Status differentiation

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Chapter 5

Status Generalization, In-Group Favoritism, and Ability Attributions: A Network Study Among Adolescents*

Abstract

Earlier experimental research in status characteristics theory suggests that status characteristics can induce status generalization that affects individuals' assumptions about each other's abilities. However, earlier research has examined status generalization predominately in laboratory settings, with groups that had a strong collective task focus. In this chapter, we contribute to existing field research and explore in-group favoritism as an alternative mechanism that might undermine status generalization processes in the field, in groups without a strong collective task focus. We study the effects that the status characteristics gender and ethnicity have on ability attributions with exponential random graph models that we apply to data collected among adolescents in 27 Hungarian school classes. Our results suggest that across classes, gender does not consistently affect ability attributions and that ethnicity affects ability attributions through status generalization, but not in-group favoritism.

*This chapter is co-authored with Károly Takács and Judit Pál and at time of writing was in preparation for re-submission to a scientific journal.

5.1 Introduction

Social distinctions with status value in society, such as gender, age, and race, can shape individuals' expectations about each other (Berger et al., 1972). *Status generalization* occurs when such characteristics affect assumptions about abilities and skills. In the USA, for example, men still have a status advantage over women (Hopcroft, 2002) and male job applicants are therefore often perceived as more able and competent than female applicants, even if they have the same formal qualifications (Moss-Racusin et al., 2012).

A large body of research in *status characteristics theory* (Berger et al., 1977) has examined conditions under which salient status characteristics affect assumptions about individual abilities in small group contexts and thereby affect group member interactions (for a review see Wagner & Berger, 2002). Studying status generalization in such contexts is particularly important, because small groups can contribute to the reproduction of social inequality. When lower status individuals repeatedly make the experience that other group members believe that they lack important abilities, they might experience strain that can undermine cognitive performance. This, in turn, can reinforce existing stereotypes (cf. Steele & Aronson, 1995).

Some scholars emphasize that existing research on status generalization is limited by its almost exclusive focus on ad hoc created experimental groups with a strong collective task focus (B. P. Cohen & Zhou, 1991; Martin, 2009). Groups with a collective task focus (such as work teams) are important building blocks of society and certainly play a significant role in both shaping and re-enforcing status differentiation and social inequality. However, many group settings do not have a collective task focus yet still play a significant role. While there is some first experimental evidence that status generalization affects ability attributions in settings without a collective task focus (e.g., Foschi et al., 1994), we still know little about how status characteristics affects ability attributions in such groups outside the laboratory.

This chapter adds to the few studies on status generalization, exploring an alternative mechanism that might undermine status generalization processes in the field, in groups that lack a strong collective task focus. Specifically, field research based on status characteristics theory has assumed that status generalization affects the ability attributions of members of status-advantaged and status-disadvantaged categories similarly, given their goal to coordinate their work on some collective task (cf. B. P. Cohen & Zhou, 1991; York & Cornwell, 2006). In this view, when gender is a status characteristic that favors men over women, both men and women tend to attribute higher abilities to men. By contrast, recent experimental research in *social identity theory* (Tajfel & Turner, 1979) suggests that a need for positive self-esteem can induce *in-group favoritism* that leads status beliefs to affect members of status-advantaged and disadvantaged categories differently (Oldmeadow & Fiske, 2010). In this view, men tend to attribute higher abilities to other men but women tend to reject such differences and attribute equal abilities to men and women. If in-group favoritism indeed affects ability attributions, we might not find a uniform effect of status characteristics.

We do not claim to be the first to recognize that in-group favoritism might affect status generalization. Several studies consider the possible effects of in-group favoritism and suggest that the two processes might combine to some extent (cf. Foschi et al., 1994; Oldmeadow et al., 2003). However, to date the relative importance of the two processes has not been examined in the field and in groups that lack a strong collective task focus. Insights from existing research might not hold in this context given that in field settings, individuals can interact repeatedly with each other over a longer period. During these interactions, they might learn about each other's actual abilities, which might undermine effects of ability stereotypes based on status characteristics. Conversely, during such interactions individuals might also learn about more subliminal sources of similarity/dissimilarity in the group, which might undermine in-group perceptions based on status characteristics; this might undermine in-group favoritism based on status characteristics. Alternatively, the lack of a strong collective task focus might render individuals more inclined to base their ability attributions on the goal to maintain a positive self-image, rather than the goal to assess the abilities of others accurately.

In this chapter, we study the effects that gender and ethnicity have on ability attributions with data collected among adolescents in 27 Hungarian school classes. Gender and ethnicity, known as fundamental dimensions of social differentiation, are often important sources of status and social identity (cf. Levin, Sidanius, Rabinowitz, & Federico, 1998; Rashotte & Webster, 2005; Schmader, 2002) and are also among the most important determinants of homophilic friendship choice (McPherson, Smith-Lovin, & Cook, 2001). The class context enables us to study their effects on ability attributions in naturally occurring groups.

Studying ability attributions in such groups is complicated in that attributions might not be statistically independent. For example, group members might to some extent be aware of the abilities that other group members attribute to each other and this might affect their own attributions. This problem has been neglected in earlier field research in status characteristics theory. We deal with this problem by using a novel approach to studying ability attributions. We use exponential random graph (ERG) models, conceptualizing ability attributions as *network ties* among the members of a given class. ERG models enable us to assess how much the structure of these networks might be driven by status generalization and in-group favoritism, while controlling for statistical interdependence of the attributions in a given class.

In what follows, we first describe the central assumptions of status characteristics theory and social identity theory and present the competing hypotheses that they lead to. Next, we describe the data and our analytical approach. We close the chapter by presenting our results and discussing their implications for future research.

5.2 Status Differences, Similarity, and Ability Attributions

5.2.1 Status characteristics theory and status generalization

Status characteristics theory is part of the expectation states framework (for overviews of the framework see Correll and Ridgeway 2003 and Wagner and Berger 2002) and explains how *status characteristics* affect the abilities that people expect others to possess. A status characteristic is any social distinction that separates individuals into at least two categories connected to (1) widely shared beliefs about social worth and (2) beliefs about the possession of general and specific abilities, such as mathematical understanding and intelligence, that enable people to perform well in a wide range of tasks (Berger et al., 1972, 1977). For simplicity, from here on we refer to such beliefs as *status beliefs* (cf. Ridgeway, 1991).

The theory holds that status generalization can occur whenever individuals feel pressured to engage in comparative ability assessments (Correll & Ridgeway, 2003). If individuals meet each other in a group context with a strong collective task focus (e.g., in work teams in which team members have to jointly solve a certain problem), status generalization occurs because group members somehow need to coordinate their work on the task based on cues they have about the relative abilities of the different group members. Yet, as Correll and Ridgeway highlighted, status characteristics should affect ability attributions whenever individuals have to engage in comparative ability evaluations, even when there is no collective task, because:

> "… [t]he anticipation of [a comparison] creates a pressure for actors to assess their task competence relative to others who they imagine are also being or have been evaluated. This coordination of rank position requires evaluating oneself in relation to the social environment. However, the standards for what constitutes a competent performance are not usually clearly defined beforehand, and others' precise scores are rarely known. In this uncertain environment, salient status characteristics are available to influence performance expectations, as they do in collective task situations. Through the process of status generalization, individuals develop performance expectations for themselves that are consistent with their state on the salient status characteristic." (Correll & Ridgeway, 2003, p. 47)

We therefore expect that status generalization occurs even in group contexts without a collective task focus.

Regardless of the presence of a collective task focus, status generalization should be most likely to occur among people with no first-hand knowledge about each other's abilities who thus can only rely on competence stereotypes associated with salient status characteristics to evaluate each other (cf. Webster & Foschi, 1988). This does not imply, however, that status generalization is always a conscious process in which people actively draw on existing status beliefs. Instead, "most instances of status generalization occur outside the realm of conscious thought" (Webster & Foschi, 1988, p. 3). By that, status generalization tends to circumvent egalitarian attitudes and motives that otherwise might lead individuals to reject discrimination, even among those who are disadvantaged by existing status beliefs (Rashotte & Webster, 2005).

Face-to-face interaction might intervene in status generalization, given that individuals can potentially learn about each other's objective abilities, which might or might not be congruent with existing stereotypes. Yet, there are reasons to expect that status generalization can affect ability attributions even among individuals who have already interacted with each other in the past. One reason is that people tend to interpret ability relevant performances in line with existing expectations. In mixed-gender work groups, for example, the performance of women often receives lower evaluations than comparable performances of men (cf. Correll & Ridgeway, 2003). Consequently, even when members of low status groups perform a certain task well, such displays of ability might not have much effect on the abilities that other group members expect them to possess. A second reason is that existing stereotypes can create cognitive strain among members of low status groups, especially when they have to perform tasks for which they are expected to perform badly. This strain can impair performance and thereby can lead to a reinforcement of existing stereotypes (Steele & Aronson, 1995).

Taken together. status characteristics theory leads to the prediction that when individuals are forced to evaluate the abilities of others in a comparative situation, members of both status-advantaged and status-disadvantaged categories will attribute higher abilities to members of the status-advantaged category than to members of the status-disadvantaged category. This effect potentially holds even in groups where individuals engage in repeated face-to-face interaction and groups lacking a strong collective task focus.

5.2.2 Social identity theory, status differences, and in-group favoritism

Social identity theory (Tajfel & Turner, 1979) is a theory of intergroup cognition and behavior (for an overview of the theory and a discussion of its extension into self-categorization theory see Hornsey, 2008). It explains how individuals' identification with salient social groups affects the way they evaluate and treat people who belong to their own and other social groups. The theory builds on two central assumptions. First, people have both a personal identity, based on individual idiosyncrasies, and a social identity based on membership in salient social groups (Tajfel & Turner, 1979). Individuals can have multiple social identities given that they can be members of multiple groups at the same time. Each identity is associated with perceptions of in- ('us') and out-groups ('them') based on similarity in the underlying criterion (Hogg, 2006). Depending on which identity is salient, in- and out-group boundaries can vary.

Second, people strive for positive social identities and engage in behaviors that create or maintain them (Tajfel & Turner, 1979). In particular, they evaluate in-groups more positively than relevant out-groups (for reviews of research on in-group favoritism see Bettencourt et al. 2001, Brown 2000, and Hewstone, Rubin, and Willis 2002). Such discriminatory evaluation establishes favorable comparisons that elevate the in-group over out-groups and thereby can indirectly benefit individuals' self-esteem (cf. Foels, 2006; Hewstone et al., 2002; Lemyre & Smith, 1985; Oakes & Turner, 1980).

Social identity theory assumes that status differentiation between a salient out-group and in-group in favor of the former can constrain in-group favoritism (Tajfel & Turner, 1979). For members of high status groups (e.g., members of a prestigious college), ability stereotypes hold that they are more able and skilled than members of lower status groups (members of a less prestigious college) and such beliefs facilitate discriminatory evaluation that favors the high status in-group. For members of lower status groups, however, ability stereotypes hold that they are less able and skilled. Such beliefs render in-group favoring evaluation more tenuous, especially when status differences appear stable, impermeable, and derive from actual ability differences (cf. Dovidio, Gaertner, & Validzic, 1998; Ellemers, van Rijswijk, Roefs, & Simons, 1997). Oldmeadow and Fiske (2010) showed that one way to deal with this 'dilemma' is to downplay ability differences with higher status groups and exaggerate differences in dimensions irrelevant to status (e.g., emotional warmth). This reduces the threat to a positive identity but does not discard existing status beliefs entirely.

Status characteristics are often important axes around which social identities form. Social identity theory therefore leads to the prediction that members of status-advantaged categories will attribute higher abilities to members of their own category than to members of status-disadvantaged categories. Members of status-disadvantaged categories, by contrast, will attribute similar abilities to members of both status categories. In groups that lack a collective task focus, the need to maintain a positive social identity might be more important than the need to evaluate the abilities of others accurately. This might lead in-group favoritism to dominate status generalization in such contexts.

5.3 The Current Study

Status characteristics theory and social identity theory lead to *similar predictions* about the attribution process among members of *status-advantaged categories*. However, they lead to *different predictions* about the attribution process among members of *status-disadvantaged* categories. We tested the theories' competing predictions with data collected in Hungarian secondary school classes. In the Hungarian educational system, classes are relatively closed units whose members mostly participate in the same courses and therefore spend most of their time together. This fact is likely to reduce interference from unobserved factors that might intervene in attribution processes.

We focused on the status characteristics gender and ethnicity. Gender is commonly considered one of the most important status characteristics with status value in many societies (cf. J. W. Balkwell & Berger, 1996; Ridgeway, 2011) and largely structures the organization of adolescent life (Coleman, 1961; Faris & Felmlee, 2011). In Hungary, gender is typically assumed to be a status characteristic that favors men over women and status differences show in many dimensions of social life such as political empowerment and economic participation (cf. Fodor & Balogh, 2010; Hadas, 2003; Nagy, 2006). We therefore defined male pupils as members of the status-advantaged category and female pupils as members of the status-disadvantaged category. In the USA, race is also an important status characteristic, particularly when it comes to differences between the white majority (status-advantaged) and the black minority (status-disadvantaged) (e.g., Steele & Aronson, 1995). Despite evident differences, ethnicity plays a similar role in Hungary (Kertesi & Kézdi, 2011). Roma are the largest ethnic minority in Hungary and are disadvantaged compared to the Hungarian majority in terms of employment, education and school performance, living and health conditions, and life expectancy (Kertesi & Kézdi, 2011; Messing, Neményi, & Zolnay, 2011). Roma people are often discriminated by negative judgments and Roma adolescents often conceive themselves as members of a stigmatized group (Neményi, 2007; Székelyi, Örkény, & Csepeli, 2001). We therefore defined Hungarian pupils as members of the status-advantaged category and Roma pupils as members of the status-disadvantaged category.

The central outcome of interest was pupils' attributions of cognitive abilities to other class members (from here on *ability attributions*), because such attributions are often assumed to represent assumptions about general abilities (e.g., Rashotte & Webster, 2005). Specifically, we examined how pupils' gender and ethnicity affected the likelihood that other class members attributed high cognitive abilities to them.

5.3.1 Sample and procedure

Data were collected in November 2010 as part of the project 'Wired into Each Other: Network Dynamics of Adolescents in the Light of Status Competition, School Performance, Exclusion, and Integration' conducted at the Research Center for Educational and Network Studies (RECENS). The data comprise information from pupils of 43 classes (in grade 9) from seven public schools distributed across Hungary. The sample purposively over-represented school classes with high Roma proportions.

The data were collected through a paper-and-pencil survey that pupils filled in at the same time in their classrooms. During data collection, at least one member of the research team was present to explain the procedure and answer questions. Participation was voluntary and required parents' permission. The average class size was 32.70 (SD = 3.71), ranging from 17 to 38. Of the initially listed N = 1406 pupils, n = 1214 participated in the study, leading to an overall response rate of about 86%. The average age of participants was 16.73 years (SD = 1.46), ranging from 14 to 22 years.

Across classes, the participation rate ranged from about 58% to 100%. A large share of missing cases in network data can lead to biased results (Kossinets, 2006), but excluding classes from the analysis based on any instance of survey non-response might reduce the sample of classes severely and this might reduce the generalizability of our results. To trade-off these conflicting concerns, we decided to only retain classes in which at most 20% of cases were missing, which left 27 classes with 812 respondents in total.[13]

Estimating the effects that status characteristics have on ability attributions among members of different status categories requires that each class has sufficient pupils belonging to each category. Thus, within the remaining 27 classes, we focused on those which had at least 20% of pupils belonging to either status-advantaged or status-disadvantaged categories. In some classes, this criterion was satisfied for gender but not for ethnicity and vice versa. Therefore, we conducted two analyses. In *Analysis 1*, we focused on those classes that had at least 20% of both male and female pupils and included variables related to ethnicity as controls in those classes in which this was possible. For this, 21 classes with a total of 648 pupils were eligible, with an average of 63% female pupils.[14] In *Analysis 2*, we focused on those classes that had at least 20% of both Hungarian and Roma pupils and included variables related to gender as controls in those classes in which this was possible. For this, 11 classes with a total of 306 pupils were eligible, with an average of 42% Roma pupils.

[13] A value of 20% missing cases is generally considered to represent a low amount of missing data in network studies and do not tend to affect results strongly (Huisman, 2009). This criterion led to the exclusion of 15 classes (leaving 28 classes). Subsequently, pupils indicating they were neither Hungarian nor Roma (18 pupils in total, see Section 5.3.3) were also treated as survey non-responses, because their relative status compared to Roma and Hungarian pupils was unclear. This led to the exclusion of one more class.

[14] Female students are overrepresented in the sample compared to the larger population, because in the highest track of the Hungarian educational system (the 'gimnázium' track), women are generally overrepresented. Men tend to be overrepresented in the vocational track; yet, the sample included two vocational schools that specialized in trade and commerce in which female students are in majority.

5.3.2 Analytical approach

We analyzed the ability attributions that occurred in the different classes with ERG models. In an ERG framework, ability attributions are modeled as a network among class members in which directed binary ties between two individuals i and j that can either be present ($1 = i$ attributes abilities to j) or absent ($0 = i$ does not attribute abilities to j; for details about how ability attributions were measured in the survey see Section 5.3.3). The parameter estimates that ERG models generate can roughly be interpreted like parameters in logistic regression analysis. This means that a positive (negative) parameter estimate for a given variable in the model implies that higher values on this variable make it more (less) likely that another pupil j attributes abilities to pupil i. ERG models enable us to estimate this likelihood, contingent on properties of i and j (i.e. *actor characteristics*, such as i's and j's gender and ethnicity), other relations that i and j share (i.e. *dyad characteristics*, such as when i considers j to be a friend, which might affects i's ability attribution to j), and on other ties that surround i's evaluation of j (i.e. *structural variables*).

Structural variables allow us to control for the possibility that ability attributions might be statistically interdependent within a given class. Consider, for example, a male pupil (say, Péter) who has managed to build a reputation for being particularly intelligent and therefore receives a large number of ability attributions from other class members. The remaining class members, both males and females, do not differ much in the number of attributions they receive. If we ignore the fact that the ability attributions that Péter receives all share the same target, we might find that male pupils are more likely to receive ability attributions than female pupils, even if this difference is due to the fact that (only) Péter receives a very large number of attributions. In ERG models, we can consider this possibility and therefore derive unbiased parameter estimates. In the appendix to this chapter (Section 5.6), we provide a detailed description of the way parameters are estimated in ERG models and discuss how we assessed the fit of our ERG models.

In an ERG framework, each class is treated as a separate, complete network for which a different set of parameter estimates is obtained. To assess whether a given variable is associated with ability attributions across the classes in our sample, we need to aggregate these estimates. Snijders and Baerveldt (2003) suggested that results from different classes could be treated as separate case studies that can be aggregated with standard meta-analytical procedures. Using their approach, we aggregated the parameter estimates across classes and report standard measures for meta-analyses (see the appendix to this chapter for details).

5.3.3 Measures

5.3.3.1 Ability attributions

The survey contained social network modules in which pupils were given a roster with the names of their classmates and were asked to indicate those whom they perceived to possess various attributes (e.g., 'has a good sense of humor' or 'is reserved'). We focused on pupils' attributions of the trait 'is clever/smart' as the dependent variable (i.e. $1 = i$ attributes abilities to j, $0 = i$ does not attribute abilities to j).

5.3.3.2 Actor characteristics

Pupils were asked to indicate whether they were male or female. We used this information for three parameters in the analysis (see details in the appendix to this chapter). *Receiver female* indicates whether an attribution from i to j was more likely when j was female (coded as 1) than when j was male (coded as 0); *both female* indicates whether an attribution from i to j was more likely when both were female (coded as 1) compared to when they were both male or differed in gender (coded as 0); *both male* indicates whether an attribution from i to j was more likely when both were male (coded as 1) compared to when they were both female or differed in gender (coded as 0).

Pupils were asked to indicate whether they considered themselves Hungarian, Roma/Gypsy, Roma/Gypsy, and Hungarian at the same time, or to belong to another ethnic group. As mentioned earlier, pupils who indicated that they belong to another ethnic group were excluded from the analysis. We defined pupils who considered themselves Roma/Gypsy and Hungarian at the same time to belong to the category Roma/Gypsy (for simplicity called *Roma*). We decided to include pupils who indicated both ethnicities (143 out of 1214) in the category *Roma*, because these students are likely to be stigmatized due to their Roma/Gypsy origin. Of the 1214 pupils, 101 did not answer this question. For 83 of them we could impute their ethnicity from their answers to the same question in two later waves of this project (collected about 6 and 18 months after the first wave). For the remaining 18 pupils, we used a polynomial regression model to approximate their ethnicity.[15] Analogous to gender, we used information about pupils' ethnicity for three parameters in the analysis: *receiver Roma*, *both Roma*, and *both Hungarian*.

5.3.3.3 Dyad characteristics

We controlled for pupils' perceptions of two additional characteristics that earlier research has reported to affect ability attributions. First, we controlled for pupils' perceptions of each other's physical attractiveness, because physical attractiveness can be a status characteristic that favors more attractive individuals over less attractive individuals (Jackson et al., 1995; Parks & Kennedy, 2007). Second, we controlled for pupils' perceptions of each other's academic

[15] We used the R-package `mice` (van Buuren & Groothuis-Oudshoorn, 2011) for imputing ethnicity. We predicted ethnicity with a polynomial model that included the following information for each pupil: gender, number of received nominations as being clever/smart, number of received nominations as being physically attractive, number of received nominations as having good grades, number of received nominations as being considered a friend, class size (to control for limits in the maximal number of nominations that pupils can receive on each of the foregoing variables), and the self-reported share of Roma and Hungarian residents in the pupils' residential area (ranging from 'Only Roma/Gipsy families are living in the neighborhood' (coded 1) to 'only Hungarian families are living in the neighborhood' (coded 5)). Given that Roma in Hungary tend to have a significantly lower income and lower educational attainment than the Hungarian majority, we also included the self-reported average number of different types of appliance present in the household (e.g., color TV, washing machine, etc.), self-reported mean number of different types of objects in personal use (e.g., a desk, a room, etc.), and self-reported father's highest education (dummy coded, indicating with 0 up to grade 8 and with 1 higher than grade 8).

achievement in terms of good grades (i.e. has good grades vs. does not have good grades), because individuals might conceive this as indicating the possession of general abilities (cf. Hysom, 2009; Ridgeway, 1991; Webster & Hysom, 1998). Similar to ability attributions, perceptions of physical attractiveness and academic achievement were measured on network items on which pupils could nominate those class members whom they thought to possess these attributes. In the analyses, we labeled these dyad variables *dyad attractive* and *dyad good grades*.

We also controlled for friendship relations between pupils, because earlier research suggests that adolescents are more likely to attribute abilities to close friends than to less close individuals (Tesser, Campbell, & Smith, 1984; Tesser & Campbell, 1982). Friendship relations were measured with a 5-point network item converted into a dummy variable to indicate whether i considered j to be a friend (coded 1, comprising the original scale points 'like' and 'good friend') or not (coded 0, comprising the original scale points 'hate', 'dislike', and 'neutral'). In the analysis, we labeled this dyadic variable *dyad friend*.

5.3.3.4 Structural variables

We included the following structural variables in the model, which enabled us to control for social processes that might induce interdependence in ability attributions (see details in the appendix to this chapter). First, we controlled for the possibility that some class members might have a reputation for being especially intelligent, which might lead to an increase in the number of attributions they receive independently from their gender or ethnicity, with the structural variable *popularity*. Second, some class members might have a reputation for being not very intelligent, which might give them low status in the class, net of their status implied by gender or ethnicity. Low status individuals might generally tend to show respect more freely to other group members and attest to their abilities (Blau, 1964). We controlled for this possibility with the structural variable *activity*, which captures the possibility that some class members might be especially inclined to make a larger number of ability attributions to others. Third, displays of respect and admiration to others (e.g., by openly complementing the abilities of others) have the potential to lower one's rank in a given group, if they are not reciprocated. Individuals therefore tend to avoid such displays if they are not reciprocated (Gould, 2002; Lynn et al., 2009). If ability attributions are to some extent public, we might expect that concerns for reciprocity partly shape the likelihood that two class members will attribute abilities to each other. We controlled for this possibility with the structural variable *reciprocity*. Finally, we also included the structural variable *arc*, which captures the baseline probability of ability attributions to occur on a given class and operates like an intercept in logistic regression models.

Variable	Analysis 1 (C = 21)		Analysis 2 (C = 11)	
	M (*SD*)	Range	*M* (*SD*)	Range
ability attributions	.24 (.14)	.06-.52	.11 (.04)	.04-.16
attractive	.17 (.06)	.09-.28	.13 (.05)	.03-.19
good grades	.21 (.13)	.04-.42	.08 (.04)	.03-.14
friend	.21 (.05)	.15-.34	.20 (.03)	.16-.27

Table 5.1 Average share of nominations that were realized across the classes included in the two analyses. Analysis 1 focuses on gender and Analysis 2 focuses on ethnicity. *C* refers to the number of classes.

Variable	Total (N = 648)		Male (N = 238)		Female (N = 410)	
	M (*SD*)	Range	*M* (*SD*)	Range	*M* (*SD*)	Range
ability attributions	7.86 (6.35)	0-31	6.04 (5.48)	0-25	8.92 (6.59)	0-31
attractive	5.53 (5.91)	0-29	2.74 (3.47)	0-20	7.15 (6.41)	0-29
good grades	6.57 (6.49)	0-31	4.81 (5.79)	0-28	7.59 (6.66)	0-31
friend	6.46 (3.45)	0-21	6.07 (3.44)	0-18	6.69 (3.44)	0-21

Table 5.2 Average number of received nominations across pupils in Analysis 1: focus on gender. *N* refers to the number of respondents.

Variable	Total (N = 306)		Hungarian (N = 179)		Roma (N = 127)	
	M (*SD*)	Range	*M* (*SD*)	Range	*M* (*SD*)	Range
ability	3.00 (2.71)	0-13	3.87 (2.90)	0-13	1.78 (1.80)	0-9
attractive	3.64 (3.70)	0-18	3.31 (3.66)	0-18	4.10 (3.73)	0-16
good grades	2.18 (2.42)	0-16	2.78 (2.78)	0-16	1.32 (1.40)	0-6
friend	5.48 (2.52)	0-15	5.35 (2.50)	0-15	5.65 (2.54)	0-12

Table 5.3 Average number of received nominations across pupils in Analysis 2: focus on ethnicity. *N* refers to the number of respondents.

5.4 Results

5.4.1 Descriptive statistics

Table 5.1 shows the share of nominations that had been realized (calculated as #observed nominations/#possible nominations), averaged across classes. The results suggest that in the 21 classes included in the analysis that focused on gender (Analysis 1), the average share of realized nominations for ‘is clever/smart’ and ‘has good grades’ were about 2.5 times larger than in the 11 classes included in the analysis that focused on ethnicity (Analysis 2). Table 5.2 shows the average number of nominations that pupils received for the classes included in Analysis 1. Compared to male pupils, female pupils were on average nominated more often as clever/smart, attractive, having good grades, and as a friend. Table 5.3 shows the average number of nominations that pupils received for the classes included in Analysis 2. Compared to Hungarian pupils, Roma pupils were on average nominated less often as clever/smart and having good grades, but were nominated more often as attractive.

Status Characteristics Theory			
		Receiver	
		Male (0)	Female (1)
Sender	Male (0)	[1] 0 (both male = 0)	[2] -1 (receiver female = -1)
	Female (1)	[3] reference	[4] -1 (receiver female + both female = -1 + 0)

Social Identity Theory			
		Receiver	
		Male (0)	Female (1)
Sender	Male (0)	[1] 0 (both male = 0)	[2] -1 (receiver female = -1)
	Female (1)	[3] reference	[4] 0 (receiver female + both female = -1 + 1)

Table 5.4 Combinations of parameter estimates that would support the different theories, illustrated for gender. Male and female gender of the senders and receivers of ability attributions are coded in the margins of the sub-tables as 0 and 1 respectively. The different cells of the sub-tables (1 to 4) show the sum of the combined parameter estimates for the different variables in the model. The values of -1 and 1 in cells 1 to 4 represent decreases and increases in the likelihood that an ability attribution occurs from the sender to the receiver, contingent on the gender of the sender and the receiver. The value 0 means that this likelihood does not change.

5.4.2 Hypothesis testing

Our hypotheses imply specific combinations of parameter estimates for the receiver and similarity variables related to gender and ethnicity. To illustrate this, we use gender as an example and show the combination of the expected effects of the different variables in Table 5.4. The table can be applied to ethnicity by replacing the appropriate status categories (i.e. by replacing 'male' with 'Hungarian' and 'female' with 'Roma'). Status characteristics theory predicts that both male and female students will be less likely to attribute abilities to female students than to male students. This would be the case if the estimated effect of *receiver female* would be significantly lower than zero (e.g., -1), whereas the estimated effects of the gender-based similarity parameters (i.e. *both female* and *both male*) would not be significantly different from 0. Social identity theory, by contrast, holds that only males will be less likely to attribute abilities to females than to males. This would be the case if the parameter estimate of *receiver female* would be negative (e.g., -1, given that men are less likely to attribute abilities to them than to females) and the parameter estimate for *both female* would be positive (e.g., 1). The parameter estimate of *both male* would not be significantly different from 0.

Tables 5.5 and 5.6 show the parameter estimates of our ERG models focusing on gender (Analysis 1) and ethnicity (Analysis 2).[16] Concerning the structural variables, after controlling

[16] In most classes, the estimation algorithm converged in the allotted time frame, typically after about 20 to 25 repetitions. Only in the analysis that focused on gender did the algorithm fail to converge for one class, even after several fitting attempts. We therefore excluded this class from the analysis. Additionally, in four classes the

Variable/Characteristics	T_θ^2		$\hat{\mu}_\theta^{WLS}$	s.e. $(\hat{\mu}_\theta^{WLS})$		$\hat{\sigma}_\theta^2$	Q	
Structural variables								
arc	993.376	**	-1.905	0.150	**	0.338	94.822	**
reciprocity	52.040	**	0.227	0.095	*	0.083	39.005	**
activity	632.668	**	-4.894	0.511	**	3.361	91.751	**
popularity	76.237	**	-1.300	0.254	**	0.374	28.994	*
Dyad characteristics								
dyad attractive	280.772	**	0.790	0.095	**	0.118	49.656	**
dyad good grades	1498.880	**	1.803	0.081	**	0.074	44.846	**
dyad friend	243.204	**	0.702	0.107	**	0.165	60.942	**
Actor characteristics								
receiver Roma	25.498	**	-0.495	0.245		0.280	15.068	*
both Hungarian	9.573		0.195	0.219		0.215	8.147	
both Roma	24.155	**	0.220	0.546		1.410	18.400	**
receiver female	53.746	**	0.093	0.109		0.136	52.844	**
both male	40.837	**	0.128	0.130		0.181	37.269	**
both female	51.891	**	0.164	0.088		0.091	42.242	**

Table 5.5 Results of meta-analysis of ERG parameter estimates that predict ability attributions from Analysis 1: focus on gender. Each estimate is based on 20 classes, except for *activity* (16), *popularity* (16), *receiver Roma* (8), *similar Hungarian* (7), and *similar Roma* (6). Two-tailed significance levels: ** $p \leq .01$, * $p \leq .05$.

for all other variables in the models, attributions were more likely to not occur than they were to occur. They also tended to be equally distributed across pupils both in terms of attributions made and attributions received and tended to be reciprocal. This is indicated by the negative and significant parameter estimates (i.e. $\hat{\mu}_{\theta,p}^{WLS}$ and $\text{s.e.}\left(\hat{\mu}_{\theta,p}^{WLS}\right)$) for *arc*, *activity*, and *popularity* and the positive estimate for *reciprocity*. Yet, the estimates of $\hat{\sigma}_{\theta,p}^2$ in combination with the Q_p statistic, which assess variation of parameter estimates across classes, indicate that the magnitude of these effects varied significantly across classes.

Concerning the dyad characteristics, in general a given pupil i was more likely to attribute abilities to another pupil j when i perceived j to be attractive, to have good grades, and to be a friend. This is indicated by the positive and significant estimates of the parameter estimates for *dyad attractive*, *dyad good grades*, and *dyad friend*. Again, the estimates of $\hat{\sigma}_{\theta,p}^2$ in combination with the Q_p statistic indicate that the magnitude of these effects varied significantly across

estimation of the parameters for *activity* and/or *popularity* created problems and sometimes led to unrealistically low estimates (well below -20 and even below -100). For these classes, we fixed the values of *activity* and/or *popularity* to -6 and -1 respectively, based on the estimates obtained from classes that were similar in terms of the share of realized ability attributions. We excluded these values from the meta-analysis. One class contained a sufficient number of both female/male and Roma/Hungarian pupils, but no ability attributions occurred among Roma pupils; the parameter of *similar Roma* could therefore not be estimated for this class and was removed from the analysis. In the analysis that focused on ethnicity, no reciprocal attributions occurred in one class and the number of pupils who nominated other pupils as attractive was very low. Both parameters could thus not be estimated in this class and were removed from the analysis.

Variable/Characteristics	T_θ^2		$\hat{\mu}_\theta^{WLS}$	s. e. $(\hat{\mu}_\theta^{WLS})$		$\hat{\sigma}_\theta^2$	Q	
Structural variables								
arc	296.060	**	-2.026	0.233	**	0.398	37.288	**
reciprocity	21.003	*	0.445	0.144	**	0.001	11.389	
activity	314.737	**	-3.542	0.497	**	2.219	51.153	**
popularity	28.413	**	-0.889	0.217	**	0.003	11.522	
Dyad characteristics								
dyad attractive	87.542	**	0.682	0.211	**	0.340	28.152	**
dyad good grades	327.231	**	1.769	0.094	**	-0.010	12.009	
dyad friend	90.860	**	0.709	0.188	**	0.288	35.690	**
Actor characteristics								
receiver female	13.504		0.070	0.166		0.074	13.249	
both male	8.392		0.019	0.263		0.212	8.052	
both female	18.533	**	0.311	0.171		0.105	13.670	*
receiver Roma	51.674	**	-0.886	0.255	**	0.411	23.912	**
both Hungarian	17.586		0.229	0.156		0.152	14.461	
both Roma	36.042	**	0.538	0.362		0.905	23.320	**

Table 5.6 Results of meta-analysis of ERG parameter estimates that predict ability attributions from Analysis 2: focus on ethnicity. Each estimate is based on 11 classes, except for *mutual* (10), *attractive* (10), *receiver female* (8), *similar male* (7), *similar female* (7), and *similar Roma* (10). Two-tailed significance levels: ** $p \leq .01$, * $p \leq .05$.

classes.

When it comes to the competing hypotheses, the results suggest that gender was not associated with ability attributions, given that neither the parameter estimates of *receiver female*, nor the estimates for *both male* and *both female* were significantly different from 0 in Analysis 1 (focus on gender) and Analysis 2 (focus on ethnicity). In the case of ethnicity, our results show that Roma pupils were less likely to receive ability attributions than Hungarian pupils in Analysis 2, regardless of whether the attributions were made by Hungarian or Roma pupils. We found a similar but not significant effect in Analysis 1. Thus, when it comes to gender, our results do not support either of the two theories. When it comes to ethnicity, our results support status characteristics theory in the analysis that focuses on ethnicity. Note that the parameter estimates of the different receiver and similarity variables also tended to vary significantly across classes.

5.5 Discussion and Conclusion

In this chapter, we contributed to the few field studies in status characteristics theory by (1) assessing ability attributions in enduring groups outside the laboratory that lack a strong collective task focus and by (2) testing competing mechanisms derived from status characteristics theory and social identity theory. Earlier work building on status characteristics theory has assumed that members of both status-advantaged categories and status-disadvantaged categories attribute higher abilities to members of status-advantaged categories. Social identity theory, by contrast, predicts that only members of status-advantaged categories attribute higher abilities to members of their own category, whereas members of status-disadvantaged categories would not discriminate between the categories.

We assessed the competing predictions that the two theories yield for the status characteristics gender and ethnicity. In the case of ethnicity, our results are in line with the predictions of status characteristics theory. Roma pupils (defined as members of the status-disadvantaged category) were generally less likely than Hungarian pupils (defined as members of the status-advantaged category) and to receive ability attributions from both Hungarian and other Roma pupils. We found that this effect was significant in the analysis that explicitly focused on ethnicity, but not in the analysis that focused on gender and in which we had included information about ethnicity as control variables. The lack of significance in the latter analysis might be explained by the relatively lower number of classes in which we could control for effect of ethnicity, which undermines statistical power.

If we reject the notion that Roma pupils are systematically less intelligent than Hungarian pupils, these results suggest that the abilities that others attribute to them are affected by the status differences that exist between Hungarians and Roma in the larger Hungarian society. This effect seems to overrule possible effects of concerns for a positive self-image among Roma pupils. An alternative explanation might be that Roma pupils on average tend to perform less well at school than Hungarian students, possibly because they are aware of existing stereotypes and therefore experience cognitive strain that negatively affects their performance. Given that school performance is often assumed to reflect cognitive abilities, this difference might render the relation between ethnicity and ability attributions spurious. However, in our analysis, ethnicity affected ability attributions even after controlling for subjective evaluations of school performance among pupils.

In the case of gender, our results do not support the predictions of either theory. That is, although women are typically status-disadvantaged in the larger Hungarian society, female pupils were not less likely to receive ability attributions than male pupils, as status characteristics theory would predict. Female pupils were also not more likely than male pupils to attribute abilities to other female pupils, as social identity theory would predict. This lack of effect might be explained by changing contents of gender stereotypes. That is, given that today women tend to outperform men in terms of educational attainment in many OECD countries, including Hungary (Fényes, 2009; Legewie & DiPrete, 2012; OECD, 2012), status differences based on gender might be less related to assumptions about individual abilities and more related to assumptions about leadership skills (Ridgeway, 2011). If this is the case, we might have missed an important form of status differentiation that might exist among male and female pupils. Future research might therefore benefit from taking such alternative dimensions of status-related stereotypes into account.

One potential shortcoming of the status characteristics that we selected for our study is that they might differ in their salience during interactions. Gender is often easy to discern and salient in face-to-face interactions. Roma or Hungarian ethnicity, by contrast, might be less salient and might therefore be less likely to affect ability attributions. In the light of this possibility, our estimate of the effect that ethnicity has on ability attributions through status generalization might be lower than it would be if ethnicity was more salient. A second shortcoming is that the data did not allow us to control for the strength with which participants identify with in-groups based on their gender or ethnicity. It seems possible that tendencies for in-group favoritism are stronger among individuals who identify more strongly with a given in-group. Relatedly, some participants indicated that they considered themselves both Hungarian and Roma at the same time. Such individuals are likely to be stigmatized by the Hungarian majority. However, among such individuals the identification with the Roma minority might be weaker than among pupils who only consider themselves Roma and this might reduce their tendency to favor Roma pupils in their ability attributions. Future research might therefore benefit from controlling for the strength of individuals' identification with a given social category.

Status characteristics theory holds that status generalization is most likely to occur when individuals have no information other than status characteristics to use for assessing each other's abilities. As we discussed earlier, there is reason to expect that ability stereotypes continue to affect ability attributions even during repeated interactions, in which individuals learn about each other's objective abilities and skills. However, such processes might weaken the average level of status generalization that we can observe in a given group. Similarly, over time individuals might discover more subliminal sources of similarity and dissimilarity that affect perceptions of in- and out-groups, which might reduce the effects of in-group favoritism based on more easily accessible characteristics such as gender and ethnicity. Future research could try to trace such possible 'decay' in the effects that gender and ethnicity have on ability attributions by collecting data at different time points throughout the school year, starting when the class is created. With our data, such longitudinal treatment is not possible, given that classes already existed a while when first wave data were collected, and because some measures used in this chapter only apply to the first wave of the study.

There was significant variation in some parameter estimates across classes, particularly among those related to gender and ethnicity. Future research could try to study the sources of such variation and thereby uncover contextual conditions that make status generalization and in-group favoritism more or less likely to occur. In some classes, for example, differences in gender and ethnicity might have been more salient than in other classes, possibly due to different treatment by teachers (e.g., teachers might try to create an inclusive atmosphere that makes other sources of similarity salient, or teachers might unconsciously favor male/female students) or differences in the communities that surround schools (e.g., communities in which inequality between the Hungarian majority and the Roma minority are openly discussed vs. communities in which this topic is not as salient). Gaining insight into the effects of such factors would enable us to determine better under what contextual conditions status generalization or in-group favoritism are more likely to occur.

Finally, we highlighted that earlier research has focused on ability attributions in groups with a collective task focus. Our results suggest that status generalization processes can affect ability attributions even in contexts without a collective task focus, at the expense of concerns for a positive self-image. This implies that the insights gained in earlier experimental research might be applicable to a range of contexts that is much wider than previously assumed.

5.6 Appendix to Chapter 5

The description of ERG models presented here is based on the volume edited by Lusher, Koskinen, and Robins (2013) and on Robins, Pattison, Kalish, and Lusher (2007), who provide extensive and detailed introductions to this class of models.

In an ERG framework, the members of a given class are represented as N nodes $i = \{1, \cdots, N\}$ and each ability attribution from one pupil i to another pupil j is treated as a random variable Y_{ij} (a tie variable) with the states $Y_{ij} = 1$ (i attributes abilities to j) and $Y_{ij} = 0$ (i does not attribute abilities to j); y_{ij}represents the observed value of Y_{ij}. These variables are collected in a stochastic adjacency matrix Y with N columns and N rows, in which the entry in the i'th row of the j'th column refers to the attribution from pupil i to pupil j. Self-attributions are not considered and the diagonal of this matrix can thus be neglected. y is a particular realization of this stochastic adjacency matrix (e.g., the observed network) and $\mathbf{Y}$ denotes the space of all possible adjacency matrices given a fixed N.

The goal of estimating an ERG model is to identify substructures in the overall network that provide support for some social mechanism of interest. When these structures occur more often than chance would imply, this suggests that the mechanism might have been involved in creating the observed network. Assume, for example, that the mechanism of interest is status generalization and that male (female) students belong to the status-advantaged (disadvantaged) category. If status generalization actually has affected the attributions in a given class, one would expect that male pupils receive on average more ability attributions than female pupils. In this case, the substructure of interest is attributions with male/female pupils as the target.

The frequency of a given substructure in a network is from here on referred to as a network statistic $g(y)$. Given a vector of such statistics, ERG models have the general form of

$$\Pr\left(Y = y|\hat{\theta}\right) = \left(\frac{1}{\kappa(\hat{\theta})}\right) \exp\left(\sum_p \hat{\theta}_p g_p(y)\right), \tag{5.1}$$

where p indexes the vector of network statistics and $\hat{\theta}_p$ is the parameter estimate associated with the respective statistic; $\kappa\left(\hat{\theta}\right)$ is a normalizing constant, defined as

$$\kappa\left(\hat{\theta}\right) = \sum_{y \in \mathbf{Y}} \exp\left(\sum_p \hat{\theta}_p g_p(y)\right), \tag{5.2}$$

which ensures that the probabilities over all possible graphs with N actors sum up to 1. Note than in Eq. (5.1) the focus is on the entire network. This enables us to assess the importance of the different network statistics in the observed network. This importance is indicated by the value of $\hat{\theta}_p$, so that a large positive parameter estimate indicates that the number of observed instances of the substructure (e.g., the number of attributions with male pupils as the target) is higher than chance would imply, controlling for all other network statistics included in Eq. (5.1).

As mentioned in the main part of this chapter, three types of network statistics can be included in ERG models. Consider first the network statistics related to actor characteristics

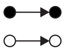
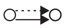
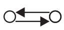
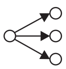
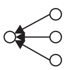
Graph element	Name	Network statistic	Parameter in model
Actor characteristics			
	receiver effect	$\sum_{i,j} x_j y_{ij}$	receiver female, receiver Roma
	similarity effect	$\sum_{i,j} x_i x_j y_{ij}$	both female, both male, both Roma, both Hungarian
Dyadic characteristics			
	dyadic effect	$\sum_{i,j} w_{ij} y_{ij}$	dyad attractive, dyad good grades, dyad friend
Structural variables			
	arc	$\sum_{i,j} y_{ij}$	arc
	reciprocity	$\sum_{i,j} y_{ij} y_{ji}$	reciprocity
	activity	$e^{\alpha_{out}}\sum_{t=1}^{N-1}\{1-(1-e^{-\alpha_{out}})^t\}D_t^{out}(y)$	activity
	popularity	$e^{\alpha_{in}}\sum_{t=1}^{N-1}\{1-(1-e^{-\alpha_{in}})^t\}D_t^{in}(y)$	popularity

Table 5.7 Network statistics used in the analysis. Circles represent individuals; arrows with solid lines represent ability attributions; arrows with dashed lines represent relations/attributions of other traits (w). The color of the circles indicates individuals' states on a given status characteristic x. D_i^{out} and D_i^{in} refer to the number of attributions that i made (i.e. out-degree) and the number of attributions i received (i.e. in-degree); α_{out} and α_{in} are scaling parameters.

and the statistics related to dyad characteristics, as shown in Table 5.7. Statistics related to actor characteristics refer to ties that share nodes (i.e. pupils) with certain properties. *Receiver effect* assesses whether pupils with a certain state on a given characteristic (e.g., female gender) are more or less likely to receive ability attributions than pupils with another state on the characteristic. *Similarity effect* indicates whether an attribution from i to j is more or less likely when two pupils share the same state on a given characteristic (e.g., when both are female). Dyad characteristics assess whether other relational objects that exist among pupils might affect ability attributions. For example, in our analyses we assessed whether the fact that i perceives j as a friend makes it more likely that i attributes abilities to j.

We argue that ability attributions in enduring groups potentially violate the assumption of statistical independence. ERG models allow us to control for non-independence by the inclusion of statistics representing structural variables, that exclusively model how observed attributions relate to each other. Table 5.7 illustrates the structural variables that we considered in this study and shows the substructures that they model. *Reciprocity* refers to the number of reciprocated

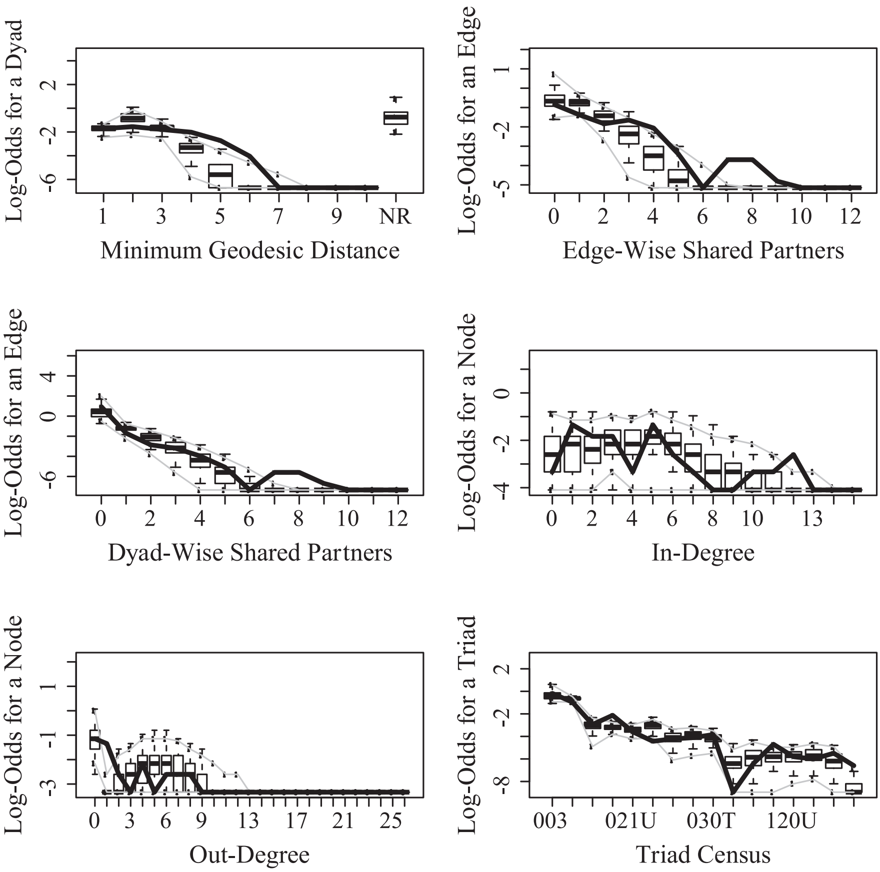


Figure 5.1 Example of goodness-of-fit assessment of ERG model in class 8. The bold black line represents observed statistics. The box plots represent the distribution of statistics obtained from simulated networks. The ticks on the x-axis of the panel that shows the triad census refer to the following triadic configurations from left to right: 003, 012, 102, 021D, 021U, 021C, 111D, 111U, 030T, 030C, 201, 120D, 120U, 120C, 210, 300.

attributions in a given class. A large positive parameter estimate for this statistic would mean that the observed attributions show a higher level of reciprocation than mere chance would imply. Similarly, *activity* and *popularity* are weighted counts of the number of attributions that class members made/received. A large positive parameter estimate for *activity* would mean a tendency for centralization in attributions so that some pupils seem more inclined to make attributions than others; a large positive parameter estimate for *popularity* would mean that some pupils receive more attributions than others, after controlling for all other covariates, which points to the possible effect of reputations. Negative estimates for these parameters imply that the distribution of attributions made and received tend to be similar across actors, controlling for all other variables in the model. *Arc* simply counts the number of attributions in the network and needs to be included as an intercept when estimating Eq. (5.1).

The estimation of ERG models relies on Markov chain Monte Carlo (MCMC) simulation

Distance	Obs.	Min.	Mean	Max.	MC p-value	Sig.
1	124	7	123.94	173	0.94	
2	142	1	248.05	423	0.14	
3	116	0	132.59	233	0.56	
4	95	0	29.02	64	0.00	**
5	50	0	4.91	25	0.00	**
6	14	0	0.80	16	0.02	*
7	1	0	0.18	7	0.08	
8	0	0	0.03	3	1.00	
9	0	0	0.01	1	1.00	
Inf	270	28	272.47	804	0.92	

Table 5.8 Goodness-of-fit assessment of ERG for class 8: model minimum geodesic distance. Two-tailed significance levels: ** $p \leq .01$, * $p \leq .05$.

Partners	Obs.	Min.	Mean	Max.	MC p-value	Sig.
0	37	6	41.01	56	0.62	
1	25	1	39.78	60	0.12	
2	17	0	24.65	48	0.58	
3	20	0	11.98	37	0.34	
4	14	0	4.53	14	0.06	
5	4	0	1.44	8	0.20	
6	0	0	0.43	4	1.00	
7	3	0	0.10	1	0.00	**
8	3	0	0.02	1	0.00	**
9	1	0	0.00	0	0.00	**

Table 5.9 Goodness-of-fit assessment of ERG for class 8: edge-wise shared partner. Two-tailed significance levels: ** $p \leq .01$, * $p \leq .05$.

methods, in which ties are randomly added or removed from a simulated graph with N actors. The goal of this simulation process is to find a parameter combination that is most likely to generate a network that is similar to the observed network. This approach thus provides maximum likelihood estimates of parameter values. In our analyses, we conducted the MCMC simulations with the R-package `statnet` (Handcock, Hunter, Butts, Goodreau, & Morris, 2008). We selected a burn-in of 100,000 and a sample size of 10,000 with an interval of 5,000; we repeated the MCMC algorithm up to 50 runs, each time using the parameter estimates obtained from the previous run as starting values, or until the estimation process had converged. In `statnet`, the structural variables *activity* and *popularity* are implemented as geometrically weighted out-degree (GWO) and geometrically weighted in-degree (GWI), which are subject to the weighting parameters α_{out} and α_{in} (see Table 5.7). Based on systematic exploration of different parameterizations, we selected the values $\alpha_{out} = .095$ and $\alpha_{in} = .693$.

Hunter, Goodreau, and Handcock (2008) proposed to assess the goodness-of-fit of an ERG model by simulating a large number of networks based on the estimated parameters and

Partners	Obs.	Min.	Mean	Max.	MC p-value	Sig.
0	583	262	481.02	810	0.32	
1	126	2	184.35	283	0.14	
2	44	0	91.10	181	0.26	
3	32	0	38.37	87	0.96	
4	15	0	12.43	44	0.74	
5	5	0	3.62	18	0.60	
6	0	0	0.87	7	1.00	
7	3	0	0.19	2	0.00	**
8	3	0	0.03	1	0.00	**
9	1	0	0.02	1	0.04	*

Table 5.10 Goodness-of-fit assessment of ERG for class 8: dyad-wise shared partner. Two-tailed significance levels: ** $p \leq .01$, * $p \leq .05$.

In-degree	Obs.	Min.	Mean	Max.	MC p-value	Sig.
0	1	0	3.05	24	0.64	
1	6	0	2.70	9	0.18	
2	4	0	2.91	9	0.72	
3	4	0	3.59	8	0.96	
4	1	0	3.55	8	0.30	
5	6	0	3.82	10	0.34	
6	2	0	3.33	9	0.74	
7	1	0	2.25	8	0.76	
8	0	0	1.43	6	0.52	
9	0	0	0.93	4	0.84	
10	1	0	0.65	3	0.90	
11	1	0	0.44	2	0.72	
12	2	0	0.18	2	0.02	*
13	0	0	0.11	1	1.00	
14	0	0	0.03	1	1.00	
15	0	0	0.02	1	1.00	
16	0	0	0.01	1	1.00	

Table 5.11 Goodness-of-fit assessment of ERG for class 8: in-degree. Two-tailed significance levels: ** $p \leq .01$, * $p \leq .05$.

comparing the average network statistics that these networks provide against the observed statistics. We employed this approach here and simulated for each class in which the MCMC algorithm had converged 100 networks based on the estimated parameters. For these networks, we compared the distribution of the following statistics against the observed data:

(1) Minimum geodesic distance = the distribution of the minimal number of directed attribution steps that (indirectly) connect each dyad of pupils in the class.

(2) Edge-wise shared partners = the distribution of the number of instances in which a pupil i attributed abilities to j and k, while j attributed abilities to k.

Out-degree	Obs.	Min.	Mean	Max.	MC p-value	Sig.
0	7	1	7.44	26	1.00	
1	6	0	0.73	2	0.00	**
2	2	0	1.31	5	0.70	
3	1	0	2.26	6	0.64	
4	3	0	2.86	8	1.00	
5	1	0	3.27	9	0.34	
6	2	0	3.23	9	0.70	
7	2	0	2.58	7	1.00	
8	2	0	2.40	6	1.00	
9	1	0	1.41	5	1.00	
10	0	0	0.71	4	1.00	
11	0	0	0.34	4	1.00	
12	0	0	0.28	2	1.00	
13	0	0	0.09	1	1.00	
14	0	0	0.05	1	1.00	
15	0	0	0.02	1	1.00	
16	0	0	0.02	1	1.00	
20	1	0	0.00	0	0.00	**
23	1	0	0.00	0	0.00	**

Table 5.12 Goodness-of-fit assessment of ERG for class 8: out-degree. Two-tailed significance levels: ** $p \leq .01$, * $p \leq .05$.

Triad type	Obs.	Min.	Mean	Max.	MC p-value	Sig.
003	1659	928	1528.06	3474	0.60	
012	1014	172	1246.54	1452	0.08	
102	183	0	175.47	324	0.88	
021D	389	4	143.32	234	0.00	**
021U	98	2	117.73	198	0.58	
021C	43	1	174.54	333	0.04	*
111D	53	0	63.59	125	0.88	
111U	59	0	77.01	153	0.52	
030T	77	1	58.07	132	0.48	
030C	0	0	7.78	35	0.08	
201	6	0	12.99	48	0.64	
120D	33	0	11.75	29	0.00	**
120U	11	0	12.64	32	0.92	
120C	9	0	14.50	36	0.60	
210	15	0	9.21	30	0.46	
300	5	0	0.80	9	0.04	*

Table 5.13 Goodness-of-fit assessment of ERG for class 8: triad census. Two-tailed significance levels: ** $p \leq .01$, * $p \leq .05$.

(3) Dyad-wise shared partners = the distribution of the number of instances in which a

pupil i attributed abilities to j and k, while j did not attribute abilities to k.

(4) In-degree = the distribution of the number of attributions received across class members.

(5) Out-degree = the distribution of the number of attributions made across class members.

(6) Triad census = the distributions of 16 different triadic configurations (i.e. patterns of attributions among three pupils); see Davis and Leinhardt (1972) for a detailed discussion of these configurations.

Figure 5.1 visually illustrates such a goodness-of-fit assessment for one class (without variables related to ethnicity) in the sample and Tables 5.8 to 5.13 show formal tests of the fit between the respective network statistic in the simulated networks and the observed network. A significant deviation means here that a given graph property is observed less or more often in the simulated networks that in the observed network. As Robins and Lusher (2013, p. 185) highlighted, an ERG model should not be expected to "fit all features of a network, just as we do not expect a regression to explain 100% of the variance", and this is particularly the case if we want to fit the same model to several networks that all have their own idiosyncrasies. Yet, a model should fit the network aspects of interest reasonably well. To illustrate this, consider in-degree and out-degree distributions, which our model addressed with the GWI and GWO parameters. Figure 5.1 and tables 5.11 and 5.12 suggest that the model captures the observed distributions well, although the simulated distribution occasionally deviates significantly from single observed statistics. For example, the model captures the in-degree distribution generally well, but it significantly underestimates the number of cases with in-degree 12 in class 8. If we would focus on only one network, we might try to adjust the model to account for this. However, if there are multiple networks, this might come at the loss of generalizability if this means that different models need to be estimated for different classes. Turning next to network statistics that were not in the focus of the analysis, the model does a good job in capturing, for example, the distribution of different triads, although the model did not include parameters that focused on triads. Together, these results suggest that the model generates networks that capture the trends across classes well, even though the model cannot capture all idiosyncrasies of all classes.

Finally, Snijders and Baerveldt (2003) suggested that the parameters obtained from applying social network models to different school classes can be treated as different case studies, which can be analyzed with standard meta-analytic procedures. In line with this, we calculated the following measures (see Snijders & Baerveldt 2003 for details; note that C refers to the number of classes in the sample):

(1) $T^2_{\theta,p}$ enables us to assess whether all estimates for a given parameter are 0 in the population of classes. The statistic follows a chi-squared distribution with C degrees of freedom.

(2) $\hat{\mu}^{WLS}_{\theta,p}$ and $\text{s.e.}\left(\hat{\mu}^{WLS}_{\theta,p}\right)$ enable us to assess whether a given variable has a significant effect on ability attributions across the sample of classes. These statistics refer to the weighted least square estimates of the average parameter estimates ($\hat{\mu}^{WLS}_{\theta,p}$) and their standard errors in the population of classes ($\text{s.e.}\left(\hat{\mu}^{WLS}_{\theta,p}\right)$). They can be used to

calculate a t-ratio that approximately follows a standard normal distribution that can be used to assess the statistical significance of a parameter estimate across classes.

(3) $\hat{\sigma}^2_{\theta,p}$ enables us to assess whether in the estimate of a given parameter varies across classes. The associated Q_p statistic, which has a chi-squared distribution with $C - 1$ degrees of freedom, makes it possible assess the significance of $\hat{\sigma}^2_{\theta,p}$.