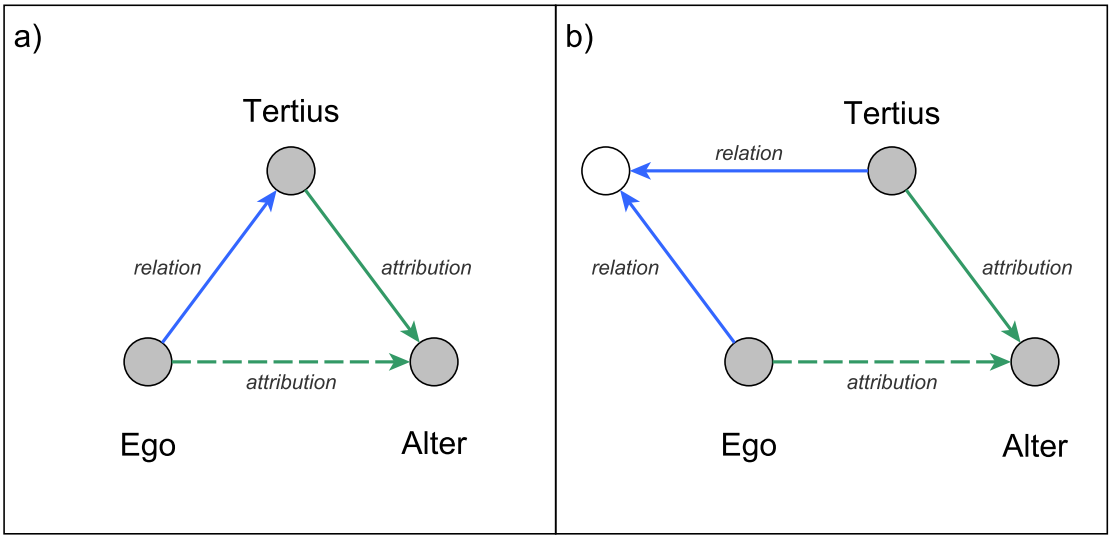

Figure 2.13: Group-formation mechanisms II.
Close relations and shared groups exercise influence through selective encounters.

effects which deal with how the structure of relationships generate opportunities for people to affect each other's attributions ot peers (Figure 2.13).

The four hypothesized mechanisms link multilateral interaction events (encounters, situations) to relational states (attributions, friendships, other relations). The effects operate in both directions. On the one hand, the existing attributions and relations of people determine the opportunities and pressures each situation will hold for them. On the other, repeated situations have the power to alter individual attributions and interpersonal relations. Therefore, these interaction-based social mechanisms have a potential impact on the macro-structure of the community.

2.5.3 Macro-level consequences: multiple status systems

In a community, there are a sequence of encounters each of which may involve a different subset of actors (those who are present). Since interpersonal attributions are multiplex, subsequent encounters can focus on different dimension of attributions, they can have different "topics". As a consequence, in certain configurations there can be multiple forces pulling actors towards forming groups with different peers. After a series of collective encounters an actor may feel that he can gain social confirmation on distinct dimensions of attributions from different peers. He may be able to engage in social interaction with many or all of them, but it is also possible that he will have to choose some to associate with.

As a result, the actor can be involved in the formation of multiple groups. On the level of the community, such processes lead to "fuzzy" group boundaries and multiple group memberships. However, membership in multiple groups can place actors in a sensitive situation when their different groups express conflicting attributions about a certain peer – they may have to face the decision of choosing between the different sides (see Heider, 1946, Krackhardt, 1999). This highlights that actors bridging different groups may be highly important for processes of group formation, as conflicts between groups can condense around them, but they may also be able to mitigate the effects of conflicting opinions.

The long-term macro-level implications the series of interaction events described so far is clear: communities tend towards differentiation in the form of the emergence of multiple groups. Each of the groups will be founded on a collection of status attributions which distinguishes its members from the rest of the community. In other words, groups will have their own status systems, shared ideas among group members about who is appreciated and who is not.

In the theoretical framework we developed here, it is natural that the horizontal differentiation (multiple groups) in a community may occur in parallel with vertical differentiation. Although in this discussion we focused on the qualitative differences between status attributions, they also have the potential to imply higher and lower statuses (see Section 2.2.2). This can lead to the development of status hierarchies. Whether there will be a single or multiple hierarchies in a community depends on the congruity of the various status systems, that is, how much groups can agree and legitimate status differences.

It is tempting to continue the theoretical discussion with the possible scenarios relating multiple groups and status hierarchies, with ideas about status differences *between* groups (e.g. Schmader et al., 2001), or with the impact of individual differences and community composition on the emergent structures (e.g. Moody, 2001).

However, for reasons discussed later there is insufficient empirical evidence about the social processes generating shared attributions and cohesion in groups. Consequently, studies into macro-structural features of communities risk overlooking important micro mechanisms and drawing false conclusions.

The papers presented here aim to carefully analyze whether it is likely that the hypothesized group-formation mechanisms play a role in the evolution of real-world communities. These analyses may help in developing a more appropriate conceptual framework for describing macro-level phenomena, such as groups and hierarchies, than what we currently have.

2.6 Research questions

This section introduces our main research questions related to the impact of informal status production on the evolution of communities. In the later chapters, we aim to provide answers to these questions through the empirical investigation of network dynamics in a set of high-school classrooms. The presented topics were selected for analysis because they all focus on or are necessary for studying the fundamental micro mechanisms of group formation proposed above. Although answering these questions will not provide a definitive verdict about the validity of the theory, but they are the ones which can be relatively directly analyzed at the current state of methods and measurement in the field of Social Network Analysis.

> **Question 1.** What are the characteristics of the structure of interpersonal attributions between adolescents? What are the relationships between different dimensions of attribution? How are these relationships connected to the goals of adolescents, and thereby to status values?

The adolescent value system is arguably mirrored in the interpersonal attributions of students. For example, the appreciation of certain activities goes along with the appreciation of those who practice these activities, as it is the case with athletes in the classic work of Coleman (1960, 1961).

Since attributions are multidimensional, the first descriptive question we can ask is how different attribution dimensions are related to one another within a community. These relations can be conceptualized as the overlap between attribution networks, that is, different networks of perceived traits, abilities, social roles, and affection – for example, how often do students like those peers who they perceive to be clever? Studying the structure of the relations between several attribution networks allows us to identify the types of attributions that most often co-occur.

Technically, this can be achieved by the cluster analysis of the overlaps between the attribution networks. By such an analysis, we can gain a picture about the structure of interpersonal attributions in the observed communities. Comparing the attribution structures of a given community at different points in time also allows for the study of the evolution of the system of interpersonal attributions.

It is expected, that certain characteristics of the structure of interpersonal attributions commonly appear in several or perhaps all of the studied communities, while others remain specific to only a few of them. The similarities and differences may be related to the connections between attributions and the goals of adolescents: there

may be certain general goals that are achieved similarly, and so are associated with similar attribution dimensions in different communities, and there can be goals that are reached by different means in each community, making distinct configurations of attributions relevant for goal-achievement.

One commonality we may expect is based on the assumption that goal-achievement, regardless of the exact content of the goal, is important for students. There may be certain attributes of peers that signal whether they are helpful or unhelpful, in general, in the goal achievement of others. Such attributions are probably most often general traits, like sociability, kindness, being shy, rude, and so on. Perceiving these traits in a peer provides information about the likelihood that he or she will be cooperative in the sense of the promotion of goal achievement.

Based on this argument, we hypothesize that there are groups of positive and negative trait perceptions which are related to this general tendency for cooperation, and which can be found in the attribution system of all of the studied school communities. This hypothesis, among the other questions discussed here will be examined in Chapter 4 of the thesis. The results are instrumental for the later studies, as they help us to new, composite network measures of interpersonal attributions.

> **Question 2.** Do friends evaluate their peers similarly? Is there an empirical association between agreement in attributions among students and friendship in classrooms?

As we have discussed earlier, as a result of encounters status attributions can be altered and social actions directed to certain peers can be motivated. According to Festinger (1954), people in ambiguous situations seek social confirmation for their views. In our case, this means that in encounters where there is a visible lack of consensus about the evaluation of a peer (for instance, if his joke was funny or not), students will require confirmation from others that their evaluation is correct. This may be achieved in two ways: they can change their opinion to that of the majority or they may try to seek out and interact with peers who have a similar opinion in order to receive social confirmation from them.

Regardless of how students achieve confirmation, the process leaves a mark on the structure of friendship and attribution networks in the classroom. If the hypothesized mechanisms indeed operate in social encounters then, if they are unsuppressed, lead to triadic structures in which friends agree in their attributions to other peers.

Whether the empirical association between friendship and agreement is strong or unnoticeable is not, of course, a definitive verdict about the validity of the proposed

theory, due to the large number of potential confounding mechanisms. However, the comparison of the association across several classrooms does give an indication about the general importance of the proposed group-formation processes. Therefore, the second descriptive question can be answered by the empirical examination of the friendship–agreement connection in the studied classes at different points in time.

To some extent, the analysis should take into account viable alternative mechanisms that may lead to group formation. Perhaps the most important of these are processes are based on similarities in individual characteristics (gender, ethnicity, etc.). Thus, it is also to be examined how student similarity in some relevant attributes is related to the friendship–agreement link. These aims can be achieved by the use of simple descriptive measures and QAP network regressions (Dekker, Krackhardt, and Snijders, 2007). The second research question is in the focus of Chapter 5.

> **Question 3.** How do interpersonal attributions and friendships co-evolve? Under what circumstances does agreement in attributions lead to the development of friendship between students? Do friends and groups affect the dynamics of attributions and the emergence of agreement between students?

The last question of the thesis turns towards the dynamics of the communities. Although the link between agreement and friendship may or may not be strong based on the observations, it is a different issue how these outcomes emerged. We hypothesize that there is a two-way dynamic interplay between friendship and agreement about interpersonal attributions: agreement leads to friendship, and friendship leads to agreement.

However, the circumstances under which these effects operate are not self-evident. As it was discussed earlier, agreement may not have the same significance for individuals when they share the majority opinion about a peer and when they are in the minority related to an attribution. It is a question whether the views of the classroom in general have an impact on the link from agreement to friendship between students.

Further, according to our theory, which is based on social events, two types of influence effects on interpersonal attributions can be suspected: one from friends directly, and one from friendship groups. Unlike direct friend effects, group influence may depend on how two students are embedded in the same social circles: the more shared friends they have, the more often they may co-participate in selective social encounters, and so the more opportunity they may have to influence each other. The open question is whether the influence from friends and fellow group members who are

not direct friends is comparable or not, and how the two types of influence combine in real situations (the influence from group member friends).

The hypothesized mechanisms can be tested simultaneously in a co-evolution model of friendship and attribution networks, which can be carried out in the framework of the Stochastic Actor-oriented Model (Snijders, Van de Bunt, and Steglich, 2010). The effects that represent the research question in the model capture how structural equivalence of students in the attribution network is associated with the presence of friendship between them. This topic is studied in the Chapter 6 of the thesis.

Chapter 3

Data and Methods

This chapter presents the dataset and the statistical methods which are used in the empirical examination of the research questions formulated previously. The three empirical chapters in the thesis study the same longitudinal multiplex network data which comes from several high-school classrooms. For various reasons discussed below, two different subsets of classrooms are used in the analyses. We refer to these as Exploratory Subsample and Dynamic Subsample. Chapter 4 is based on the former, while Chapters 5 and 6 on the latter subsample. Here we discuss the background of the data collection and provide a basic description about student composition and network measures in the classrooms from the two subsamples.

The three empirical chapters of the thesis use three different methods. Chapter 4 aims at reducing the dimensions of a strongly multiplex perception network, for which it applies a novel analytical procedure developed in this thesis, called the Cluster Analysis of Multiplex Networks. Chapter 5 studies the empirical correlation between friendship and perception agreement and uses QAP permutation tests and network regressions. Chapter 6 applies Stochastic Actor-oriented Models to investigate the co-evolution of friendship and perceptions among students. The current Chapter provides an intuitive overview of the methods used in the empirical studies.

3.1 The RECENS high-school network panel dataset

The data analyzed in the thesis come from a 4-wave longitudinal network survey conducted in 43 Hungarian high-school classrooms in the period of 2010-13. The data was collected as part of the "Wired into each other" network study by the Research Center for Educational and Network Studies (RECENS).[1] The classrooms

[1]The data collection was supported by the Hungarian Research Funds (OTKA), reference no. K81336.

in the dataset were distributed in 7 schools from the capital, one large town, and two smaller towns in Hungary. In each participating school, all classes in the first-grade cohort (14-15 year-olds) of 2010-11 were followed for the first three of their four years in high school. Students answered self-administered pen-and-paper questionnaires four times during this period: twice in the first year (two months after the start of first grade and six months later), then once per year in the next two (1.5 and 2.5 years after the first wave).

The questionnaires in each classroom and wave were filled out in the course of a 45-minute class at school, under the supervision of at least two trained researchers participating in the study. Before each wave, students and their parents received information about the survey and were asked for participation and consent. Network ties were reported by students using a classroom-level roster, that is, the number of ties to classmates was not limited, but ties to people outside one's own class were not permitted. Affective relationships were measured on a 5-point scale: friendship, liking, neutrality, dislike, and hate, where choices were mutually exclusive. In addition to these items, questions about bullying and victimization networks, shared activities and perceptions of peers' attributes, behavior, social roles, and status were asked in the questionnaires. Altogether, the dataset contains information on various social ties between students along 40 dimensions in each classroom.

The studies in the thesis analyze the first two waves of the RECENS dataset. Wave 1 was collected in October 2010, only about a month after the start of the first high-school year, and wave 2 in April 2011. These observations frame an intense six-month period when classroom members become familiar with their new environment, get to know each other, and start to develop shared views about which behaviors or opinions are acceptable in the class and which are to be rejected. The evolution of the value systems (as used in Coleman, 1961) of classrooms goes hand in hand with changes in adolescents' perceptions about and affections to their classmates, and may also affect the relationships between the different dimensions of peer perceptions in the community. As a consequence, the analysis of the two waves may highlight certain general tendencies of the ongoing social dynamics.

3.1.1 The 18-classroom "Exploratory Subsample"

For the analysis in Chapter 4, we selected a random subsample of 18 classrooms so that each school, classroom training program (vocational, technical, or grammar)[2],

[2]In the Hungarian public education system, secondary schools often run classrooms with different training programs in a single grade.

Table 3.1: The distribution of classrooms in schools, locations, and training programs in the Exploratory Subsample and the full sample.

School	Number of classrooms (in subsample / in full sample)			
	Grammar	Technical	Vocational	Total
Bigtown 1	2 / 5	—	—	2 / 5
Bigtown 2	—	2 / 4	2 / 6	4 / 10
SmalltownA 1	1 / 3	0 / 1	1 / 3	2 / 7
SmalltownB 1	—	2 / 4	—	2 / 4
SmalltownB 2	—	1 / 2	1 / 3	2 / 5
Capital 1	2 / 4	—	—	2 / 4
Capital 2	—	2 / 4	2 / 4	4 / 8
Total	5 / 12 (42%)	7 / 15 (47%)	6 / 16 (38%)	18 / 43 (42%)

and town size (capital, large town and small town) is independently represented by at least 2 classes (see Table 3.1 and Table A.1 for an overview of the subsample). These contextual variables capture regional and school-level differences and the systematic variation in students' background between training programs (Dobos, Gloviczki, Halász, Kaposi, Kovács, Lannert, Loboda, and Setényi, 2011), which may all be related to the structuring of perceptual dimensions in the classrooms. Thus, our subsample retains the variation of the full sample in some important contextual aspects, while it remains small enough to be conveniently explored. The selection of at least two cases in each category also provides protection against idiosyncrasies in classroom-level results. Finally, using a subset of classrooms from the full dataset leaves open the possibility of future cross-validation.

Basic descriptive information about the studied classrooms is presented in Table 3.2. The subsample we analyze here consists of 5 grammar, 7 technical, and 6 vocational school classes. The size of the classrooms varies between 26 and 38 students, with an average of 32 over the two waves. Girls are in a majority in most of the classes (14 out of 18), and their average proportion is 63%. It has to be noted that across all three training programs, girls are overrepresented in our sample compared to their national share in the time period of the study: 69%, 62%, 60% against 57%, 49%, 38% in grammar, technical, and vocational training respectively (KSH, 2011; KSH, 2012; KSH, 2013).[3] However, our classrooms still show considerable heterogeneity in

[3]This non-representativity does not seem to be related to the specifics of sample selection, it can be regarded as a random deviation from the country-level mean. Note that already in this small sample we can see a large variation in sex ratio from class to class.

Table 3.2: Classroom-level descriptive statistics for the Exploratory Subsample.

Class	Training program	Size	Girls %	Age mean (std.dev.)	Size Δ	Leavers	Joiners	Girls %Δ
1100	grammar	32	66%	15.1 (0.28)	–1	1	0	–0.01
1500	grammar	29	76%	15.1 (0.37)	–1	2	1	–0.01
3100	grammar	29	48%	14.9 (0.37)	0	0	0	0.00
6100	grammar	33	82%	15.1 (0.37)	0	0	0	0.00
6400	grammar	36	72%	15.0 (0.34)	0	0	0	0.00
2200	technical	31	71%	15.2 (0.48)	–5	5	0	0.02
2400	technical	29	62%	15.1 (0.48)	2	2	4	–0.01
4200	technical	35	54%	15.0 (0.33)	1	0	1	0.01
4400	technical	38	79%	15.1 (0.47)	–1	1	0	–0.01
5500	technical	35	40%	15.4 (0.51)	0	2	2	–0.06
7200	technical	31	61%	15.5 (0.72)	–3	3	0	–0.01
7300	technical	31	65%	15.6 (0.76)	–2	5	3	0.01
2900	vocational	32	59%	15.2 (0.48)	3	4	7	0.01
2000	vocational	30	47%	16.0 (0.92)	–3	5	2	0.05
3500	vocational	37	41%	15.7 (0.67)	1	1	2	–0.01
5100	vocational	33	79%	15.5 (0.81)	1	1	2	–0.02
7500	vocational	33	67%	15.6 (1.03)	–7	9	2	–0.05
7800	vocational	35	69%	15.9 (0.96)	–6	6	0	–0.03

gender composition: the lowest observed proportion of girls is 34%, while the highest is 80%. The differences in the ratio of boys and girls are not associated with training program or classroom size in our subsample.

The average age of students was 15.3 years at the time of wave 1 (with the mean of within-class standard deviations being 0.57 years). There are significant differences between training programs with regard to the classroom-level means and variances of age: vocational school classes have the highest average age and also the largest within-class variance, then come technical classes, followed by the grammar training program (p-values of all pairwise tests are below 0.05). This is in line with the general tendency in Hungarian education: between 2005-2007, the proportion of students who failed and had to repeat a grade was more than three times as high in vocational (5%) and twice as high in technical training (3%) than in grammar classes (1.5%) (Fehérvári, 2009:7). Later studies report that the gap further widened since then, leading to a 7%:1% ratio of fails between vocational and grammar classrooms in 2008/2009, with one out of every six vocational students failing first grade in high school (Dobos et al., 2011:171).

It can further be noted that there is some change in classroom compositions, due

Table 3.3: Absence rates among all students and active students in the Exploratory Subsample classrooms.

Class	Training program	All absent (%) w1	Active absent (%) w1	All absent (%) w2	Active absent (%) w2
1100	grammar	6%	6%	3%	3%
1500	grammar	3%	3%	0%	0%
3100	grammar	3%	3%	3%	3%
6100	grammar	6%	6%	3%	3%
6400	grammar	3%	3%	0%	0%
2200	technical	6%	3%	8%	4%
2400	technical	3%	0%	6%	3%
4200	technical	0%	0%	0%	0%
4400	technical	0%	0%	0%	0%
5500	technical	9%	6%	23%	13%
7200	technical	32%	22%	21%	12%
7300	technical	3%	0%	14%	4%
2900	vocational	9%	3%	29%	7%
2000	vocational	20%	8%	30%	10%
3500	vocational	27%	10%	45%	9%
5100	vocational	18%	13%	35%	21%
7500	vocational	36%	28%	35%	19%
7800	vocational	23%	16%	10%	4%

to joiners and leavers, between the two waves. The turnover rate is higher for technical and vocational (mean=4.2 students) than for grammar classes (mean=0.8 students, p=0.01 for the test of zero difference). However, it is likely that most of this fluctuation is due the swapping of problematic, school-avoiding students between schools – as suggested by a high positive correlation (0.77, $p < 0.01$) between the number of changes in the classroom roster and the number leaving and joining students who were absent at wave 1 and 2 respectively. Classroom sizes and the ratio of boys and girls are not altered substantially by the changing composition.

The differences between training programs are reflected also in participation rates. While on average 90% and 85% of students answered the questionnaires in wave 1 and 2 respectively, there is a large disparity between vocational classes and the two other types (see Table 3.3). In grammar and technical classrooms, typically less than 10% of students were absent from school at the time of the data collections or chose to opt out from the study, but the same rate is over 20% in vocational classes on average (the difference is significant at $p < 0.01$).

These tendencies also provide reasonable proxies for general data quality. The researchers in the field consistently reported that grammar and technical students

had fewer difficulties while filling out the questionnaire, and their responses in general may be more reliable than those of vocational students.

Based on field interviews with the head teachers of the vocational classrooms, several students who were absent were notorious for avoiding school, and some even faced to be expelled from the given institution because of this. Indeed, if we exclude absent students who left their classroom (and probably their school) by the third data collection, absence rates drop quite a bit – as it can be seen in Table 3.3.

The problem of absent later drop-outs is clearly one about drawing the boundary of the networks. Do these students belong to the classroom community even though they are mostly not at school? We decided to keep them for the present analysis, for two reasons. On the one hand, we argue that students who are absent more often than not are not active members of their class community. As a consequence, it is not important for us to know how they evaluate their classmates (all of whom they might not even know). Additionally, their missing responses do not pose a problem for the analysis in Chapter 4.

On the other hand, these people, as rarely as they may contact them in or outside of school, can still exert significant influence on their classmates' interpersonal evaluations, especially as extreme role models. Therefore, taking into account the nominations they receive from classmates may help to better identify the structure of perceptual dimensions among the active members of the classrooms. To summarize, we argue that the higher rate of absence in vocational classes should not lead to biased results regarding the active part of the classes in Chapter 4, and so systematic differences between classrooms should not arise from this phenomenon.

Further descriptive statistics about the Exploratory Subsample classrooms are reported in Appendix A. The information presented there includes the density of all networks used in Chapter 4 at wave 1 and wave 2, and the stability of ties between the two observations in every original item and in the resulting composite networks.

3.1.2 The 27-classroom "Dynamic Subsample"

Chapters 5 and 6 study a subset of classrooms from the RECENS dataset different from the one introduced above. This subsample includes 27 classes which were selected based on their suitability for dynamic network analysis with Stochastic Actor-oriented Models (Section 3.4). As a first step, students who joined or left their classroom between the two waves were removed from the dataset (see Section 3.4.4). After this, the classes from the full sample which had a missing ratio larger than 0.25 in any of the networks used in the two chapters were dropped (cf. Ripley, Snijders,

Table 3.4: The size and composition of classrooms in the Dynamic Subsample.

Class	Training program	Size	Girls %	Roma %	High educ. %	Smoker %	High asp. %	Sports %
1100	grammar	31	65%	0%	100%	13%	81%	48%
1200	grammar	34	68%	0%	97%	18%	76%	44%
1300	grammar	35	80%	0%	94%	11%	80%	69%
1400	grammar	33	70%	0%	91%	9%	67%	48%
1500	grammar	27	78%	0%	96%	19%	85%	59%
3100	grammar	29	48%	3%	93%	7%	69%	52%
3200	grammar	34	76%	12%	79%	6%	71%	29%
3400	grammar	35	40%	11%	71%	31%	60%	89%
6100	grammar	33	82%	6%	97%	24%	73%	64%
6200	grammar	34	68%	0%	91%	12%	74%	68%
6400	grammar	36	72%	0%	94%	11%	89%	36%
2100	technical	23	87%	57%	52%	48%	43%	35%
2200	technical	26	73%	50%	38%	46%	19%	19%
2400	technical	27	59%	22%	78%	63%	41%	30%
3300	technical	34	6%	21%	74%	32%	9%	44%
4100	technical	17	53%	6%	100%	6%	76%	53%
4200	technical	35	54%	3%	94%	3%	77%	43%
4300	technical	33	61%	6%	82%	3%	48%	27%
4400	technical	37	78%	19%	57%	32%	38%	27%
5400	technical	33	48%	24%	55%	33%	27%	33%
5500	technical	33	36%	9%	64%	45%	36%	39%
7100	technical	30	77%	20%	87%	40%	27%	40%
7300	technical	26	62%	15%	77%	35%	23%	19%
7400	technical	30	83%	13%	70%	53%	10%	23%
2800	vocational	29	62%	62%	55%	48%	10%	21%
5600	vocational	23	100%	74%	13%	65%	13%	9%
7800	vocational	29	66%	24%	76%	38%	3%	24%

Boda, Vörös, and Preciado, 2014:32). In the remaining classes, tie stability between the two waves were in acceptable intervals (Ripley et al., 2014:19-20), so these were retained for the analysis. Missing ratios, network densities, and tie stability measures in each classroom and wave are reported in Appendix B.

Table 3.4 provides some descriptive statistics about classrooms in the Dynamic Subsample. It is to be noted that while almost every grammar and technical class were found appropriate for Chapter 6, only 3 of 16 vocational training classrooms made it to the subsample (cf. Table 3.1). This is due to the generally lower quality of data and higher absence rates in vocational classes. (It is also apparent that these three classrooms typically differ from the rest of the subsample in composition, along

the dimensions considered here.)

Further, Table 3.4 presents an overview of the composition of classrooms in six individual characteristics which are considered in Chapter 5. To simplify the empirical analysis, some of the original survey items were dichotomized after the inspection of their distribution in the sample.

Ethnicity is measured as ethnic self-identification (recoded to Roma–non-Roma). We use one measure for the family background of students: the highest education of their mothers. The two categories we use here is 8 or fewer finished school years (low education) and more which includes high school and university degrees (high education). The majority of parents in the subsample has a highest degree of either a finished primary or a secondary school.[4]

Smoking was measured in the questionnaires on a four point scale. Those who indicated that they smoke regularly, either in company or also alone, were treated as smokers here, while those students who at most tried smoking are coded as non-smokers. Academic aspirations are represented by a simple variable, which indicates plans after finishing secondary school. From a multiple choice question of several options, those students who chose that they plan to continue studying in some form were coded as having high academic aspirations, and those who excluded these possibilities were assumed to have low aspirations. Finally, the sports variable distinguishes students who actively and regularly attend athletic training of any kind from those who do not pursue these activities.

3.2 Cluster Analysis of Multiplex Networks

Strongly multiplex network datasets, ones which may contain dozens of different relational measures, are difficult to analyze even with the most advanced statistical network methods. Studies which attempt at all to examine more than 4-5 network dimensions, have to resort to the separate or perhaps pairwise analysis of the items. In the case of non-network, monadic data there is a well-established research strategy for dealing with the problem of too many variables: dimension reduction.

The Cluster Analysis of Multiplex Networks is an analytical procedure for reducing the dimensions of strongly multiplex network data. The procedure is based on the ideas that, just like in the case of scale construction in psychology, we may be able to define fewer and more valid relational measures based on the analysis of the similarities

[4]The categorization of students family background based on the highest level of education of the *fathers* shows a similar picture.

between a large set of items. In fact, it is even easy to carry out in practice by tailoring already existing statistical methods (such as Cluster Analysis) to network data.

To our present knowledge, such a dimension reduction technique for network data has not yet been proposed. Therefore, we develop an empirical procedure in this thesis by which aggregated network measures can be constructed from a large set of relational items. Chapter 4 describes the procedure and presents its application on peer-perception dimensions in high-school classrooms. The example shows that the method can be applied simultaneously to multiple groups (in our case: 18), and may lead to aggregated network definitions which represent latent relationship types in larger populations.

3.3 QAP correlation and network regression

The statistical analysis of network data has to account for the dependencies between network ties. Unlike in the case of non-network, monadic data, the usual assumption of the independence of observations (or some simple forms of dependence) does not hold. For example, the number of e-mails person A sends to person B surely depends on how many e-mails B sends to A, and vice versa. Further, it is possible that the number times A calls B on the phone depends on the number of calls A makes to C, a third actor, and the calls from C to B (e.g. A may not have to tell everything to B directly if some of the information is passed on to B via C).

What happens if we ignore that e-mails and phone calls are embedded in a social structure and calculate the correlation between the number of e-mails and calls between people in a community? Of course, we get the same correlation coefficient as we would if the observations were really independent. However, regular standard errors are unreliable in this case and the typical statistical tests (e.g. t-tests) are not applicable. Statistical inference based on these tests is potentially incorrect.

One way of dealing with this issue is represented by the Quadratic Assignment Procedure or QAP for short (Krackhardt, 1988). The QAP test of a correlation between two networks is based on a null distribution generated by randomly rearranging the rows and columns of the adjacency matrices of the analyzed networks. This results in a set of hypothetical network pairs which have the exact same structure as the original networks, but in which actors are randomly swapped. The statistical significance of the observed correlation is then determined by comparing it with the correlations we can expect between networks with the same structures. In this sense,

we can say that the QAP test deals with the dependencies between ties by controlling for network structure, and not by modeling it (Snijders, 2011).

The QAP method has also been developed for a multiple regression framework (Dekker et al., 2007). MRQAP is an intuitive network regression technique which can be used and interpreted very similarly to non-network regression models. In this case, the null distribution for each parameter in the model is generated by a procedure called 'double semi-partialing' (Dekker et al., 2007). Both linear and logistic regression methods for MRQAP are developed and implemented in popular statistical packages for network analysis (e.g. Ucinet, R). We use QAP tests and regression for the descriptive analyses presented in Chapter 5.

3.4 Stochastic Actor-oriented Models for network dynamics

During the past decades, important advances were made in multivariate regression models specifically designed for network data. The most notable of these methods are Exponential Random Graph Models (ERGMs) (Lusher, Koskinen, and Robins, 2012) and Stochastic Actor-oriented Models (SAOMs) (Snijders et al., 2010). The advantage of these methods, over MRQAP for example, is that they do not treat the dependencies between network ties simply as a problem to be dealt with (e.g. correlated error terms, biased standard errors). Instead, they aim to explicitly model network structure (Snijders, 2011). This makes ERGMs and SAOMs capable of addressing research questions and hypotheses that cannot be assessed with other techniques.

Chapter 6 of this thesis requires exactly this kind of modeling approach. Despite recent developments in dynamic ERGMs (see e.g. Lusher et al., 2012, Chapter 11; Krivitsky and Handcock, 2014), SAOMs were deemed more suitable for answering our research questions. The main reason for this is the actor-oriented nature of the SAOM: it models network evolution as a series of actor decisions, which makes inference about general decision heuristics of students possible. In the following we briefly summarize the principles of the Stochastic Actor-oriented Model and describe the types of SAOMs and the modeling strategies we employ in Chapter 6.

3.4.1 Basic principles of SAOMs

The Stochastic Actor-oriented Model can be used to analyze the various processes which drove the evolution of a network between two or more observed time points. The SAOM is essentially an agent-based simulation model which is calibrated based

on observations of real-world networks. Alternatively, we may also think of the SAOM as a generalized linear model with lots of missing data – the sequence of unobserved network states which link the actually observed networks at the different time points; simulations are used to impute the steps in this unobserved change process.

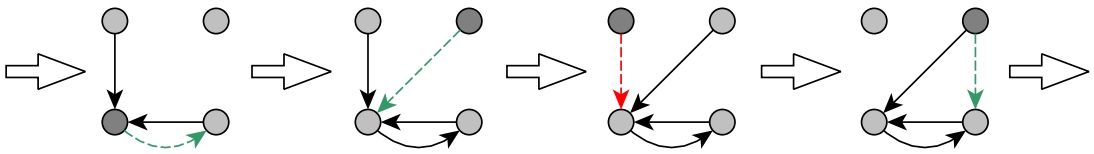

Figure 3.5: A hypothetical series of ministeps in a network of four actors.

SAOMs are based on a few distinctive principles. First, network change is assumed to be organized by actors: the evolution process can be imagined as a series of (conscious or subconscious) decisions of actors to create, maintain, or delete their ties to other actors (hence the term 'actor-oriented'). This does not imply that SAOMs represent any single theory of action (e.g. rational choice, bounded rationality), it only reflects a modeling approach in which changes in an actor's ties are dependent on the network neighborhood surrounding this actor (and not on the neighborhood of a given tie, for example, as in the case of ERGMs) (Ripley et al., 2014, p. 10).

Second, the process linking the observed states of the network is assumed to be a continuous-time Markov chain. The continuous-time assumption is the basis for understanding a single tie change (creation, maintenance, or deletion) as the smallest possible step in the evolution of the network. In the model's terminology, this is called a 'ministep'. Network change is, thus, imagined as a sequence of ministeps. In each ministep, one actor has the opportunity to change a single one of his or her ties (so coordination is not allowed). Figure 3.5 provides an illustration. Following from the Markov assumption, the outcome of a ministep (the 'choice' of the actor) depends on the current state of the network (and on other covariates in the model), so in this sense the process has no memory of the earlier past (Snijders et al., 2010).

The model consists of two sub-processes. The first models the opportunities for change, that is, it determines how actors are selected to make a change in their ties in the subsequent ministeps. The second process models which tie change an actor makes when selected for a ministep. The opportunity process is expressed by the so-called 'rate function' and the change determination process by an 'objective function' in the model. Now we focus on further explaining the objective function, as it is more essential for the interpretation of the results in Chapter 6. For more details about

the rate function, see Section 5.1.3 in Ripley et al. (2014), or Section 4.1 in Snijders et al. (2010).

In general, the objective function in a SAOM is formulated as

$$f_i(\beta, x) = \sum \beta_k s_{ki}(x). \tag{3.1}$$

This function expresses that the attractiveness of a given tie change for actor i in a ministep is determined by a set of variables ($s_{ki}(x)$), so-called 'effects', which depend on the state of the network, x, and by their respective weights (β_k). The effects are the explanatory variables of the model, and they represent various configurations in the network around the focal actor i, which may or may not be desirable for i. Some basic effects can be the number of reciprocated ties or the number of closed triangles in an actor's local network.

The β_k parameters are to be estimated by the model, and they express whether and how much the configuration represented by each effect is attractive for the actors. Actors are more likely to make changes which lead to more of the attractive configurations in their network neighborhood, and they try to avoid unattractive configurations. For example, if actors in a network have a tendency to reciprocate incoming ties over a time period, this will be reflected by a positive parameter for the reciprocity effect in the model. In a ministep, actors will be more likely, given all other effects in the model are equal, to create or maintain a tie which is reciprocated than one which is asymmetric.

It is clear from the discussion so far, that the dependent variable in a SAOM is the existence of a network tie from one actor to another (the model assumes binary networks). Therefore, the estimated model is a repetition of multinomial logistic regression models in which the observations are the actor decisions in the simulated sequences of ministeps, and the parameters represent the average tendencies of actors for or against forming certain network configurations over the simulated period.

What links the simulations to the real-world is that the model aims to optimize the parameter vector for the effects so that the networks resulting from the simulations are similar to the networks observed at the panel waves; the individual tie changes are not assumed to be observed. There are several estimation methods for achieving this, currently Method of Moments, Maximum Likelihood, and Bayesian estimations are elaborated for the method.

Estimation methods for SAOMs are implemented in the *RSiena* software package which can be used within the R framework. We use this software for modeling the dynamics of the studied classroom networks in Chapter 6. For more detailed

descriptions of the basics of the model, see Snijders et al. (2010) and Ripley et al. (2014). Snijders (2011) presents the context of statistical network modeling and helps to position the SAOM in this scenery.

3.4.2 The co-evolution of multiplex networks

The previous section described some key features of the basic type of SAOMs. There is a more complex variant of the model which allows for the analysis of the co-evolution of multiple networks (Snijders, Lomi, and Torló, 2013). Using this extension, one may, for example, model the simultaneous dynamics of friendships and peer-perceptions in a community, including how one type of relation may influence the evolution of the other. The basic principles of SAOMs apply in multiple-network models, as well. The difference from the single-network SAOM is that here we have multiple dependent variables (one for each modeled network), and accordingly, multiple rate and objective functions (separately specified).

The ministeps only change slightly in this case: before an actor is selected to make a change it is determined, based on the rate functions, in which of the dependent networks the next change will occur. When an actor makes a decision about a tie change, the structure of all networks in the model may affect this choice, depending on the effects in the model. The networks which are not modeled in a given ministep are treated as given, like covariates.

The multiple-network SAOM can be used to analyze the co-evolution of partially overlapping networks (for example, friendship and trust). Additionally, ordered networks which may represent different strength of a relation (e.g. liking–friendship, dislike–hate) or disjunct networks with no overlapping ties (e.g like–dislike), or any combination of these types can be included in a single model. In principle, the number of dependent networks in a model is not limited. However, it is practically not feasible to use SAOMs for studying more than three-four networks at once, because the large number of possible interlinks between the networks makes the interpretation of the model difficult (consider network configurations that involve four types of relations!).

3.4.3 Modeling networks in multiple groups

The RSiena package provides three options for studying the co-evolution of multiple networks in several groups (in our case: classrooms). The first strategy is the meta-analysis of group-level models. The second option is the so-called 'multi-group' model, in which one model is estimated for all of the studied groups. In a multi-group analysis

it is assumed that the parameters are identical in all of the studied groups. While this may easily be untrue, it is possible to interact certain effects with group dummies to allow for between-group variation in at least some of the parameters. The third approach is a random effects hierarchical SAOM, which is the multi-level extension of the basic models.

All three methods have advantages and disadvantages. With the meta-analysis, we can estimate group-specific parameters for all of the effects in the model, but the size of the groups constrains the complexity of the model (observations vs. variables). This can be a problem especially for co-evolution models, where there are numerous cross-network mechanisms one needs to represent by effects.

The multi-group analysis overcomes the power problem by pooling the groups in a single dataset (but respecting that ties between groups are not allowed). However, it is difficult to account for all the heterogeneity in the effect parameters between the groups, so it is likely that the estimates will be less informative and reliable.

The multi-level SAOM presents the middle ground between the other two options, as it allows for the estimation of varying and fixed effects while it draws power from all of the analyzed groups. However, this model requires the most computing time, and its implementation was still in a test phase when the relevant part of this thesis was written.

After the consideration of arguments for and against the three methods, the multi-group option was chosen for the analyses presented in Chapter 6. This allows us to specify models which are complex enough to provide answers for the research questions.

3.4.4 Further functionalities of the model

Goodness of Fit. It is not possible to apply simple, R^2-type measures to assess the goodness of fit of a SAOM. This is because the parameter estimates are not optimized for the simulations to reproduce the observed network tie-by-tie, but to generate networks which are similar to the observed one in important structural properties (the configurations represented by the included effects). As a consequence, fit can be defined in several ways.

Lospinoso (2012) developed the currently used Goodness of Fit framework for SAOMs. The principle of the method is that one may choose a structural network property of interest which is not explicitly modeled (for example, the distribution of degrees) and assess whether networks simulated based on the estimated SAOM are similar enough to the observed network in the given property. This way it is possible

to determine whether a specified model does well at reproducing emergent network features which are not directly included as effects in its objective function.

Missing data. SAOMs distinguish between two types of missing data. The first is random missingness, for example, because the relationship between two actors is not known, although their other ties are known. Just as non-network regression models, SAOMs can deal with some randomly missing data. As a rule of thumb, the ratio of missing ties is too high above 20% (Ripley et al., 2014, p. 13). Too much missing data may lead to an unstable estimation and unreliable results (especially if missings are not random).

Composition change. The second type of missing data in SAOMs is the absence of information about all ties sent by an actor. In many cases, this is related to composition change in the network: actors may leave and join a community between observations. There are several implemented options for handling these cases. However, joiners and leavers have little effect on the model results in cases when there are only two observed time points (and so one modeled period). This is exactly the case of the study in Chapter 6, and for this reason we remove joiners and leavers from the analyzed classroom datasets (see Section 3.1.2).

Tie stability. If the subsequent observations from a network are very similar, there is little change based on which SAOM parameters can be estimated. On the contrary, if ties change rapidly and the two observations are very different, it is not reasonable to assume a time-homogeneous process (i.e. some ties had to dissolve, others had to form) – an assumption which underlies SAOM estimates. Consequently, the use of SAOMs is likely to be less successful under extreme values of tie stability. The rule of thumb for the "safe" range of stability, expressed as the Jaccard index (see Section 4.2.3), is larger than 0.3 (Ripley et al., 2014, pp. 19–20); lower values are not entirely excluded though (Snijders et al., 2010). It may be possible to acquire convergent estimates even when tie stability lies outside of this region, however, the concerns outlined here should be kept in mind.

3.4.5 List of effects used in the current study

Tables 3.6 and 3.7 present the SAOM effects that are used by the models in Chapter 6. The names of the effects in the tables are similar to how we refer to them later. We provide the mathematical formula of the so-called change statistic for each effect (more details below), along with their intuitive interpretation.

In case of single-network effects (Table 3.6), the notations are straightforward: x_{ab} refers to the state of the tie from an actor a to an other actor b, which takes the value

Table 3.6: The description of the SAOM effects used in the models I. Single-network effects.

	Effect name	Effect of an additional tie	*The effect from creating or maintining a tie...*
Single-network structural effects			
1.	Outdegree (density)	x_{ij}	... (intercept).
2.	Reciprocity	$x_{ij}x_{ji}$	... which reciprocates an incoming tie.
3.	Indegree Alter	$x_{ij}\sum_j x_{hj}$	... to someone who already receives many ties
4.	Outdegree Alter	$x_{ij}\sum_j x_{jh}$	... to someone who sends many ties.
5.	Outdegree Ego	$x_{ij}\sum_h x_{ih}$	... by someone who already sends many ties.
6.	Balance	$x_{ij}\sum_h(b_0 - \lvert x_{ih} - x_{jh}\rvert)$	... which is embedded in clusters based on agreement.
7.	Transitive recipr. triplets	$\sum_h x_{ij}x_{ji}x_{ih}x_{hj}$	... which is reciprocal and is embedded in clusters.
Single-network covariate effects			
8.	Sex Ego	$x_{ij}v_i$	... depending on the sex of the sender (centered; higher cat.= girl.)
9.	Sex Alter	$x_{ij}v_j$	... depending on the sex of the receiver (centered; higher cat.= girl.)
10.	Same sex	$x_{ij}I\{v_i = v_j\}$	... to same-sex peers.

of 1 if the tie exist and 0 otherwise. For every effect, the situation considered is the creation of maintenance of a tie by actor i to j, that is, x_{ij}. Further, v_i and v_j denote here the sex of the sender (i) and receiver (j), respectively (note that these variables are centered in the models by the mean of the given dataset).

The formulae for the cross-network effects (Table 3.7) feature an additional tie variable, w. In very case, x refers to the dependent network tie (which can be either a friendship or a perception), and w is the tie which taken as given in the considered situation. Note that for effect 15 and 17, we only consider the possibility when the dependent network is friendship, and for effects 16 and 18 when the dependent is a perception network.

The change statistic expresses the change in the explanatory variable associated with the creation of a dependent network tie which is embedded in a structural

Table 3.7: The description of the SAOM effects used in the models
II. Cross-network effects.

	Effect name	Effect of an additional tie	*The effect from creating or maintining a tie...*
Cross-network structural effects			
11.	Friendship/Perception	$x_{ij}w_{ij}$	... to someone who is already nominated by the sender in the other network.
12.	F/P indegree Alter	$x_{ij}(\sum_h w_{hj} - \bar{w})$	... to someone who receives many ties in the other network.
13.	F/P outdegree Alter	$x_{ij}(\sum_h w_{jh} - \bar{w})$	... to someone who sends many ties in the other network.
14.	F/P outdegree Ego	$x_{ij}(\sum_h w_{ih} - \bar{w})$	... by someone who sends many ties in the other network.
15.	Perception agreement	$x_{ij}\sum_h w_{ih}w_{jh}$	... of friendship to someone whose perceptions are similar.
16.	Friendship influence	$x_{ij}\sum_h w_{ih}x_{hj}$	... of perception to someone who is perceived similarly by the sender's friends.
17.	Perception agreement × Target indegree	$x_{ij}\sum_{h,k}(w_{ih}w_{jh}w_{kh})$	... of friendship based on perception similarity if the same perception is shared by many classmates.
18.	Peer influence × # shared friends	$x_{ij}\sum_{h,k} x_{kj}w_{ih}w_{kh}$	... of perception based on influence from someone who has many common friends with the sender.

configuration represented by the effect. For example, the formula for reciprocity in Table 3.6 can be interpreted in the following way: the creation of a tie from i to j increases the variable of reciprocity by 1 if there also exists a tie from j to i, and by 0 if this tie is not present. How the increase of the reciprocity statistic will change the objective function (and affect actor decisions) depends on the parameter for the effect estimated by the model: a positive parameter would mean that actors "prefer" changes that lead to more reciprocity, and a negative parameter would signal the opposite. The rest of the effects shall be interpreted accordingly.

Chapter 4

Dimensions of peer-perceptions in school: Defining composite network measures

Social relations are multiplex by nature: actors in a group are tied together by various types of relationships. To understand and explain group processes it is, therefore, important to study multiple social networks simultaneously in a given group. However, with multiplexity the complexity of data also increases. Although some multivariate network methods (e.g., ERGMs, SAOMs) allow to jointly analyze multiple networks, modeling becomes complicated when it focuses on more than a few (2-4) network dimensions. In such cases, dimension reduction methods are called for to obtain a manageable set of variables. Drawing on existing statistical methods and measures, we propose a procedure to reduce the dimensions of multiplex network data measured in multiple groups. We achieve this by clustering the networks using their pairwise similarities, and constructing composite network measures as combinations of the networks in each resulting cluster. The procedure is demonstrated on a dataset of 21 interpersonal network dimensions in 18 Hungarian high-school classrooms. The results indicate that the network items organize into three well-interpretable clusters: positive, negative, and social role attributions. We show that the composite networks defined on these three relationship groups overlap but do not fully coincide with the network measures most often used in adolescent research, such as friendship and dislike.[1]

[1]This paper is co-authored with Tom Snijders. His advice on choosing the right statistical measures and methods, as well as his careful revisions of the text were felt to be over the regular involvement of a supervisor. The application and adjustment of the methods to the problem at hand and the presentation of the results are the candidates own work.

4.1 Introduction

In a classic study of U.S. high schools in the late 1950s, Coleman and his colleagues asked students to name both their peers from school whom they considered as friends and those whom they most wished to be like (Coleman, 1961). The distinction between friend and role model relations led the researchers to discover that every school had a distinct group of "local leaders" (students popular as friends) and "system leaders" (students popular as role models), and that it was the latter group which had a larger impact on the school community as a whole (Coleman, 1961, Chapter 4). This phenomenon, important as it is in understanding the value system of adolescents, would not have been revealed had the study focused solely on friendships between students. The work of Coleman and colleagues demonstrates that without taking into account the multiplexity of relations, the social forces shaping communities cannot be fully understood.

The importance of multiplexity has long been recognized in the research tradition of Social Network Analysis (Kadushin, 2012; Prell, 2011; Borgatti, Mehra, Brass, and Labianca, 2009), but its potential for aiding explanations is far from being fully exploited. The collection of rich multiplex network datasets has begun already several decades ago (e.g. Sampson, 1969; Coleman, 1961; Homans, 1950).[2] Additionally, one can also witness the early development of methods appropriate for analyzing this kind of data (e.g. Davis, 1968; Fienberg, Meyer, and Wasserman, 1985). However, most multiplex studies and methods focus on only two or three types of relations at most. Common sense tells us that social ties, may they connect people, firms, or countries, are more heterogeneous than that. Yet, even nowadays we rarely see network studies that measure a large number, say dozens, of relational dimensions in a given social context. This seems surprising especially in times when network data, even on a large scale, are becoming easier to collect and computational capacity is sufficient for analyzing complex data structures.

Studying a small set of relations can be a good practice as long as we have well-grounded knowledge about, and valid measures of, the most important types of social ties in a given context. However, this seems usually not to be the case, and simplicity of measurement tends to outweigh validity and thoroughness. For example, affective relations are quite often studied by friendship ties. Friendship is a complex

[2]The popular software packages for network analysis contain a variety of classic multiplex datasets. For example, networks among Sampson's monks and the bank wiring room data (Roethlisberger and Dickson, 1939) studied by Homans are available in UCINET (Borgatti, Everett, and Freeman, 2002).

relationship, yet it is mostly measured by the single quesion "Whom do you consider a friend?". As a price, additional work is needed to find out what people actually mean when they answer this simple question. And we do know, for instance, that they mean a lot of different things (Fischer, 1982), that what they mean changes with age (Berndt, 1982:1449), and that friendship is multidimensional (Marsden and Campbell, 1984). Consequently, it seems to be a better practice to complement our analyses of friendship networks with several related network dimensions.

Measuring a large number of relational dimensions, maybe dozens, makes it possible to define each of them very specifically, and thereby to obtain valid measures of various concrete social relations between actors (rhyming with the old wisdom of sociometricians). Even more importantly, however, by exploring the interrelations between these measures, one may be able to construct aggregated networks that represent some latent dimensions of social relations – just as in the case of psychological scale construction, but now tailored to networks. This approach to multiplexity can help us define more valid measures of complex relationships, such as friendship, and potentially new measures of so far unexplored relational concepts. The present paper attempts to contribute to a step in this direction by outlining a suitable analytical procedure and demonstrating its value on a real-world example.

4.1.1 Multiplexity as a challenge

The complexity of multiplex network data with many relational dimensions presents two general challenges compared to studying only one or a few networks at once. First, from a substantive point of view, with more network dimensions studied, the number of potential mechanisms involved in a social phenomenon increases rapidly. For example, in the context of Coleman's high-school study we may be interested in why certain students become popular in their community. The potential answers to this question become numerous as soon as we recognize that there are two distinct pathways to popularity: e.g., making friends and becoming a role model. How can students become role models outside of their local group? How can role models become popular in their local friendship groups? Do students tend to see their friends as role models? Or do they want to befriend those who they wish to be like? These examples highlight the need for a series of theoretically and empirically grounded ideas about how multiple types of relationships are interlinked in a given context. Taking into account the multitude of possible interdependencies between several network dimensions, hypotheses about numerous social mechanisms may be necessary. These are bound to be ad hoc unless a strong theoretical framework is available.

The second, and related, challenge posed by the complexity of multiplex data is of a technical nature. It becomes necessary to use statistical tools which are able to efficiently and comprehensibly model the complex interdependencies of network ties within and between the types of social relations in question. Some of the recent multivariate statistical methods in the field allow the analysis of multiplex networks. For example, the structure of a dependent network can be explained by other networks using MRQAP (Krackhardt, 1988; Dekker et al., 2007), ERGMs (Lusher et al., 2012), or SAOMs (Snijders et al., 2010). Furthermore, the mutually dependent modeling of multiple network dimensions is also an option in case of the latter two methods (Lusher et al., 2012, Chapter 10; Snijders et al., 2013). These two techniques are flexible enough to model various specific forms of interdependencies between multiple networks, including actor-level, dyadic, and triadic interrelations. However, the same flexibility makes working with these techniques a daunting task already in case of three or four networks, let alone more.

4.1.2 Dimension reduction to the rescue

Dimension reduction is one of the successful research strategies to tackle both the substantive and the technical challenges that come with "too much" data. The general approach represented by Cluster Analysis, Factor Analysis, or other methods for dimension reduction of non-network, monadic data has been frequently applied to different problems in the analysis of social networks. It is enough to think about blockmodeling (Doreian, Batagelj, and Ferligoj, 2005; White, Boorman, and Breiger, 1976) which aims to identify subsets of actors based on their position in the network. In some cases, the classification of actors may be based on their position in multiplex relational structures (e.g. Dabkowski, Breiger, and Szidarovszky, 2015; Lazega, 2001).

Of the classic techniques of scaling, we can find applications of Correspondence Analysis for the simultaneous clustering of tie senders and receivers in one-mode and two-mode networks (Faust, 2005; Wasserman, Faust, and Galaskiewicz, 1990; Wasserman and Faust, 1989), or for the comparison of structural features of networks measured in multiple groups (Faust and Skvoretz, 2002; Skvoretz and Faust, 2002). Cluster Analysis also appears as a method to classify groups based on their network structure (Brandes, Lerner, and Nagel, 2011). Further, Multi-dimensional Scaling is used to visualize similarities between network actors (e.g., Hanneman and Riddle, 2005), or to assess the presence of a relational hierarchy in certain types of networks

(Borgatti, 1994).[3]

Many more applications of dimension reduction methods to social networks could be mentioned. What seems to be missing from the literature, however, are studies that aim to analyze the multivariate similarities between multiple relational measures. Analogous to the approach of scale construction in the case of psychological tests, we could consider defining aggregated networks based on a large set of relational variables found to be similar in some respect.

4.1.3 A precursor in psychology: peer ratings of behavior in school

The first steps in constructing scale-type, aggregated network measures were actually taken in the discipline of psychology several decades ago. Starting from the middle of the 20th century, psychologists concerned with social adjustment problems of children and adolescents have studied the relationships between sociometric status and behavior in peer groups (for a review of this research stream, see Asher and Coie, 1990). To find the behavioral correlates of sociometric status in school, researchers developed tests in which students had to evaluate their peers on several (30-50) items which described various social behaviors.

As examples for the rich collection of tests that have been employed, we can mention the Peer Nomination Inventory (Wiggins and Winder, 1961), the Class Play Method (Bower, 1960; Masten, Morison, and Pellegrini, 1985), the Pupil Evaluation Inventory (Pekarik, Prinz, Liebert, Weintraub, and Neale, 1976), and the Adjustment Scales for Sociometric Evaluation of Secondary-School Students or ASSESS (Prinz, Swan, Liebert, Weintraub, and Neale, 1978).

In all of these cases, peer nominations are aggregated within the classroom or group to individual scores that represent the number of nominations students received in each item. The individual scores are then usually studied by Factor Analysis to identify the latent dimensions underlying the pool of behavior items. Finally, the relationships between the factor variables and sociometric status, which is based on nominations received in independent like-dislike items, are explored.

Although the mentioned peer assessment methods vary in the selection procedure and final list of behavioral items, their findings point in the same general direction. In all age groups, sociometric status of children appears to be associated with the

[3]Although a linear model, we can also mention Canonical Correlation Analysis which some authors have applied to study and summarize the dyadic interrelations between a few types of relations in multiplex datasets (Carroll, 2006; Wasserman and Faust, 1989).

sociable/cooperative and the aggressive/disruptive dimensions of behavior. The peer evaluation approach outlined here has contributed greatly to the study of social processes related to rejection (Newcomb, Bukowski, and Pattee, 1993; Asher and Coie, 1990; Coie, Dodge, and Coppotelli, 1982) and popularity (Cillessen, Schwartz, and Mayeux, 2011) among children and adolescents.

An important strength of the above described studies is that they follow a multiplex network approach to the identification of the main behavioral dimensions in peer groups. The researchers start with a large set of network measures and arrive at only a few aggregated variables which are easier to handle and which retain a significant part of the information in the original data. The networks of interest are interpersonal perceptions about various forms of social behavior among children. The classification of perception items depend on the pairwise similarities (inter-item correlations) between students' indegree centrality in each network: two perceived behavior networks will be more likely to end up on the same factor if students who receive many (few) nominations on one item, also receive many (few) on the other. Such a conceptualization suits the aim of the psychologists of the area as they investigate the differences in the behavioral profile of children in distinct sociometric status positions (e.g. rejected, popular).

In these studies, dyadic perceptions are aggregated to individual-level indegrees. This step discards network structure entirely and creates a risk of ecological fallacy: tie-level and individual-level, or even group-level, processes will be confounded by this aggregation. The case of sociometric status and aggression can serve as an example. Different studies found that aggression is related to popular (Cillessen and Rose, 2005:104), controversial (Coie et al., 1982:565), and rejected status (Coie, Dodge, and Kupersmidt, 1990:20). This variation in results may be due to differences between the studied groups with respect to dyadic and group-level social processes: the tendency of children to like or dislike those who they think are aggressive, and the tendency of the group to agree on which peers are aggressive or likeable. It is hard to tell the two apart. Reducing perceptional data to indegree scores is equivalent to assuming the independence of network ties, which obscures heterogeneities in the network, such as the existence of subgroups with different perceptions.

4.1.4 Multiplexity as an opportunity: the cluster analysis of multiplex networks

The argument discussed so far does not hold only for peer perceptions and sociometric status among children but points to a more general approach of dimension reduction in

multiplex network data. In such data, the several network dimensions will be referred to as *network items*, because we regard them similarly as items in a psychological test: questions that are intended to measure an aspect of social reality – in this case a relational, not an individual aspect.

When the focus is on relations, similarity on the level of dyads is of more crucial importance than similarity between individuals. If actors tend to nominate the same peers in one network dimension as in another, then the two network items may capture different sides of the same relationship. For example, sharing secrets and willingness to borrow money may be thought of as constituents of trust. The classification of multiplex networks based on their dyadic similarities allows us to aggregate information on the level of network ties. That is, we could say that if two actors share their secrets and are willing to borrow money to each other, then they can be considered to have a trust relationship. This way we are be able to reduce a large multiplex dataset to a few composite networks, representing the main underlying relational dimensions emergent from the dyadic patterns of ties across the several measured items.

Similar to the approach represented by Factor and Cluster Analysis of monadic variables, here we present an analytical procedure for dimension reduction in multiplex network data measured in multiple groups. A network dimension, or network item, we define operationally by the question posed or the measurement instrument used; sometimes we refer to this just as the 'network' or 'relation'. The data structure is a crossed structure of network items by groups. By exploring the multivariate similarities between the measured network dimensions, the procedure aims at finding clusters of relations that are similar for each of the groups. For this purpose we apply Cluster Analysis to the similarity structure in every group. In doing so, we assume throughout that the studied groups are homogeneous in the sense that the measured network dimensions are related in more or less the same way in each of them, while allowing for some differences between the groups — related perhaps to their peculiar composition

Based on a cluster solution that is reasonable for all of the studied groups, we define composite network measures. In some cases there may be straightforward ways for doing this, such as taking the union or the intersection of all networks that belong to a given cluster (see some examples in De Domenico, Solé-Ribalta, Cozzo, Kivelä, Moreno, Porter, Gómez, and Arenas, 2013). Instead of choosing either of these two extremes, we propose to explore several possibilities, with a tie in at least t (where t may range from 1 to the number of networks in a cluster) of the networks required to be present between two actors to qualify as a tie in the composed

network. Exploring the properties of the resulting composite networks at different thresholds t, and also their relations with each other and with other basic network measures (such as friendship), can inform the specification of composite networks. We demonstrate that this procedure is capable of reducing the number of studied networks to a level that can be analyzed with existing multiplex network models, and it can also result in composite networks that meaningfully complement analyses based on more conventional network measures in the studied context.

The proposed procedure is explorative. It would perhaps be interesting to derive a procedure from an explicit model such as a model with latent networks that are measured with error or with item-specific contributions, like in Factor Analysis or other latent variable models. However, we fear that such a procedure would be quite cumbersome and subject to a variety of assumptions that are difficult to test, and therefore we restrict ourselves to what we think is a sensible explorative step-by-step approach.

In the following sections, we first describe the procedure in general terms, and then provide an example about the dimensions of peer perception in Hungarian high schools. We arrive at a clustering that represents the similarity between the networks in all groups to a reasonable extent. We highlight a number of decisions that need to be made by the researcher during the analysis, taking into account the context of the study. Some practical considerations and issues regarding future developments are discussed in the last section. We hope that the proposed analytical strategy may be useful for researchers in finding the main dimensions of relationships in a given social context, as a preliminary step for analyzing highly multiplex network data with existing statistical models, and that it may also provide clues for the construction of valid and rich multiplex network measures.

4.2 Defining composite network measures: an empirical procedure

When analyzing social processes within a group, we may be interested in a multitude of networks – relations, perceptions, common activities, etc. – among its members. Having measured a variety of network dimensions, we face data of high complexity that is difficult to analyze, even with the most advanced network methods. This is further complicated when we would like to investigate and compare processes across several groups. Below we propose and demonstrate a procedure, utilizing a set of ex-

isting statistical methods, that can aid researchers in reducing the number of studied networks by the construction of composite network measures in multiple groups.

4.2.1 The problem

We assume that we have conducted a network study in G disjoint groups (communities, firms, regions, etc.) where the g^{th} group has n_g actors. In each of the groups, we have measured the same set of K networks representing various types of relations between the actors. The observed groups are likely to be heterogeneous in terms of network structure and the interrelations between network dimensions. However, we assume that there are inherent similarities between them, so that it is meaningful to look for consistent patterns across groups. We further assume that the number of measured network dimensions, K, is large enough so that the data cannot be analyzed with the multivariate methods mentioned above (practically, much larger than four).

We propose a procedure to reduce the complexity of such network datasets by identifying clusters of networks such that networks in the same cluster are similar and networks in different clusters are dissimilar; therefore it may be called a *cluster analysis of networks in a multiplex network data structure with multiple groups*. The procedure serves a similar purpose as Factor or Cluster Analysis of monadic variables: starting with a relatively large number of network items in a sample of groups, it results in a smaller number of composite networks which may capture the latent relational dimensions underlying the data better than the original items.

The five (plus one) steps of the procedure represent a strategy that is natural for Cluster Analysis in general. Here we briefly go through the steps and then elaborate on them in the following sections. Throughout the paper the terms "network", "network item", "item", or "network dimension" are used interchangeably to refer to a specific instance of the K measured networks.

- Step 0. Before starting the analysis, it is worthwhile to think and state explicitly the aim of the application, initial hypotheses about the clustering of the K network items, etc. This step can help in making decisions later in the procedure. A few basic questions are collected below.

- Step 1. The set of K networks in G groups in our case have the same role as objects in a Cluster Analysis or items in a Scale Analysis. Accordingly, we choose a measure of pairwise similarity between the observed networks in each group – some suitable measures are presented below. For each of the G networks, this step results in a $K \times K$ similarity matrix.

- Step 2. The consistency of similarities across the groups are assessed, and network dimensions with highly inconsistent relations to the rest of the networks are dropped from further analysis. This is in line with the assumption that the observed groups are similar with respect to the network dimensions that are used for the clustering.

- Step 3. Network dimensions are clustered using their pairwise similarities, with the aim of finding a classification that is appropriate for all G groups. The procedure proposed here is ordinal: it is based on only the rank order of the similarities.

- Step 4. The fit of the global solution is tested in each group.

- Step 5. Assuming that a well-fitting clustering solution has been found, it is used to combine the network dimensions belonging to the same clusters to create composite network measures.

4.2.2 Step 0: Thinking

Prior to the analysis, it is advisable to consider questions such as the following, as they may assist in making some of the decisions in later steps of the procedure. The answers should be based on theoretical considerations and prior empirical evidence. First of all, what is the aim of the study? What do we want to use the composite networks for? What should their ties represent? Given the aims, what are the best candidate measures of the similarities between the network items? Then, does it seem meaningful to compare all of our items? Are there some which are substantively not comparable with the rest? If the comparison seems appropriate, can we come up with an *a priori* intuitively acceptable grouping of the items? Are the groups themselves comparable, or are there systematic differences between them? Do they represent similar social settings? Finally, have others found something of relevance about the association between these or similar network items in similar groups?

4.2.3 Step 1: Measuring network similarity

The first step is to decide on how to measure similarity. This choice primarily depends on the level of analysis that is the focus of study: dyads or actors. The Jaccard index (Jaccard, 1908; Batagelj and Bren, 1995) and the simple matching coefficient (Sokal and Michener, 1958, Wasserman and Faust, 1994:370) can be used to quantify similarities between two networks on the level of dyads. In- or outdegree correlations

are simple measures of actor-level similarity between two networks, as we have seen in the examples from adolescent research (for a more recent application, see Szell, Lambiotte, and Thurner, 2010).

Depending on the researcher's interest, further measures may be defined and used, e.g., measures of similarity between block structures. However, note that not all measures are equally appropriate for every research question, and the chosen measure has to fit to the aim of the application. This issue is discussed further in Sections 4.1.3, 4.2.2, and 4.5.

As our present aim is to combine information from several network items on the level of ties, we use a dyadic similarity measure, the Jaccard index. The Jaccard index between networks k and m ($k, m \in \{1, ..., K\}$) in a given group can be formulated as

$$J_{km} = \frac{n_{km,11}}{n_{km,11} + n_{km,10} + n_{km,01}}, \tag{4.1}$$

where

$$n_{km,ab} = \sum_{i,j} I\{x_{kij} = a, x_{mij} = b\} \qquad (a, b \in \{0, 1\};\ k, m \in \{1, \ldots, K\}), \tag{4.2}$$

where $I\{A\}$ is the indicator function of set A and x_k and x_m are the adjacency matrices of the two networks. E.g., $n_{km,11}$ is the number of ties present in network k as well as m. The value of the Jaccard index ranges between 0 and 1, with 0 showing that there are no overlapping ties and 1 that exactly the same pairs of actors are tied in the two networks. By calculating the Jaccard index for each pair of the K networks, we get a $K \times K$ matrix of pairwise similarities for each of the G groups in our dataset.[4]

Projecting and visualizing the similarity structure

Before starting any further analysis, it is advisable to visualize the similarity structure of the networks in each group. A good representation may give a preliminary idea about the main dimensions of relations between the network dimensions. In addition, comparing images from each group can inform us about between-group differences that should be taken into account in the later steps. Since the starting point was that we have measured more than just a few networks, a comprehensible visualization should be preceded by the projection of the pairwise similarities into a few dimensions.

[4]Some of the statistical techniques applied below take distances rather than similarities as an input. For sake of clarity, we only use "similarity" throughout the arguments, but note that the two concepts carry the same information. For instance, the Jaccard distance can be expressed simply as $1 - Jaccard\,index$.

A method suitable for such a problem is Ordinal Multidimensional Scaling (Ordinal MDS). The aim of MDS in general is to place items (in our case, networks) in a low-dimensional, preferably 2D or 3D, space so that the pairwise similarity matrix reproduced from the location of items in this space represents the original similarity matrix as well as possible. In Ordinal (or non-metric) MDS the aim is to produce a solution in which the rank order of similarities optimally matches the rank order of the Euclidean distances between the items; the numerical value of the reproduced similarity measure is not important. The result of the MDS, the coordinates of items in the projection, can be used to visualize pairwise similarities. For more detailed descriptions of MDS see Bartholomew, Steele, Galbraith, and Moustaki (2008), Chapter 3 and Cox and Cox (2010).

4.2.4 Step 2: Checking the consistency of similarities across groups

For the set of network items to be clusterable, their similarity matrices across the various groups should show a consistent pattern. This means that, roughly, in different groups, the same pairs of items should be similar and the same should be dissimilar. Items having an erratic pattern in their similarities to other items would disturb the clustering process and should be left out. How to assess the consistency of this pattern? If an item is identically related to the other items across all groups, the rank order of similarities between this item and the other items will be the same across groups. Thus, for item k, we are considering row k of the similarity matrices for all groups, and we require the rank order of the cells in this row to be similar across the groups. In other words, if r_{gkm} denotes the rank of network m in the order of similarities to k for group g, then the rows $(r_{gk1}, \ldots, r_{gkK})$ should be approximately equal in all groups g.

To quantify the consistency of network similarities across the groups, we apply a nonparametric measure, Kendall's coefficient of concordance, or Kendall's W (Kendall and Smith, 1939; Legendre, 2005). The level of concordance of a network k is calculated by comparing the rank orders of the similarities of the remaining $K-1$ networks to k in the G groups. If a network item is perfectly consistent in its relation to the rest of the items, that is, the order of items based on their similarity to the network in question is the same in all groups, Kendall's W takes the value of 1. Smaller values indicate lower consistency with the index being close to 0 if the order of similarities is basically random across the groups.

Formally, we can write Kendall's W for a given network k in G groups as

$$W_k = \frac{12 \sum_{m \neq k}^{K} (R_m - \bar{R})^2}{G^2((K-1)^3 - (K-1))} \ , \tag{4.3}$$

where G denotes the number of groups across which we compare the rank order of similarities, K is the number of network items (including k), R_m is the sum of the ranks of the similarity between network k and another network m over all G groups,

$$R_m = \sum_{g=1}^{G} r_{gkm} \ , \tag{4.4}$$

and $\bar{R}$ is the average sum of ranks given the number of groups and networks (note again that K includes k),

$$\bar{R} = \frac{1}{2} GK \ . \tag{4.5}$$

For each network item k, we calculate Kendall's W_k and inspect their values. We use these values not to test a null hypothesis, but to assess descriptively the homogeneity of the groups with respect to how this item relates to the other items. If many items have a very small W_k (though there is no strict rule for what counts as "small"), then the G groups are very heterogeneous in how the networks relate to each other, and chances for finding a clustering that would work well in all groups are low. However, it may be possible to make similarities more consistent by dropping from the analysis network items with low W; but this will affect the W_k values between the remaining networks. Therefore we do it in a recursive fashion: in each step drop the network with the lowest W, then recalculate the coefficients, now without the excluded network. After dropping a small number of items, it may be possible to obtain a restricted set of networks, all of which have a sufficiently high consistency measure.

Deciding on a stopping rule in this procedure is a qualitative decision that does not only depend on the values and the distribution of Kendall's W, but also on judgment about item content. The conclusion of this step in the analysis might be that finding a clustering of networks that is valid in all groups is not feasible. In such a case, a different strategy might be necessary (for example, involving the classification of the groups based on the clustering of the items in each of them), which we do not treat in the present paper. We assume that at the end of Step 2, a set of items was obtained with sufficient homogeneity.

4.2.5 Step 3: Finding group-level and global clusters in multiple groups

As a result of the previous steps, we now have similarity matrices, raw and reproduced from Ordinal MDS, between a potentially reduced number of K' networks in all G groups. Although the similarity structures will usually still differ between groups, these differences were reduced in Step 2 so that the groups may be regarded as being more homogeneous. In the current step, we explore the cluster structures of the network items in each group separately. For doing so, we can apply a suitable method of Cluster Analysis on the similarity matrices. Here we use Ward hierarchical clustering which has been found to produce well-interpretable solutions in various situations (Bartholomew et al., 2008:24). Ward's minimum variance method is an agglomerative hierarchical clustering procedure. In our example the method starts with K' clusters (each network item individually) and groups them one by one so that in each step the two clusters having the lowest between-cluster variance are merged.

In this step, we also attempt to define a cluster structure which will be a candidate for a global grouping. There may be several ways for doing this, but we have found it useful to simply calculate the mean similarity matrix from the group-wise similarity matrices, and use the clusters obtained from that as a potential global solution. Note that this is justifiable only if the group-level clusterings were relatively similar to each other – which we have promoted by dropping inconsistent network items in Step 2. In the next section we provide an option for assessing how well the global cluster structure fits the group-level ones.

4.2.6 Step 4: Checking the fit of the global solution

Our aim is to find a single clustering of network items that reasonably represents the similarity structure in all groups. Therefore, before we use the global clustering as a basis for creating composite networks, we need to assess how well it fits the cluster solution of each group separately. For this purpose, we use the Rand index, a measure of comparing two cluster solutions based on whether they group each pair of items similarly (Rand, 1971; Hubert and Arabie, 1985). The Rand index for comparing a global clustering with the clustering obtained individually from group g can be formulated as

$$R_g = \frac{\text{no. of agreements}}{\text{all pairs of networks}} = \frac{a+b}{\binom{K'}{2}}, \tag{4.6}$$

where a and b are the number of agreements, that is, the pairs of network items that belong to the same cluster (a) or to different clusters (b) in both solutions and $\binom{K'}{2}$

is the number of pairs that can be made of our K' network items. The Rand index takes the value 1 if cluster memberships in the two compared solutions are identical, and 0 if there is no pair of items that are grouped the same way in both clusterings. The Rand index thus can be used to measure how similar the group-level clusterings are to the global structure we consider imposing on them. If the fit is satisfactory, we may define the same set of composite network measures in all of our groups. If not, we might drop some of the groups or some of the network items, and restart the whole procedure.

4.2.7 Step 5: Defining composite networks

The final step in the procedure is to construct a small number of binary networks as a combination of network items that were grouped together by our analysis. There may be several ways of doing so, but here we apply an approach that can be regarded as taking a "relaxed" union of ties in networks that belong to the same cluster. We say a tie exists in a composite network belonging to a cluster of items if the given tie is present in at least t of the constituent networks. If $t = 1$, this defines the union; if t is equal to the cluster size, it is the intersection of the networks in the cluster; but t could also be in between the extremes. There may be more than one good solutions of this step, and it is up to researchers to determine the value of t that best fits their substantive interest. The choice may be based on the number of items in each cluster, prior knowledge about the density of the composite network dimension, expectations about its similarity (e.g., as measured by the Jaccard index) to other networks external to the ones that were used to obtain the clusterings, etc. The defined composite networks then can be used as separate network dimensions in the analyses of substantive questions (which includes the possibility of defining multiple, ordered relational measures). An overview of the whole procedure suggested here is presented in Figure 4.1.

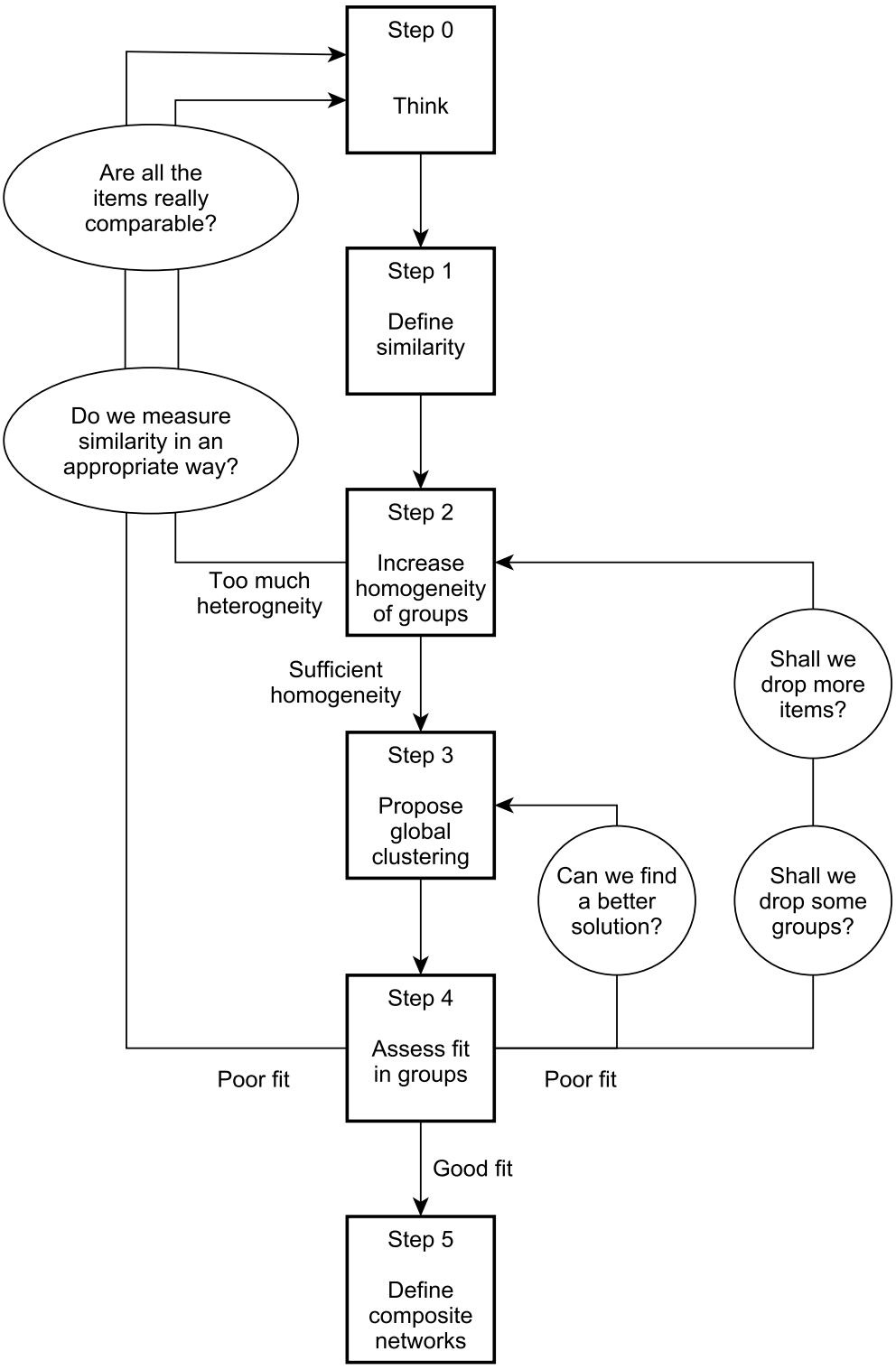

Figure 4.1: An overview of the procedure for the cluster analysis of multiplex networks

4.3 An application: peer-perception dimensions in Hungarian high schools

To demonstrate the procedure proposed above, we examine two waves of multiplex social network data from first-grade high-school classrooms in Hungary. The full dataset contains self-reported information about affective relations (*friendship*, *liking*, *dislike*, *hate*), shared activities, attribute, behavior and role perceptions, and bully-victim relations between the members of 43 classrooms. Here we use 21 interpersonal perception networks from a random subset of 18 school classes (see Appendix B), for the possibility of future cross-validation. To these 21 network dimensions in 18 groups, we apply the five-step procedure outlined above. The analysis identifies three main relational dimensions in the data: positive attributions, social role attributions and negative attributions. We use these three clusters to construct four composite networks representing these latent dimensions, and show that they significantly complement the information obtained from standard measures of affective relations, such as friendship or dislike.[5]

4.3.1 Data

For the analysis presented here, we use the Exploratory Subsample from the RECENS high-school dataset. This subset of 18 classrooms was selected randomly from the dataset in order for each school, classroom training program, and town size to be represented by at least two classes. The current paper focuses on the interrelations between 21 perception networks in these classrooms. Further descriptive information about the subsample is given in Section 3.1.1 and Appendix A.

4.3.2 Step 0: The network items and their expected grouping

Our analysis focuses on those network items from the RECENS dataset which are related to students' perceptions about their classmates. Specifically, we examine the similarities between 21 networks measuring different perceived attributes, behaviors,

[5]The analysis was carried out in version 3.2.0 of the R environment. For calculating Kendall's W we used the *kendall* function in the *irr* package (v0.84). Multidimensional Scaling was done by the *isoMDS* function in package *MASS* (v7.3-40). Hierarchical Cluster Analysis results are from the *hclust* function with Ward's method of package *MASS*, applied to Jaccard distances. The Rand index was calculated by the *randIndex* function in the *flexclust* package (v1.3-4). In addition to the base R functions for plotting, we relied on the functionalities of the packages *ape* (v3.2) (for cluster trees), *vioplot* (v0.2) (for violin plots), *venneuler* (v1.1-0) (for Venn diagrams) *lattice* (v0.20-31), and *gridExtra* (v0.9.1) (for heatmaps).

and social roles in the 18 classrooms.[6] Table 4.2 lists the network items we use in the current study: the translation of their original formulation in the questionnaire and the short labels by which we refer to them in the following. Further, it indicates if items identical or similar to ours can be found in the psychological tests we discussed in Section 4.1.3, namely PNI (Wiggins and Winder, 1961), RCP – the Revised Class Play (Masten et al., 1985), PEI (Pekarik et al., 1976), or ASSESS (Prinz et al., 1978).

As can be seen in Table 4.2, many of the perceptual dimensions we study here show up in some form in the earlier sociometric measures. Some of our network items are related to the Sociability/Likeability (*funny*, *clever*, *kind*), Withdrawal (*shy*), Hostility (*smug*), Aggression (*gossipy*, *fights*), and Social Competence (*argues*, *protects*, *dispute*, *decides*, *organize*) factors of the mentioned tests.

However, there are also quite a few items which don't have a precedent in these studies. The differences can be explained by the sociological focus of the RECENS dataset: perceptions connected to dyadic trust, social roles/leadership, social status, and physical attractiveness were important network dimensions in this study. Based on these earlier findings and the substantive content of the items, we can propose an a priori classification for the 21 analyzed items. The expected grouping may or may not be confirmed by the data, but it provides guidance in the decisions we need to make during the investigation.

When thinking about clusters among our network items, we have to keep in mind that unlike the cited psychological studies, we focus on the measurement of networks and not of individuals. This leads to important differences in interpretation. For example, let's assume that the items *teacher's pet* and *organize* have a high indegree correlation but a low Jaccard index in one of the classrooms. From the former fact only, we would conclude that students who are despised for trying to have too good relations with teachers are nonetheless appreciated by their peers as efficient organizers – perhaps because it is easier to get things done in school for people who are recognized by teachers – and we might be led to a conclusion about ambiguous dyadic perceptions, negative on the one hand and positive on the other. However, the low Jaccard similarity between these items would alter the interpretation by showing

[6]The analysis was also replicated with the two positive and two negative affection networks included. The positions of the *friendship* and *liking* network items were ambiguous in the similarity structure depending on whether the clustering was based on raw similarities or those reproduced from the MDS projection. This suggests that the overlaps between *friendship*, *liking*, and the rest of the networks should be examined separately, and so these two items were dropped from the procedure. The inclusion or exclusion of the *dislike* and *hate* items did not alter the rest of the results, and for consistency, these were also omitted from the analysis reported in the paper.

Table 4.2: Description of the analyzed perception network items

	Label	Item description	Expected grouping	Test with similar item
1.	funny	He/She is funny.	Positive attributes	PEI, PNI, RCP
2.	clever	He/She is clever.	Positive attributes	PEI, PNI
3.	kind	He/She is kind.	Positive attributes	PEI, PNI
4.	shy	He/She is shy, reserved.	Negative attributes	PEI, PNI, ASSESS
5.	smug	He/She is stuck-up, smug.	Negative attributes	PEI, RCP
6.	gossipy	He/She is gossipy.	Negative attributes	PEI, PNI, ASSESS
7.	fights	He/She often gets involved in fights.	Negative attributes	PEI, PNI, ASSESS
8.	nerd	He/She is a nerd.	Negative attributes	–
9.	t. pet	He/She is a teacher's pet.	Negative attributes	–
10.	look down	I look down on him/her.	Negative attributes	–
11.	argues	He/She dares to argue with teachers.	Leadership	ASSESS
12.	protects	He/She protects the weak.	Leadership	ASSESS, RCP
13.	dispute	He/She would be able to solve disputes.	Leadership	ASSESS, RCP
14.	decides	He/She decides what we do after school.	Leadership	ASSESS, RCP
15.	organize	He/She could organize a class trip.	Leadership	ASSESS
16.	look up	I look up to him/her.	Leadership	–
17.	trust	I trust my secrets with him/her.	Trust	–
18.	help	I could ask him/her for help.	Trust	–
19.	pretty	He/She is handsome/pretty.	Attractiveness	–
20.	would date	I would date him/her.	Attractiveness	–
21.	money	He/She has a lot of money.	Social status	–

Abbreviations: *PNI - Peer Nomination Inventory, RCP - Revised Class Play, PEI - Peer Evaluation Inventory, ASSESS - Adjustment Scales for Sociometric Evaluation of Secondary-School Students.*

that the perceptions of teacher's pet and good organizers are held by different sets of classmates.

Thus, we can say that dyadic similarity measures, by retaining more information available in the networks than degree-level measures, take into account the structure of the studied groups, the fact that communities can contain cliques that may have quite different opinions about certain peers. This further underlines that unlike the earlier studies, we are not trying to identify typical student profiles based on received nominations, but rather types of perceptions that usually go together. Such an approach will present a natural way for constructing aggregated network measures.

Based on earlier findings and intuition, we can assign our network items into a few groups. The first three networks (*funny*, *clever*, *kind*) clearly represent perceptions about general positive characteristics of social behavior. We may call this group positive attributions. The following seven items in Table 4.2 capture negative perceptions about peers (*shy*, *smug*, *gossipy*, *fights*, *nerd*, *teacher's pet*, and *look down*), hence we label them as negative attributions.[7]

The third, larger group, titled leadership, contains perceptions that are related to being active, independent, a leader in social situations (*argues*, *protects*, *dispute*, *decides*, *organize*, and *look up*). The network items *trust* and *help* form the fourth group, and they may be understood as two specific dimensions of general trust in dyadic relations. As a fifth category, there are two more items (*pretty* and *would date*) which represent the dimension of romantic attractiveness. The last perception network, *money*, is not similar to any of the other items as it represents impressions about the social standing or status of peers.

4.3.3 Step 1: The similarity structure of peer-perception networks

First we calculate the Jaccard index between each pair of the 21 networks in every classroom using the formula from Section 4.2.3. The values observed in the 18 classes range from 0 (wave 1-2) to 0.53 (wave 1) and 0.66 (wave 2), with a mean of 0.11 and 0.12. These numbers tell us that the pairwise overlap between the items in the sample is typically low, but varies greatly depending on the classroom and the items

[7]It is to be noted here that the classification of items, just as in any application of Cluster Analysis, is based on multivariate similarities. This means that it is not necessary for all pairwise similarities within groups to be equally high, only higher than between groups. As an example, *shy* and *fights* being in the same group is not a contradiction, neither substantively nor technically. Choosing an appropriately high combination threshold (see Section 4.2.7) ensures that the interpretation of ties in the composite networks will not be ambiguous.

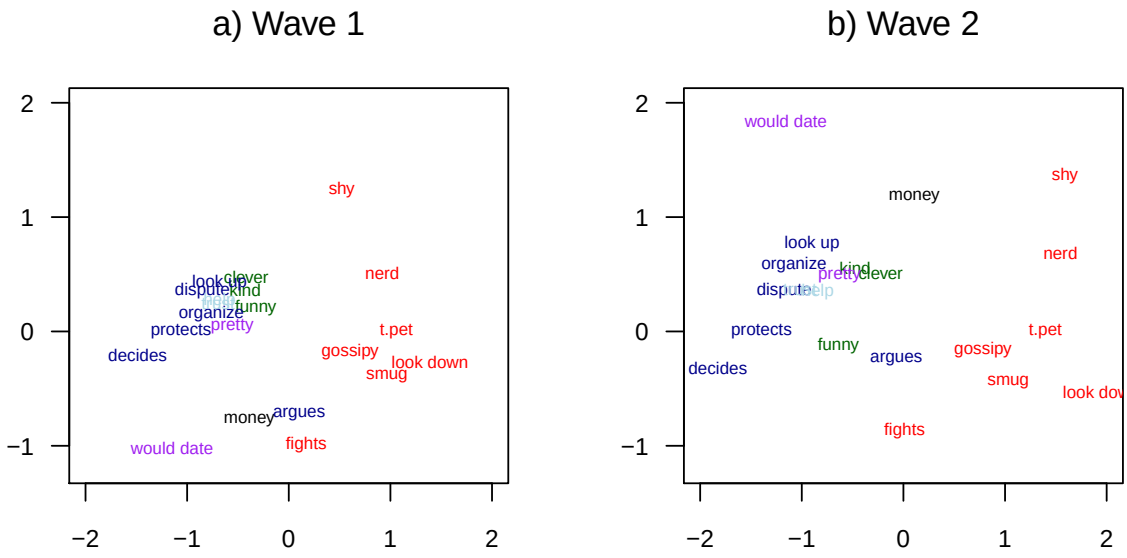

Figure 4.3: Visual representation of average similarities between the 21 network items at wave 1 (a) and 2 (b).
(Coordinates obtained from the 2-dimensional MDS projection of mean Jaccard index values.)

compared. In the second step of the procedure, we will aim exactly to identify those network items that contribute most to the variability between classrooms, and only then we shall turn to examine the patterns in between-item similarities. Here we do not further describe the raw Jaccard index values between our networks.

Before we proceed, however, it is worthwhile to visualize the average similarities using ordinal MDS, as described in Section 4.2.3. Figure 4.3 presents the 2-dimensional projection at the two time points. Stress in both cases was below 15% which suggests the two dimensions provide a reasonable representation of the mean similarities (Bartholomew et al., 2008:65). Items are identified in the figure by their labels from Table 4.2 (and their colors represent their *a priori* grouping).

It is visible that most of our items categorized as negative attributes (labels in red) are well separated from the rest, with the sole exception of the *fights* item. On the other hand, positive attributes (green), leadership-related attributions (blue), and trust (light blue) are all generally close to one another, suggesting significant overlap between these networks. Only the *argues* and *decides* items are distant from their group in both waves.

The two items we associated with attractiveness are placed far from each other: *pretty* is close to the just described "busy area", while *would date* is on the periphery

at both observations. The last item, *money*, is closest to *fights*, *argues* and *would date* in wave 1, but more distant from all items in wave 2.

The inspection of the figure shows that our prior expectations for the grouping of networks are roughly correct, and suggests that we might find confirmation for the existence of at least two groups: one of negative attributes and one of positive and leadership attributions and trust. However, this first impression may not be entirely correct if the classrooms are highly heterogeneous with regard to the similarities between items – we shall turn to this issue in the following.

4.3.4 Step 2: The consistency of the similarity structure across classrooms

As described in Section 4.2.4, we use Kendall's W to assess how consistently each of the network items are related to the rest of the items across the classes.[8] Figure 4.4a and 4.4b present the distribution of W for all of the 21 networks in wave 1 and 2, respectively. The items on the left side of each plot have the lowest, those on the right the highest concordance coefficients. The vertical positioning of the labels serves only to emphasize the rank order of the W values. Label sizes are proportional to the average density of items in the classes (the class-wise densities of the networks are reported in Appendix A).

W ranges between 0.2 and 0.85 in both waves. The figures also show that most dense networks typically have higher W values. The correlation between average density and W is 0.65 in wave 1 ($p<0.01$) and 0.53 in wave 2 ($p=0.01$). A simple explanation for this tendency is that in case of sparse networks, chance may have a larger impact on the relative frequency of ties overlapping with other networks. However, we also see some sparse network items with larger coefficients (e.g. *trust*, *dispute*, *organize*, *protects*), which highlights that our choices of excluding items should not be solely determined by their density.

An acceptable distribution of concordance coefficients can be reached after dropping four network items: *fights*, *money*, *argues*, and *would date*. The distribution of Kendall's W after stepwise excluding these networks is shown in Figure 4.4c and 4.4d. At this step, all W values are larger than 0.4, which is a notable increase from 0.2. Some remaining items have a higher W in the reduced item set than in the initial set.

Note that the stepwise nature of the procedure redefined the position of *argues* in wave 2 with respect to the other items: initially it had the fifth smallest W value

[8]The W values reported here are corrected for ties in rank orders. However, this makes little difference, since exactly equal Jaccard indices are rare.

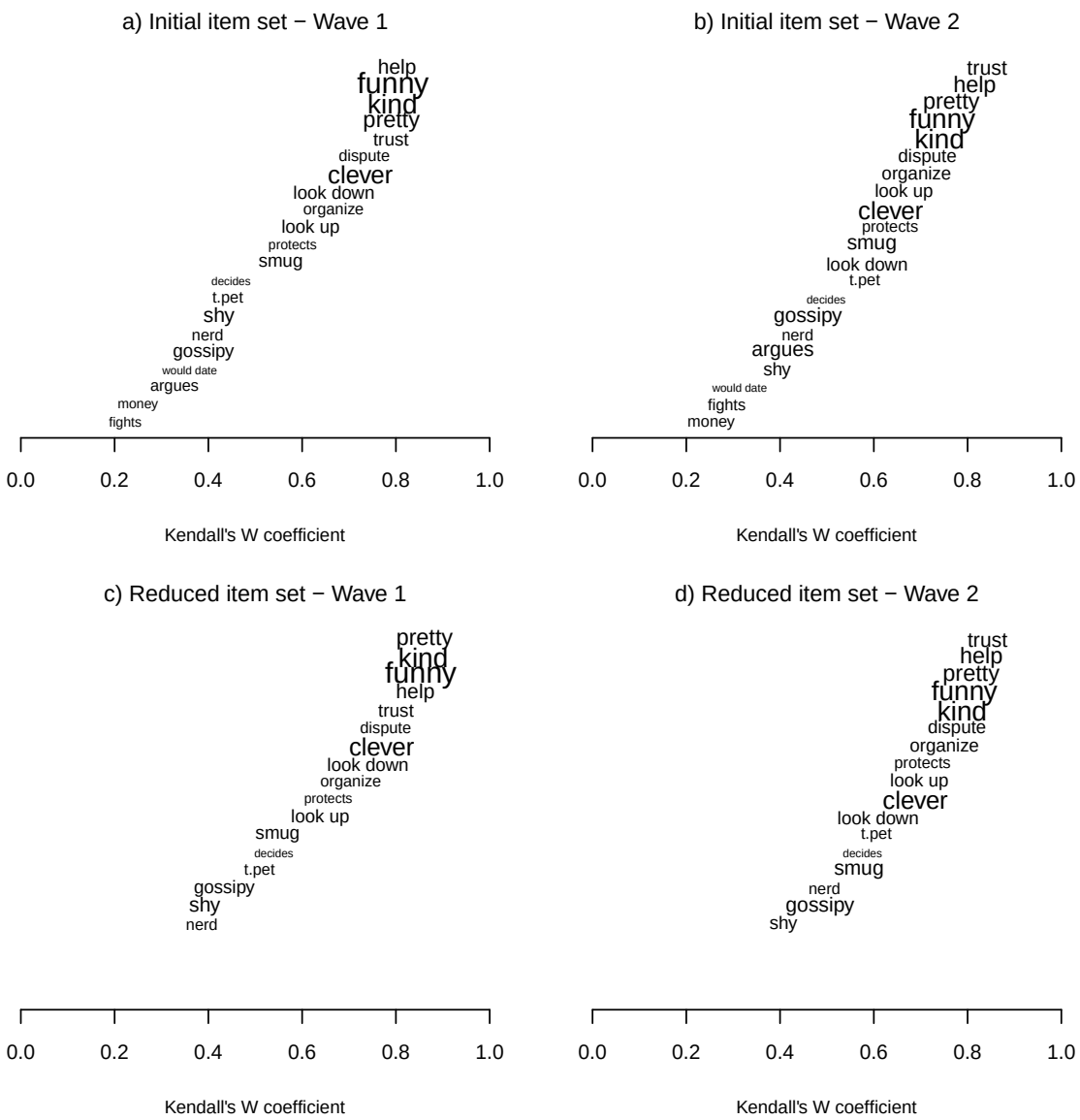

Figure 4.4: Distribution of Kendall's W for the full and reduced item set in wave 1 (a, c) and wave 2 (b, d).

(W values were calculated based on 18 classes; the horizontal axis measures Kendall's W, while the items are similarly ordered along the vertical axis; label sizes are proportional to the average density of items in the classrooms.)

(Figure 4.4b), but in the fourth step it was removed (and *shy* retained). Further, the correlation between average density and Kendall's W in the reduced item set is 0.60 in wave 1 ($p<0.01$) and 0.43 in wave 2 ($p=0.08$), smaller than in the case of all 21 networks. This shows that the removal affected the networks with the lowest density, those most prone to chance overlap with the other networks.

Dropping more than four networks generates worse solutions than the ones presented here. The items we classified as negative attributions are next on the list, but excluding some of them largely decreases the consistency measures of the rest. The next natural stopping point in the procedure is where all networks from the negative attribute group are removed. We find this an unnecessary loss of substantial information. Finally, we draw attention to the fact that the four removed network items are the same which were placed far from the others in Figure 4.3. Based on the presented results, we continue the analysis with the remaining 17 networks.

4.3.5 Step 3: Three dimensions of peer perceptions: the global solution

We apply Ward Hierarchical Cluster Analysis to study the structure of similarities among the remaining network items (see Section 4.2.5). This is done for each classroom separately and then for a similarity matrix containing the average Jaccard index for each pair of items. Figure 4.5 presents the cluster trees based on the mean similarities at the two observations. The colors highlight the cluster membership of items in well-fitting solutions for wave 1 (a) and wave 2 (b).

Three clusters seem appropriate in the former case, five in the latter. However, it is apparent that the groupings are almost identical at the two time points. At the top of the figures, four items form a group in both waves: *pretty*, *funny*, *clever*, and *kind*. This cluster is similar to the group of positive perceptions from Section 4.3.2, with the addition of the *pretty/handsome* item. We shall refer to this cluster of network items as *positive attributions*.

At the bottom of the plots, five items are grouped together in wave 1: *nerd*, *shy*, *teacher's pet*, *gossipy*, *look down*, and *smug*. This cluster may be labeled as the group of *negative attributions*. Although *nerd* and *shy* emerge as a separate cluster in wave 2, they are still clearly close to the other negative items.

Based on the first observation, the remaining seven networks form a single cluster. This group contains most of the items we referred to earlier as attributions of some kind of social leadership (*protects*, *decides*, *dispute*, *organize*, *look up*), but also those

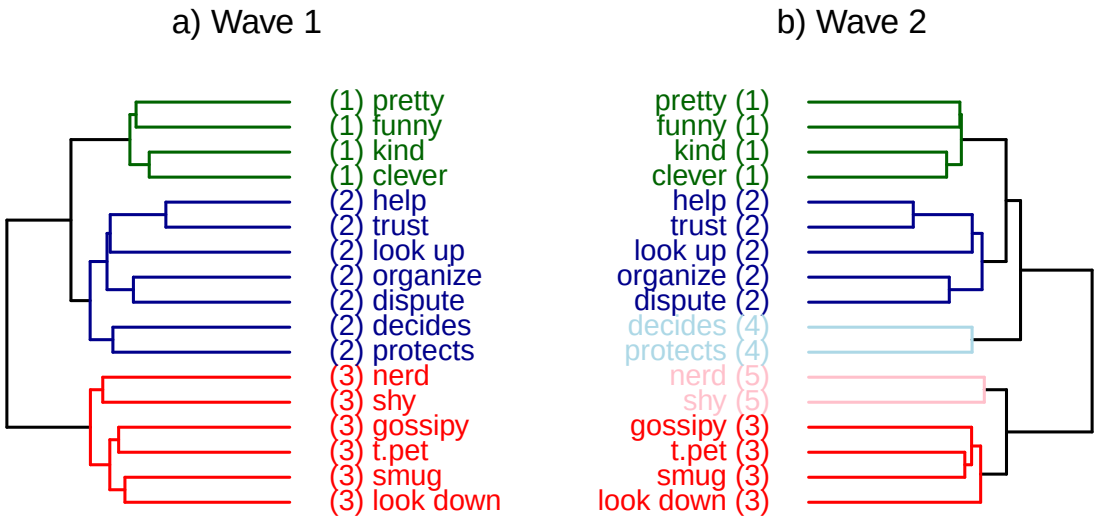

Figure 4.5: Cluster trees from the average similarities in wave 1 (a) and 2 (b). *(The colors and numbers represent the resulting clusters.)*

related to dyadic trust (*trust*, *help*). We may thus use the more general term of *social role attributions* for the items in this cluster.[9]

In wave 2, *protects* and *decides* are together, like in wave 1, but form a separate cluster. We treat this discrepancy between the waves as a nuance for two reasons. First, *protects* and *decides* are the sparsest networks in our sample (see Figure 4.4 and Figure A.2) so that their similarities to other items may be more affected by small changes in network ties. Second, the two items still belong clearly to the groups of positive and role attributions.

It has to be emphasized that the overall similarity structure among our items is remarkably stable at the two ends of a six-month period, while the networks themselves do change to an appreciable extent (see Figure A.3 in the Appendix). Some ties are created, some are dropped between the waves, and the Jaccard similarities also increase and decrease. Our key finding is that the studied networks change in a way that their relative similarities remain essentially unchanged, leading to almost the same clustering solution.[10]

[9]Note that the roles in our reduced item set all seem to bear a positive value for the community. Of course, social roles can be negative or ambivalent, as well. Consider the case of *fights* or 'argues with the teacher', items which we dropped due to their inconsistent position among the other items in the studied classrooms. Here we use the term "social roles" to incidate positive social roles, but different item pools may allow further distinctions between various types of roles.

[10]On the full sample of 43 classrooms, the resulting clusters at the two time points are identical.

We use the three-cluster result from the first wave for both observations, in order to have a consistent basis for the definition of aggregated networks. However, before we proceed to define new network measures, we need to check if the clusters obtained from the mean similarities at the first time point are acceptable classifications for all of the classrooms in both waves.

4.3.6 Step 4: The fit of the global solution across classes

In this section, we assess how well the proposed three-cluster solution fits the individual classrooms. Note that in Step 2 of the procedure some network items were dropped in order to increase the homogeneity of classrooms. This means that we already did some work ahead to increase the chances for finding a well-fitting solution. There are numerous ways to measure the fit of a clustering solution. We present results from just a few simple tests.

First of all, we inspect the distribution of the pairwise similarities between the networks in the studied classrooms. If the proposed clustering is indeed reasonable for all or most of the groups, similarities should be high within clusters and low between clusters. The distribution of the Jaccard indices is represented in Figure 4.6. The six heatmaps show the minimum, median, and maximum of the values observed between the items across the 18 classes at the two time points. Brighter cells refer to higher levels of similarity. The colors are comparable across the six images in that the same color refers to the same degree of similarity in all of them.[11]

We can see in the figure that the three diagonal block areas marking our three clusters are generally brighter than the surrounding cells. Although there is considerable overlap between items in the positive and social role attribution clusters, the distinction between the two groups is clear (although *trust* and *help* might belong to either cluster). This provides some confirmation that the proposed clustering is a reasonable representation of the similarities in the 18 classrooms.

Further, Figure 4.7 shows the distribution of the Rand index in the studied classrooms at the two observations. The Rand index (see Section 4.2.6) here refers to the comparison of the three-cluster solutions obtained per classroom with the three-cluster global solution proposed in the previous section. The results show that the global classification of networks is reasonably similar to those we can obtain directly from the class-level data. In all cases, more than two thirds of all pairs of items are

[11]The diagonal elements of the similarity matrices, that is the similarity of an item to itself, are obviously 1. However, for the purpose of this presentation they were replaced by the value of 0.7 which is the highest off-diagonal similarity, observed in the second wave (see the bottom right image).

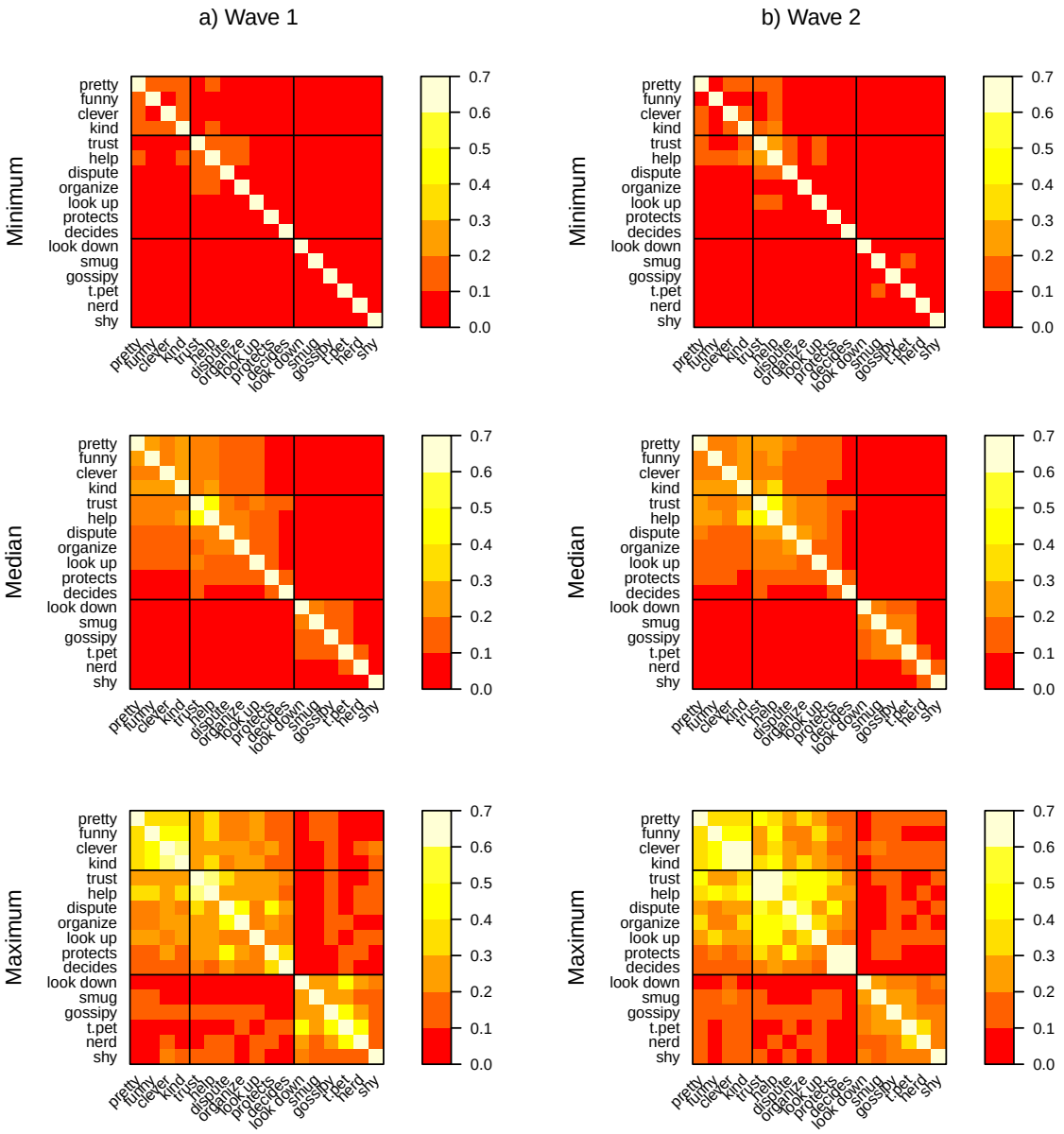

Figure 4.6: The minimum, median, and maximum Jaccard index values among the 17 clustered items in wave 1 (a) and 2 (b).

(The diagonal values were set to the off-diagonal maximum of the six matrices.)

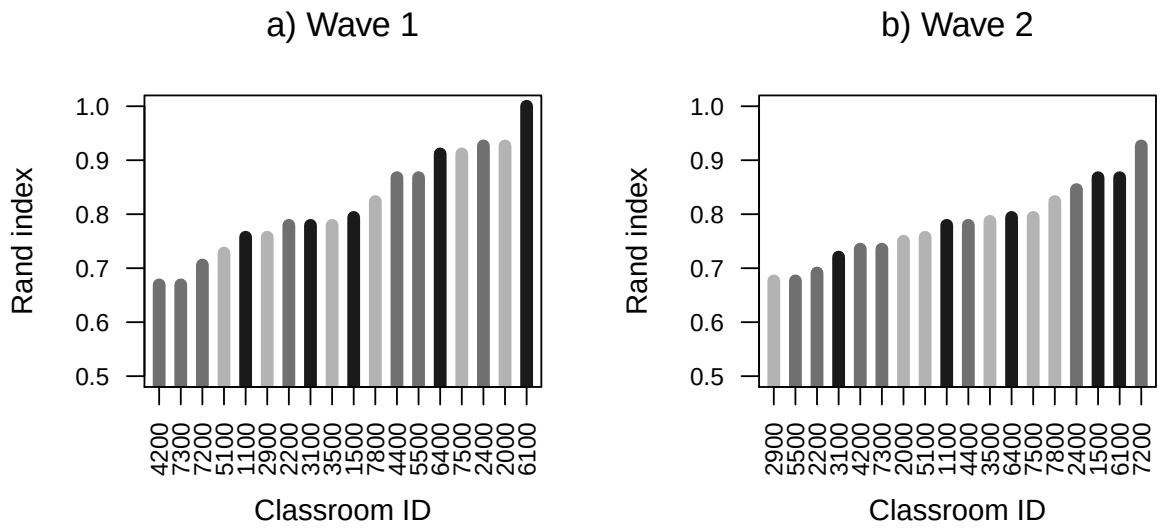

Figure 4.7: Comparison of class-level clusterings to the global solution in wave 1 (a) and 2 (b).
(Classroom-level three-cluster solutions are compared with the clustering in Figure 4.5a. The colors of the bars represent the three classroom training programs.)

similarly classified in the compared clusterings, and this is above 75% for more than half of the classrooms in both waves. The shade of the bars in the figure signal the training program of classrooms: light gray – vocational, medium gray – technical, dark gray – grammar. There is no significant tendency for classrooms of any training program to have a more "prototypical" clustering than the others.

Given the sizes of clusters in the classifications compared, the Rand index will not be lower than a certain value, by definition. This means that any randomly proposed global clustering can be relatively similar to that obtained from a given classroom. Consequently, another way of assessing the fit of the global solution to the class-level solutions is showing that the proposed classification of items represents the classroom results better than a random solution with similar cluster sizes.

Figure 4.8 displays the Rand index values from the previous figure (the top row of data points), along with null distributions based on 10,000 random permutations of the clusterings in each classroom. It is clear that even in the worst cases, the observed values are higher than the 95% critical values of the null distributions (black rectangles). This means that our global solution performs better in all classrooms than similar but random clusterings.[12]

[12]We also assessed in the same way whether the five-cluster solution from the mean Jaccard values in wave 2 (Figure 4.5b) is a better proposal for the classrooms in both waves. The overall levels of fit

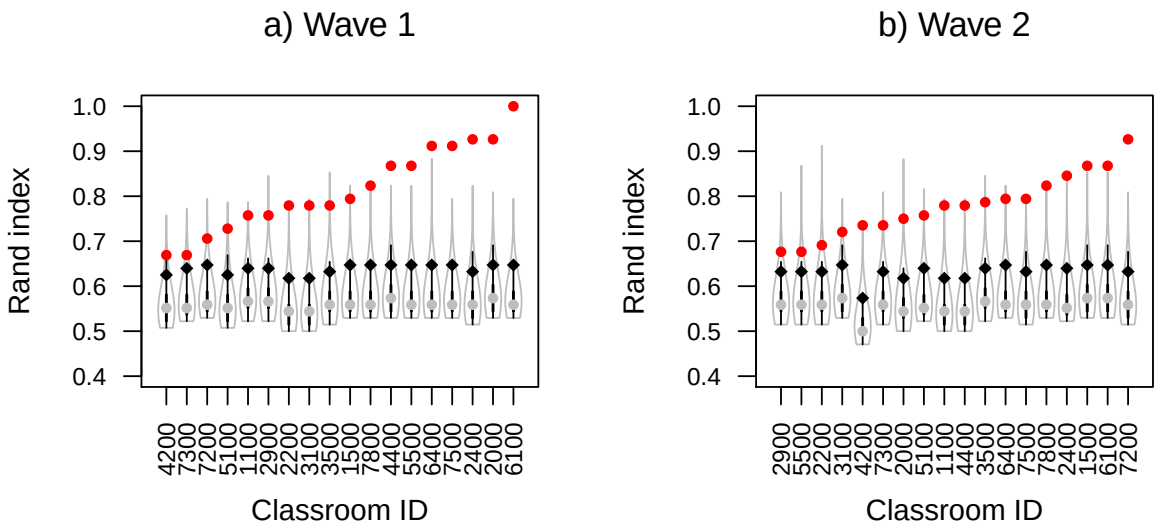

Figure 4.8: Permutation tests for the comparison of class-level and global clusterings in wave 1 (a) and 2 (b).
(Classroom-level three-cluster solutions are compared with the clustering in Figure 4.5a. Null-distributions are generated by 10,000 random permutations of the cluster membership vectors in each case. Dots at the top represent the observed similarity values, the lower gray circles the means of the simulated distributions, and black rectangles the 95% critical values for one-sided t-tests.)

One can think of plenty of other ways for testing fit, especially considering the challenges of clustering in multiple groups. However, the focus of this paper lies elsewhere, so for the moment we are satisfied with the demonstrated evidence which suggests that our three-cluster solution is reasonable for the studied set of classrooms. We will return to certain issues of goodness of fit in the discussion.

4.3.7 Step 5: Defining positive, negative, and social role attributions

Now that we have established that the proposed three-cluster grouping is a reasonable representation of the similarities between the network items in the studied classrooms, we can turn to the definition of composite network measures. As described in Section 4.2.7, we use a simple "at-least-t-ties" rule to combine the tie-level information present in the networks of a given cluster. A practical question here is the choice of the

are approximately equal in both cases, but there are significant classroom-level differences. This is expected as the two solutions presented in Figure 4.5 are very similar; but this simple test provides further support that the three-cluster structure we impose on every classroom is close to a (locally) optimal solution given the data at hand.

Table 4.9: The definition of the four composite networks.

Composite network	Combination rule	Group of original networks
Positive attributions	at least 2 ties from	pretty, funny, clever, kind
Social role attributions	at least 2 ties from	trust, help, dispute, organize, look up, protects, decides
Weak negative attributions	at least 2 ties from	look down, gossipy, smug, nerd, t.pet, shy
Strong negative attributions	at least 3 ties from	look down, gossipy, smug, nerd, t.pet, shy

threshold t. A too low value of t may lead to a too general interpretation of ties in the resulting aggregated network. For example, if we take the union of ties ($t = 1$) from the networks in our negative attribution cluster, then a tie in our composed network could mean a perception that the receiver is either shy or smug – clearly very different attributions. Increasing t reduces the prevalence of these problems. However, with a t too high the definition of a tie may become too strict, and the density of the composed network too low. The possibility of measurement errors also advises against extreme values of t, as these definitions are more sensitive to such errors. Clearly, there is no universal recipe for choosing a combination threshold, and it is up to the researcher to decide on its appropriate value.

For the present dataset, we propose the definition of four composite networks: one of positive, one of social role attributions, and two variants for negative attributions. In case of the first two item groups, we choose the combination threshold $t = 2$. For reasons discussed below, two networks are defined for the cluster of negative attributions, one at a threshold of 2 and another at 3. Thus the latter network contains only a subset of the ties in the former, and represents stronger negative attributions. The definitions of our four composed networks are summarized in Table 4.9.

To have a first impression about the new measures and to be reassured that the clustering procedure was successful, Figure 4.10 presents two heatmaps similar to those used above. Here, however, the four composite networks are compared with the 17 items used in the cluster analysis and with the four affective networks available in the dataset. The brightness of the cells in the figures is based on the median Jaccard index values between each row and column item over the groups. The main results discussed here are found in every studied classroom.

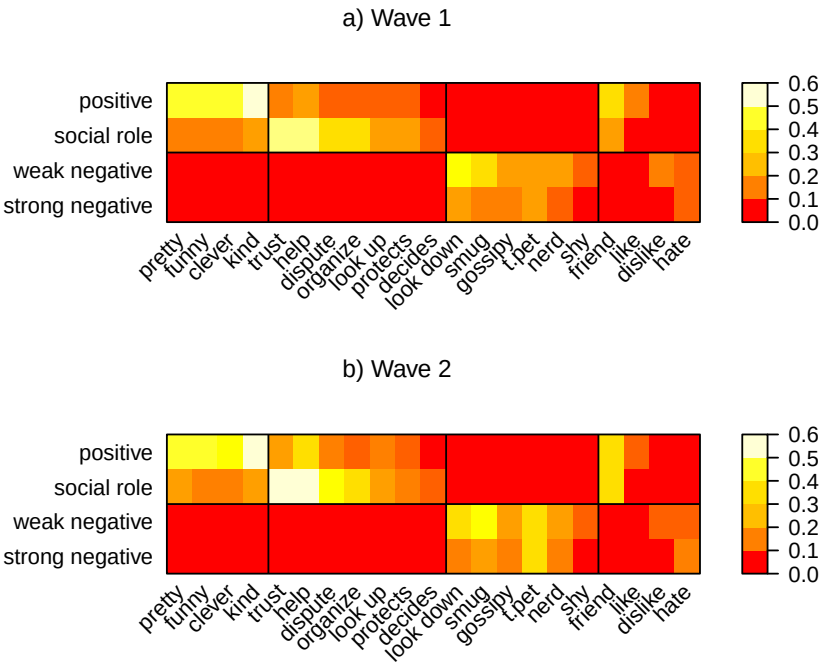

Figure 4.10: Median values of the Jaccard index between the composite networks and the original and affective items in wave 1 (a) and 2 (b).

The figures confirm that the composed networks have the highest overlap with the network items based on which they were defined – this shows that the success of the clustering procedure. Further, one cannot miss the minimal overlap between positive and negative items. Finally, it has to be highlighted that positive and social role attributions tend to coincide with positive affections (friendship and liking), while to some extent this is true for negative attributions and negative affections (dislike and hate). We study these connections in more detail in the following section.

4.3.8 Comparing the aggregated attribution networks with affective relations

How are the defined composite networks related to the more common relational measures in the field? This question needs to be answered in order to assess how the inclusion of these (or similar) new network dimensions in future studies could expand our understanding of social dynamics in adolescence. Now we examine our composite networks are related to four basic networks of affection that are more regularly studied in the context of adolescent research: *friendship*, *liking*, *dislike*, and *hate*.[13]

[13]See Appendix A for the measurement of these relations in this specific study.

Figure 4.11 provides a more detailed picture of the overlaps between the eight networks at the two time points. Unlike the ones above, these heatmaps show the asymmetric relations between the items: each cell represents the amount of overlapping ties between the row and column networks, relative to the total number of ties in the *row* network (compare with Section 4.2.3). The figures are based on the mean values of this overlap index across the 18 classes.

First of all, we have to note that plots from wave 1 and 2 looking strikingly similar, suggesting that the structure of the relations between these networks remained remarkably stable over the six-month period, despite the considerable changes in network ties (see Figure A.3). Second, we can see in the figure that positive and social role attributions are asymmetrically related, as shown by the 2-by-2 cell block in the top left corner. Most social role ties are coupled with positive attributions, but many positive attribution ties exist without social role attributions. This is true for all classrooms in both waves.

Further, the two positive composite networks have interesting connections to friendship and liking. Looking at the third 2-by-2 cell block from the left in the first row, we can see social role attributions more often run parallel with friendship than do positive perceptions. On the contrary, more of the positive attribution ties coincide with liking than do social role attributions. These findings hold for 16 out of the 18 classes in both waves. Comparing to the number of friendship and liking ties (first block in the third row) tells us that a larger part of friendship ties are also social role or positive attributions than liking ties. This is again true in 16 classrooms at both observations.

Results for the negative networks vary more strongly between classrooms. Still, it seems that more strong negative attributions are also hate ties than weak negative attributions (see the last 2-by-2 block in row 2). We find this tendency in 11 and 12 classes in wave 1 and 2, respectively. This means that by choosing a higher threshold for negative attributions, we retain a disproportionate amount of ties which are associated with hate. The same difference between strong and weak negative attributions is not so prevalent in the case of dislike: only in case of 6 (wave 1) and 3 (wave 2) classes can we observe a similar pattern.

Somewhat on the contrary, it is typical that a larger proportion of dislike and hate ties are paired with weaker rather than stronger negative attributions (see the second block in the bottom row). In general, hate more often comes with the two other forms of negativity than does dislike. These findings are true in 12 and 14 classrooms in wave 1 and 2, respectively.

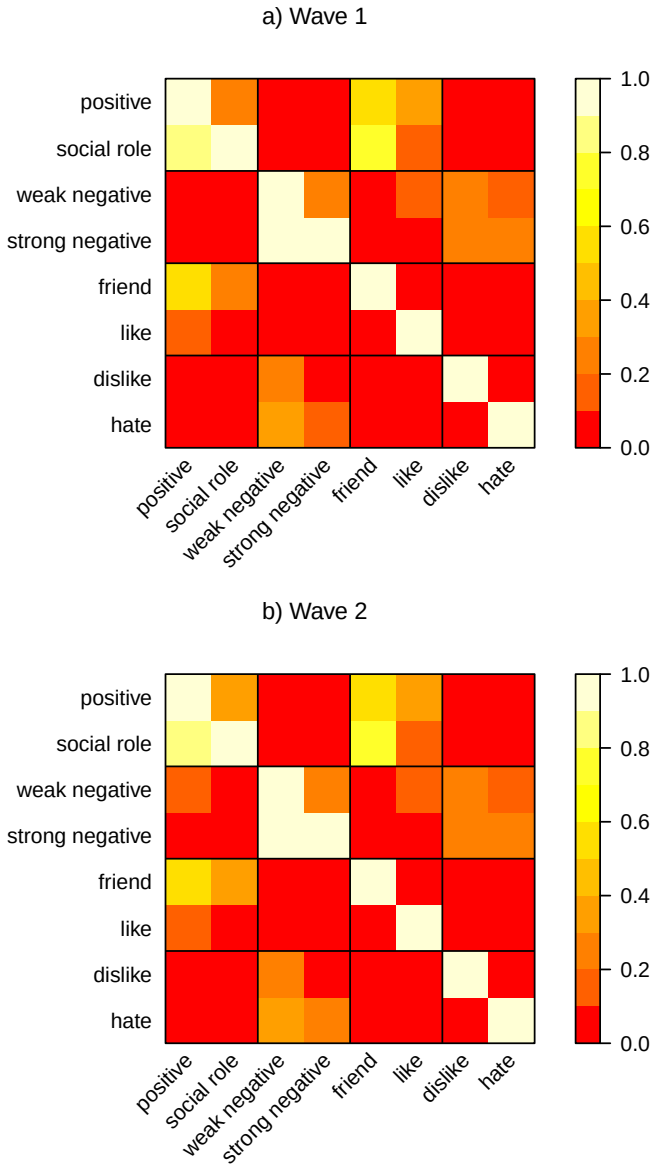

Figure 4.11: Average overlap between the composite networks and the affective items in wave 1 (a) and 2 (b).
(Cell values represent the proportion of overlapping ties relative to the row networks density.)

We provide a concise overview of the results discussed so far in Figure 4.12. The circles represent ties in the eight networks; their sizes are proportional to their average density in the 18 classrooms. Moreover, the size of each intersection area (pairwise and three-way) is approximately proportional to the average amount of ties in the given category.[14] We only present one figure as the results from the two waves are almost identical (see Figure 4.11).

For the sake of the illustration, we disregarded the overlap between the "two worlds" of negative and positive networks. This helped to make the visual representation of the remaining overlaps more realistic. We have seen in Figure 4.11 that positive-negative overlaps are very scarce: only a little ambivalence is captured by the eight measures (although the affective networks are mutually exclusive, there were no constraints on the other 17 items used to construct the new network measures).

It is clear that positive and social role attributions are coupled with friendship or liking in the vast majority of cases. This may be somewhat surprising for positive attributions, but remember that we used a threshold of 2 when constructing this measure, which means that a tie requires positive perceptions in at least two specific dimensions. Indeed, with a lower cut point at $t = 1$, we would see more positive attributions without positive affection (we do not present these results here).

Social role attributions are typically strongly embedded in friendships in the studied sample. Although they sometimes also occur in liking relations, it is very rare that social roles are attributed without the presence of any positive affection. On the contrary, weak and strong negative attributions quite often exist without dislike or hate – though there is a significant level of overlap.

4.4 Conclusions from the example

In this paper, we presented an analytical strategy for reducing the number of network dimensions in highly multiplex network data. Applying statistical methods that are already well established for monadic variables, we demonstrated that different types of social relations may be classified based on their pairwise similarities. The resulting clustering may reveal important latent dimensions of relationships in a given context. We also showed a simple yet flexible approach to construct composite network

[14] Approximately, because Venn diagrams of more than two sets cannot exactly represent the relative areas of cell parts in most cases. However, we used the algorithm programmed in the *venneuler* R-package for placing the sets to ensure the image is as close to the observed values as possible. A stress-type measure (see Section 4.3.3) shows that this two-dimensional figure represents the relative size of the set parts very well ($p < 0.05$).

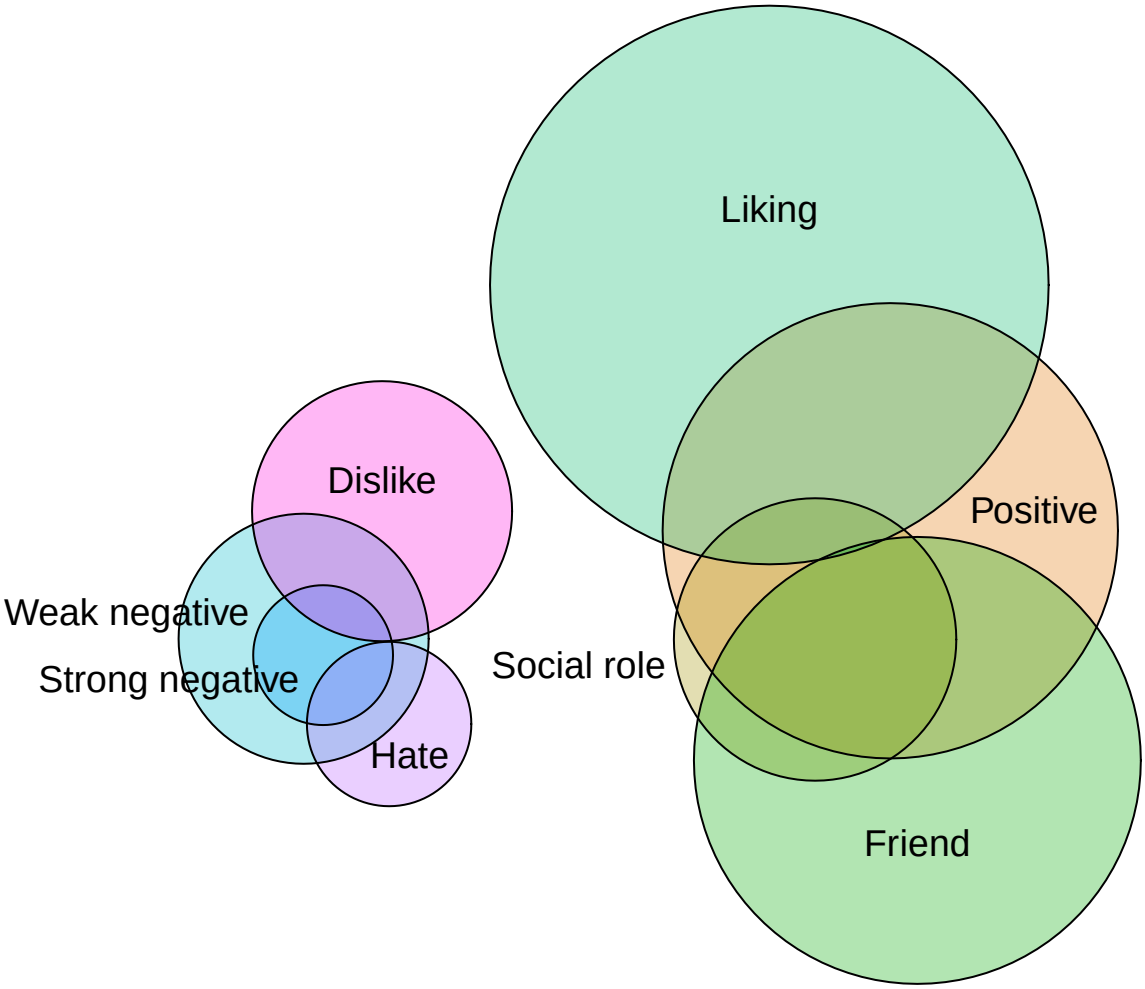

Figure 4.12: The structure of relations between the aggregated and affective network measures

(The sets were placed algorithmically to best represent the overlaps observed between the networks; the area of each set part is proportional to the frequency of ties that fall within; the overlaps between the four positive and four negative networks were disregarded; calculations are based on the average distribution of network ties across the 18 classrooms in wave 1)

measures. This is primarily meaningful when the items are clustered based on their similarity on the level of network ties. Statistical models for multiplex networks can be more easily applied to the aggregated networks compared to the original, large set of dimensions.

The application of the presented procedure to our observation of 21 interpersonal networks from 18 high-school classrooms at two time points resulted in the identification of three well-interpretable groups of perceptions. These we labeled as positive, negative, and social role attributions. Whilst there was substantial change in peer nominations, the global similarity structure among the relational dimensions remained remarkably stable between the two waves.

The stability of the overall clustering points to two interesting phenomena. First, it provides evidence that attributions in the same cluster are connected also dynamically: the ties change but the cluster structure of attributions remains stable. Second, although the group-level cluster solution changes between the waves for many classes, these changes seem to cancel out when we average over all classes. This proves that it is indeed a promising direction to look for the latent structures connecting several network items, and that when doing this it is helpful to consider a set of groups rather than one particular group.

Based on some simple tests, we concluded that the proposed global clustering of items fits the similarity structure of the individual classrooms reasonably well, independent of the academic level as indicated by the classroom training program, which is known to be strongly associated with the socio-economic background, academic achievement, and aspirations of students. Apparently, the clustering found for the network items taps underlying dimensions that are stronger than variations between classrooms in subcultures and value systems.

Relying on the identified three-cluster solution for the items, we created four aggregated network measures. A combination threshold of 2 was applied to compose a positive and a social role attribution network. We found that these two composite networks are asymmetrically related in the studied classrooms: positive attributions seem to represent general perceptions which often exist without role attributions, while the assignment social roles almost always coincides positive perceptions. Further, social role attributions also appear to be closely linked to friendship, which highlights the functional features of positive relations at school. Finally, our results suggest that positive attributions (or similar measures) may not only be instrumental in explaining how positive affections develop but also in studying how affective relations become stronger, e.g. how liking evolves into friendship.

In the case of negative attributions, we defined two composite networks at the thresholds of 2 and 3. Thus we acquired networks representing "weaker" and a "stronger" negative perceptions. We found in many of the classrooms that strong negative attributions more often coincide with strong negative affections than do weaker attributions. However, it is notable that many negative attributions, both weak and strong, exist between students who did not report any negative feelings (dislike or hate) about each other. These results exemplify that defining a set of ordered composite network measures from the items in one cluster represents a fruitful way of studying social relations from different aspects.

4.5 Discussion

The proposed procedure for the cluster analysis of multiplex networks opens novel possibilities and also presents new challenges for social network research. While statistical methods of dimension reduction have proven useful for the construction of reliable monadic measures in the social sciences, they have hardly been applied to dyadic data with the aim to define aggregated network measures. The main contribution this paper intends to give is the combination of a set of already available methods and measures to create composite networks. We believe that this is an innovative application which requires some new practices and rules of thumb further to be developed. Therefore, here we give a detailed account of some critical decisions and questions brought up by the procedure.

First, we have to note that the choice between similarity measures obviously affects the results and interpretations greatly. The use of the Jaccard index, a dyadic measure, fits well to the aim of combining information from several networks on the level of social ties. As explained in Section 4.1.3, actor-level similarity, expressed for instance by indegree correlation, can also be a meaningful basis for classifying the networks. However, comparisons based on actor-level measures do not take into account the dyadic essence of network structure. Therefore, actor-level similarity measures may be useful primarily when the ultimate goal is the classification of actors based on their position in a group, and not the construction of aggregated networks.

On the side, we may note that perhaps a more common application of Cluster Analysis to networks would be the classification of networks based on a set of aggregate structural measures, such as density, hierarchy, centralization, and so on. However, such an approach seems more valuable for descriptive studies about the structural similarities between different types of networks than for the aim of finding

common dimensions for networks measured in the same groups in highly multiplex datasets.

As a second and related point, we have to mention that for assessing network similarities, different rules of thumb should be used than for inter-item correlations of monadic variables in scale construction or Factor Analysis. For instance, a correlation of .5 between scale items may be labeled as rather low, but a Jaccard index of the same magnitude means that there are exactly as many overlapping ties in two networks as ties that are present in only one of the two – which is definitely a high level of similarity. In light of this, it is important to keep in mind that what counts as low or high similarity depends on the measure we use.

Third, plenty of available options were deliberately left unexplored in case of goodness of fit assessment. On the one hand, further tests can include the application of additional measures, such as the cophenetic correlation coefficient (Rohlf and Sokal, 1981). On the other, the main challenge here is empirical and theoretical: the general problem of finding a single clustering that fits the data from multiple groups (in our case, classrooms). There is no simple general solution to this issue, and it deserves separate and more thorough treatment.

A few words need to be said, however, about one related issue. Obviously, the chances for finding a well-fitting global clustering depends on the homogeneity of the groups with regard to the inter-item similarities. The second step of the procedure (see Section 4.2.4) aims at increasing this homogeneity. Yet, it still is possible that the studied groups are systematically different from each other. With many groups it may thus be a viable approach to classify the groups themselves based on the results from the cluster analysis of the network dimensions, and so identify the general types of communities in our sample.

This way we may not only learn about the studied groups, but also about the network items which cause most of the differences (like *argues*, *money*, *would date*, and *fights* in the presented analysis). Why are these networks heterogeneous in their relations to the other items? Do they have a certain consistent meaning in some groups and a different one in others? Are the differences related to sociologically relevant factors? Is it possible that the heterogeneities are due to omitted network items? The last question leads us to the next point.

Fourth, in any multiplex network study, the results will depend on the set of network items being considered, and we cannot be sure that we measured all of the important items connected to the relational dimensions of interest. We may be unaware of the number of latent relational dimensions in a given social context. In

which ways are the results of the procedure affected by the item pool that we use? At this point, it is difficult to give conclusive answers to this question. We can only say that since the classification of network items in our approach is based on relative similarity (i.e., two items are more similar to each other than to the other items), the omission of a set of networks measuring something different would probably not affect the results strongly.

It is likely, however, that the relative number of items belonging to each category has an impact on both the results in each group and the similarity of clusters across multiple groups. In the example presented, there were fewer negative than positive items, and networks in the former group showed lower consistency across groups. This may also be related to density: if the networks measuring a relational dimension are sparse, we may need more of them to acquire robust results. This suggests that in order to arrive at good measures for rare social relations (i.e., with low average degrees), researchers should look for and employ a larger number of specific items than in cases of more common ties.

The measurement of bullying is a good example here. Specific questions may facilitate a better identification of bully-victim relations than more general ones, but they may yield very sparse networks. However, with a sufficiently large number of items chances are better for the identification of a separate cluster of bullying relations across groups. This cluster then might be used to construct more valid, and perhaps multiple, measures of bullying relations. The conclusion of this exercise might also be that specific forms of bullying cannot be separated from other social relations that have their own specificity, such as teasing, rivalry, or dominance. In any case, however, the results would contribute to our understanding of bullying among children.

Further, quite naturally, with few items one cannot distinguish between the possible sub-dimensions in a given set of networks. That is, with fewer positive items, we probably wouldn't have been able to distinguish between positive attributions and social role attributions; on the other hand, measuring more negative items might have revealed interesting substructures in the negative attribution cluster. Leaving out key network items in a given dimension is likely to make the identification of all dimensions more difficult, as boundaries between clusters may become more fuzzy. However, we need to collect further experience with the structure of network similarities before we can give more specific answers to the questions raised here.

In spite of the uncertainties due to the lack of experience with the procedure, the first results seem to be substantively meaningful and relevant. Based on our findings, studies into the co-evolution of positive attributions and affections of different strength

promise to clarify how friendships develop in school, and may unveil a so far omitted variation in adolescents' friendship relations. The closer examination of the part that social roles play in friendship may be important in understanding why (some) friends are more influential when it comes to academic achievement, aspirations, risky behaviors, and so on. Our results also showed there is more negativity in student relations than what is captured by the simple questions of dislike and hate. This suggests that by using an appropriate set of measures for negative perceptions we may be able to acquire a more complete picture of negative relations in a social setting. Such data could contribute greatly to studies of social exclusion, status competition, intergroup conflict, and bullying – in or outside of the school setting.

In summary, the paper proposed an approach for dimension reduction in highly multiplex network data in multiple groups, and demonstrated on a real-life example that this approach is viable and leads to well-interpretable results. Some parts of the procedure need to be further developed. Also, more examples and experience are necessary to set up rules of thumb that can guide researchers when applying this procedure, and explore the effects of imperfect measurement on the results. Despite these issues, however, the proposed analytical strategy holds some potential to help uncovering the latent dimensions of relationships in different social contexts. Further, elaborating and applying this approach in research promises to relax the dependence on the measurement of complex types of relations by a single, often loosely defined item, as it is usually done for friendship. Studying multiple relational items with a well-specified meaning may improve the validity of our interpretations and may help us develop better measures of social relations.

Chapter 5

Do friends think alike about their peers? The friendship–agreement link under heterogeneity in student characteristics

The question whether friends agree more in their opinions about others in a community than non-friends may sound simple at first. However, in real-life situations there are numerous social factors which might lead us to over- or underestimate the relationship between friendship and agreement. In a classroom setting, the most important of these factors is possibly the similarity of students in different background characteristics (e.g. sex, ethnicity). In this chapter, we conduct a descriptive analysis of the empirical relationship between friendship and agreement in positive and negative perceptions. The study is based on two waves of network data from 27 Hungarian high-school classrooms. We calculate simple statistical measures, such as Pearson correlations, and apply QAP permutation tests and network regressions to obtain test statistics suitable for network data. The results show that, while there is considerable variation between classrooms, friends tend to agree more in their perceptions than non-friends. The positive correlations seem to hold even when we consider the similarity of students in six individual variables; however, the within-category correlations are rarely significant statistically. Lastly, friendship and agreement also appear to be longitudinally interrelated.

5.1 Introduction

The theory proposed in this thesis argues that group formation in school settings occurs via the alignment of friendships and agreement in valued perceptions about

other community members. As discussed above, there are two main mechanisms that may directly lead to such an alignment: first, students may be likely to select their friends from those who think similarly about the others; second, friends may influence each other to become more similar in their perceptions over time. These processes are explained and illustrated in Section 2.5. Identification of the selection and influence processes at work in classrooms is a highly important substantive issue and, therefore, it is in the focus of the investigation in Chapter 6.

The present chapter takes one step back and asks the following, more basic, questions. Regardless of the mechanisms generating it, can we observe a correlation between friendship and agreement in peer perceptions? If a traveling social scientist wanders into a school, will he or she find that friends have more similar perceptions about others than non-friends? And are those who agree to a greater extent also more likely to be friends? Are there other factors, for example segregation and perception differences related to gender, that may hide or overemphasize this correlation? Does the relation between friendship and agreement change over time, as students get to know each other better? The answers to these questions will affect our judgment about the validity of the presented theory.

5.1.1 Group formation based on individual characteristics

Even if we find a positive statistical relation between friendship and perception agreement in classrooms, this may be the outcome of mechanisms very different from those hypothesized in the earlier chapters. One of the strong alternative explanations is that agreement and friendship between two students have a common cause: their similarity in some individual characteristics. There is compelling empirical evidence for friendship homophily along several dimensions in different social settings (McPherson et al., 2001; Feld, 1982), that is, similar people are usually indeed more likely to become friends.

Furthermore, a recent study has pointed out the potential role of "homophilous influence" in school settings: students' opinions (e.g. musical taste) were influenced more by peers similar to themselves (e.g. smokers) than by friends or dissimilar others (Block, 2015). Such a selective influence process is likely to be mediated either by more frequent interactions between similar people (e.g. smokers meet and talk in the smoking area) or certain forms of social control (e.g. the fear of what other boys/girls might think).

Homophily and homophilous influence together suggest that similarity in some individual characteristics can simply become a basis for group formation in classrooms.

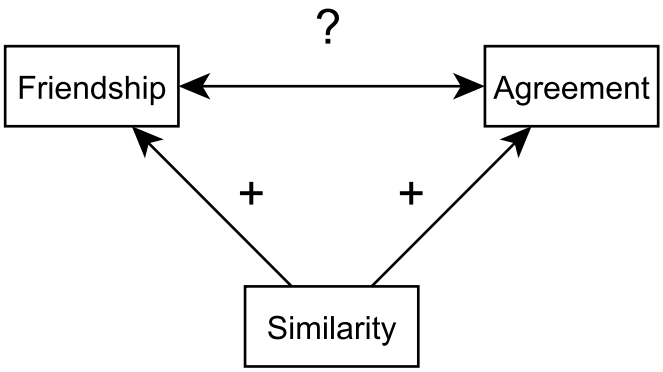

Figure 5.1: Similarity in individual characteristics as the common cause of friendship and perception agreement

If we do not take this possibility into account in our analyses, we may overestimate the strength of the relationship between friendship and perception agreement, and we might draw false conclusions regarding the validity of the theoretical predictions. The schema of the common cause confounding variable tailored to our example is presented in Figure 5.1.

Naturally, the student characteristics which play a role in group formation may vary from community to community. However, prior research has shown that certain attributes are salient in many school settings and affect friendship formation and group dynamics. These include gender (Shrum, Cheek Jr, and MacD Hunter, 1988), ethnicity (e.g. Moody, 2001; Boda and Néray, 2015[1]), family background (Kandel, 1978), some forms of delinquent behavior (Haynie, 2001), grades and academic attitudes (Hartup, 1996; Kandel, 1978), and sports (Coleman, 1960). We consider the effects of these six types of student characteristics in the following analysis.

5.2 Research questions

Following the above argument, this chapter aims to answer the following descriptive questions:

1. Are friends more similar in their perceptions about classmates than non-friends?

2. Does similarity in individual characteristics matter in friendship choice and perception agreement in the studied classrooms? Which dimensions play a role

[1]Their results are from a different subsample of the same dataset analyzed in this thesis.

most often: gender, ethnicity, family background, delinquency, academic values, or sporting activity?

3. How does the similarity of students moderate the relation between friendship and perception agreement?

4. How do friendship and perception agreement correlate longitudinally? Does the perception of friends become more and more aligned over time? Is the dissolution of a friendship tie associated with decreasing levels of agreement?

5.3 Methodology

5.3.1 Data

In order to answer the research questions posed above, we analyze the 27-classroom Dynamic Subsample of the RECENS high-school dataset. This ensures comparability with the next chapter which focuses on the co-evolution of friendship and perceptions using the same subset of classes. In the cross-sectional analyses, we study both available data waves separately, while the longitudinal models, naturally, utilize information from both observations. A detailed description of the Dynamic Subsample is provided in Section 3.1.2.

5.3.2 Measures

Friendship. Friendship is measured as the network resulting from the +2 nominations in the affection scale in each classroom (see Section 3.1 for details). Our analysis related to the first three questions stated above are dyad-based, which means that we do not distinguish between non-reciprocated and reciprocated friendship ties: if either of two students nominates the other as a friend, we count them as a friendship dyad. This decision was made after background analysis had confirmed that the key tendencies do not differ systematically for reciprocated and non-reciprocated friendships.[2] In case of the last research question, we switch to tie-based models in order to be able to separately study the cases of friendship creation, maintenance, and deletion over time.

[2]The correlations presented below are not systematically different for reciprocated friendships and non-reciprocated friendships. While this may sound surprising at first, a reasonable explanation is that most non-reciprocated friendships are not completely one-sided relations – students tend to at least like each other.

Positive and negative perceptions. In the present chapter, we consider two types of aggregated perception networks: positive and negative dyadic attributions between students. These measures are defined exactly as the "positive" and "weak negative" networks in Chapter 4, where we identified the positive and negative attribution clusters in the set of 18 perception networks. See Section 4.3.7 for the exact definitions. Various other choices of aggregated network measures could have been made, but these two were selected based on their overlaps with friendship (presented earlier) and their substantive interpretations. Although the clustering results presented previously were obtained on a different subsample of the RECENS dataset, they are valid for the full set of classrooms (see Appendix C). All the analyses discussed here were conducted on the positive and the negative perception networks separately.

The level of agreement in perceptions between students was measured in two ways: by a raw count of matching choices and by the Jaccard index (see Section 4.2.3). The first measure is calculated simply by adding up the number of times two students sent a tie to the same classmate in the perception network in question. In the second case, this raw count of agreements is divided by the total number of peers who are nominated by either of the two students, yielding a Jaccard-type measure. The calculation of each measure results in a matrix of pairwise similarities between the students in each classroom. The analyses discussed below were repeated for both measures, for positive and negative perceptions, and for each data wave.

Individual variables. We aim to study the effects of the six types of student characteristics mentioned earlier. To this end, six dummy variables were defined: gender (boy–girl), ethnic identity (Roma–non-Roma), mother's education (at most primary – at least primary), smoking (smoker–non-smoker), academic plans after high school (continue education – start working), sport (doing sports – not doing sports). See Section 3.1.2 for descriptive information about these variables. It is recognized that last three characteristics (smoking, academic aspirations, and sports) are endogenous to the social system of the classrooms: friends and those with similar perceptions may also become similar in these variables. However, for sake of the simplicity of the analysis, we do not consider these causal directions for the moment.

5.3.3 Methods

To answer the first three research questions, we employ simple descriptive measures and study the bivariate relations between friendship, perception agreement, and the six individual covariates. In some cases, QAP permutation tests were applied to acquire reliable standard errors. For the last question, we apply QAP regressions to

explain the level of agreement in perceptions (linear QAP regression) and friendship (logistic QAP regression). Section 3.3 introduces the QAP method in more detail. The exact strategy of the following analysis is described in the next section.[3]

5.4 Analytical strategy

To investigate the topic discussed so far, we conduct a descriptive analysis on our sample of Hungarian high-school classrooms in four steps. First of all, we establish whether there is a bivariate relation between the level of agreement in perceptions and friendship between students in each class. Second, we assess whether students' similarity in potentially relevant individual characteristics is related to friendship and agreement, as implied by homophily and homophilous influence, respectively.

In the third step, we examine the correlation between friendship and agreement within subsets of the classrooms. Namely, we compare the relation between friends and agreement among students who are similar in individual characteristics with the classroom-level tendency. Our main interest here lies in the moderating effect of similarity in individual characteristics on the relationship between friendship and agreement.

Table 5.2: The outline of the followed analytical strategy.

	Studied relation	Type of analysis	
Step 1	friendship–agreement	bivariate	cross-sectional
Step 2	friendship–covariates agreement–covariates	bivariate	cross-sectional
Step 3	friendship–agreement|covariates	multivariate	cross-sectional
Step 4	friendship–agreement|covariates	multivariate	longitudinal

The first three steps of the presented analysis are cross-sectional, conducted separately for each data wave available. The fourth step provides a glance at the dynamic processes in the data. Using similar regression models as earlier, we study how agreement in perceptions contributes to the creation and maintenance of friendships, and whether the dynamics of friend relations is linked to increases or decreases in the levels of agreement. The four steps of the descriptive analysis is summarized in Table 5.2.

[3]The analyses were programmed in version 3.2.0 of the R environment. Over the basics, we used various functions from the *sna* package (v2.3-2), such as qaptest, netlm, and netlogit.

In each step of the analysis, we aim to study the key correlations from different perspectives. This means the separate examination of positive and negative perceptions, measured either by raw counts or the Jaccard index. In Step 1 to 3, the tests and models are replicated for both data waves. This results in 8 tests in the first step. Assessing the correlations of the 6 individual covariates with friendship requires 12 tests, while that of the four measures of agreement requires 48.

Step 3 focuses on the friendship–agreement link in among students who are similar along six individual dimensions, which leads to 48 comparisons. In the last step, we build four models which explain friendship creation, maintenance, perception agreement in wave 2, and change in agreement between wave 1 and 2; with the four perception measures, this sums up to 16 models. The results were relatively similar across the corresponding versions of each test, therefore, our presentation of the main findings will focus on a smaller set of calculations and models.

5.5 Hypotheses

We formulate our hypotheses in line with the described analytical strategy and the measures available. With the exception of H2, the hypotheses are descriptive tests of the predictions of our theory of group formation discussed in Section 2.5. That is, rejecting these statements means evidence against the theory.

An implicit assumption that we make throughout is that group formation processes are at work in the studied communities. We think that this has to be true in general, as our snapshots of the classrooms come from a period when students have to find their places in a new community, make new friends, define rules and norms, and so on. However, there is little knowledge about the exact timing and speed of the emergence of groups. In some cases, it may happen very early and quickly, while in others it may take a longer time. Some classes may have been in the state of intense group formation at the time of the data collections, while others may have been at a stage of disintegration. As a result, we need to state the following baseline hypothesis:

> Hb: *There is considerable heterogeneity in correlations and effect sizes between classrooms. However, the main tendencies expressed in H1, H3, and H4 below hold in most of the classes.*

The first hypothesis to be examined is the cross-sectional formulation of the basic correlation predicted by the theory:

H1: *Friendship and agreement in peer perceptions between students are positively correlated in the studied classrooms.*

As noted above, we recognize that student similarity in such important domains as sex, ethnic identity, family background, delinquent behavior, academic values, and doing sports may be bases of group formation in some of the studied classrooms. In order for this to have an impact on the evaluation of our theory, it has to be true that:

H2a: *Students with the same individual characteristics are more likely to be friends than those who are different.*

H2b: *Students with the same individual characteristics tend to agree more in their peer perceptions than those who are different.*

Even if group formation is based on individual variables, we still expect that a substantial part of the relation between friendship and agreement is left unexplained by these factors.

H3a: *The differences in agreement between friends and non-friends is smaller among students who share the same individual characteristics than in the classroom in general.*

H3b: *Even among students who are similar in individual characteristics, friends tend to agree more than non-friends in their peer perceptions.*

Finally, keeping in mind the considerations expressed in H0, the undisturbed operation of the group formation mechanisms theorized here should lead to an increasing association between friendship and agreement over time, even when the role of individual similarity is taken into account.

H4a: *The level of agreement in peer perceptions between friends increases over time compared with students who are not friends.*

H4b: *Students who agree more in their peer perceptions are more likely to become and remain friends over time.*

These hypotheses are tested in the course of the following analysis. It can be noted that the four steps of the empirical investigation follows structure of the four hypotheses formulated here.

5.6 Results

Considering the number of tests reported in Table 5.2, and due to the fact that all calculations had to be replicated for 27 classrooms, it is clear that there is a very large number of results that could be reported. However, there are some similarities between the explored types of measurement and approaches which make it possible to illustrate the general tendencies in the data without an overwhelming amount of figures and tables.

First of all, it appears that the measurement of agreement in perceptions as the raw count of coinciding choices and as the Jaccard index does not lead to very different results. Here we decided to present the case of the Jaccard index, because it is a better interpretable measure.

Second, in Step 3 of the analysis we only cover the results for wave 2 of the data. Again, the main findings do not differ substantially between the waves. Further, examining the second wave of the dataset is more informative for interpreting the results of the following chapter (which models the co-evolution of friendship and perceptions in a continuous-time framework, with the second wave as the dependent variable).

Finally, Step 4 only discusses the effects of perception agreement on friendship maintenance, but not on creation, due to the similarities betweeen the findings. For similar reasons, we present the MRQAP models explaining agreement at wave 2 by friendship trajectories, and omit the models on the actual change of agreement between the waves.

5.6.1 Friendship and agreement in perceptions

Figure 5.3 presents the differences between the average level of positive agreement among friends and among non-friends in the 27 classrooms at both waves. The classes are ordered in the figure according to the mean level of agreement between non-friends in wave 1. We can see that friends typically agree more in positive perceptions than non-friends in almost every classroom in both waves. The size of the difference is quite variable, but it seems to become slightly larger by the second time point in quite a few cases. The changes in the overall level of similarity are again variable by classroom, but we see more Jaccard measures close to or above 0.3 in wave 2 than in wave 1.

Figure 5.4 presents a similar plot for negative perceptions as the ones discussed so far. What is clear from the figure is that the typical agreement levels are lower in case

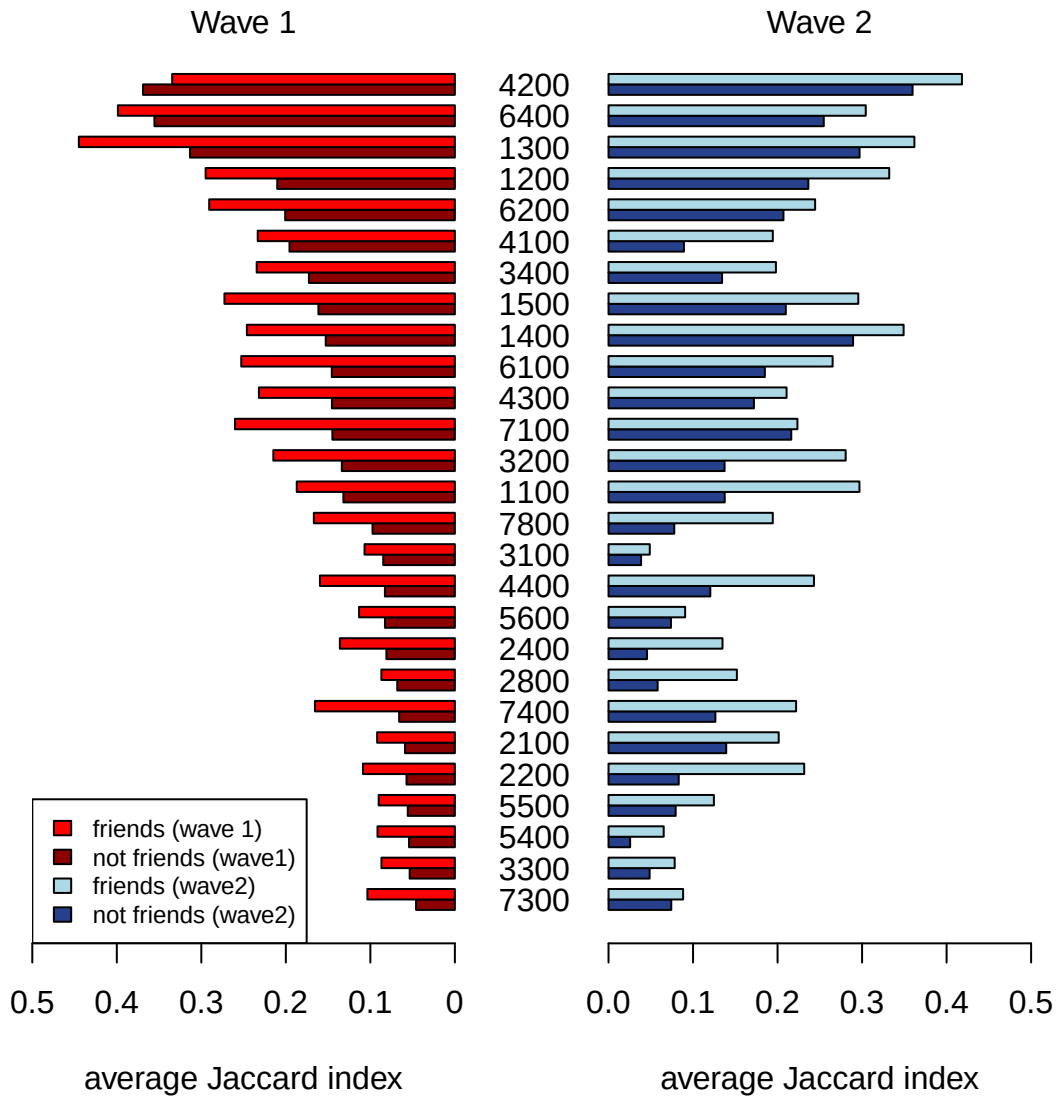

Figure 5.3: Average levels of agreement in positive perceptions between friends and non-friends in the studied classrooms in wave 1 and 2.

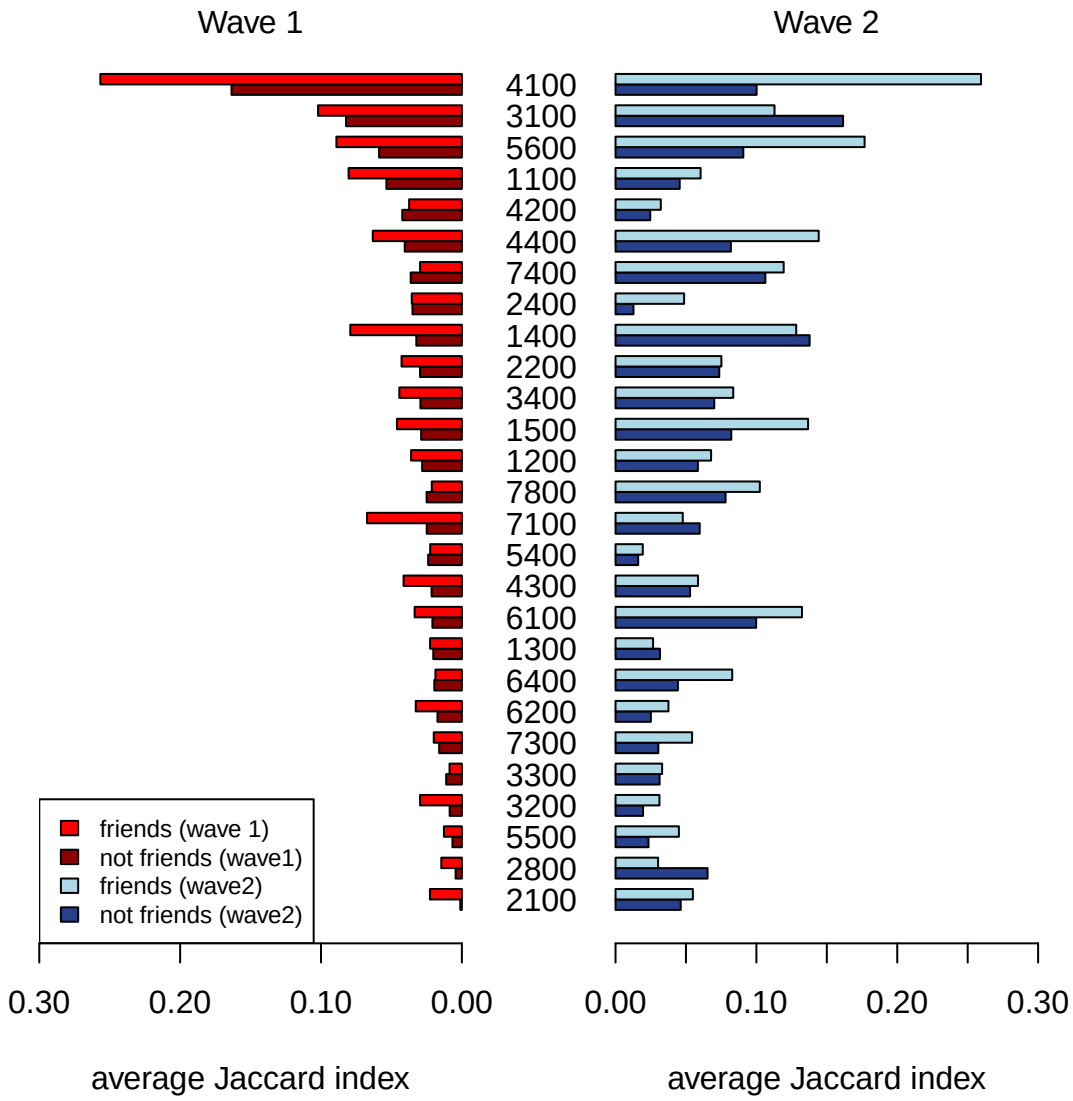

Figure 5.4: Average levels of agreement in negative perceptions between friends and non-friends in the studied classrooms in wave 1 and 2.

of negative perceptions than for positive ones. The general increase in agreement is also more visible here. Friends seem to agree more in negative perception than non-friends, on average, in most cases, but the differences are most often very minimal.

In summary, we can find evidence that friends agree in their peer-perceptions more often than non-friends. The differences between the means are typically larger in case of positive perceptions than for negative perceptions, but the gap between friends and non-friends seems to widen more for the latter type of network. Thus, from this simple investigation it seems that H1 has support for positive agreement, and also to some extent for negative agreement.

5.6.2 The role of student similarity in friendship and agreement

In the next step of our analysis, we assess whether student similarity in six individual characteristics is related to friendship and perception agreement in the studied classes. The exploration of the link between friendship and similarity requires the mapping of the tendencies for homophily along these dimensions. To this end, we present a series of plots in Figure 5.5–5.7. The six pictures provide an overview of the state of homophilous tendencies in friendship formation in the studied classrooms along the six individual variables in the two waves.

The calculations for these figures are based on a measure similar to the E-I index (see e.g. Krackhardt and Stern, 1988) and which is normalized by the number of possible friendship choices within and between individual covariate categories. We calculate this measure simply by subtracting the proportion of friendship ties that exist between students who are different in the given covariate from the proportion that exist between students who are similar. In other words, we report the differences between the density of same-covariate friendships and mixed-covariate friendships. Thus, positive values indicate a tendency for homophilous over heterophilous friendships, while negative values show the opposite.

Figure 5.5a shows that in almost every classroom both boys and girls have friends of the same sex as themselves. Also, most of these values are significantly larger for both sexes than what would be expected by randomly reassigning gender categories in the class. What we can also see in the plot is that green solid circles are often to the right of their empty square counterparts. This means that there is a tendency for boys to become *less* homophilous in their friendship choices over time. The same thing is not true for girls, who tend to have a similar or increasing "preference" for girl friends over boy friends.

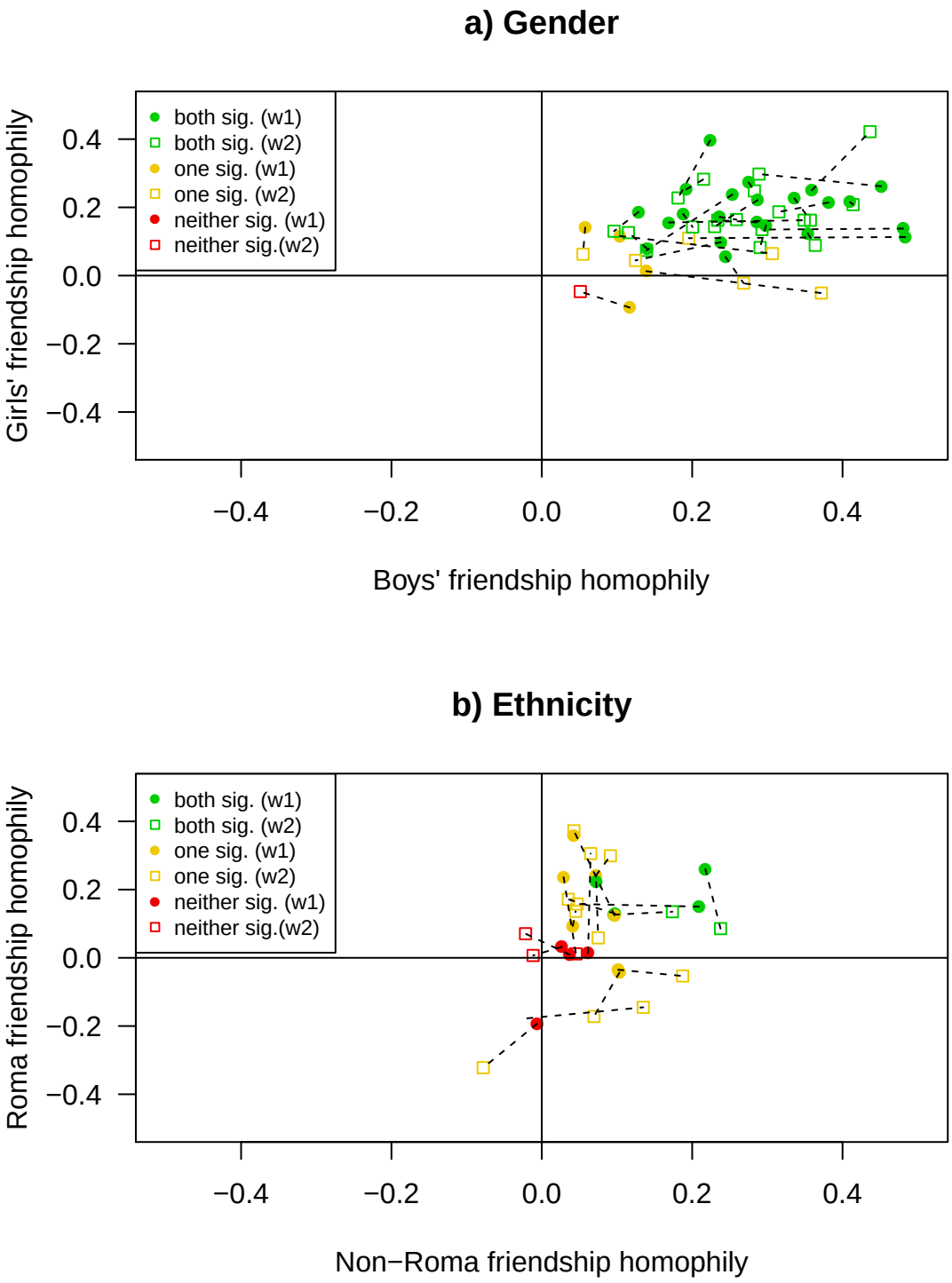

Figure 5.5: Friendship homophily I. Gender and ethnicity.
(The shape of data points represents the two waves; colors show whether the index is significantly different ($p<0.05$) from that with randomly permuted covariate values for both [green], either [yellow], or neither [red] of the covariate groups; data points for the same classroom are connected by dashed lines.)

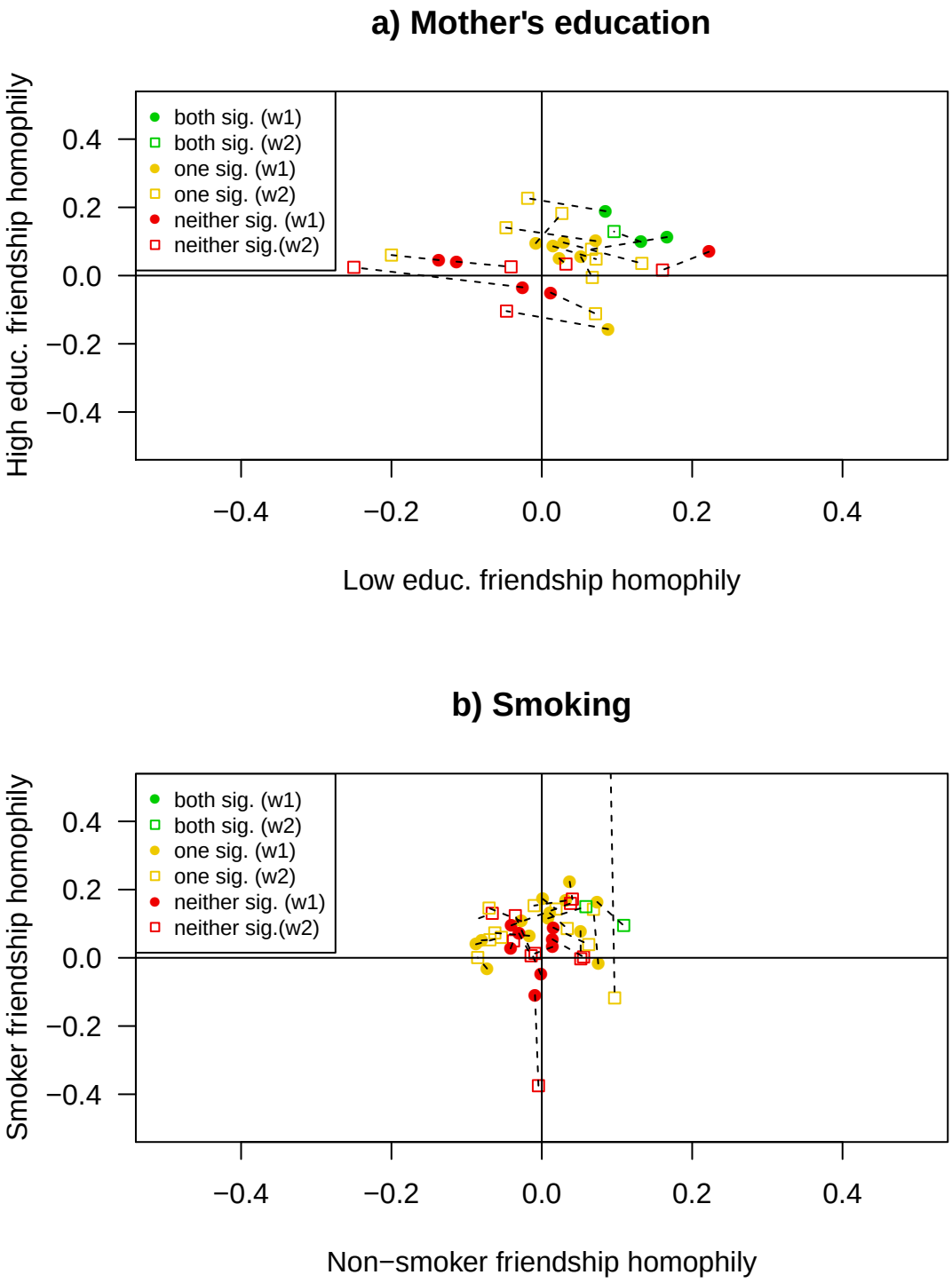

Figure 5.6: Friendship homophily II. Mother's education and smoking. *(The shape of data points represents the two waves; colors show whether the index is significantly different ($p<0.05$) from that with randomly permuted covariate values for both [green], either [yellow], or neither [red] of the covariate groups; data points for the same classroom are connected by dashed lines.)*

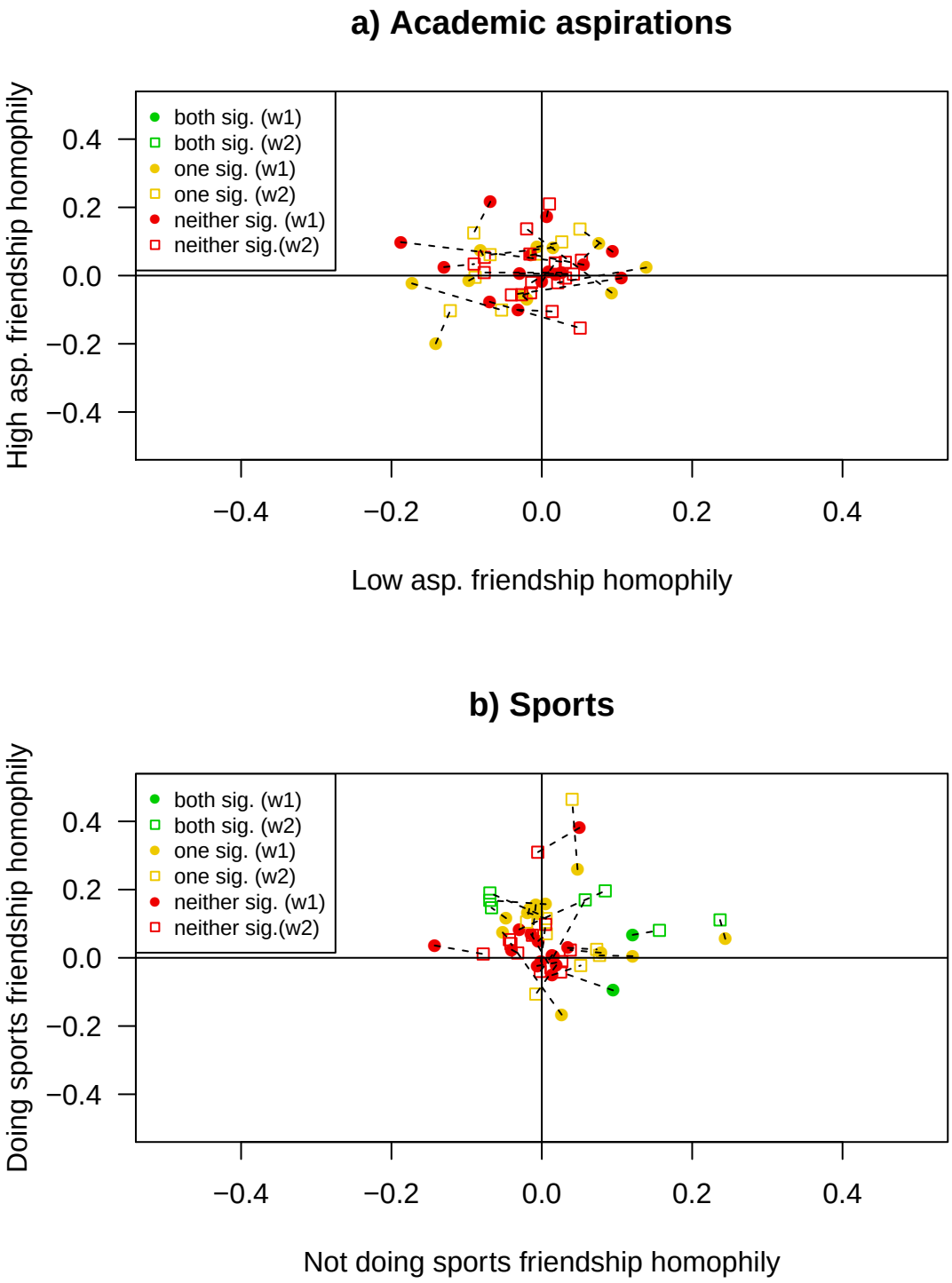

Figure 5.7: Friendship homophily III. Academic aspirations and sports. *(The shape of data points represents the two waves; colors show whether the index is significantly different ($p<0.05$) from that with randomly permuted covariate values for both [green], either [yellow], or neither [red] of the covariate groups; data points for the same classroom are connected by dashed lines.)*

Figure 5.5b presents an overview of homophily between students of Roma and non-Roma ethnic identity. There are fewer data points in this plot because some classrooms do not have Roma students at all (see Section 3.1.2 for details). Homophily appears to be an important factor in friendship formation also in this case, but the picture is more mixed than for gender. There are only a couple of classes where both Roma and non-Roma students prefer same-ethnic friends significantly more than those with different ethnicity. There are, however, quite a few communities where only one ethnic group is significantly homophilous, while the other is only mildly so or slightly heterophilous. There is no systematic tendency in the changes between waves.

Based on Figure 5.6, homophily related to family background, as measured by the mother's education, is also a significant factor of friendship formation in quite a few classes, but the differences between within- and between- category densities are smaller than in the previous cases. The same is true for smoking with the exception that non-smokers in some classes slightly "prefer" smokers over other non-smokers, while smokers tend to be homophilous in their friendship choice.

We can see an even more mixed overall picture in case of academic aspirations and sports, as presented in Figure 5.6. When it comes to academic aspirations, homophily and heterophily both occur, but mostly this factor is not significant in friend selection. Those who do sports typically appear to choose friends who also do so, while those who do not participate in any training sometimes prefer similar, sometimes more active peers as friends. However, homophily related to this variable seems to have a small and often statistically insignificant effect on friendship choice

Now we examine the links between perception agreement, measured as the Jaccard index, and the background attributes of students. Tables 5.8 and 5.8 provide a summary of the relations between similarity in the six individual variables and the level of agreement in positive and negative perceptions, respectively. The tables show the number of classrooms in which average agreement among similar students (boys, girls, non-Roma, etc.) is larger and smaller than the agreement level between dissimilar students in the class. The numbers in parentheses reflect the classrooms where the given difference is significant at $p<0.05$.

The two tables tell us that students who are similar in any of the six characteristics typically agree more in their perceptions than dissimilar students. The differences are also significant in around half or more of the classrooms. These tendencies appear to be stable in the two studied observations. The size of the difference between similar and dissimilar students (which is not reported here due to space limitations) is often quite considerable. In case of positive perceptions, it is usually between 0.1 and 0.2,

Table 5.8: Summary of the relation between similarity and positive agreement in the 27 classrooms in wave 1 and 2.

Positive	Wave 1		Wave 2	
agreement	Larger	Smaller	Larger	Smaller
boys	26 (14)	0 (0)	24 (15)	2 (0)
girls	26 (21)	0 (0)	26 (21)	0 (0)
non-Roma	18 (13)	2 (0)	19 (13)	1 (1)
Roma	19 (9)	1 (0)	19 (6)	1 (0)
low educ.	18 (9)	1 (0)	18 (8)	1 (0)
high educ.	17 (9)	2 (0)	17 (11)	2 (0)
non-smokers	21 (14)	6 (0)	23 (14)	4 (0)
smokers	27 (18)	0 (0)	26 (17)	1 (0)
low asp.	27 (15)	0 (0)	27 (12)	0 (0)
high asp.	27 (17)	0 (0)	25 (13)	2 (0)
no sports	27 (15)	0 (0)	24 (15)	3 (0)
sports	27 (17)	0 (0)	27 (22)	0 (0)

The cells contain the number of classrooms (out of 27) in which the average level of agreement (measured as the Jaccard index) between students in the same covariate category is larger or smaller than between students from different categories; the numbers in brackets count the classes where the difference is significant at $p<0.05$.

Table 5.9: Summary of the relation between similarity and negative agreement in the 27 classrooms in wave 1 and 2.

Negative	Wave 1		Wave 2	
agreement	Larger	Smaller	Larger	Smaller
boys	26 (10)	0 (0)	26 (13)	0 (0)
girls	24 (22)	0 (0)	25 (21)	1 (0)
non-Roma	18 (10)	2 (0)	18 (8)	2 (0)
Roma	19 (6)	1 (0)	19 (3)	1 (0)
low educ.	17 (7)	2 (0)	17 (6)	2 (0)
high educ.	17 (8)	2 (0)	17 (12)	2 (0)
non-smokers	25 (9)	2 (0)	25 (10)	2 (0)
smokers	26 (14)	1 (0)	27 (14)	0 (0)
low asp.	27 (11)	0 (0)	27 (14)	0 (0)
high asp.	25 (13)	2 (0)	26 (14)	1 (0)
no sports	24 (13)	3 (0)	23 (11)	4 (0)
sports	26 (14)	1 (0)	27 (18)	0 (0)

The cells contain the number of classrooms (out of 27) in which the average level of agreement (measured as the Jaccard index) between students in the same covariate category is larger or smaller than between students from different categories; the numbers in brackets count the classes where the difference is significant at $p<0.05$.

and a little less, $0.05 - 0.2$ for negative perceptions. Given that the Jaccard index takes values between 0 and 1, these differences are not small.

In summary, we found general support for hypothesis H2. Individual similarity often plays a role in friendship formation (H2a): similar students tend to be friends more often than dissimilar students. Gender homophily seems to be the most universal grouping mechanism in our sample. Same ethnic identity is usually also an important factor in friendships, while the other four covariates are relevant in some classes but not in others.

Similarity between students is associated with stronger agreement in perceptions in many classrooms (H2b). This tendency appears to hold for all of the six studied characteristics. Due to the connections between individual variables, friendship, and agreement, it is highly important to have a second look at the friendship–agreement link, this time in a multivariate analysis.

5.6.3 The friendship–agreement link in the presence of individual covariates

In this section, we examine how the similarity of students moderates the relation between friendship and perception agreement (measured by the Jaccard coefficient). To this end, we compare friendship–agreement correlations on the classroom-level with those among similar students in the six covariate dimensions analyzed so far. In this analysis, we distinguish between the covariate categories: for example, we assess the relation between friendship and agreement among girls and boys separately. Those classes where there are less than three students in either category were omitted from the calculations for the given covariate. In addition correlations larger than 0.9 in absolute value are not presented, since they come from cases where a covariate group was rather small (3-4 students).

Figures 5.10 and 5.11 provide an overview of the correlations between friendship and agreement among similar students in the studied classrooms at wave 2 (the results in wave 1 are generally similar, and so are not reported for brevity). The first figure treats agreement in positive perceptions, while the second in negative perceptions. The horizontal axis of each plot marks the classroom-level correlations (among all students in a given class). The correlations among similar students are measured on the vertical axis. There are two data points connected by a dashed line: one for each of the covariate categories. If a point is located above the solid line across each plot, that means that the within-category correlation is larger than the class-level

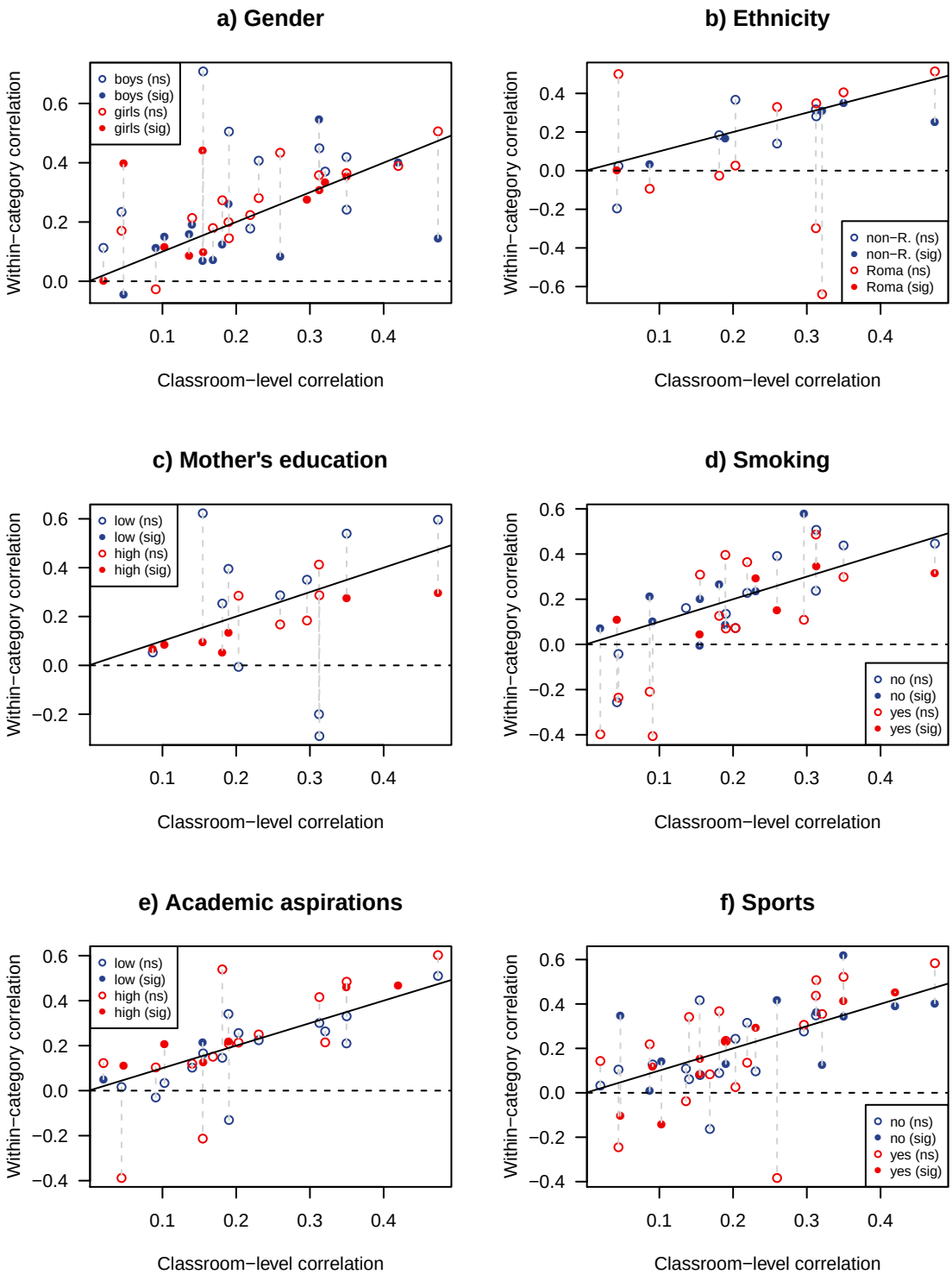

Figure 5.10: Within-category and classroom-level correlations between positive agreement and friendship in wave 2.

(Significance refers to QAP permutation tests where the observed correlation is larger than 95% of those in the simulated null-distribution.)

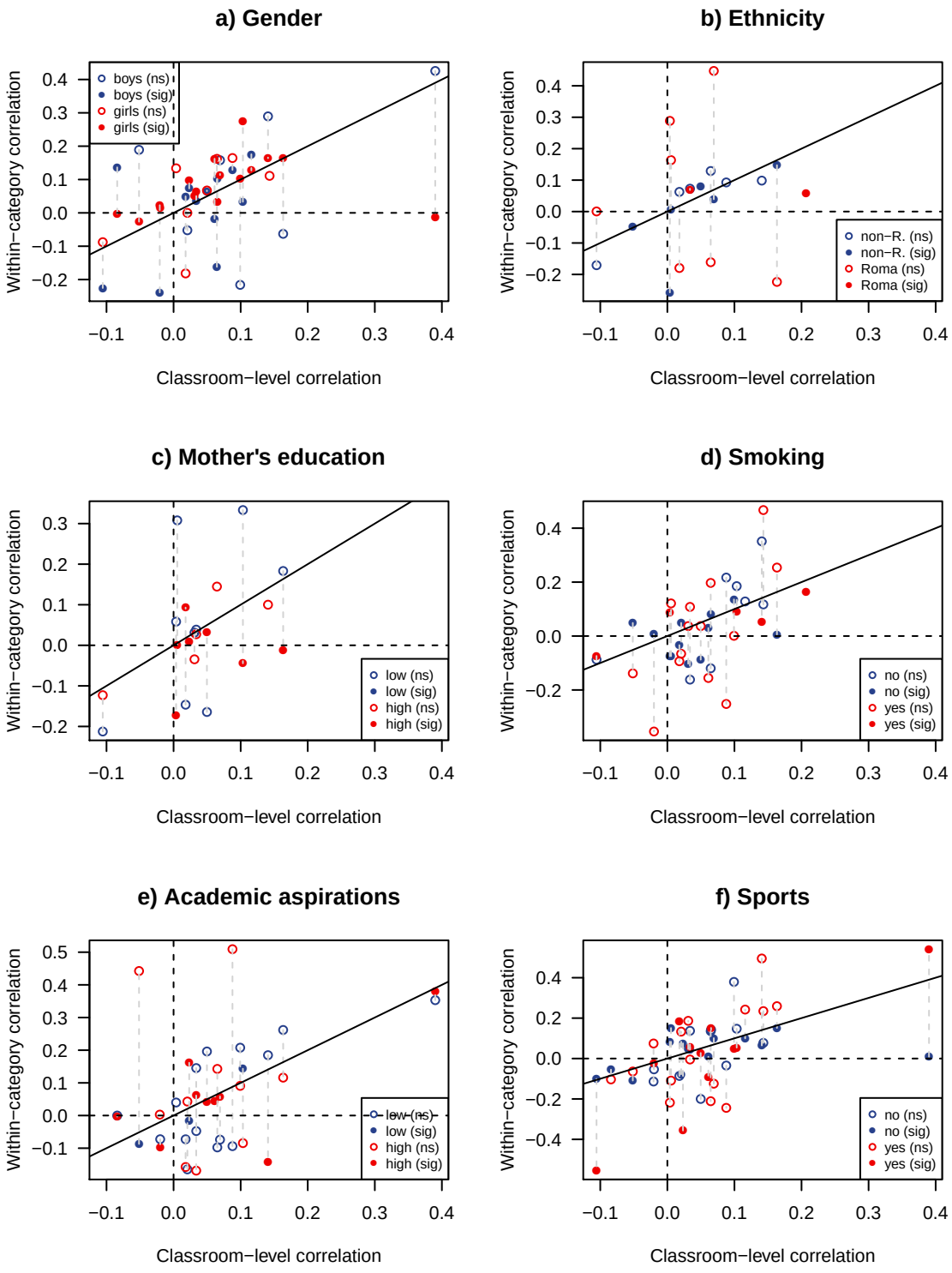

Figure 5.11: Within-category and classroom-level correlations between negative agreement and friendship in wave 2.

(Significance refers to QAP permutation tests where the observed correlation is larger than 95% of those in the simulated null-distribution.)

correlation between friendship and agreement. Points below the solid line mean the opposite.

We can see in the figures that the within-category correlations are quite heterogeneous across the classrooms: some are larger, some are smaller than the corresponding classroom-level tendency There do not seem to be systematic differences between the categories of each covariate. Based on this, we can say that H3a is generally not supported, since many within-category correlations are larger than their class-level counterparts. H3b, however, mostly appears to hold: the friendship–agreement link among similar students is typically positive, even when it is smaller than the relation for the entire classroom. There are some exceptions, though, especially in case of negative perceptions.

5.6.4 Longitudinal relations between friendship and agreement

The final step of our analysis focuses on the dynamic links between friendship and agreement in perceptions. We are interested in how friendship trajectories (tie creation, maintenance, and deletion) are related to changes in agreement between the two studied data waves. To investigate this topic, we estimate two sets of QAP regression models: one in which agreement change and one in which friendship change is the dependent variable. In both cases, we include additional right-hand side variables for student similarity in the six covariates analyzed so far. For simplicity, we do not distinguish between the covariate categories in this analysis (e.g. boy-boy or girl-girl dyads), as the focus is on similarity only. In classes where the variance of an individual variable is zero, it is omitted from the model. We use linear regression when the dependent variable is agreement, and logistic regression when it is friendship.

Figure 5.12 examines the effects of the different friendship histories on the level of agreement in positive perceptions in wave 2. The six similarity variables used before were also included in these models. In addition, though not reported in the figure, we controlled for the level of agreement at the first observation, so the estimated parameters can be interpreted as effects on the change in agreement among students (under the assumption of an additive functional form).

In the uppermost plot in Figure 5.12, we can see three series of data points marking the parameters related to friendship creation, maintenance, and deletion. The reference category are the friendship ties that did not exist at either waves. We can see that most typically friendship creation and maintenance are related to the increase of positive agreement. Those who broke a friendship tie between the two time points

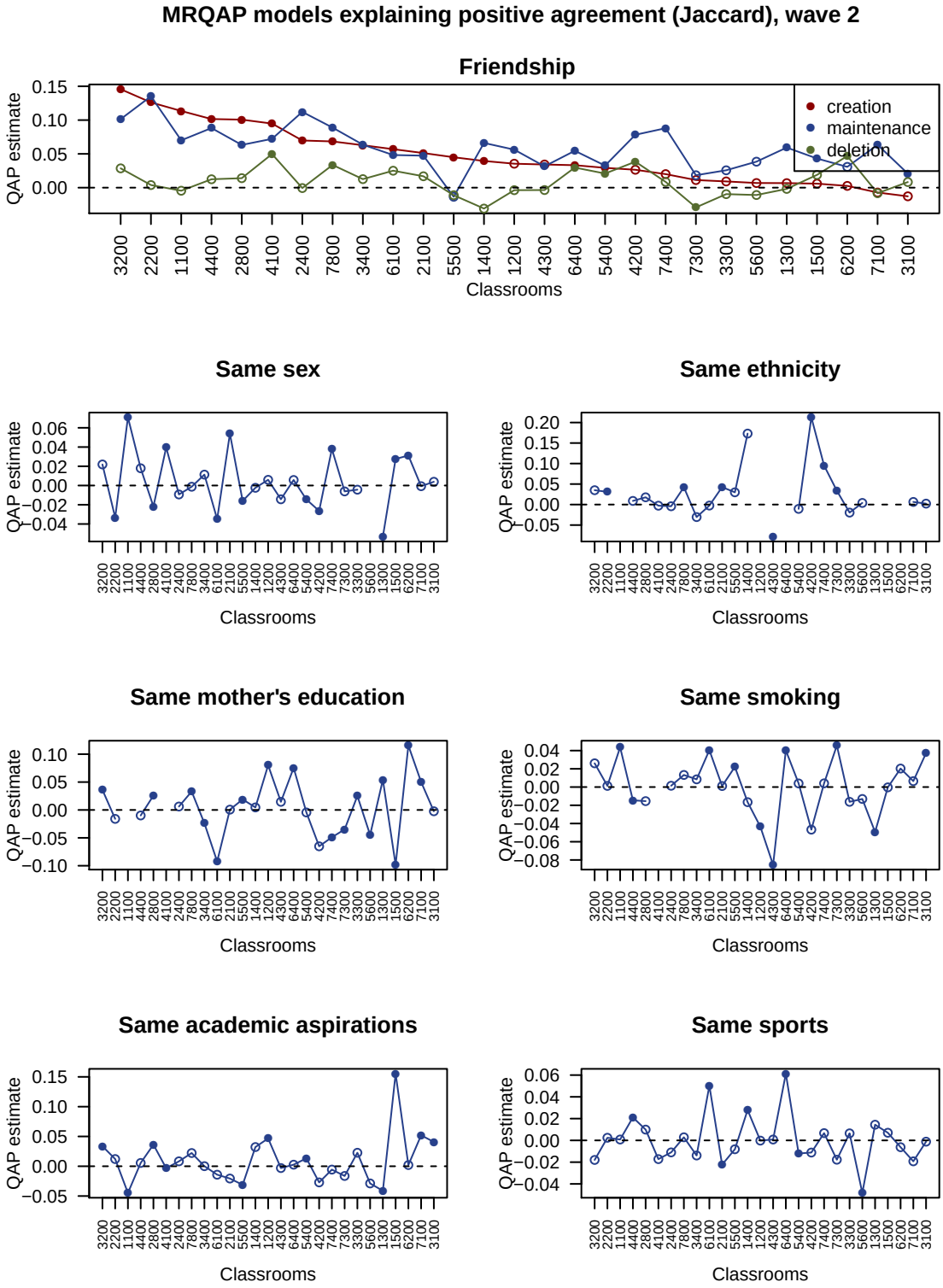

Figure 5.12: The effect of friendship trajectories on positive agreement. *(Solid data points represent significant parameters at $p<0.05$; classes are in descending order of estimates for friendship creation.)*

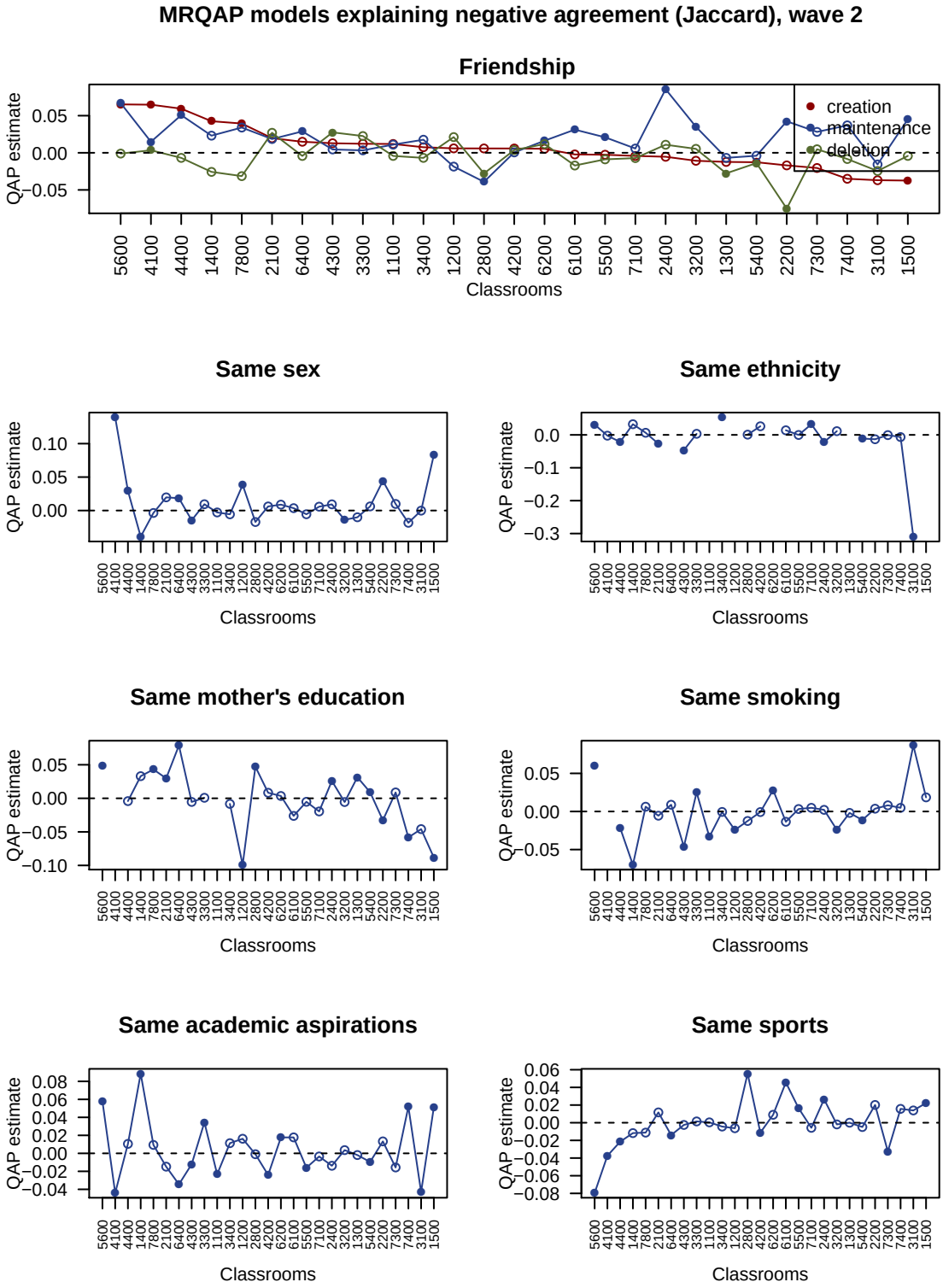

Figure 5.13: The effect of friendship trajectories on negative agreement. *(Solid data points represent significant parameters at $p<0.05$; classes are in descending order of estimates for friendship creation.)*

can have a smaller tendency to become more similar in some classrooms, but most often the effect of tie deletion is close to zero and non-significant.

Figure 5.13 presents the same models for agreement in negative perceptions. Similar to the previous section, the estimates for the main explanatory variables are smaller in this case than for positive perceptions. Friendship maintenance seems to be associated with increasing agreement the most often, while creation has a strong positive role in only a few classes, and the effect of tie deletion is almost always negligible.

Figure 5.14 summarizes models with friendship tie maintenance as the dependent variable. This basically means that now we are considering a subset of the friendship networks in wave 2: only those case where a friendship tie existed earlier, in wave 1. (As mentioned above, result for tie creation are essentially similar those presented here.) There are two key explanatory variables here: the level of positive agreement in wave 1 and the change in positive agreement. Since these models are logistic regressions the estimates reported are again the log odds ratios.

Based on the figure, initial agreement and increasing agreement in positive perceptions is associated with a significantly higher odds of friendship maintenance against deletion in about half of the classrooms. The effects are smaller positive, but non-significant in the other half. We can also see that in some classrooms where the dynamics of agreement has little or no effect, having the same sex, ethnicity, and family background contributes greatly to tie maintenance.

The picture for negative perceptions is quite familiar. As it is shown in Figure 5.15, there are a couple of very large effects of agreement on friendship, but in most of the classrooms the estimates are small and non-significant. Again, same sex, ethnicity, and family background have considerable effect on friendship maintenance in quite a few classrooms.

In summary, the fourth hypothesis is mainly supported for positive perceptions, but not really for negative perceptions. In most classrooms, students who become or remain friends in the studied period tend to agree more and more in their positive perceptions. In addition, increasing negative agreement is more a characteristic of stable friendships only, in about half of the classrooms. This provides some basic support for H4a. We found a positive effect of increasing agreement on friendship maintenance only in half of the classes for positive perceptions, and only a couple of them for negative perceptions. While the signs of estimates are typically in the expected direction, H4b was not strongly supported.

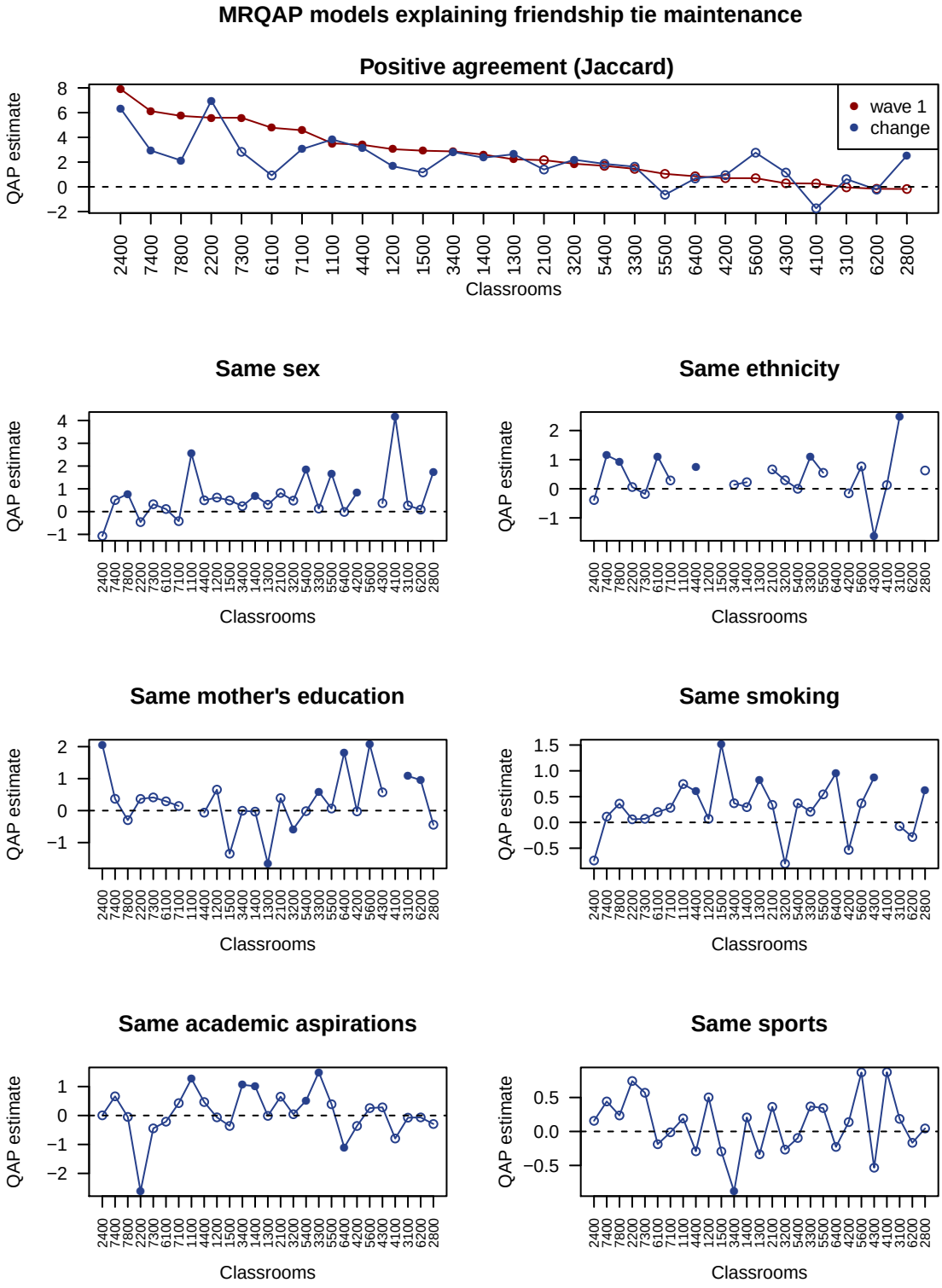

Figure 5.14: The effect of positive agreement on friendship maintenance. *(Solid data points represent significant parameters at $p<0.05$; classes are in descending order of estimates for agreement in wave 1.)*

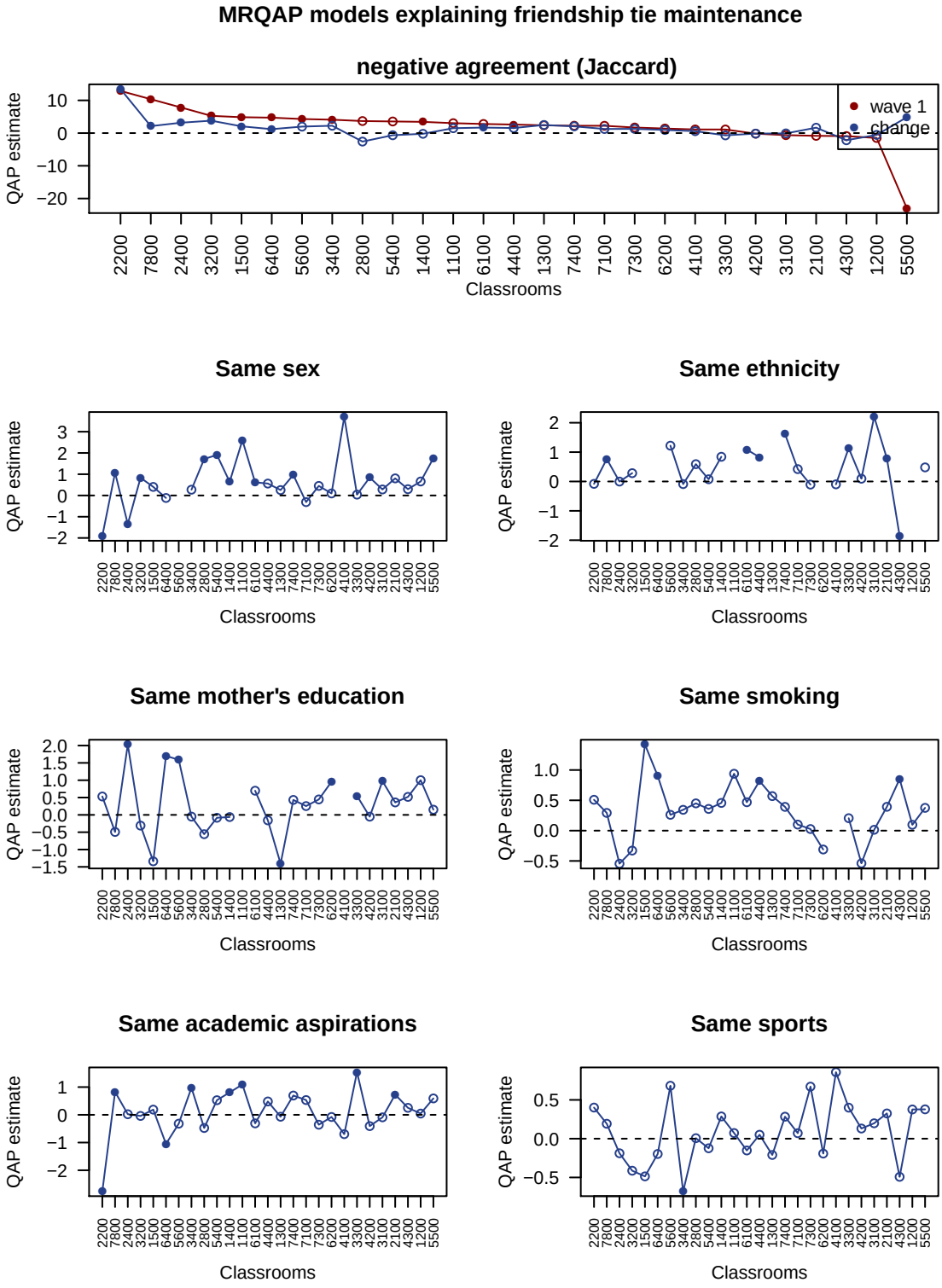

Figure 5.15: The effect of negative agreement on friendship maintenance. *(Solid data points represent significant parameters at $p<0.05$; classes are in descending order of estimates for agreement in wave 1.)*

5.7 Conclusions

As a summary of our investigation into the links between friendship and perception agreement, we can say that our hypotheses received mixed support. The first part of our baseline hypothesis which suggested considerable heterogeneity between the studied classrooms (H0) turned out to be valid, but our expectations were confirmed for a majority of classes only in the case of positive perceptions. There is evidence in our data for bivariate cross-sectional relations between friendship and agreement in perceptions (H1). However, the correlations are typically small or medium-sized, and sometimes even slightly negative for negative perceptions.

Friendship homophily (H2a) appears to be especially important in the dimension of gender in most classrooms. Similarity in ethnic identity is a relevant factor in friendship formation in fewer classes. The other four variables considered play a role in some classrooms but not in others. For both positive and negative perceptions, we found that similar students tend to agree more in their perceptions than dissimilar students (H2b). This is true for around half or more of the classes, depending on the covariate, and the effect sizes are often considerable.

Friendship–agreement correlations are typically not much lower, or are higher, among students who are similar in the studied individual dimensions than in the classrooms in general (H3a). In case of positive perceptions, there is evidence from most classrooms that the link is positive in a majority of cases even when we take into account student similarity (H3b). For negative perceptions, there is weaker evidence, correlations are more often negative.

With regard to the longitudinal relations between friendship and agreement, we found support for our last hypothesis for positive perceptions, and again less so for negative perceptions. Stable and emerging friendships are positively related to increases in positive agreement, while tie dissolution does not have a consistent and strong effect in multivariate models (H5a). In case of negative agreement, only stable friendships seem to contribute to higher levels over time, and in less than half of the classrooms. Increasing positive agreement is related to friendship maintenance in about half of the classrooms (H5b). The same is true for negative only as non-significant tendencies in many cases.

5.8 Discussion

This chapter provided sufficient descriptive evidence that there is indeed a correlation between friendship and agreement in perceptions, and that this link can be detected even when similarities between students in certain background dimensions are taken into account. This is in line with the basic predictions of the theory of group formation elaborated in this thesis.

There are apparent differences, however, between the results for positive and negative perceptions. Analyses on the latter networks were able to find significant evidence for the friendship–agreement link only in a small part of the sample. This may be related to the fact that negative perception networks are relatively sparse. It is possible that the total agreement in two students' negative perceptions is less important for close relations to develop between them. What might have a stronger effect is whether they agree in the negative evaluation of one or two classmates or all their perceptions are divergent.

Of the studied individual variables, gender seems to be the most universal grouping characteristic in the sample. Ethnic identity is also often relevant, but tends to have an asymmetric effect: in many cases either non-Roma students tend to prefer other non-Roma as friends over Roma peers, or the other way around. The other four covariates are also related to friendship formation and perception agreement, but only in a couple of classrooms, and their effects are quite variable.

Obviously, these findings about the role of student similarity in sociological dimensions are not meant to be conclusive. In future analyses on the same dataset, the measurement of individual characteristics shall be improved. The dataset we use provides additional options for creating more detailed, better measures of family background, academic values, or delinquency. However, our present aim was to conduct a descriptive study which explores the impact of different definitions of perception agreement in cross-sectional and longitudinal views. This was achieved to a reasonable extent by the presented analyses.

We also have to note that the presented multivariate models focus on similarities and do not differentiate between the categories in each individual dimensions. That is, in some cases we did not study the difference in friendship or perception activity and popularity between boys/girls, Roma/non-Roma, and so on. Since at certain steps of the analysis the effects of similarity were asymmetric, this is an issue that requires further attention. Accordingly, we control for differential activity and popularity in the network co-evolution models presented in the following chapter.

An important question related to individual characteristics is whether class composition in the sociological dimensions is systematically associated with the strength of the friendship–agreement link. Simple background analyses were conducted into this problem. These have so far revealed no significant bivariate correlations or consistent non-linear patterns between class composition and the effects of the key explanatory variables in the multivariate models.

One of the most important substantive issues of the analyses presented here is that they do not explicitly model the structure and changes of friendship and perception networks. Based on these models, we do not get a clear picture about how the link between friendship and agreement in perceptions emerges, about the directions of the possible causal connection, and about how similarities between students interacts with the hypothesized mechanisms of group formation. To further investigate these questions, we analyze the co-evolution of friendship and perceptions in a stochastic actor-oriented framework in the next chapter.

Chapter 6

Minority-agreement selection and the circles of influence: The co-evolution of friendships and perceptions in classrooms

How do friendships and peer-perceptions co-evolve? The theory of group formation processes proposed in this thesis suggests that agreement in perceptions between members of a community contributes to friendship formation. Further, once friendship ties are established, friends also influence each other's perceptions and become more similar. These mechanisms are examined on two waves of network panel data from 27 Hungarian high-school classrooms. We study the joint dynamics of friendships with positive and with negative perceptions. The Stochastic Actor-oriented Model allows us to assess how much selection and influence processes are likely to contribute to the co-evolution of the networks in question in the studied time period. We find that agreement in perceptions may lead to the formation of friendships between students especially when they are in a minority with their opinion in the classroom. There is also evidence for friend influence which seems to be moderated by the context of the friendship groups two students are jointly embedded in. The results provide some corroboration for the theorized network mechanisms.

6.1 Introduction

This chapter further analyzes the dynamic network mechanisms central to the proposed theory of group formation in informal settings: the alignment of positive affections and agreement in perceptions among community members. Previously, we have provided descriptive evidence that the relation exists in the dataset we study, even

when we take into account some of the possible dimensions of group formation, such as sex similarity and other individual characteristics.

It remains a question, however, how the predicted network configurations evolve. Does agreement in perceptions about peers lead to friendship? Does friendship lead to increasing levels of agreement about peers? Is this process affected by the embeddedness of individuals in groups and by the structure of the community as a whole?

Here we apply a dynamic network modeling framework to identify the generating mechanisms behind the relation between friendship and perception agreement. We aim to model the co-evolution of multiple networks among high-school students (for empirical work with a similar approach, see e.g. Snijders et al., 2013; Stark and Flache, 2012; Rambaran, Dijkstra, Munniksma, and Cillessen, 2015). The model allows us to infer the likely choices of actors in an unobserved period framed by two measurements, based on the changes in the network structures.

First, we study the dynamics of single networks of affection and two types of peer-perception. Since the latter two networks are aggregated measures which have not been employed in earlier studies, it is important to explore the basic tendencies which characterize their evolution. Second, we build models for the co-evolution of affections and perceptions to answer our research questions. Unlike the analysis presented in Chapter 5, now we explicitly model the joint dynamics of multiple networks, and do not only control for their structure.

Since the hypothesized social mechanisms operate in triadic or higher-order network configurations, a key element of our modeling approach is to control for the most important sub-configurations (on the level of dyads and actors) which present competing explanations for the focal effects. We also take into account similarities between individuals in dimensions found to be important in the previous chapter.

6.2 Research questions

In line with the mechanisms outlined in Section 2.5, the current chapter aims to answer the following research questions:

1. Does agreement in perceptions between students promote the creation and maintenance of friendship ties?

2. Do friends tend to develop similar perceptions about their classmates?

3. Does agreement in perceptions matter more for friendship when it goes against the opinion of the classrooms?

4. Do students who have shared friendship groups influence each other's perceptions? In this sense, can we talk about a "group influence" that is distinct from the influence of friends or that of the classroom in general?

6.3 Methodology

6.3.1 Data

To answer the research questions of the current chapter, we again study the 27-classroom Dynamic Subsample of the RECENS high-school dataset. We utilize some of the insights gained about these classes in the previous chapter. In the first step of the analysis, we analyze the evolution of each classroom community separately and compare the results across classes. The second and third steps employ single, so-called multi-group, models for all of the groups. A description of the Dynamic Subsample classrooms is provided in Section 3.1.2 and Appendix B.

6.3.2 Measures

Friendship. Similar to the previous chapter, we measure friendship as the network resulting from the +2 nominations in the affection scale in each classroom (see Section 3.1 for details). In line with the employed statistical modeling framework, we use directed networks, that is, we distinguish between non-reciprocated and reciprocated friendships throughout the analysis.

Positive and negative perceptions. Just as earlier, here we consider two types of aggregated perception networks: positive and negative dyadic attributions between students. These measures are defined as in Chapter 4, where we identified the positive and negative attribution clusters in the set of 18 perception networks. See Section 4.3.7 for the exact definitions. The validation of the presented clustering results for the full set of classrooms is summarized in (Appendix C).

This chapter moves beyond the study in Chapter 5 in that it aims at the simultaneous modeling of the structure of friendship and perception networks. Consequently, we do not only focus on measures of agreement between students, but utilize all the information available in the perception networks and treat them as directed relations. The technical definition of agreement is discussed in terms of the model specification in the Results section.

Individual variables. In the present study, we take into account gender similarity between students when modeling the co-evolution of friendship and perceptions. For

the moment, we decided to use this individual characteristic only, for two reasons. First, in Chapter 5 we have seen indications that among the considered variables sex similarity had the most substantial and systematic relation to friendship and perception agreement. Second, the models presented below include many exploratory features (the types of networks being analyzed, the triadic and higher-order effects considered), and so it appeared to be reasonable to keep the number of control variables low in order to avoid additional modeling problems.

Despite the inclusion of gender only, the analyses in this chapter are still more detailed than in the previous one, as they take into account activity and popularity differences between boys and girls, and thus they are able to capture differential tendencies for homophily between the two gender categories. For descriptive information about the sex variable in the studied classrooms, see Section 3.1.2. Here we only note that in the presented models, boys were coded 0 and girls 1. The gender-related results shall be interpreted accordingly.

6.3.3 Methods

This chapter applies different types of Stochastic Actor-oriented Models. The method is explained in detail in Section 3.4. The first part of the analysis below uses single-network models to study the key characteristics of the evolution of friendship and the two perception networks separately in the 27 classrooms. Then, we turn to co-evolution models which include two networks at a time (friendship and positive perceptions, friendship and negative perceptions). Instead of classroom-level models, we present results from pooled multi-group estimations in which only the outdegree parameter of the models is assumed to vary between classes.[1]

6.4 Analytical strategy

The following analysis consists of three steps. First, we present results from single-network SAOMs applied separately for each classroom and each of the three networks studied. We use a theoretically appropriate model specification which also provided reasonable levels of fit in basic structural characteristics. The comparison of the class-level models allows us to present an overall picture of the basic network processes which play a role in the dynamics of the three types of networks.

[1]The analyses were programmed in R 3.2.0. We used the package *RSienaTest* (v1.1-288) to estimate Stochastic Actor-oriented Models.

The second step of the analysis is a multiple group study of the co-evolution of friendship and positive perception networks. We use a stepwise strategy for model building and present the results from four models which provide answers to the research questions outlined above. The third step of the analysis is a replication of the same models for the co-evolution of friendship and negative perceptions.

6.5 Hypotheses

A number of hypotheses have to be formulated in order to answer the four research questions posed above. Based on the type of network configurations they refer to, these can be organized into four groups (H1–H4). Hypotheses in the first two groups can be viewed as auxiliary to H3 and H4 which aim to test the research questions directly.

The first set of hypotheses (H1) focuses on structural processes that involve a single relation. Based on earlier works on clustering in friendship networks (e.g. Davis, 1970), we expect tendencies for triadic closure in this dimension (H1f). According to the presented group formation theory (see Section 2.5), agreement in perceptions contributes to the positive evaluation of peers. Therefore, we expect tendencies for triad closure in case of positive perceptions (H1p) but not negative perceptions (H1n).

H1: Single-network triadic effects – closure

H1f: (+) The more friends two students have in common, the more likely they are to become or stay friends.

H1p: (+) The more two students agree in their positive perceptions, the more likely they are to perceive each other positively.

H1n: (−) The more two students agree in their negative perceptions, the less likely they are to perceive each other negatively.

The hypotheses in H2 are related to the dyadic interconnections between the three networks in question. In particular, our theoretical argument assumes that perceptions about a peer have an impact on affections towards the same person. Consequently, it is hypothesized that positive perceptions contribute to friendship formation (H2pf), while negative ones work against it (H2nf). However, effects in the opposite direction shall also be taken into account. Friendship contributes to the emergence and maintenance of positive perceptions (H2fp), but its presence makes negative perceptions unlikely (H2fn). The theoretical groundings for these effects are discussed mainly in Sections 2.2.2, 2.4.1, and 2.4.2.

H2: Cross-network dyadic effects – tie entrainment

H2pf: (+) Students are more likely to become or stay friends with those they perceive positively, than with those they do not.

H2nf: (−) Students are less likely to become or stay friends with those they perceive negatively, than with those they do not.

H2fp: (+) Students tend to develop and maintain positive perceptions about their friends.

H2fn: (−) Students tend not to develop and maintain negative perceptions about their friends.

Over the interconnections between the three networks stated above, we argue that there are multiplex triadic mechanisms which link perceptions to friendships. We hypothesize that agreement in perceptions leads to friendship (H3sp, H3sn) and friends influence each others' perceptions (H3ip, H3in) in both the positive and the negative cases.

H3: Cross-network triadic effects – agreement-based selection and friend influence

H3sp: (+) The more two students agree in their positive perceptions, the more likely they are to become or stay friends.

H3sn: (+) The more two students agree in their negative perceptions, the more likely they are to become or stay friends.

H3ip: (+) Friends tend to agree more in their positive perceptions.

H3in: (+) Friends tend to agree more in their negative perceptions.

As an elaboration of the effects in H3, we assume that group-level processes moderate the triadic interconnections between friendship and perception. In particular, our theory suggests that agreement-based selection is stronger when the opinion it reflects goes against the judgment of the community in general, and that not only direct friends but shared friendship context contributes to influence in perceptions (see Section 2.5)

H4: Cross-network group-level effects – minority agreement selection and influence circles

H4sp: (−) Agreement in positive perceptions contributes to friendship more if it is about a student who is generally not perceived positively in the classroom.

H4sn: (−) Agreement in negative perceptions contributes to friendship more if it is about a student who is generally not perceived negatively in the classroom.

H4ip: (+) The more common friends two students share, the more they agree in their positive perceptions.

H4in: (+) The more common friends two students share, the more they agree in their negative perceptions.

The effects considered in H3 and H4 may be partially or entirely mediated by those in H1 and H2. Therefore, it is important to include all these effects in a single model to test the key hypotheses (and also other, degree-level effects which are substantively less important at the moment).

6.6 Results

6.6.1 Classroom-level single-network models

As the first step of the analysis, we ran SAOMs for each of the three networks separately in every classroom. These models do not yet allow us to test our key hypotheses, however, they were necessary for two reasons. First, although there is a long record of studies on friendship networks using SAOMs, the two perception networks analyzed here are novel constructions, and so the main features of their dynamics require exploration. Second, before studying the co-evolution of networks in multiple groups, it is good practice to compare the results from simple models on each network in each group.

The aims of the modeling strategy we followed in this step was threefold: finding a specification for each network which leads to models with 1) effects which fit our theoretical frame, 2) adequate convergence in all classes, and 3) comparable levels of fit with commonly accepted specifications. This led to the model specifications presented in Table 6.1. These models provide an overall fit for the indegree, outdegree, and triad distributions across the 27 classes which is similar to that obtained from various models using different combinations of the 'transitive triplets', '3-cycles', and 'transitive reciprocated triplets' effects. A similar fit between models means that

Table 6.1: Specifications for the single-network Stochastic Actor-oriented Models.

Effect	Friendship	Positive perception	Negative perception
Outdegree (density)	x	x	x
Reciprocity	x	x	x
Balance	x	x	x
Transitive recip. triplets	x	x	
Indegree Alter	x	x	x
Outdegree Alter	x		
Outdegree Ego	x	x	x
Sex Ego	x	x	x
Sex Alter	x	x	x
Same sex	x	x	x

The definition of the effects can be found in Section 3.4.5.

the p-values for the Mahalanobis distances were not systematically lower or higher between the chosen and the other tested specifications across the classrooms. In the following, we present the main findings from these models.

Friendship. Figure 6.2 visualizes the distributions of the SAOM estimates for the friendship model in so-called funnel plots. The horizontal axis of each plot in the figure measures the size of the estimated parameter, and the other axis the respective standard error. The black solid lines represent the 95% percent confidence level: the points below these lines are significant at $p < 0.05$ (the farther they are from the line, the lower the p-value is). Similarly, the points above the solid lines are considered non-significant estimates at the same confidence level.

The studied classrooms appear to be similar in certain tendencies of friendship dynamics. There are positive and significant reciprocity effects in almost all of them. Balance also has a positive estimate, which means that students with similar friendship choices tend to become and remain friends (which is the first confirmation of H1f). Additionally, most classrooms seem to be polarized by friendship activity: those who nominate many friends are more likely to create even more ties or maintain existing ones than those who nominate few.

There are two more effects which have parameters close to significance in quite a few classes and for which the estimates typically have the same sign. The negative transitive reciprocated triplets effects suggest that students may be likely to form loose friendship clusters as opposed to large, dense cliques. Students of the same sex might also be more likely to become or remain friends than opposite-sex dyads. In these two cases, we may be able to find more significant estimates if classrooms

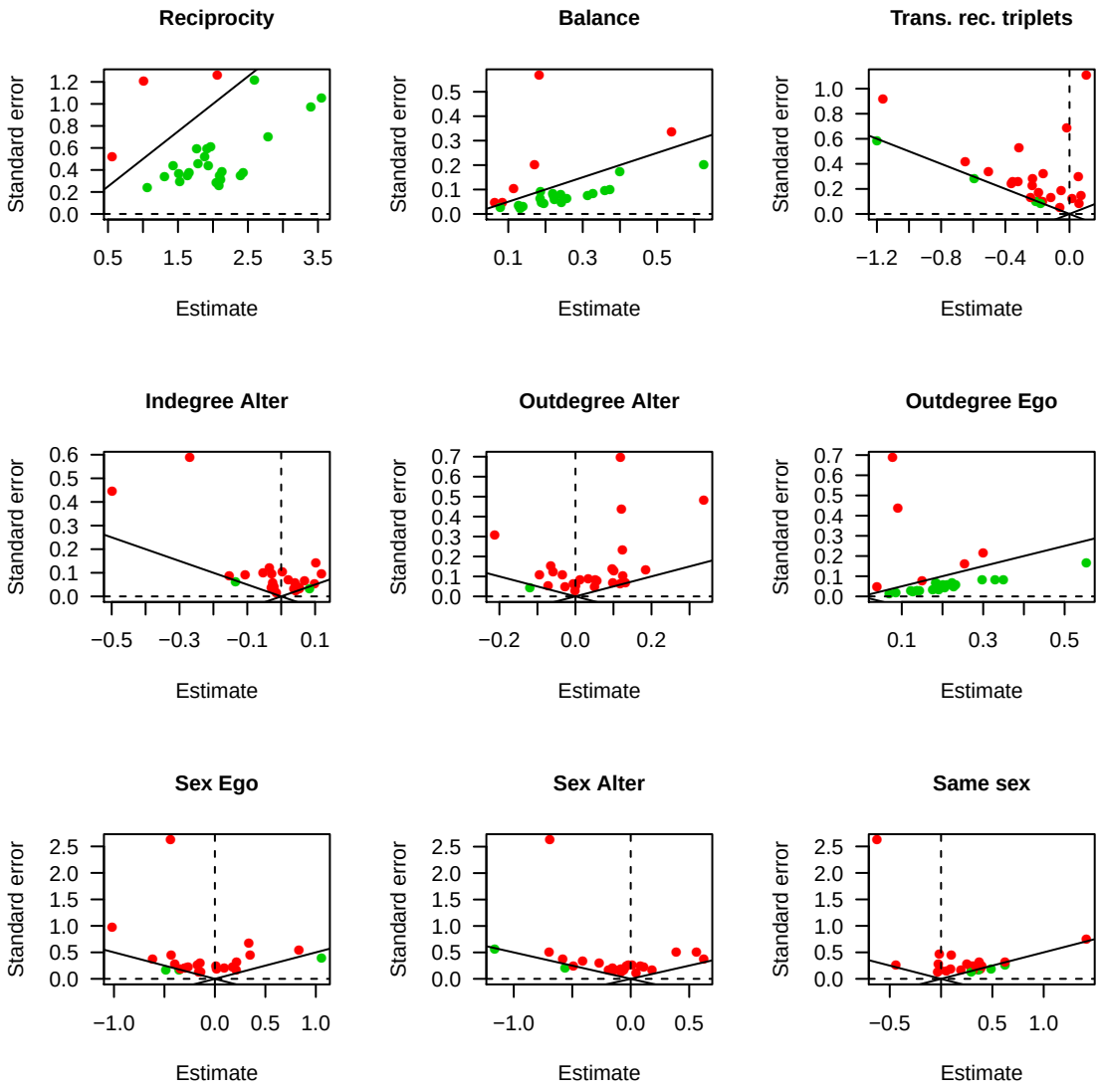

Figure 6.2: SAOM parameter estimates from the friendship models in the 27 classrooms.

were larger. Finally, the classes appear to be quite heterogeneous with respect to the remaining four effects, in the sense that the estimated parameters for them are positive in some and negative in other classrooms (and mostly non-significant).

Positive perceptions. We find partially similar results when we look at the models on the evolution of positive perceptions (Figure 6.3). Tendencies for reciprocity are positive, although just below significance in a couple of cases. Importantly for our investigation, students who agree more in their positive perceptions are more likely to perceive each other positively in almost every classroom (providing evidence for H1p). Again, there seems to be a differentiation between more and less active nominators.

According to our results, an important difference between friendships and positive perceptions is the role of indegree-related popularity. Almost all estimates in the present case are positive, and quite a few of them are significant. This suggests that there is often an emerging or existing class-level agreement in who is perceived positively: those students who receive many positive nominations tend to get even more and maintain their popularity. This tendency seems to be strong even though positive perceptions generated by agreement (balance) and sex similarity (same sex) are also taken into account. Finally, we see some indications of same sex nominations being more common than positive perception between boys and girls.

Negative perceptions. The dynamics of negative perception networks appears to differ characteristically from the previous two cases, as shown in Figure 6.4. The reciprocity parameter is most often positive but close to zero in quite a few classes, even negative (but non-significant) in five of them. There is no indication of tendencies for or against the clustering of negative perceptions (contrary to H1n). One similarity to the other networks is the typically positive outdegree-related activity effects, which are often just under the edge of significance at the 95% level.

From our results, it seems that the most important effect in the structural evolution of negative perception networks is indegree-related popularity. As seen before, this effect represents a tendency for a classroom-level consensus in who is perceived negatively to emerge and be maintained. This effect is estimated to be positive in all classrooms, and statistically significant in all but three of them. One of the factors behind the importance of degree-related effects in case of negative perceptions can be the low density of these networks (see Figure B.2 in Appendix B), since this makes the formation of closed triadic and higher-order structures unlikely.

In summary, we our results replicate the usual findings for reciprocity and clustering (with indications for loose clusters) in friendship networks. The dynamics of positive perceptions shows similarities to that of friendship. However, classroom-level

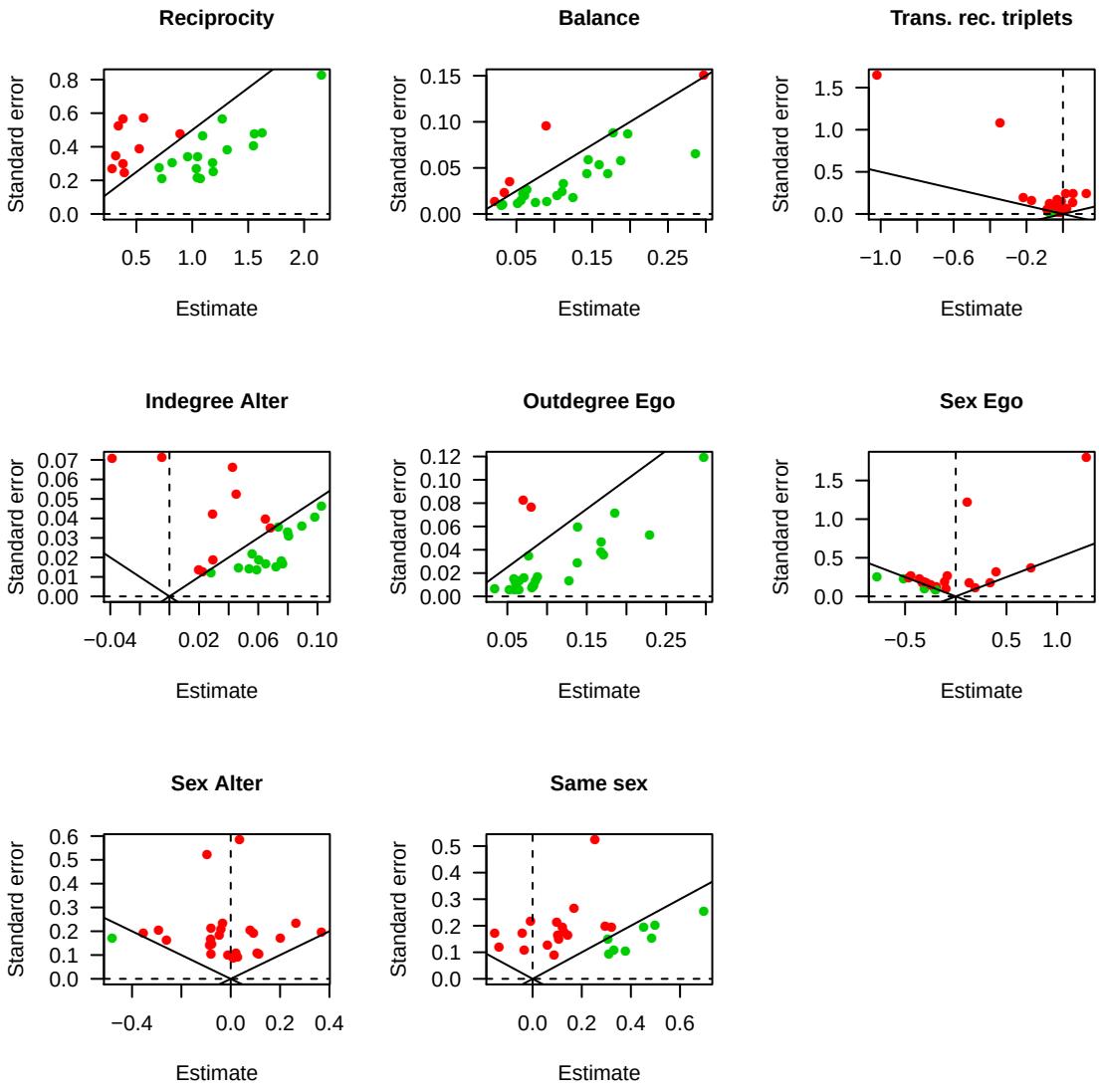

Figure 6.3: SAOM parameter estimates from the positive perception models in the 27 classrooms.

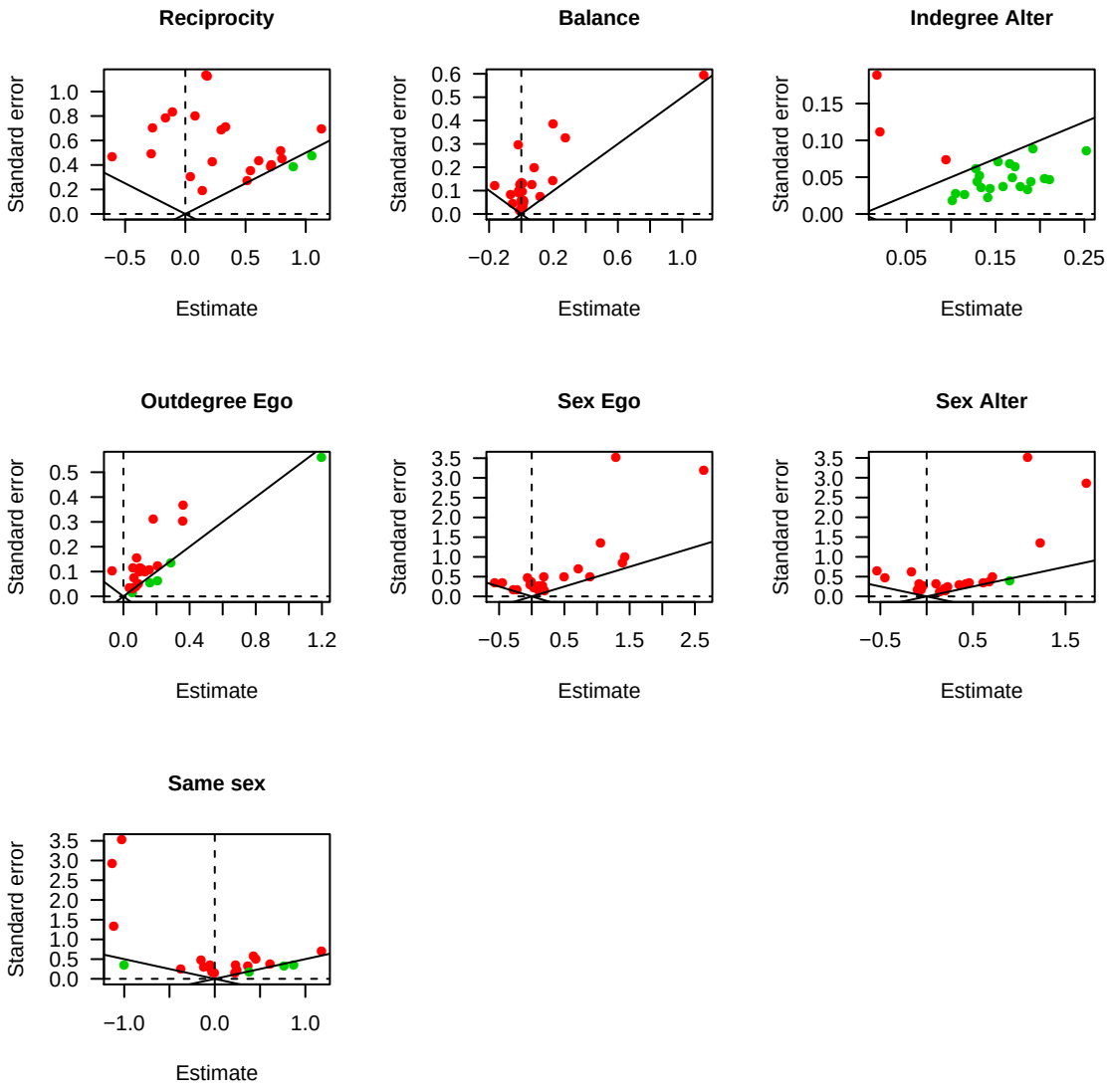

Figure 6.4: SAOM parameter estimates from the negative perception models in the 27 classrooms.

agreement is definitely important in this case. We get the same result for negative perception networks, the evolution of which is mainly characterized by tendencies for agreement in the classroom about who is perceived negatively. The main puzzle is whether the processes towards the polarization of indegrees within classrooms can be partially or fully explained by the influence of friends and groups, and by the selection of friends based on perception agreement. We investigate this issue with multiple network SAOMs in the next sections.

6.6.2 The co-evolution of friendship and positive attributions

This section and the following present results from multiple network SAOMs, each modeling the joint dynamics of friendship and one of the perception networks. For these analyses, we applied a multi-group modeling strategy which pools the separate classroom networks in a single adjacency matrix (see Section 3.4.3). The main benefit of this approach is larger statistical power, while the biggest shortcoming is that it assumes constant parameter values across all groups – an assumption too strong, as confirmed by the results of the previous section.

To somewhat remedy the weakness of the multi-group option, classroom indicator variables (dummies) are included in the two presented models for the outdegree effect in each network (friendship and perception). This means that the model allows the classrooms to differ in their parameters for network density (see Section 3.4.5). Still, the classes can be quite heterogeneous in the rest of the effect parameters, but including the mentioned set of variables is sufficient for these models to converge properly. Of course, the interpretation of the results should be done with caution, as the parameters represent overall tendencies in the 27 groups. However, the multi-group models presented here appear to be useful for exploratory analysis.

Tables 6.5 and 6.6 present the results from four different models of friendship and positive perception co-evolution. Estimates for effects on friendship dynamics are in the first table, while effects on perception dynamics are in the respective columns of the second. When reading the tables, it has to be kept in mind that each model consists of two parts.

Model 1 does not explicitly model the co-evolution of the networks (it only contains single-network effects), and it serves as a baseline. Model 2 contains three cross-network degree effects and one dyadic effect (tie entrainment) for both friendship and perceptions (see Section 3.4.5 for effect definitions). Up to this point the two model parts are specified similarly.

Table 6.5: Results from multi-group SAOMs on friendship – positive perception co-evolution I. Friendship dynamics

Dependent network: friendship	FP Model 1		FP Model 2		FP Model 3		FP Model 4	
Effect name	par.	s.e.	par.	s.e.	par.	s.e.	par.	s.e.
Outdegree (density)	–2.888***	0.092	–3.253***	0.312	–3.289***	0.246	–2.432***	0.147
Reciprocity	1.775***	0.065	1.683***	0.073	1.680***	0.072	1.750***	0.065
Balance	0.146***	0.009	0.142***	0.010	0.142***	0.010	0.147***	0.009
Transitive reciprocated triplets	–0.100***	0.025	–0.087**	0.027	–0.090***	0.027	–0.095***	0.026
Indegree-related popularity	0.020**	0.007	–0.040	0.033	–0.035	0.026	–0.039*	0.016
Outdegree-related popularity	–0.019	0.013	–0.047**	0.017	–0.043**	0.016	–0.035*	0.015
Outdegree-related activity	0.133***	0.006	0.143***	0.007	0.142***	0.007	0.133***	0.006
Gender-related activity	–0.084*	0.039	–0.149***	0.044	–0.145***	0.043	–0.102*	0.040
Gender-related popularity	–0.076*	0.036	–0.368***	0.070	–0.354***	0.064	–0.237***	0.047
Same gender	0.193***	0.034	0.331***	0.043	0.328***	0.043	0.216***	0.035
Positive indegree-related popularity	–.–	–.–	0.012	0.025	0.008	0.018	0.054***	0.011
Positive outdegree-related popularity	–.–	–.–	0.032**	0.011	0.030**	0.010	0.018*	0.007
Positive outdegree-related activity	–.–	–.–	–0.055***	0.011	–0.055***	0.010	0.004	0.006
Positive tie	–.–	–.–	1.925***	0.229	1.917***	0.217	–.–	–.–
Positive agreement	–.–	–.–	–0.020	0.015	–0.014	0.037	0.064*	0.031
Positive agreement × Target indegree	–.–	–.–	–.–	–.–	0.001	0.002	–0.004**	0.002

† $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$;

Absolute convergence t ratios all < 0.06.

Overall maximum convergence ratios all < 0.26.

Table 6.6: Results from multi-group SAOMs on friendship – positive perception co-evolution II. Perception dynamics

Dependent network: positive perception	FP Model 1		FP Model 2		FP Model 3		FP Model 4	
Effect name	par.	s.e.	par.	s.e.	par.	s.e.	par.	s.e.
Outdegree (density)	–2.316***	0.088	–2.324***	0.222	–2.355***	0.143	–2.089***	0.131
Reciprocity	0.964***	0.053	0.586***	0.058	0.566***	0.061	0.918***	0.050
Balance	0.044***	0.004	0.022***	0.005	0.020***	0.005	0.038***	0.004
Transitive reciprocated triplets	–0.037***	0.011	–0.024*	0.010	–0.019†	0.010	–0.035***	0.009
Indegree-related popularity (peer inf.)	0.058***	0.005	0.031*	0.015	0.034***	0.010	0.018*	0.008
Outdegree-related popularity	–0.021***	0.006	–0.023*	0.010	–0.023**	0.007	–0.024**	0.007
Outdegree-related activity	0.062***	0.002	0.062***	0.002	0.060**	0.002	0.061***	0.002
Sex-related activity	–0.128***	0.028	0.009	0.027	–0.001	0.029	–0.134***	0.028
Sex-related popularity	0.008	0.027	0.226***	0.053	0.210***	0.043	0.060†	0.036
Same sex	0.164***	0.026	–0.141***	0.033	–0.138***	0.032	0.127***	0.026
Friendship indegree-related popularity	–.–	–.–	0.034	0.027	0.033†	0.018	0.055***	0.016
Friendship outdegree-related popularity	–.–	–.–	0.023***	0.007	0.021***	0.006	0.016**	0.005
Friendship outdegree-related activity	–.–	–.–	–0.067***	0.012	–0.066***	0.011	–0.035**	0.012
Friendship tie	–.–	–.–	1.432***	0.083	1.424***	0.086	–.–	–.–
Friend influence	–.–	–.–	0.061†	0.032	0.132*	0.064	0.176**	0.062
Peer influence × # shared friends	–.–	–.–	–.–	–.–	–0.008†	0.005	–0.009*	0.004

† $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$;

Absolute convergence t ratios all < 0.06.

Overall maximum convergence ratios all < 0.26.

There are two additional effects in Model 2 which express H3. The 'positive agreement' effect (in Table 6.5) captures the differential tendency for students who agree more in their perceptions to become and remain friends compared with students who agree less (H3sp). In the perception dynamics part, 'friendship influence' represents the tendency of students to align to perceptions to those who they nominate as friends (H3ip).

Model 3 has two more effects than Model 2: two interaction terms which relate to H4. In the friendship dynamics part of the model, this variable expresses the differential effect of agreement on friendship depending on the perception indegree centrality of the targets of agreement (H4sp). The added effect for perception dynamics is actually a 4-cycle effect, which captures how much students tend to align their perceptions not to their direct friends but peers with whom they have common friends (H4ip). We discuss these effects in more detail later. Model 4 is almost identical to Model 3 except for the omission of the two cross-network dyadic effects.

Turning to the four hypotheses, we can see in all models that the balance effect is positive and strongly significant in both networks, which supports H1f and H1p. It is also visible that the dyadic effects between the two networks are quite strong ('positive tie' and 'friendship tie' effects). This provides support for H2fp and H2pf.

Hypotheses H3sp and H4sp can be evaluated by looking at the friendship side of the model. The 'positive agreement' and its interaction with the target's perception indegree are non-significant in Models 2 and 4. However, they become significant once the 'positive tie' effect is dropped from the model. This means that the agreement-related effects pick up most of the effect otherwise captured by direct tie entrainment – hinting at the mediating role of this mechanism. In Model 4, 'positive agreement' has a positive effect on friendship formation, and the interaction term has a negative parameter. These results are in line with H3sp and H4sp. We return to the detailed interpretation of the findings below.

The remaining two hypotheses about influence are covered in the positive perception side of the model (Table 6.6). The influence of friends on perceptions appears to be positive, in line with H3ip. The influence from having more shared friends is negative, which goes against H4ip. However, these findings together suggests that influence in groups may have an interesting and complex structure. Therefore, this set of results is also treated in more detail later.

Table 6.7: Results from multi-group SAOMs on friendship – negative perception co-evolution I. Friendship dynamics

Dependent network: friendship	FN Model 1		FN Model 2		FN Model 3		FN Model 4	
Effect name	par.	s.e.	par.	s.e.	par.	s.e.	par.	s.e.
Outdegree (density)	–2.881***	0.093	–2.811***	0.109	–2.684***	0.134	–2.686***	0.130
Reciprocity	1.774***	0.066	1.820***	0.083	1.834***	0.083	1.787***	0.073
Balance	0.145***	0.009	0.151***	0.010	0.160***	0.012	0.157***	0.011
Transitive reciprocated triplets	–0.098***	0.026	–0.105***	0.028	–0.113***	0.030	–0.110***	0.029
Indegree-related popularity	0.020**	0.007	0.007	0.010	–0.010	0.015	–0.012	0.015
Outdegree-related popularity	–0.020	0.014	–0.021	0.015	–0.020	0.015	–0.020	0.015
Outdegree-related activity	0.132***	0.006	0.138***	0.007	0.141***	0.008	0.137*	0.007
Sex-related activity	–0.084*	0.041	–0.091*	0.042	–0.088*	0.044	–0.079†	0.042
Sex-related popularity	–0.076†	0.044	–0.018	0.043	0.016	0.049	0.018	0.047
Same sex	0.192***	0.035	0.219***	0.039	0.215***	0.038	0.188***	0.036
Negative indegree-related popularity	–.–	–.–	–0.038†	0.022	–0.057*	0.028	–0.095***	0.026
Negative outdegree-related popularity	–.–	–.–	0.003	0.013	–0.001	0.013	–0.005	0.014
Negative outdegree-related activity	–.–	–.–	0.027	0.019	0.024	0.018	–0.020	0.014
Negative tie	–.–	–.–	–2.154*	1.005	–2.274*	0.972	–.–	–.–
Negative agreement	–.–	–.–	0.040	0.089	0.986*	0.431	0.988**	0.380
Negative agreement × Target indegree	–.–	–.–	–.–	–.–	–0.149*	0.071	–0.140*	0.062

† $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$;

Absolute convergence t ratios all < 0.06.

Overall maximum convergence ratios all < 0.24.

Table 6.8: Results from multi-group SAOMs on friendship – negative perception co-evolution II. Perception dynamics

Dependent network: negative perception	FN Model 1		FN Model 2		FN Model 3		FN Model 4	
Effect name	par.	s.e.	par.	s.e.	par.	s.e.	par.	s.e.
Outdegree (density)	–2.349***	0.127	–2.323***	0.154	–2.304***	0.151	–2.310***	0.118
Reciprocity	0.536***	0.109	0.487***	0.106	0.514***	0.097	0.544***	0.094
Balance	–0.054	0.034	–0.044	0.030	–0.058†	0.032	–0.065*	0.029
Transitive reciprocated triplets	–0.156	0.154	–0.127	0.168	–0.151	0.157	–0.149	0.151
Indegree-related popularity (peer inf.)	0.147***	0.008	0.110***	0.020	0.120***	0.015	0.114***	0.015
Outdegree-related popularity	–0.066*	0.032	–0.056	0.035	–0.069*	0.034	–0.076**	0.028
Outdegree-related activity	0.032	0.029	0.040	0.027	0.029	0.029	0.022	0.024
Sex-related activity	0.100†	0.053	0.055	0.049	0.054	0.054	0.064	0.053
Sex-related popularity	0.175***	0.050	0.180**	0.063	0.190***	0.050	0.203***	0.048
Same sex	0.173***	0.048	0.241***	0.048	0.238***	0.049	0.192***	0.049
Friendship indegree-related popularity	–.–	–.–	–0.019	0.013	–0.024†	0.014	–0.034*	0.013
Friendship outdegree-related popularity	–.–	–.–	–0.009	0.007	–0.010	0.006	–0.010	0.006
Friendship outdegree-related activity	–.–	–.–	–0.023*	0.010	–0.019†	0.010	–0.033**	0.010
Friendship tie	–.–	–.–	–0.520**	0.168	–0.505**	0.182	–.–	–.–
Friend influence	–.–	–.–	0.119*	0.051	0.268**	0.090	0.302**	0.102
Peer influence × # shared friends	–.–	–.–	–.–	–.–	–0.030†	0.017	–0.030†	0.017

† $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$;

Absolute convergence t ratios all < 0.06.

Overall maximum convergence ratios all < 0.24.

6.6.3 The co-evolution of friendship and negative attributions

We ran similar models to the ones presented above for the co-evolution of friendship and negative perceptions. The modeling strategy and the specifications are identical to what has been described in the previous section. The results are collected in Tables 6.7 (friendship dynamics) and 6.8 (perception dynamics).

The balance effect is again positive in the case of friendship, and negative but mostly non-significant for negative perceptions. In this sense, the results provide little support for H1n. As far as dyadic interrelations are concerned, we can clearly see negative tie entrainment effects between the networks, which is in line with H2fn and H2nf.

In Table 6.7, we can see that 'negative agreement' has a positive effect on friendship formation, but its interaction with the negative perception indegree of the target of the agreement has a negative effect. These estimates are in line with H3sn and H4sn and are further interpreted below. The inclusion or exclusion of the dyadic effect of negative perceptions on friendship does not alter the parameters substantially.

Regarding influence processes, Table 6.8 provides evidence for the effects of friends on perceptions (H3in). The effect of the number of shared friends on peer influence is again negative and significant at $p<0.1$. This goes against H4in.

6.7 Conclusions

This chapter analyzed the evolution of friendship and two perception networks. First, we looked at the tendencies in the dynamics of each network in the studied classrooms separately, and then modeled the co-evolution of friendship with the positive and the negative perception networks by two separate SAOMs in multiple-classrooms.

The tendencies depicted by the co-evolution models appear to be similar for positive and negative perceptions. The results supported most of the formulated hypotheses. However, one interesting exception is the negative effect of the number of shared friends on peer influence. We summarize the main results in the following sections and give further interpretations for this peculiar finding.

6.7.1 Characteristics of the evolution of perception networks

The classroom-level single-network SAOMs showed that the dynamics of positive perception networks shows some similarities to that of friendships, especially in ten-

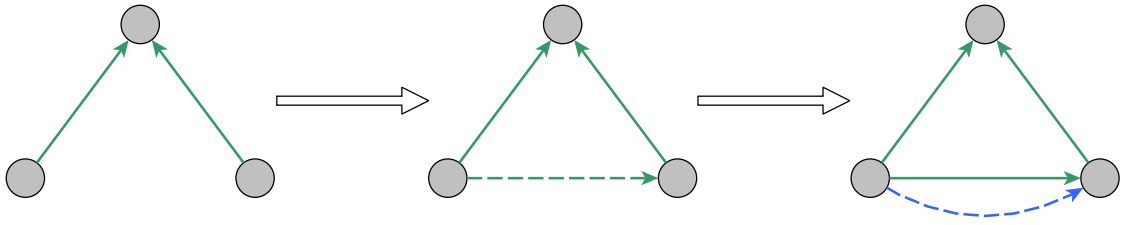

Figure 6.9: The hypothesized process of agreement-based friend selection mediated by positive perceptions.
(The blue ties represent friendship, green ties positive perceptions; dashed lines show the tie that is created.)

dencies for reciprocity and clustering. On the contrary, negative perception networks seem to have quite different dynamic features in which the main systematic processes are degree-related. Both perception networks differ from friendships, however, in the importance of classroom consensus in their dynamics. We found positive indegree popularity effects for the perception parts of the co-evolution models, as well. This suggests that when it comes to perceptions about peers, the general opinion of the classroom (and not only that of, say, friends) affects how individual students change their network ties. This process points towards an emergent agreement among classmates in who is perceived positively and negatively.

6.7.2 Minority-agreement friend selection

The co-evolution models provided consistent support for the positive effect of perception agreement on friendship formation in case of both perception networks. The agreement effects, however, became non-significant in the positive perception model when the tie-level effect of perceptions on friendship has been taken into account.

This suggests that direct tie entrainment mediates the effect of agreement on friendship. Students tend to befriend those with whom they agree, but this happens in two steps: first agreement leads to positive perceptions which tend to evolve into friendships (Figure 6.9). It is possible that a co-evolution model of all three networks would have revealed similar pathways (negative agreement leading to positive perceptions leading to friendship) for negative perceptions, as well.

Another important result related to agreement-based friend selection is the moderating role of classroom-level consensus. It seems from both models that perception agreement has the largest effect on friendship formation when the "object" of the agreement (the perceived student) is not perceived by many other classmates posi-

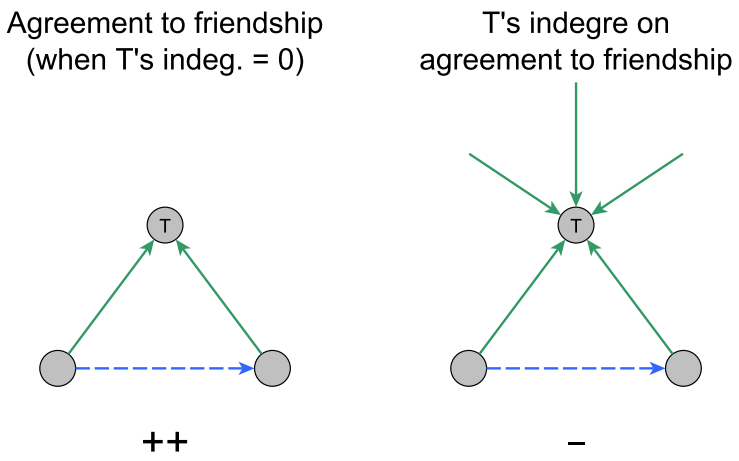

Figure 6.10: Minority-agreement selection – network configurations. *(Blue ties represent friendships, green ties perceptions, either all positive or all negative; dashed lines show the tie considered for change; the signs illustrate the direction and relative size of respective effects from the co-evolution SAOMs.)*

tively or negatively (Figure 6.10). In other words, agreement matters more when it is in a minority, against the opinion of the classroom.

6.7.3 The circles of influence

According to our theory, influence occurs in interaction events or encounters (Section 2.5). It seems plausible that one is more likely to interact with a peer if they have shared friends, and so these peers have a larger influence than others without common friends. In this light, the finding that the number of shared friends has a negative effect on peer influence in both models looks puzzling at first sight.

How can we interpret these results? The key is to consider all the effects which are involved in influence situations. Of these, we had three in our models (Figure 6.11). Friends had a positive influence, peers with shared friends a negative one. Additionally, the indegree-related popularity effect on perceptions can be understood as a general peer influence effect. The estimate for this network configuration was positive in every model.

Given all three of these effects, we can give the following interpretation of influence processes based on our models. The strongest sources of influence are friends. However, friendships are usually embedded in groups, which means that friends have some common friends. The negative effect of shared friends can be viewed as a balance between group influence and friend influence. When students are members of a

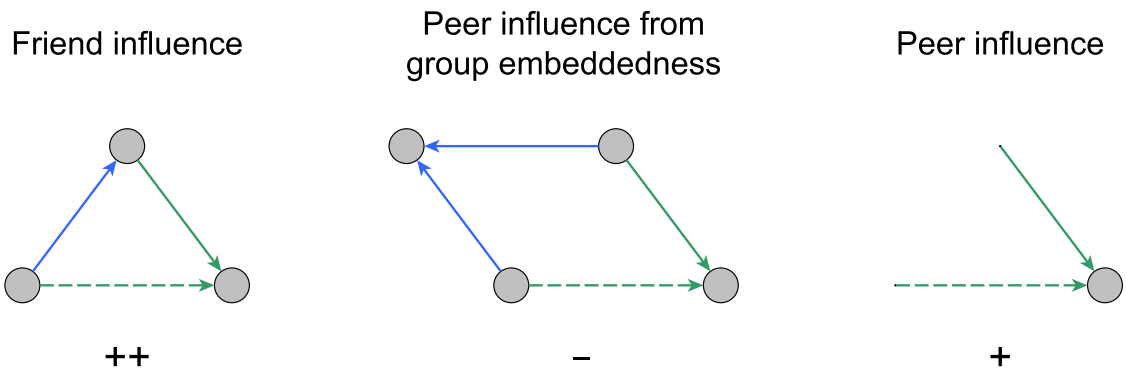

Figure 6.11: Three sources of influence – network configurations.
(Blue ties represent friendships, green ties perceptions, either all positive or all negative; dashed lines show the tie considered for change; the signs illustrate the direction and relative size of respective effects from the co-evolution SAOMs.)

group, each individual friend has a smaller influence on their opinions. The group as a whole can exert a much larger effect than each member alone, given the perceptions within the group are aligned, and depending on the influenced member's position in the group. Apart from friends and groups, students are also somewhat affected by the "social background": they tend to agree with the opinion of the classroom in general.

This sketch of influence flows in adolescent communities is in line with the idea that group size and group cohesion (now understood as friendship density) are related to the strength of group influence. A larger group can influence individuals more but only if it is unanimous in the opinion and question, and only if it is cohesive enough, which may be hard to reach in large groups. An important contribution of our analysis is showing how agreement and cohesion in groups are dynamically interrelated: opinion divides lead to stronger cohesion among those who agree, and group members who are closer friends have a much larger influence on each other than do more distant group members. This process may be imagined as the constant evolution of different (sometimes embedded or overlapping) circles of influence, which can potentially be one of the key mechanisms in the emergence of multiple subgroups in communities.

6.8 Discusssion

This chapter aimed at testing certain prediction which are key from the point of view of the group-formation theory elaborated in this thesis. We could not test the hypothesized interaction processes directly, which are at the basis of the theory, but we

managed to study some of the relational consequences derived from the assumed processes. Although there is no single analysis by which the validity of the whole theory can be assessed, here we considered whether it captures some important aspects of the social structure and dynamics of friendships and perceptions.

We found evidence for a friend selection process which is based on agreement in perceptions about peers, especially if it does not meet the general opinion of the classroom. It is suspected that the selection process is mediated by positive perceptions, which tend to appear between those who agree in their perceptions, and they often develop into friendships.

The results also indicated that influence has multiple sources in the studied communities. Friends have a large influence on perceptions, but this is mitigated by the embeddedness of friendships in groups. In addition, there is a gentle push towards classroom-level agreement. It is suggested that the resulting circles of influence, together with agreement-based selection, may contribute to the macro-level outcome of group formation in communities and subgroup formation in groups.

At the moment, the conclusions of this chapter have to be considered as working hypotheses until results with more adequate modeling strategies are reached. One direction for achieving this may be acquiring convergent co-evolution models from each classroom separately, which then can be meta-analyzed. However, the detection of such small parameters as those we have seen for the 4-cycle effect will surely be difficult, if at all possible, given classroom sizes in the sample. Another potential modeling approach can be the random-effects multi-level SAOM, which is, however, still in a test phase.

Another improvement on the modeling side can be the application of new effects measuring agreement between students. A recent addition to the RSiena software is an agreement-based selection effect which is based on the Jaccard index. This may provide with more intuitive interpretations than the currently used balance effect.

A further note on the interpretation of the effects: we aimed to include effects in the models which represent the substructures of the network configurations most important for the hypotheses. However, a few relevant subconfigurations are not yet available in the software framework, which also makes it hard to draw strong conclusions from the results. To say the least, our models do not distinguish between the effects of shared friends on influence by a friend or by a non-friend classmate. Therefore, it is an important next step to identify the most relevant alternative explanations based on theory, and implement these configurations as new effects in the RSiena software. However, despite the questions left open for future research, the fact

that the results are generally similar for the two quite different perception networks is an encouraging sign.

Chapter 7

Conclusions

In a pursuit to better understand group formation in informal settings, this thesis developed a conceptual framework of informal social processes by which the status of individuals is produced in encounters. Based on this framework, we outlined a theory for the emergence of groups in communities. The multiplex network approach of the study helped to reinterpret findings from earlier research and identify the local structures in interpersonal relations which are likely to be connected to group formation. We hypothesize that these network configurations are brought about by the mechanisms of status production. These mechanisms are suspected to lie behind both the group and the status structure in a community.

Building on the theoretical arguments, three empirical research questions were formulated: the first about the connections between multiple peer-perception dimensions in communities, the second about the empirical association between friendship and agreement in perceptions, and the third about the co-evolution of friendships and peer-perceptions. The empirical chapters of the thesis aimed at providing answers to these questions by studying a unique longitudinal social network dataset collected in several Hungarian high-school classrooms. In the analyses, we applied the most advanced statistical methods available for network data, and we also suggested a novel procedure for handling strongly multiplex datasets.

This concluding chapter presents an overview of the most important theoretical and empirical findings of the thesis. Further, the main substantive, empirical, and methodological limitations of the presented study are discussed. Lastly, we sketch a research agenda which highlights a few general directions for the continuation of the started work.

7.1 Summary of the key findings

In order to answer the research questions formulated in the thesis, a methodological obstacle related to the analysis of strongly multiplex network data had to be overcome. This challenge led to the development of an empirical procedure for identifying latent relational dimensions through the cluster analysis of multiplex network data structures (first question, Chapter 4). We applied the method to the studied network dataset and identified three dimensions of peer-perceptions from 21 network items in the classrooms. We labeled these as positive, negative, and social role attributions. Aggregated network measures were defined based on the three dimensions, and they were shown to overlap with relational measures more commonly measured in the school context, such as friendship and dislike. The proposed clustering procedure has proven to be viable, and it can be applied in a wide range of multiplex network studies in the future.

Using two of the new aggregated network measures, positive and negative attributions, we examined the empirical relations between friendship and agreement in peer-perceptions among students (second question, Chapter 5). Our results show that friends indeed tend to agree more than non-friends in their positive and negative evaluations about classmates. However, in some cases the differences may not be apparent to the observer, partly because both friendship and agreement are related to student similarity in various background characteristics (such as sex or ethnicity). We still found a general tendency for friends to agree more than non-friends in many classrooms even when similarities in six individual variables were taken into account.

Following the descriptive study, we applied Stochastic Actor-oriented Models to examine the dynamics of the newly defined perception networks, and to model the co-evolution of friendships and peer-perceptions (third question, Chapter 6). The most important finding from the single-network models is that the dynamics of perceptions is characteristically different from that of friendships (and other typically studied relations). Namely, a Matthew-effect, the tendency of "popular" students (those who already receive many positive or negative ties) to attract new nominations and keep old ones seems to be an important process in case of both perception networks. This suggests that a consensus is likely to develop in classrooms over time about who is to be perceived positively or negatively.

From the co-evolution models for friendship and each of the perception networks, we learned that class-consensus is not the only mechanism behind the agreement in perceptions between students. In fact, it seems that friendship networks cannot

be omitted from the study of perceptions dynamics. We found evidence that those students who agree more in their perceptions are more likely to become friends (there is some indication that this process might unfold in multiple steps). In turn, friends also influence each other's perceptions, which contributes to their stronger agreement. The systematic positive popularity effects in single-network perception models are partly explained by this interactive dynamics between friendship and agreement.

The study of the co-evolution between friendships and perceptions shed some light on the role of group-level processes in friend selection and influence related to agreement. We found evidence for two of these processes in both types of perceptions. The first effect, which we labeled as *minority-agreement selection*, highlights that the contribution of agreement to friendship formation is stronger when the opinion of the dyad goes against the general classroom opinion. Students who both perceive a classmate positively or negatively are most likely to become friends due to this when nobody else in the classroom shares their opinion. The formation of close relationships (friendship) can, thus, be a process through which people acquire social confirmation and manage to maintain their minority opinions. This can be interpreted as the real-life relational consequence of the 'partner effect' in interactions, which has been found in many social conformity experiments (see Turner, 1991, p. 15).

The second identified group-related effect hints at a structural phenomenon which, for the time being, we named *circles of influence*. The model results suggest that being embedded in friendship groups with a peer, may he be friend or not, moderates his influence on (both positive and negative) perceptions. In particular, it seems that having more shared friends decreases the influence from a single peer. When multiple sources of influence (from friends, groups, classmates) are at work simultaneously, they may generate cross-cutting circles of influence within communities which pull individuals in various directions to form multiple groups. However, more studies are needed to further elaborate this hypothesis.

In summary, the studies presented in the thesis provide empirical corroboration for the proposed theory of group formation. The dynamic interplay between close personal relations and the alignment of interpersonal attributions may indeed be responsible for the emergence of groups in informal settings. However, our results also highlight that the evolving groups always provide context and may alter the course of the dyadic and triadic network mechanisms. This further underlines that group formation is an endogenous social process in communities. It has to be noted that the analysis presented in the thesis do not provide a definitive test for the proposed

theoretical ideas, and the results should be viewed as working hypothesis for future work.

7.2 Limitations of the study

The most important challenges regarding the presented results pertain to one of the three main building blocks of the study: the theoretical arguments, the empirical data, or the use of the statistical methods. Here we discuss some of the key issues and their implications for the present work.

The theoretical scope of our investigation is limited, because it focuses only on informal social processes. This may raise the question whether the proposed theory of group formation is practically useful at all, since in real-life we can hardly ever find purely informal communities. The question is whether our theory is able to incorporate how formal social phenomena alter the informal processes. Is it possible that formal constraints, such as institutional hierarchies, completely cancel out the informal mechanisms of group formation? Or do they only moderate their effects to some extent? This is a key question because, arguably, one of the functions of formal social institutions is that they promote stability against the shorter-term informal processes.

By further developing the theoretical framework elaborated here, we can be able to find answers to this question. In principle, it is possible to derive expectations about social outcomes (the number of groups, how fixed their boundaries are, and so on) from the theory. Then, these hypotheses can be tested in multiple contexts which differ in the prevalence and types of formal social institutions and processes. The theoretical framework can readily incorporate some formal and exogenous factors, such as formal evaluations of actors, previous experience, or perceptions about social objects (i.e. opinions, evaluations, attitudes). One can extend the theory in a straightforward way to cover how these exogenous aspects of social life translate into endogenous perceptions and relations. With input from such studies, the theory could potentially be refined to incorporate the effects of various formal social phenomena on informal processes.

Another theoretical challenge is related to the characteristics of groups. The current state of the arguments do not discuss the role of group identity, which is obviously an important factor in how much people act as group members. How do identities develop? They are not dyadic, relational phenomena – should they be defined on the level of the individual or at a higher, group level? Focusing on the

role of social interactions in the development of perceptions and identities may help to incorporate this important element of group formation into the theory.

Regarding the analyzed data, one important limitation is that perceptions and social relations are only measured within classrooms. This means that we ignore all potential social ties between classrooms, grades, but also outside of school. However, it may still be a relatively reasonable assumption that opinions about classmates matter most inside the classroom and less for other students or people outside the school.

A second data-related issue is the pool of perception network items available to study. Although the items included in the survey were carefully selected to cover most of the important aspects in student life, the choices were still based on expert opinion. Until studies focusing on compiling adequate network item lists are conducted (similar to the practice in psychology), we cannot be sure whether we use the really relevant network items and find the appropriate dimensions in multiplex perceptions (see the next section). Future work should focus on compiling valid tests of multiplex relations in various settings, similar to the research strategy of scale construction in psychology.

A third data-related limitation of the results presented is their possibly low external validity. Although the studied dataset aimed at collecting data about a small but heterogeneous set of high-school classrooms, its scope is still limited to the context of Hungary, where the education system and children's attitudes surely have specific characteristics. However, we do not see this as a key limitation to the presented analyses, since the explicit aim of the studies in this thesis were to generate well-grounded hypotheses for further investigation into the phenomenon of group formation – a goal that has been achieved. Further, during the analyses we did not rely on any assumptions specific to the Hungarian context, so we expect that the key findings from this dataset will be replicated on other similar datasets in the future. Which brings us to the final point: a current (but hopefully temporary) obstacle to establishing high external validity to our results is the lack of comparable, strongly multiplex datasets in similar social settings (as we argued throughout the thesis). However, the present work also aimed at showing an example on how useful such datasets are and how they can be analyzed – hopefully encouraging similar research.

The last challenges we mention are related to the used network methods. As a start, more reliable results shall be obtained from Stochastic Actor-oriented Models, which requires a different modeling strategy. The multi-group models provided initial advantages, but the strong heterogeneity between classrooms questions their reliability. A better strategy would be using the multi-level extension of the SAOM. This

model type has recently been developed and is now available for use. In the multi-level framework, the current model specifications will have to the modified. Primarily, by adding new effects to the model we need to be able to distinguish between the impact of shared groups on the influence of friends and of non-friends.

7.3 An agenda for future research

The research presented here highlights a number of interesting issues which appear to be worth pursuing in the future. We attempt to briefly introduce some of the main directions. The selected topics can be viewed as parts a general research agenda which focuses on the effects of groups and status on individuals and communities, while taking a multiplex dynamic network approach to studying the links between interactions and social relations in real-life situations.

The role of interactions and identities in group formation

Despite the large amount of research devoted to the topic, group formation is still a theoretical and empirical challenge. As discussed at the beginning of the thesis, it seems particularly difficult to connect all relevant group-processes in a single framework. This is so because groups form and affect individuals in multiple scenes: they are present in social interaction events, they alter the states of social relations between pairs of individuals, they appear as collective perceptions and identities in the head of individuals. An efficient way of analyzing, and also thinking about, the links between interactions, relations, and identities still needs to be developed.

The issue is further complicated by the fact that groups are not a dichotomy: they are most likely to exist in changing, diffuse states, somewhere between the extremes of a perfectly cohesive unit and a disconnected set of individuals. This makes the detection of groups, and their study, even more difficult – contrary to what is suggested by the idea of groups as cohesive subsets in a single network graph.

Consequently, analyses that try to "catch" groups (e.g. by identifying their members in a given moment) and then, once they are in hand, explore their effects on individual and collective outcomes might be following the wrong strategy. Instead, we should aim at observing more precisely the micro-mechanisms and the local network configurations which we know, from prior research, are relevant for the formation and functioning of groups. The third study presented here already pointed out that it may be possible to detect group effects on individuals and dyads without having to enforce an arbitrary group definition to the data.

Approaching the study of groups from the micro level will require different types of data over survey and experimental lab results. By innovative data collection techniques which utilize the recent developments in communication technology, we may be able to gather good-quality, high-resolution data about social encounters in informal settings. This kind of data, when combined with regular observational and survey sources, could provide an unprecedented insight into how groups emerge and dissolve, and how they affect individuals and communities in the process.[1]

The common origin of status hierarchies and groups in informal settings

A potentially important direction for future theoretical research is the relation between groups and status. These two phenomena have an unquestionable reality for individuals and small communities (as anyone's high-school experience can confirm). In addition, they contribute to the large-scale structure of society in general: multiple local hierarchies and groups can be more or less connected.

A theory which is able to trace back the existence of hierarchies and groups to a common origin may inform us about the ways in which these two main dimensions of social differentiation in societies are intertwined. The theoretical framework proposed in this thesis only takes an initial step in this direction. It is subject to further work to decide whether this framework can be rendered useful for explaining status hierarchies and their connections to groups. In any case, the importance of formal social phenomena may raise some concern related to the viability of such a theoretical approach, as it is discussed below.

The dynamics of informal and institutional social structures

A question that looms over the entire analysis in this thesis is the relation between informal social processes and formal, institutional structures. It feels intuitive to imagine that informal groups may at some point institutionalize some of their norms or goals to ensure the efficiency of the group. But when does this really happen and when do such attempts fail? Could we explain the transition from informal processes to social institutions by status hierarchies and groups jointly? Furthermore, under what conditions can informal pressures reshape already existing institutions (from student organizations to political systems)? Can the study of informal social structure

[1] Many of these ideas were developed in discussions with the social networks research group at the ETH Zürich, led by Christoph Stadtfeld. I recently had the opportunity to work closely with this group. We submitted a grant proposal which could provide the funding for an empirical study along the described lines, starting next year.

and social differentiation in communities provide useful answers to such questions? Research in this direction may contribute to forming the bridge between sociology and social psychology.

The dimensions of multiplex interpersonal relations

The last topic to be mentioned for future research is related to the multiplexity of social relations. It can be argued that the fact that people are connected by a multitude of different ties (e.g. perceptions, affections, role and status attributions) is relatively understudied. More research into how the dimensions of social relations are structured is inevitable for studying the other key issues discussed in this section.

The need for a deeper knowledge of the layers of human relations calls for a new direction of empirical research on networks. Similar to the construction of personality measures in psychological studies, we could identify different sets of (say, 30 or even more) observational and survey network items which provide more valid measures for key relational constructs than the ones we use now (for instance, single-item friendship scales). These tests could help to advance our substantive knowledge about group processes, status formation, and many other social phenomena.

Appendix A

Exploratory Subsample: additional descriptives

Table A.1: Identification of classrooms in the Exploratory Subsample

School	Classroom IDs per training program					
	Grammar		Technical		Vocational	
Bigtown 1	1100	1500	—	—	—	—
Bigtown 2	—	—	2200	2400	2900	2000
SmalltownA 1	3100	—	—	—	3500	—
SmalltownB 1	—	—	4200	4400	—	—
SmalltownB 2	—	—	5500	—	5100	—
Capital 1	6100	6400	—	—	—	—
Capital 2	—	—	7200	7300	7500	7800

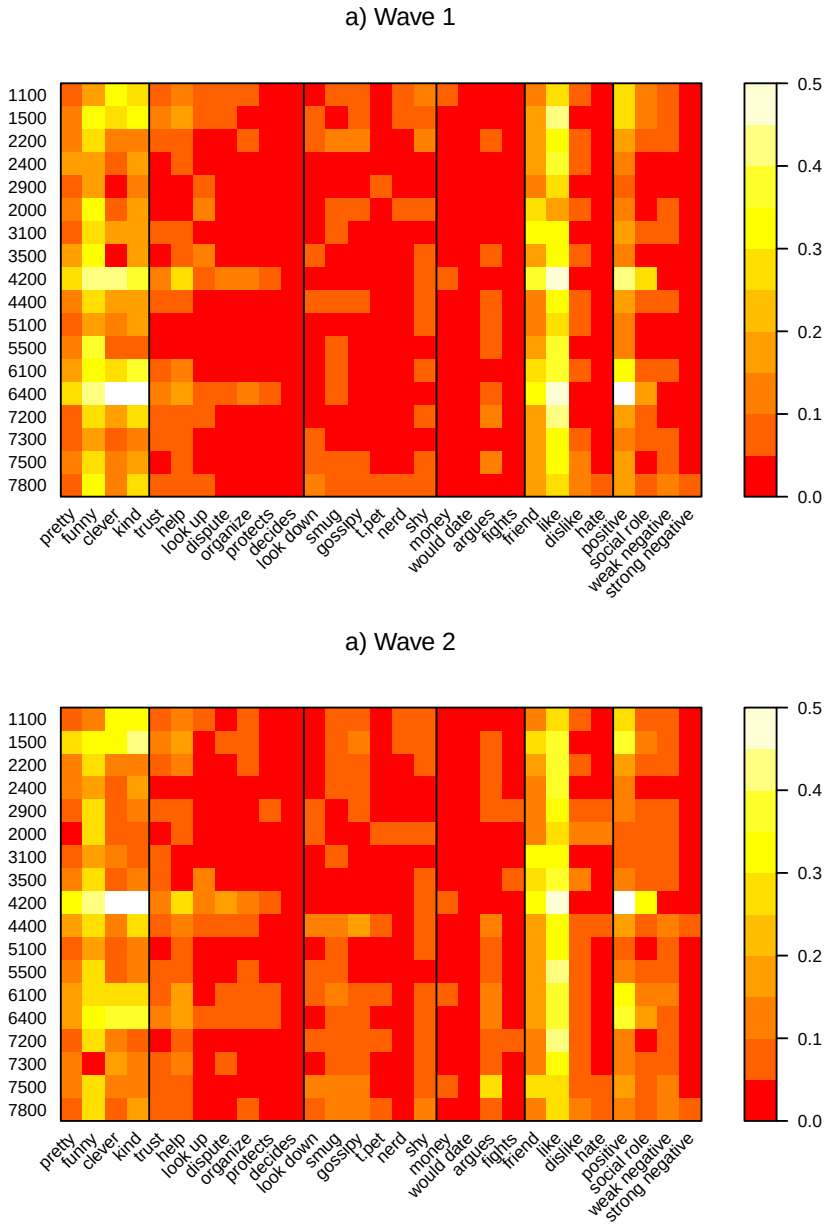

Figure A.2: The density of all networks in the Exploratory Subsample classrooms at wave 1 (a) and 2 (b).

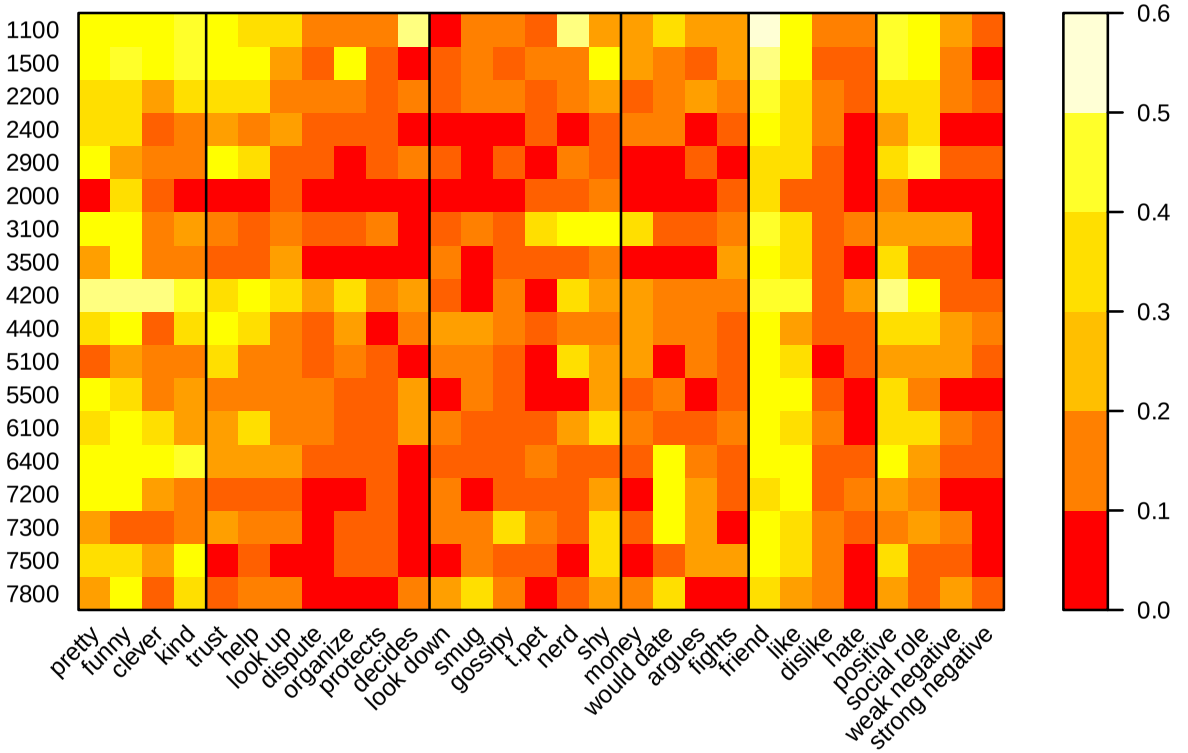

Figure A.3: The stability of ties in all networks in the Exploratory Subsample between wave 1 and 2. *(Stability is measured by the Jaccard index between the wave 1 and wave 2 instances of each network item; larger values represent greater stability; e.g. 0.5 means that the number of stable ties equals the number of changing ties in a network.)*

Appendix B

Dynamic Subsample: additional descriptives

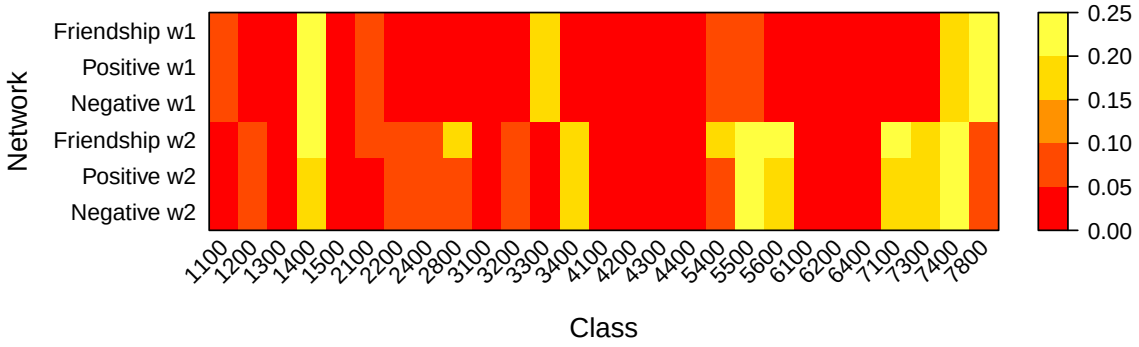

Figure B.1: The proportion of missing values in the studied networks of the Dynamic Subsample at wave 1 and 2.

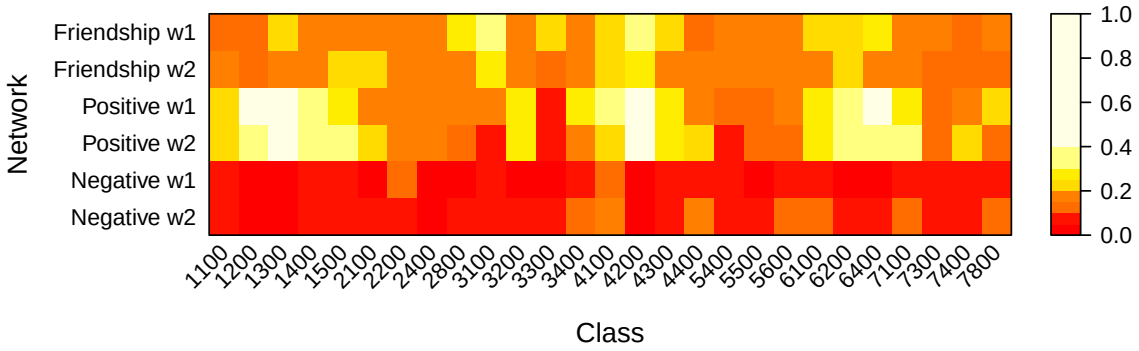

Figure B.2: The density of the studied networks in the Dynamic Subsample classrooms at wave 1 and 2.

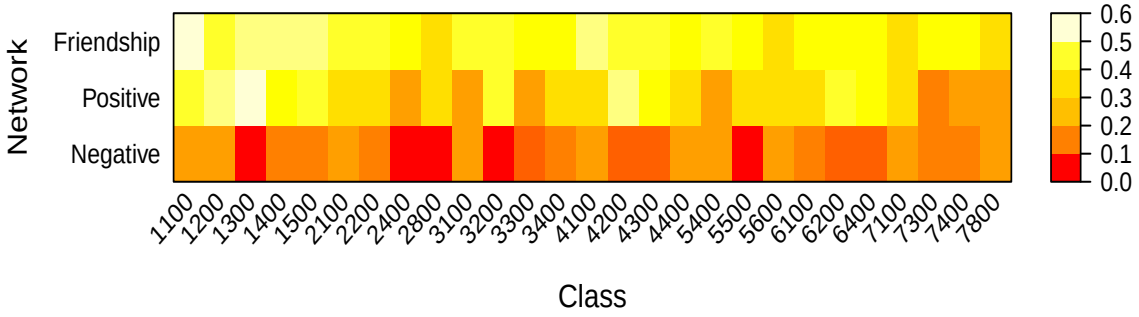

Figure B.3: The stability of ties in the studied networks of the Dynamic Subsample between wave 1 and 2.

(Stability is measured by the Jaccard index between the wave 1 and wave 2 instances of each network item; larger values represent greater stability; e.g. 0.5 means that the number of stable ties equals the number of changing ties in a network.)

Appendix C

The validation of peer-perception dimensions on the full sample

The cluster analysis of 21 perception network items in the Exploratory Subsample was reported in Chapter 4. The study was replicated on the entire sample of 43 classrooms in the RECENS dataset (see Section 3.1). This was necessary, because Chapter 5 and Chapter 6 use the network measures derived from the cluster analysis, but on a different subsample of classrooms (due to alternative selection criteria required by the applied method).

Here we present the key figures from the validation of the clustering results, using identical visualizations to those in Chapter 4 for easier understanding. Figure C.1 demonstrates the item selection procedure: just as in the original analysis, dropping four network items increased the homogeneity of similarity structures across the classrooms. The excluded items were identical to those dropped in Chapter 4: *fights*, *money*, *argues*, and *would date* (cf. Figure 4.3).

Figure C.2 compares the resulting cluster structure of the 17 items in the two waves. Using the full sample produces an even clearer picture than the Exploratory Subsample (Figure 4.4): the same three-cluster solution was reproduced in both waves. This suggests that in a larger pool of classrooms changes in the similarity structure through time average out.

In Figure C.3, we present the distribution of pairwise similarities between the original 17 network items, which shows a picture similar to that of the original analysis (Figure 4.7), and suggests that the three-cluster solution is appropriate for describing the data.

Finally, Figure C.3 gives an impression about the pairwise similarities between the four affective network items and the four composite networks. The latter items

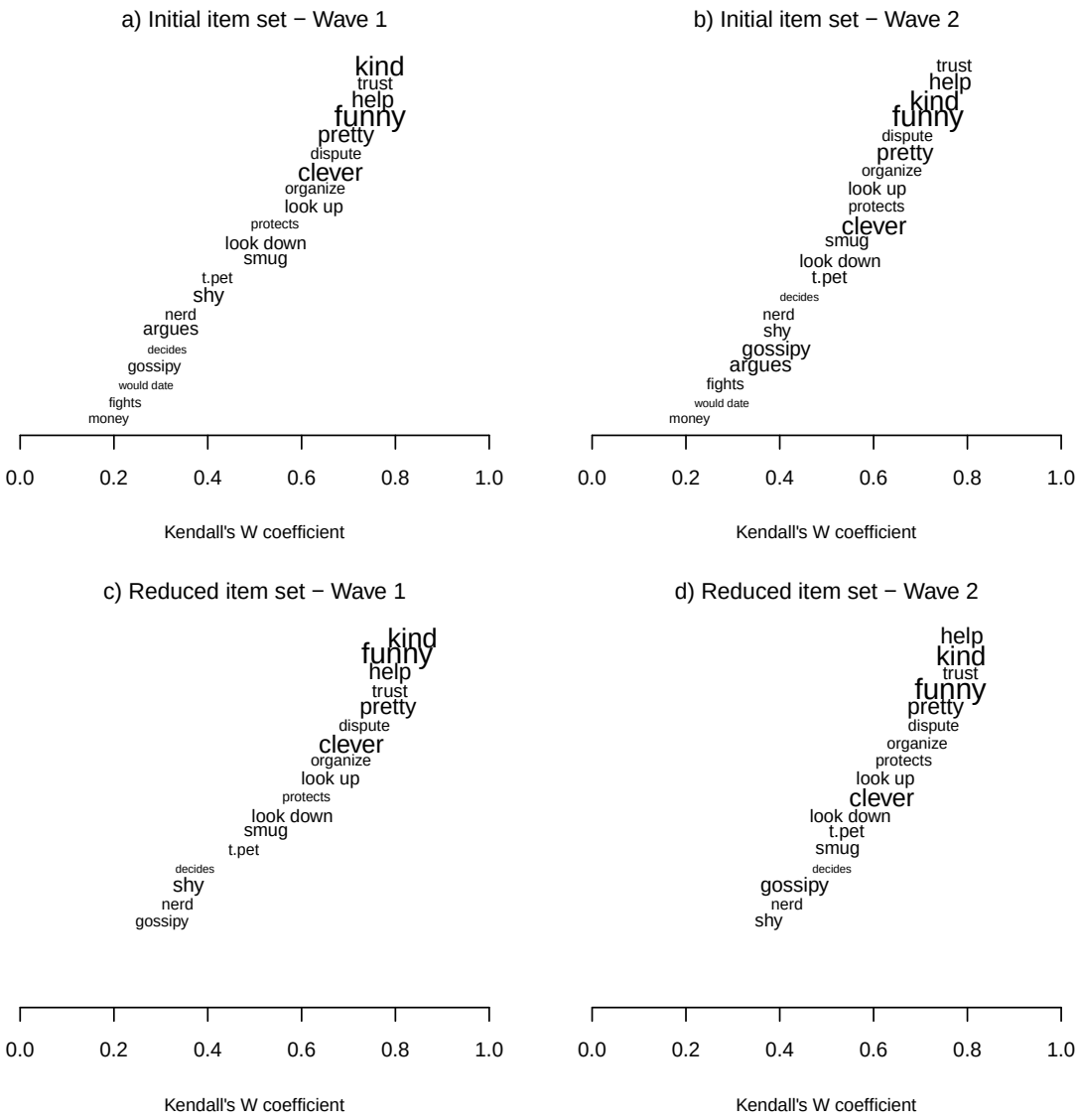

Figure C.1: Distribution of Kendall's W for the full and reduced item set in the full sample.

(W values were calculated based on 18 classes; the horizontal axis measures Kendall's W, while the items are similarly ordered along the vertical axis; label sizes are proportional to the average density of items in the classrooms.)

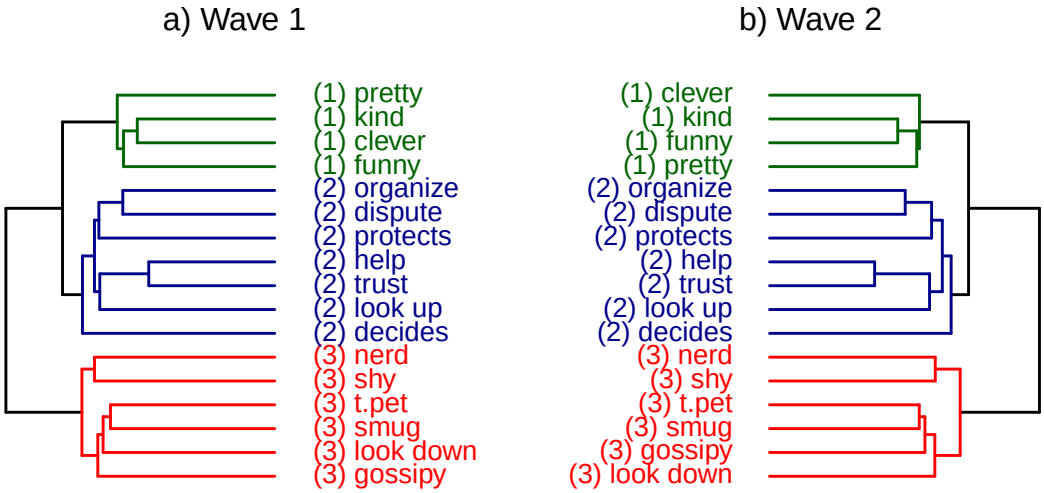

Figure C.2: Cluster trees from the average similarities in the full sample.
(The colors and numbers represent the resulting clusters.)

were defined based on the same rules as in Chapter 4 (see Table 4.9). The results here are also similar to those presented in Figure 4.10).

Based on the results from the replication, we conclude that the clustering solution and composite networks more thoroughly presented in Chapter 4 are suitable for use on the Dynamic Subsample classrooms in the subsequent empirical analyses.

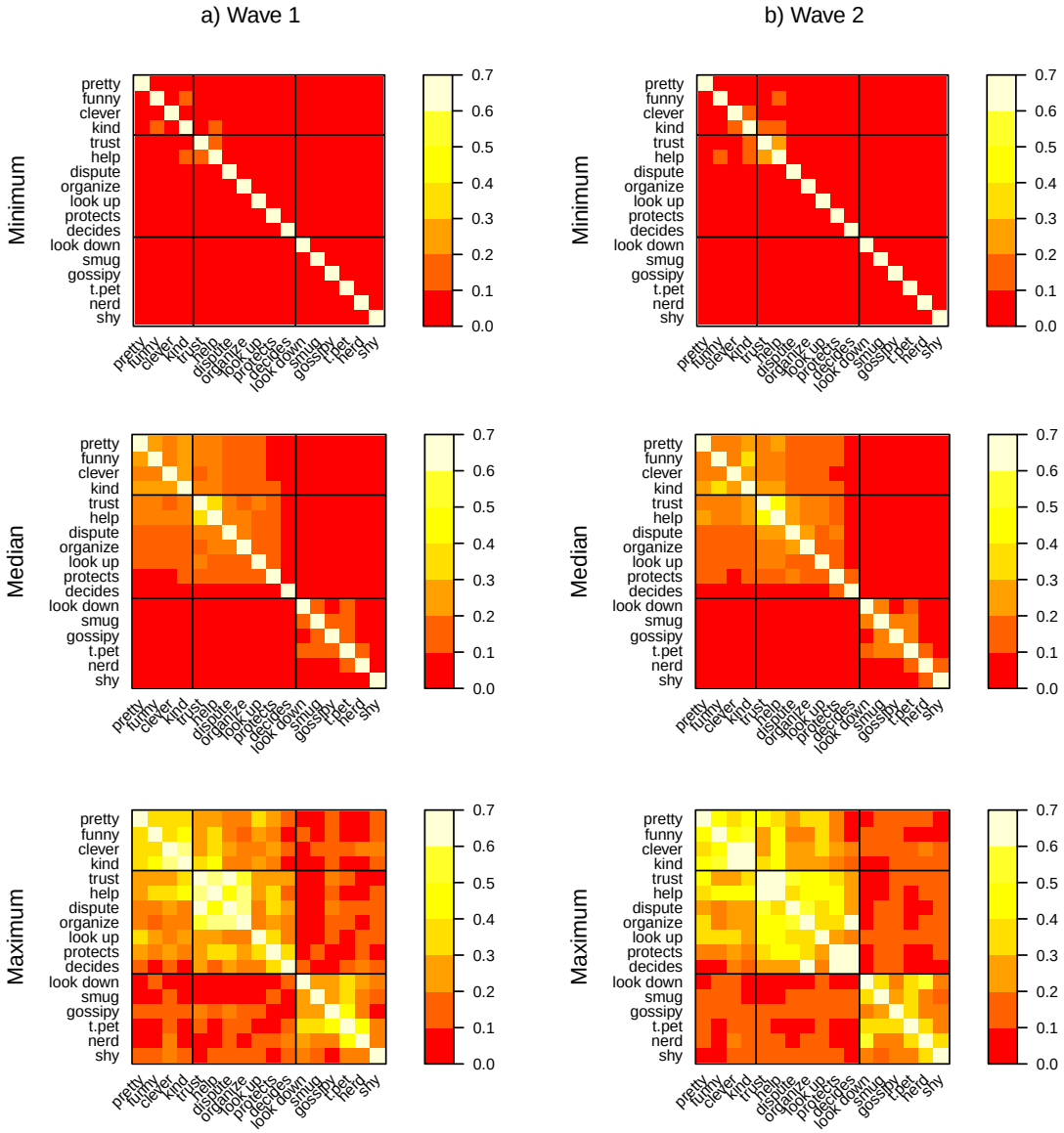

Figure C.3: The minimum, median, and maximum Jaccard index values among the 17 clustered items in the full sample.

(The diagonal values were set to the off-diagonal maximum of the six matrices.)

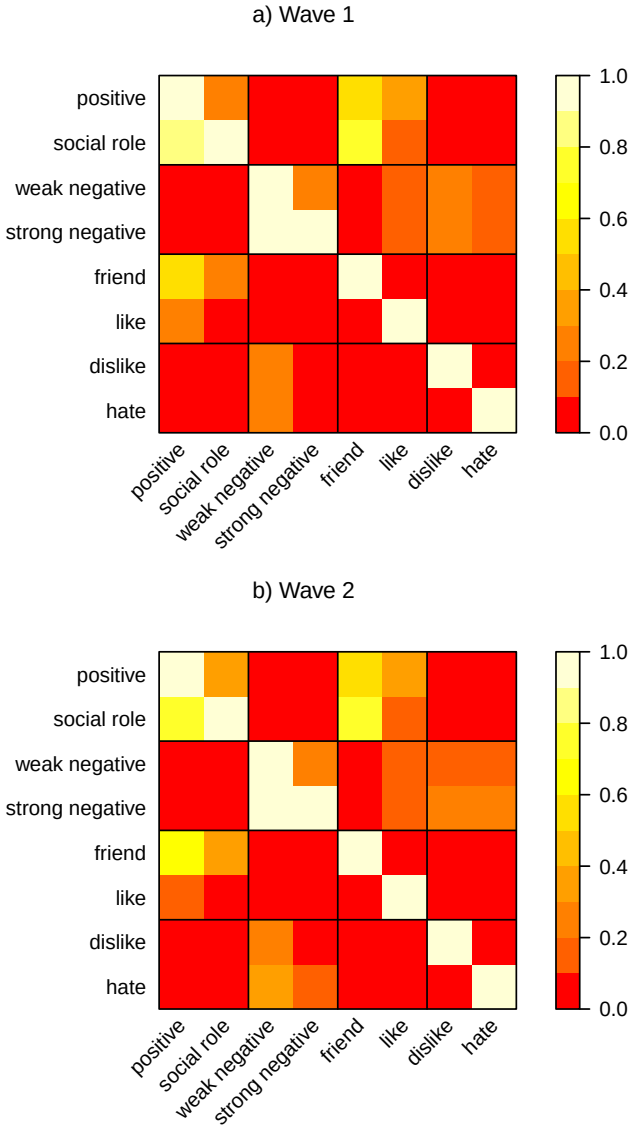

Figure C.4: Average overlap between the composite networks and the affective items in the full sample.
(Cell values represent the proportion of overlapping ties relative to the row networks density.)

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