Interpersonal Status Systems.

An Inquiry into Social Networks and Status Dynamics in Schools, Science, and Hollywood

Inauguraldissertation
zur Erlangung des Doktorgrades
der Wirtschafts- und
Sozialwissenschaftlichen Fakultät
Der Universität zu Köln

2022

presented by Mark Wittek
from Kiel

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Dissertation defended on 17.10.2022

Acknowledgments

Becoming a sociologist taught me that persons would cease to exist without their social environment and that almost all characteristics, actions, and perceptions we think of as genuine to ourselves can be understood by considering the social processes we are embedded in. Consequently, I am deeply grateful for all the good time, love, music, advice, support, and fun my personal social network offered me during the last four years.

First and foremost, I thank my advisor Clemens Kroneberg. I met Clemens ten years ago in an undergraduate course and continue to learn from every exchange we have. Without his extensive feedback, broad horizon, analytical rigor, and his encouragement for unorthodox intellectual projects, this thesis would not have been possible. I could not have wished for a better mentor. In addition, I thank Hanno Kruse for being an academic older brother to me by helping with R scripts, providing feedback on paper drafts, and easing the psychological strains that are unavoidable in the publication business.

Second, I thank my colleagues from the ERC project SOCIALBOND, Agnes Tarnowski, Sven Lenkewitz, Andrea Wingen, Heike Krüger, and Kathrin Lämmermann, for the great teamwork, countless canteen lunches, the relaxed workspace atmosphere, and their advice and companionship. Moreover, I benefited greatly from the institutional environment of the Institute of Sociology and Social Psychology in Cologne (ISS), first as a student and later as a researcher. I learned the craft of empirical social science from Marita Jacob, Michael Kühhirt, Judith Offerhaus, Merlin Schaeffer, and Sarah Carol by visiting their courses and being their student assistant. In addition, I am thankful for the friendly and intellectually stimulating exchanges with numerous researchers and students at the institute, in particular with André Ernst, Maria Gerth, Harald Beier, Stephan Dochow-Sondershaus, Shannon Taflinger, and Susanne Böller. Moreover, the seminar series organized by Clemens Kroneberg allowed me to receive crucial feedback on my dissertation from various outstanding scholars whom I would like to thank, among them Tom Snijders, Stephen Vaisey, Achim Edelmann, and Mario Small. Also, I thank Richard Benton for reading and commenting a draft for Chapter 3, Jennifer Lena for her feedback on a version of Chapter 4, and Lea Ellwardt for her comments and suggestion regarding Chapter 1.

Third, I thank my coauthors, Frank Berthold and Christoph Bartenhagen, for their engagement and their willingness to cross disciplinary boundaries. Also, I thank my coauthors, Katharina Burgdorf and Xinwei Xu, for all the beautiful discussions, reading circle exchanges, joint work, and friendship. In addition, I thank Raphael Heiberger and Olliver Wieczorek for offering me the opportunity to engage in collaborative work with them. Last but not least, I thank Sven Lenkewitz for being both a great colleague and coauthor, for his patience, disciplined work, and support.

Fourth, I thank my friends who enrich my life in various regards. I thank Jan-Frieder Harmsen for being my oldest friend, as we have known each other since 10^{th} grade. Without Jan, I would not have moved to Cologne. Also, he taught me many things about sport and continues to be a source of support and advice. I thank Raphael Röchter and Philipp Sieg for making music together, discussing Thomas Metzinger’s writings, eating pizza at Golfo di Napoli, and joking around after rehearsals. I thank Franca Ehrlinspiel, Marina Plugge, and Anna-Lu Rausch for our conversations and the willingness to maintain our friendships despite our lack of shared foci of interaction. I thank Tim Burberg and Silvan Geara for being the best flatmates I ever had, their good humor, and the wonderful time we spent together. A special thanks goes to Jonas Wiedner for our fierce discussions, which broadened my perspective on social science and helped me challenge and re-evaluate my positions on the role of theory for empirical sociology. Also, I thank Jonas for his friendship, our vacations, and for picking up my Prophet-08 synthesizer in Berlin.

Fifth, I thank my partner Luisa Meyer for her love, loyalty, and support. Luisa listened patiently to lengthy monologues on sociological theory and network models and supported me

in periods of intense self-doubt. Having her at my side is contributing significantly to my well-being and helped me to get through the more challenging phases of my PhD.

Finally, I would like to thank my parents, Margarete and Ditmar Wittek, for their loving upbringing and their hard work that provided me with the necessary education and resources to pursue tertiary education. Also, I thank my sister Julia Wittek for being a great companion and for all the funny and serious moments we shared.

Contents

Chapter 1

Introduction

1.1 Status and networks

As soon as persons are embedded in a context for regular interaction—e.g., by sharing the same school, university, workplace, or field of activity in music, art, or science—they develop reputations which gain a mysterious life of their own. Children who repeatedly meet on a playground (see the first pages of White's (1992) *Identity and Control*), students who see each other during schooling hours (Coleman 1961), scientists who attend conferences and workshops (Blau 1994; Bourdieu 1988; Merton 1968), captives in the same prison (Kreager et al. 2017), or musicians who socialize after concerts (Berliner 2009; Faulkner 1983; Faulkner and Becker 2009)—in all of these different domains persons tend to form vertical orders based on reputations. Some students are perceived as cooler than others and remembered by their peers many years after they have left school. A small number of artists and musicians are celebrated as geniuses, while the majority never gains recognition beyond a small circle of friends and collaborators.

Thereby, status systems are crucial for individual life outcomes, and understanding them can inform the political discourse on how societies should organize the distribution of recognition and prestige. In the school setting, status processes among students foster a range of detrimental behaviors such as bullying (Adler and Adler 1998; Faris 2012; Faris and Felmlee 2014; van der Ploeg, Steglich, and Veenstra 2019), delinquency (Kreager, Rulison, and Moody 2011; Snijders and Baerveldt 2003), and substance abuse (Ennett et al. 2006; Moody et al. 2011). In scientific fields, a scholar's renown among her academic peers affects her chances to acquire funding, a tenured position, and collaborations with other high-status scientists (Blau 1994; Bourdieu 1988; Lamont 2009; Ma et al. 2020; Merton 1968). Consequently, the increasing pressure to build and maintain a good reputation, e.g., by producing a vast body of visible publications, can decrease the scope and quality of academic work, which is undesirable for societies and academic communities alike (Münch 2014). These examples illustrate that studying the contextual conditions for status processes can inform debates on whether and how political actors should regulate contests for status.[1]

Due to the universality and importance of status processes, social scientists have researched extensively how status affects individuals and how status systems emerge in the first place (Fiske 2011; Frank 1985; Gould 2002, 2003; Merton 1968; Podolny 2010; Ridgeway 1991; Sauder, Lynn, and Podolny 2012). Status theories have been used to explain a broad range of social phenomena, such as the influence of status characteristics on interactions in task-oriented groups (Ridgeway 1991), peer relations in schools and universities (Cillessen and Rose 2005; Faris and Felmlee 2014; Moody et al. 2011; Torlò and Lomi 2017), or strategic behavior in markets and organizational fields (see Sauder, Lynn, and Podolny 2012).

The widespread usage of status as a conceptual lens in different fields of literature resulted in the lack of a unified definition of status (Bothner, Godart, and Lee 2010; Martin 2009a; Martin and Murphy 2020; Sauder et al. 2012). Some scholars see status as the distribution of psychological deference among actors (Gould 2002; Lynn, Podolny, and Tao 2009; Manzo and Baldassarri 2014), while others stress the importance of antagonistic encounters producing dominance hierarchies in small groups (Chase 1980; Davis 1970; Fararo and Skvoretz 1986; Mazur 1985), or entire societies (Sidanius and Pratto 2001). Yet another strand of literature focuses on status as popularity or social standing and investigates whether the actions of persons can be explained by their strive for status (Faris and Felmlee 2014; Rodkin et al. 2013; Sijtsema et al. 2009).

This diversity of definitions and explanatory approaches has been intellectually stimulating for different research fields in the social sciences and has led to a specialized investigation of

[1] I discuss potential policy implications of my findings at the end of each empirical application and in the concluding chapter.

status processes in various domains.[2] While these specialized inquiries are important to understand how status works in a particular domain, one can also argue that a lack of conceptual unity has fostered a fragmentation of the research landscape. Thereby, similarities across different empirical domains remain under-investigated, hindering the construction of a general theory of status processes. An integrative perspective on status is desirable, because as Roger V. Gould highlighted: the ubiquity of status systems probably points to a set of underlying organizing principles—such as self-reinforcing dynamics and peer influences in evaluating others—that lead to the emergence of status systems in various domains (Gould 2002: 1143). Gould proposed a general formal theory of status dynamics and applied his framework to empirical networks among university students (Newcomb 1961), toddlers (Blatz 1937), and members of task-oriented groups (Bales 1970). Some followed in Gould's footsteps and extended his formal model (Lynn et al. 2009; Manzo and Baldassarri 2014), but the idea to compare status systems across different contexts or empirical domains was seldom explored further by contemporary scholars (for an exception, see McMahan 2017). This is problematic since a growing branch of literature calls for a contextualization of relational processes—such as networks of intimate relationships or professional collaboration, but also ties of aversion, conflict, or exchange—in order to better understand how social order arises (Fuhse and Gondal 2022; Martin 2009b; McFarland et al. 2014; Mohr et al. 2020).

[2] Including the school setting (Faris and Felmlee 2014; Kornbluh and Neal 2016; Moody et al. 2011), workplaces (Carnabuci, Emery, and Brinberg 2018; Dong et al. 2015; Kilduff and Krackhardt 2008; Lazega 2001; Lazega et al. 2012), task-oriented groups (Ridgeway 2019; Skvoretz and Fararo 1996), scientific fields (Blau 1994; Burris 2004; Gondal 2018; Han 2003; Ma et al. 2020; Petersen et al. 2014), and organizational fields (Bothner, Kim, and Smith 2012; Bothner, Stuart, and White 2004; Chen et al. 2012; Podolny 2010; Sauder, Lynn, and Podolny 2012).

I will address this research gap and investigate how status recognition affects stratification and segregation in social networks among persons in three different empirical domains.[3] I use a variety of network-analytical tools (An 2015; Duxbury 2021; Lusher, Koskinen, and Robins 2013; Snijders, van de Bunt, and Steglich 2010; Snijders and Steglich 2015) to investigate which contextual characteristics—such as size, demographic compositions, and maturity—foster the emergence of a highly-visible and socially-closed elite of actors. In particular, I investigate how status molds the structure of friendship networks in schools, coauthor networks in the scientific field of neuroblastoma research, and collaborative networks among Hollywood filmmakers. These three domains vary in the average age of participants, the type of networks forming within them, and the institutional environments surrounding them. Differences between domains allow for fruitful analytical contrasts. For instance, I will highlight that the structure of personal networks—such as friendship networks in school—reacts differently to status in comparison to networks of professional collaboration in scientific and artistic fields. Moreover, studying the historical trajectories of neuroblastoma research together with collaborators Frank Berthold and Christoph Bartenhagen and Hollywood filmmaking with my coauthor Katharina Burgdorf allows me to investigate how the same context changes its social organization in the long run. This approach is complemented by my investigation of over 300 school classes and 60 grade levels which enables me to study variation of the status-network nexus between contexts. Furthermore, the domains under study are researched by long

[3] Leaving aside status differences connected to group memberships such as gender, race, or ethnicity (Ridgeway 1991, 2019; Ridgeway and Correll 2006; Tilly 1998), status orders among organizations (Espeland and Sauder 2007; Podolny 2010; Sauder et al. 2012), or the ascription of status to cultural products such as records (Askin and Mauskapf 2017; Dowd et al. 2002; Lynn, Walker, and Peterson 2016) might seem like an unnecessary narrowing of the scope of my investigation. Yet, as Martin (2011) points out, groups and organizations are social objects made up of complex bundles of relations among persons, confronting analysts with significant theoretical and methodological difficulties, especially when the goal is to compare processes across different domains. In contrast, it is easier to gather data on persons, and social scientists show a greater consensus on what a person is.

traditions of scholarly work that utilized the school setting (Adler and Adler 1998; Coleman 1961; Faris and Felmlee 2014; McFarland et al. 2014; Milner 2013; Smith and Faris 2015), scientific fields (Bourdieu 1988; Gondal 2018; Ma et al. 2020; Merton 1968; Mullins 1972), and cultural fields (Askin and Mauskapf 2017; Bourdieu 1993; Cattani and Ferriani 2008; Lena and Pachucki 2013; Pachucki 2012) as strategic research sites to study status. I hope that my comparative analysis of different domains illustrates how these streams can inform each other. I will discuss potential avenues for future research in chapter 5.

In contrast to the usage of status as a conceptual lens in economics (Frank 1985) or psychology (Anderson, Hildreth, and Howland 2015), the theoretical considerations presented here shift attention away from individuals—their motives, desires, behaviors, and characteristics—to the self-organizing properties of social systems. Seeing status as something that is awarded by others rather than achieved by individuals allows me to mobilize the analytical strength of sociological accounts devoted to the question of how social order arises from a concatenation of encounters between members of a local context or larger community (Bearman 1993; Bourdieu 2013; Collins 2004; Gould 2002; Hedström, Bearman, and Bearman 2009; Martin 2009b; White 2008). In particular, the focus on interpersonal processes embeds my account in a tradition of relational theories of social status (Berger, Cohen, and Zelditch 1972; Chase 1980; Fararo and Skvoretz 1986; Gould 2002; Homans 1950; Martin 2009a; Mazur 1985; McMahan 2017; Podolny 2010; Ridgeway 1991; Whyte 2012 [1943]). Proponents of these theories understand status orders as "a process emerging from sequences of individual acts of deference possibly characterized by complex self-organizing properties" (Torlò and Lomi 2017: 30). Based on this notion, an similarity of different relational approaches to status is that they infer the presence of status orders from patterns in observed relational behavior (Borkenhagen and Martin 2018; Burris 2004; Dong et al. 2015; Martin 2009a; McMahan 2017; Ridgeway and Erickson 2000), the display of publicly visible status signals (Podolny 2010;

Rossman, Esparza, and Bonacich 2010), or the structure of social networks (Ball and Newman 2013; Lazega et al. 2012; McFarland et al. 2014; Torlò and Lomi 2017).

I follow these accounts and investigate how status orders and social networks co-evolve in different domains and contexts. While it would be interesting to compare how other forms of relational processes such as conversations (Gibson 2005; Iosub et al. 2014; McFarland, Jurafsky, and Rawlings 2013; McMahan 2017), acts of physical aggression (Martin 2009a), or subtle bodily cues (Hall, Coats, and LeBeau 2005) are structured by underlying status processes in different domains, concentrating on social networks constituted of relationships among persons offers several analytical benefits.

First, network-analytical tools are tailored to study relational information (Wasserman and Faust 1994). While regression techniques confine analysts to correlate characteristics of individuals and assume independence between observations (Angrist and Pischke 2008), network models allow for explicit modeling of dependencies between actors (Lusher et al. 2013; Snijders 2011). Thereby, they provide a way to investigate whether networks exhibit local structural configurations indicative of status processes (Gondal 2018; McFarland et al. 2014; Torlò and Lomi 2017).

Second, drawing upon the network literature facilitates a comparative view on network processes (Barabási and Albert 1999; Faust 2007; Goodreau, Kitts, and Morris 2009; McFarland et al. 2014; Moody 2001). Network theories are well suited to guide efforts that explore how contextual characteristics mold social networks (Fuhse and Gondal 2022; Martin 2009b; McFarland et al. 2014; White 2008), and recent advancements in network analysis allow analysts to study how the principles that organize networks vary between contexts and across the different stages of network development (Duxbury 2021; Lewis and Kaufman 2018; McFarland et al. 2014; Smith et al. 2016).

Third, social networks are of interest to many scholars who study the consequences of networks for individual outcomes such as academic achievements, educational aspirations, and decisions (Carbonaro and Workman 2016; Carolan 2018; Carolan and Lardier Jr 2018; Cherng, Calarco, and Kao 2013; Coleman 1961; DeLay, Zhang, et al. 2016; Raabe, Boda, and Stadtfeld 2019; Raabe and Wölfer 2018; Sinclair, Carlsson, and Bjorklund 2014), health behavior (Baggio, Luisier, and Vladescu 2017; Christakis and Fowler 2013; Daw, Margolis, and Verdery 2015; DeLay, Laursen, et al. 2016; Haas and Schaefer 2014; Quist et al. 2014; Rostila et al. 2013; Schaefer and Simpkins 2014), or labor market outcomes and career success (Lazega et al. 2006; Li, Liao, and Yen 2013; Li, Savage, and Warde 2008; Lin 2002; Lutter 2015). Furthermore, scholars investigate how network topology conditions segregation between societal groups and the spread of beliefs, attitudes, and lifestyles (DellaPosta, Shi, and Macy 2015; DiMaggio and Garip 2012; Macy and Flache 2009; McPherson, Smith-Lovin, and Cook 2001; Wimmer and Lewis 2010). Therefore, studying contextual antecedents for the emergence of socially-closed elites who hold a disproportional stock of network partners also informs research on the outcomes of networks. For example, understanding the formation of elites is relevant for studies interested in individual academic or labor market achievements because actors who are part of these elites have easier access to information and resources through numerous high-status network partners.

In summary, this thesis synthesizes previous literatures on social status into a framework that links interpersonal status processes to the structure of social networks and allows for a comparison of the status-network nexus across domains and contexts. Empirically, the theoretical framework is applied to three different domains: status systems among adolescents (Chapter 2), scientists (Chapter 3), and filmmakers (Chapter 4). The final chapter compares findings obtained for the different domains and outlines directions for further research (Chapter 5). In the next section, I discuss previous studies on social status and derive a taxonomy of different types of status.

1.2 Why do humans form vertical orders?

A straight-forward explanation for the reoccurring unequal distribution of attention, admiration and esteem is that elites contribute more to the needs of their communities than their peers and are therefore awarded with social status (Blau 1964). Another common explanation is that some individuals are simply better equipped with the necessary traits or more often show behaviors which allow them to fulfill the innate human desire for a high social status (e.g., Sijtsema et al. 2009). Following these arguments, we would expect that students who help others and are fun to hang out with, scientists who solve the hardest intellectual problems and musicians who make the most beautiful and interesting music naturally rise to the top of status orders.

Yet, empirically we find ample evidence for a decoupling of status from contributions to group goals or individual merit: popular students partially perpetuate their social standing by instrumental aggression and are more often disliked among peers than less popular students (Adler and Adler 1998; Eder 1995; Faris and Felmlee 2014; Fujimoto, Snijders, and Valente 2017). Many members of scientific elites embody an institutional conservatism that rewards convention and repetition more than innovation (Bourdieu 1988; Feyerabend 1993; Latour and Woolgar 1986). "Musical geniuses" are sometimes re-discovered after centuries of oblivion—for the classical composer Johann Sebastian Bach see, Wolff (2001)—or misrecognized by audiences, peers and critics alike in the first decades of their careers (for the jazz pianist and composer Thelonious Monk see, Kelley 2010).

These examples show that the actions and characteristics of individuals are not sufficient to explain how positions in a status system crystalize. Behind the back of actors—often quite literally by talking about others in their absence—a succession of situations coalesces into a social reality which permeates the relationships between persons and dictates who ought to be treated with respect and who can be ignored. To study how this shared understanding emerges and molds actors' social networks, I draw upon a rich tradition of network theories and research.

Traditional social network analysis tended to apply the same methods and theoretical considerations to diverse types of networks (Burt 2009; Granovetter 1973; White, Boorman, and Breiger 1976). However, during the last two decades, scholars started to pay more attention to the implications of relationships' content, such as expectations for behavior and cultural meanings attached to a particular type of relationship, for the structure of networks (Fuhse and Gondal 2022; Martin 2009b; Mohr et al. 2020; Small 2017; White 2008; Yeung 2005). An important insight of this literature is that different tie types exhibit different structural configurations in response to the same organizing principles.

For instance, the presence of ethnic and racial homophily—a preference to interact with others who belong to the same ethnic or racial group—is typically inferred from homogeneity according to group membership in close social relationships such as friendship (Bojanowski and Corten 2014; Kruse and Kroneberg 2019; Moody 2001; Mouw and Entwisle 2006; Smith et al. 2016; Wimmer and Lewis 2010). In particular, analysts often obtain measures for homophily by taking into account other aspects which organize networks, such as the opportunity structure for tie formation or endogenous network processes (Moody 2001; Smith et al. 2016; Wimmer and Lewis 2010). Recent research complements this approach by studying how multiple types of ties are affected by ethnic homophily (Boda and Néray 2015; Kisfalusi, Pál, and Boda 2018). In a study about the role of ethnic group membership for negative ties, my coauthors and I reported that friendship and violence relationships among adolescents exhibit structures indicative of ethnic homophily, while antipathy flows more often between members of different ethnic groups (Wittek, Kroneberg, and Lämmermann 2020). This suggests that ethnic group membership carries different implications for the structure of networks depending on the tie type under study and its properties. These results only make sense if we acknowledge that violence and friendship are both enacted during face-to-face contact and occur in close social circles, therefore they tend to form *within* ethnic groups. By contrast, antipathy is a relational cognition (Borgatti, Everett, and Johnson 2013) and traverses longer social distances *between* ethnic groups.

Here, I similarly argue that status molds networks conditional on the content of the relationship under study. The content of a relationship is constituted by actors' mutual expectations for behavior and whether a relationship is primarily enacted during actors' co-presence in physical space or relatively detached from face-to-face interaction. Next, I consider how different types of status should affect personal and professional social networks.

Affection

The first type of status I consider arises from feelings of affection and liking. Across a variety of domains, some members of a context are well-liked and perceived as attractive partners for social interaction. Others receive less positive attention or are even ostracized and bullied by their peers (Adler and Adler 1998; Huitsing and Veenstra 2012; Kilduff and Krackhardt 2008; Prinstein 2017).

In principle, affection should play a decisive role for relationships with a content that revolves around intimacy and strong mutual expectations for behavior such as friendships (Hays 1988; Kitts and Leal 2021) and romantic ties (Bearman, Moody, and Stovel 2004; McMillan, Kreager, and Veenstra 2022). Regarding the implications of affectionate status for the structure of networks, it seems plausible to expect inequality in the allocation of network ties—some actors attract many interaction partners while many actors have few interaction partners—because some persons are more likable than others. Yet, constraints on time, energy, and the expectations of interaction partners that personal relationships are based on equality (Gould 2003) should mitigate inequality that could arise from affectionate status (see Gould 2002; Martin and Murphy 2020).

Concerning professional networks, affection influences relational processes in organizations (Ellwardt, Steglich, and Wittek 2012; Kilduff and Krackhardt 2008; Lazega 2001), but the role of affection for collaborations in broader organizational or cultural fields is rarely considered. This is probably the case because other forms of status have a higher relevance for collaborations crossing organizational boundaries (see e.g., Ma et al. 2020 for the role of *organizational status* for scientific collaboration) and that structural prerequisites such as the distribution of resources among institutions are more important for the structure of professional networks than feelings of inter-personal affection (Blau 1994; Knorr 1999; Latour and Woolgar 1986; Lazega et al. 2006; Mullins 1972).

In addition, endogenous network processes such as the tendency to form relationships with others who are close in social and physical space, and to choose similar others as interaction partners should counteract inequality arising from affection. For instance, friendships form in foci for interaction such as classrooms, and exhibit homogeneity along various dimensions (Feld 1981; Goodreau et al. 2009; McPherson et al. 2001; Moody 2001; Smith et al. 2016; Vörös, Block, and Boda 2019). Likewise, collaborations among scientists cluster within departments and national contexts, exhibit transitive closure, and same-gender collaborations are more prevalent than cross-gender collaborations (Dahlander and McFarland 2013; Ferligoj et al. 2015; Kronegger et al. 2012; Moody 2004; Stark, Rambaran, and McFarland 2020). Thereby, actors cannot always establish a relationship to others they like, because the liked person might be too distant in social space or she is not sharing the same group membership (e.g., gender or ethnicity), which makes it harder to form a tie.

In sum, I expect that affectionate status is not leading to networks marked by an unequal distribution of ties. While some inequality in the distribution of network partners might arise from an unequal distribution of affectionate status among members of a context, most of the potential for inequality inherent in affection should be buffered by the content of personal and professional ties and their endogenous network dynamics.

Popularity

Another type of status which should be treated as theoretically distinct from affection is popularity—although these types of status are often empirically associated (for the school setting see, e.g., Kornbluh and Neal 2016) and sometimes used interchangeably by researchers (Gest et al. 2007; Shi and Moody 2016). While others' feelings of affection and sympathy are constitutive of a person's affectionate status, her popularity is defined by how widely she is known. This type of status involves a higher degree of social construction as it requires that actors develop a public reputation—i.e., public images of persons can only arise when people talk about others who are distant in social space (Fine 2014). Therefore, popularity is probably the type of status closest to a folk sociological understanding of interpersonal status: students who are part of a highly-visible leading crowd (Adler and Adler 1998; Coleman 1961), esteemed artists in scenes or broader cultural fields (Bourdieu 1993; Lena 2012; Lena and Pachucki 2013), celebrities, and politicians (Fine 2014) are all examples of persons who acquired a high popularity-based inter-personal status above and beyond their organizational roles.

Face-to-face interactions are not necessary for this type of status as communication about absent others can carry reputations long distances through social space. This decoupling from local interaction allows for more inequality in the accumulation of popularity-based status and can translate into more inequality in the distribution of interaction partners if the type of relationship under study permits it (cf., Martin and Murphy 2020).

Professional ties should be prone to this type of status because they do not necessarily involve regular interactions between members of a collaboration dyad. Knorr's study of epistemic cultures illustrates that scientists sharing a collaboration often do not see each other for months or never meet in person (Knorr 1999). This considerable independence of professional networks from face-to-face interaction should allow for more inequality in the distribution of professional ties. Previous studies showed that citations and collaborations among scholars are distributed highly unequal (Eom and Fortunato 2011; Newman 2001a).

In contrast, personal relationships such as friendship and romantic ties depend much stronger on interaction in physical space and should not exhibit stark inequality in the allocation of ties in response to popularity (see Martin 2009b). Following a similar line of argumentation, Dunbar (1992, 1998, 2008) argued that the limited cognitive capacities of Homo Sapiens constrain the number and content of relationships actors can maintain.

Moreover, endogenous network dynamics of personal relationships, especially the tendency to reciprocate ties, should further hamper inequality—e.g., a student might aspire to be friends with popular students but eventually withdraws these efforts as the popular students do not react with positive attention (e.g., Adler and Adler 1998).

So far, I have discussed inequality in the distribution of network partners as a potential outcome of underlying status processes. In addition, popularity should also lead to *segregation* according to status differences in professional *and* personal ties. This should be the case because popularity provides a basis for the emergence of group identities (e.g., in the school setting: Coleman 1961; Eckert 1989; Logis et al. 2013). Thereby, discourse about a set of visible individuals can lead to strategic relationship choices based on the amount of popularity a person holds and salient boundaries between more or less popular groups within a context emerge (Adler and Adler 1998; Dijkstra, Cillessen, and Borch 2013; Ebbers and Wijnberg 2010; Ma et al. 2020; Rossier 2020). Students who form friendships with similarly popular others (Adler and Adler 1998; Eckert 1989; Eder 1995; Milner 2013), and circles of scientific elites policing their boundaries (Bourdieu 1988; Lamont 2009; Ma et al. 2020) are two examples for segregation in social networks according to the popularity-based status of interaction partners.

To summarize, popularity-based status should lead to inequality in networks if the type of relationship under study permits it—i.e., fewer constraints on the number of possible ties a person can maintain and less dependence on face-to-face interaction allow for higher levels of inequality. In addition, if more members of a context agree on a popularity ranking this can lead to increasing network segregation according to status even if inequality is hampered by constraints on actors' time and energy or endogenous network dynamics.

Dominance

Dominance is the third type of status I consider. Dominance-related behavior, such as workplace harassment (Bowling and Beehr 2006) and workplace aggression (Hershcovis et al. 2007), is prevalent in many domains. Actors holding powerful positions in organizations sometimes engage in psychological and physical aggression towards their subordinates, and aggressive behavior among co-workers is a widespread phenomenon (Schat, Frone, and Kelloway 2006; Hershcovis et al. 2007). Moreover, aggression is common among children and adolescents. It can take different forms, such as cyber victimization (Felmlee and Faris 2016), physical fights (Martin 2009a), gossip (Eder 1995), or bullying (Faris and Felmlee 2014; van der Ploeg, Steglich, and Veenstra 2019; Huitsing et al. 2012). However, I argue that acts of aggression are only under certain conditions organized into status orders. While dominance-related behavior can be frequent in a context, antagonistic encounters do not necessarily concatenate into a rank order with dominant actors at the top and dominated actors at the bottom (cf., Martin 2009b). This argument draws upon the literature concerned with dominance-based status orders and social networks, which I will review in the next section.

Early formal theorizing in the network tradition stressed that status orders result from a concatenation of antagonistic encounters in which one actor dominates another actor (Chase 1980; Fararo and Skvoretz 1986). In a theoretical ideal case, a hierarchy forms, organized as a perfectly transitive pecking order. As Martin (2009b) points out, dominance orders are based on dyadic antagonistic encounters—i.e., actors have to defer to one another in a way that is understood by everyone in a context, for instance, by losing in a public fight.

Furthermore, the idea that dominance orders can be uncovered by observing antagonistic encounters or deferential gestures was applied to study social networks by inferring status from asymmetries in liking relations or friendships (Davis 1970). Thereby, the analyst assumes that if an actor (A) likes another actor (B) less than B likes A, a status difference in favor of A is implicitly established. Furthermore, if an actor C is now less liked by B than she likes B, this induces a status difference in relation to C, resulting in an order with A at the top, B in the middle, and C at the bottom. Scholars incorporated the notion that asymmetric social relationships point to an underlying status order in their theoretical frameworks and empirical investigations (Gould 2002, 2003; Ball and Newman 2013; McFarland et al. 2014; McMahan 2017; for a critical review see Vörös et al. 2019).

I build on this scholarship by assuming that dominance leaves its mark on personal networks by inducing asymmetry and hierarchical structures, e.g., friendship nominations that are not reciprocated and linked into open triadic configurations (following McFarland et al. 2014). Also, I assume that the structural implications of dominance for personal networks will be mitigated by endogenous network processes. For instance, friendships show a strong tendency towards reciprocity, and triads are often closed among friends (Goodreau et al. 2009; Robins, Pattison, and Wang 2009; Wimmer and Lewis 2010). Furthermore, friendships and other close social relationships are usually based on the norm of equality (e.g., Gould 2003). Therefore, unreciprocated friendships are less common and less stable over time than reciprocal friendships (An and McConnell 2015; Ball and Newman 2013; Smith and Faris 2015). These tendencies should partially counteract the asymmetrical, open triads that theoretically follow from a dominance-based status ordering in personal networks.[4]

While status systems in some domains are partially based on dominance, I agree with Martin (2009b) that specific contextual conditions are necessary for a dominance-based status order. I

[4] Please note that other relational processes—such as acts of aggression (Martin 2009a) or the structure of discussion networks (McMahan 2017)—show different endogenous network tendencies and it is more likely that analysts find a higher prevalence of hierarchical structures in these types of ties.

share his assessment that dominance-based status orders are empirically rare. Dominance-based status systems only take shape if actors are "caged", i.e., they cannot avoid antagonistic encounters with other members of a context, have no other means to negotiate status, and no norms are in place which inhibit antagonistic behavior should. This should especially be the case for the networks of children and adolescents. Antagonistic behavior, such as physical or verbal fights, are constitutive of social groups in kindergartens and schools (Adler and Adler 1998; Eder 1995; Huitsing et al. 2012; Huitsing and Veenstra 2012; Kreager et al. 2011; Rodkin et al. 2013). Also, children and adolescents are often confined to the same limited physical space and cannot avoid antagonistic interactions with others in the same way adults usually can (Martin 2009b, 2009a).

Some workplace environments also cage actors and offer them only limited opportunities to escape from antagonistic encounters or negotiate status by other means than aggression. Also, dominance-related behaviors are widespread in workplace environments (Schat, Frone, and Kelloway 2006; Hershcovis et al. 2007; Bowling and Beehr 2006). Yet, I argue that these acts of aggression usually do not concatenate into a *status order* that determines actors' position in their field of expertise or their position in social networks. Status orders in the corporate world or academia are characterized by reputations that depend on visibility and status signals such as degrees from elite universities, employment in influential companies, or collaboration with already established actors. While displaying dominant behavior can help actors to gain status, antagonistic acts usually do not organize into a stable order which is visible to all members of a context in professional networks.

Table 1.1 provides an overview of the main types of status and their implications for the structure of personal and professional networks. In the next section, I discuss under which circumstances the role of status for network structure should be exacerbated.

Table 1.1 Summary of different types of status and their implication for network structure

Type of Status	*Primary mode for status construction*	*Structure of personal networks*	*Structure of professional networks*
Affection	Face-to-face contact, time spent together	Mild preferential attachment, potential inequality mitigated by relationship content and endogenous network processes	No implications because other types of status and resources are more important
Popularity	Communication about absent others	Mild preferential attachment and status homogeneity, inequality mitigated by relationship content and endogenous network processes	Strong preferential attachment and status homogeneity due to missing constraints on network structure, endogenous process should still counteract extreme inequality
Dominance	Concatenation of antagonistic encounters	Bounded asymmetry and hierarchy, mitigated by relationship content and endogenous network processes	No implications because other types of status and resources are more important

1.3 Contextual antecedents that amplify the status-network link

A recent stream of literature introduced the notion that networks change their structure according to contextual characteristics such as size, maturity, demographic composition, or cultural profile of a context (Goodreau et al. 2009; Lewis and Kaufman 2018; Martin 2009b; McFarland et al. 2014; Simpson 2019; Smith et al. 2016; White 2008). Thereby, the idea surfaced that contexts characterized by higher uncertainty lead to a higher importance of status processes for networks (Dahlander and McFarland 2013; Lynn 2014; McFarland et al. 2014; Podolny 2010). The notion that status recognition is a cognitive heuristic which reduces uncertainty and helps actors to navigate complex social environments is a basic assumption in several theories of social status (Fiske 2011; Lynn et al. 2009; Podolny 2001; Ridgeway 2019; Ridgeway and Erickson 2000). The role of uncertainty for networks also is considered by scholars who investigate the cognitive representation of close social ties and assert that humans rely on simplification in the management of their relationships (Brashears 2013; Brashears and Quintane 2015; Kilduff and Krackhardt 2008).[5] A commonality of these different strands of literature is that they assume a link between the limited cognitive capabilities of actors and the need to simplify a large amount of information in an uncertain environment (also see Dunbar 1992, 1998, 2008).

If uncertainty is high, actors have to process more information before they can adjust their behavior in interactions. Sorting others on a vertical dimension—i.e., by status recognition—is a helpful tool to cope with increased complexity; therefore, status should be more important for behavior in settings marked by elevated uncertainty (McFarland et al. 2014; Podolny 2010). Similarly, Ridgeway (1991) proposed that status recognition is a useful cognitive device to reduce uncertainty about how to behave correctly in face-to-face interactions of task groups. This claim is consistent with neuropsychological studies (Fiske 2011) and supported by evidence from social-psychological experiments (Ridgeway and Correll 2006; Ridgeway and Erickson 2000). In the realm of organizational fields, Podolny (2010) found supporting evidence for the notion that uncertainty amplifies status processes, e.g., by showing that the decoupling of quality and status is intensified for the trade of assets involving higher uncertainty in the investment-banking sector. Regarding personal relationships, McFarland et al. (2014) reported evidence for more rank-ordering in friendships among students in larger schools and in schools with more demographic heterogeneity in terms of racial and age composition. They

[5] For instance, research suggests that humans apply different compression heuristics—helpful cognitive schemes such as triadic closure and kinship labels—to store large amounts of relational information (Brashears 2013).

argued that these patterns are indicative of more pronounced status recognition due to elevated uncertainty and anonymity in larger schools.

Following this literature, I expect that status processes will be exacerbated by conditions of higher uncertainty. If actors navigate an environment marked by more uncertainty, status recognition should become more useful as a cognitive heuristic which reduces complexity. Hence, in line with network-ecological theory (McFarland et al. 2014), characteristics of a context affect which kind of behaviors and ties are selected, retained or dissolved among actors as they vary in fitness across settings and over time. The following sections will outline how the size of a context and other contextual characteristics should alter the link between status and network structure.

Size and uncertainty

The size of a social system has been considered as influential factor for many social processes in classical and contemporary sociological theory (Blau 1968, 1994; Mayhew 1973; Mayhew and Levinger 1976; Michels 1915; Simmel 1950). A recurring line of reasoning is that size increases the uncertainty encountered by members of a context because the interaction density among them decreases. Mayhew and Levinger (1976) offered a formalization of this argument and proposed that the limited capacity of humans to process information explains why the group size changes the frequency and quality of encounters. Similarly, Blau (1968, 1994) argued that larger organizations develop steeper hierarchies to cope with coordination problems induced by an increased size.

If a context consists of a small set of actors, it is feasible to monitor the actions of others in detail. In larger contexts it becomes harder, or even impossible, to keep track of what others are doing. To retain their capacity to navigate a context, actors have to apply filters to the relational information they receive. Therefore, I assume that status recognition is less relevant in small contexts, but guides behavior in larger contexts: status recognition helps actors to cope with the increasing complexity of the context linked to its increasing size.

McFarland et al. (2014) translated these theoretical considerations to the structure of networks and argued that larger schools should lead to greater uncertainty and anonymity among students with consequences for the structure of students' friendship networks. Connecting these arguments to the idea that uncertainty fuels status recognition, I expect that larger contexts will exhibit higher levels of uncertainty and therefore show intensified status processes in all domains. In addition, following the theoretical ideas developed above, I expect that personal and professional ties are affected differently by a larger context size depending on their content and endogenous network processes (see table 1.1). As size is a universal property of social systems, I formulate a proposition for all three domains under study.

Size-status proposition: Professional ties should show more pronounced preferential attachment in larger contexts. Personal ties should show more rank ordering in larger contexts. Both tie types should exhibit more status homogeneity in larger contexts.

Further contextual moderators for the status-network nexus

In addition to the size-status proposition, I will develop theoretical expectations for three further contextual moderators: demographic composition, maturity, and the institutional environment of a context.

Demographic composition

Previous literature highlighted the importance of the demographic composition of small groups, organizations, or entire societies for outcomes such as social cohesion, economic success, collective action, or the creation of group identities (Blau 1977; Blau and Schwartz 1984; McPherson 2004; Putnam 2007; Wimmer 2013). Far less work has been concerned with how, for instance, a context's ethnic or gender composition affects the interplay between status orders and networks. One of the few studies that considered the role of demographic composition for the status-network nexus by McFarland et al. (2014) proposed that settings showing high compositional heterogeneity should exhibit more uncertainty and, in turn, high importance of status recognition for network formation. Following researchers who study the link between ethnic diversity and social cohesion on the neighborhood level (Stolle, Soroka, and Johnston 2008), McFarland et al. (2014) argued that a heterogenous demographic composition, creates uncertain settings with more salient group boundaries and more rank-ordered social relationships (McFarland et al. 2014: 1092–1093).

In addition, I assume that if compositional heterogeneity fosters uncertainty, elevated uncertainty in heterogeneous contexts should have a genuine influence on the interplay between status and networks—above and beyond the salience of group boundaries. This should be the case because the heuristic usefulness of status recognition should lead to more relationships marked by status in uncertain contexts, as argued above. Furthermore, I add to the theoretical considerations put forward by McFarland et al. (2014) that higher uncertainty should not only increase rank-ordering but also should elevate status homogeneity in close ties (see table 1.1). To test these ideas, my investigation of the school setting will consider the demographic composition of classrooms and grade levels—i.e., ethnic heterogeneity and gender heterogeneity—as additional moderators for the emergence of status systems. The school setting is well suited as it offers rich contextual variation of demographic compositions.

Maturity

The second contextual moderator for the status-network nexus considered here is maturity, i.e., the age of a context. As social systems unfold, actors' reputations and identities are fuzzy at the outset but crystallize over time (cf., White 1992, 2008). In the case of status orders, novel contexts are often marked by the absence of a clear-cut order as actors have not yet negotiated how status should be ascribed. This phenomenon can be found in new task-oriented groups (Ridgeway 2019), the first months of a classroom (Smith and Faris 2015), or at the beginning of a summer camp (Martin 2009a). Analysts usually report that status ambiguity quickly resolves into an order with a relatively stable structure. In contrast, theoretical accounts concerned with fields of cultural production, such as scientific fields or artistic fields, highlight that it can take longer periods of ambiguity before status orders evolve, and that the traits according to which actors ascribe status can be contested during transformations of a field (Crane 1972; Mullins 1972; Mullins et al. 1977; Espeland and Sauder 2007; Dubois 2018; Bourdieu 1993). Building on this dynamic and relational perspective on fields of cultural production, I argue that status processes will show an elevated importance for professional networks as fields mature. In chapters 3 and 4, I develop two main arguments for this theoretical expectation.

First, actors in novel fields often lack the resources to attract a large number of collaboration partners. For instance, actors in scientific fields gain and perpetuate their position by offsetting "accumulation cycles" (Latour 1987): by successfully applying for funding, scientists can offer PhD students and postdoctoral researchers positions which in turn generate collaboration partners and publications necessary to apply for more funding (Mullins, 1972; Alberts et al., 2014; Laudel, 2006). A new field of scientific inquiry often faces severe resistance by peers and institutions alike. Fellow scientists are reluctant to accept new ideas and funding agencies seldom finance high-risk endeavors (Bourdieu, 1988; Latour 1987; Frickel and Gross, 2005). Consequently, a field has to gain legitimacy before more resources become available and before some field participants can attain an elite position by attracting disproportional shares of resources and collaboration partners.

Second, a consensus regarding which actions and properties of persons should be rewarded with status has to evolve before a status order can solidify and structure social networks. Only when a canon of authoritative works has formed, can actors start to build their reputations by imitating consecrated cultural products (Bourdieu 1993; Becker 2008). In new musical genres little consensus exists on which musical elements should be included in the genre before a canon of highly praised musicians evolves whose styles are imitated (Lena 2012; Lena and Pachucki 2013; Philips 2013). Likewise, new scientific specialties lack a consensus on which methods should be used and how phenomena should be described (Latour 1987, Latour and Woolgar 1986; Griffith and Mullins 1972; Koppman and Leahey 2016). Thereby, the rules of the game are not fully defined at the outset of fields which should make it harder for actors to attain an elite status. The role of maturity for the status-network nexus will be investigated for the case of neuroblastoma research (chapter 3) and Hollywood filmmaking (chapter 4) as these domains offer information on long-term changes in networks' structure.

Institutional environments

Whereas size and maturity are generic properties of all domains, institutional environments genuine to particular domains should also shape the status-network nexus. As pointed out by Bourdieu (1993; 1988), the distribution of power across institutions—for instance, a concentration of power in elite institutions such as the École normale supérieure de Paris in French academia—determines which positions actors can attain in a field of cultural production and shapes the ascription of status among field participants. I argue that if institutional ecologies change, e.g., by new institutions entering the field, this can alter the link between status recognition and social networks on an interpersonal level. In particular, changes in the institutional environment should influence the set of traits and behaviors that are rewarded with status.

In our investigation of filmmakers' collaborations, my coauthor Katharina Burgdorf and I highlight the role of the New Hollywood movement (1960-1985) which promoted a novel style of artistic filmmaking (Baumann 2007). Similar to other cultural and organizational fields (Dubois 2018; Espeland and Sauder 2007; Evans 2008; Kuhn 1970; Moody 2004; Munoz-Najar

Galvez, Heiberger, and McFarland 2019; Padgett and Powell 2012; Powell et al. 2005; White and White 1993), Hollywood was marked by periods of stability but also by profound transformations (Baumann 2007; Biskind 1999; King 2002). We argue that filmmakers, critics, and institutions such as film schools changed the way status was ascribed and fostered an artistic status order mirrored in filmmakers' references.

In summary, the following chapters will apply the proposed theoretical framework to three domains and test different aspects of the framework. The school setting allows me to investigate contextual variation in the role of status processes for networks and to derive measures for all three types of status (affection, popularity, and dominance). In contrast, collaborations in the scientific field of neuroblastoma research and among Hollywood filmmakers should be primarily affected by popularity-based status. The focus in these domains will lie on long-term changes that are not observable in the school setting since classrooms and grade levels dissolve after a few years.

While the empirical applications will delve deeper into the particularities of each domain, chapter 5 will return to the general considerations presented here. Thereby, I will arrive at a comparative perspective and identify directions for future investigations as well as potential implications for political actors.

Chapter 2

Towards a multiplex ecology of status orders. A theoretical framework and empirical application in the school setting*

* This work has been supported by funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No 716461). I use data from the study 'Friendship and Violence in Adolescence,' funded by the German Research Foundation (DFG), Grant KR 4040/2. I would like to thank Clemens Kroneberg, Hanno Kruse, Steve Vaisey, Achim Edelmann, and Tom Snijders for valuable comments on this work. Earlier versions were presented at the Networks, Culture, and Action workshop at the University of Cologne, in September 2018. I thank the various participants for their helpful feedback.

Abstract

Previous research on status relied on the assumption that close relationships organize into hierarchical status orders irrespective of contexts' characteristics. While recent scholarship has challenged the long-held assumption that status dynamics operate similarly across contexts, scholars continue to infer the presence of status orders from the structure of close relationships. This chapter highlights the theoretical difference between status ascriptions and close relationships and proposes that contextual variation in status orders can only be understood by studying both tie types simultaneously. I demonstrate the merit of this multiplex ecological perspective by applying network-analytical methods to three data sets on friendship and status ascription networks of more than 23,000 students. The results demonstrate that the structure of close relationships by itself is not reflecting status orders after controlling for endogenous network processes but that status ascriptions are focused on a small elite of actors and structure friendship choices. Furthermore, my analyses reveal that in both larger classrooms and grades, status ascriptions are focused on a smaller set of students, and friendship networks are more segregated along lines of status. In contrast, hierarchy in close ties is not more pronounced in larger settings, and demographic diversity shows inconclusive associations with status processes. These findings have important implications for research on status dynamics in the school setting and for general network-theoretic approaches to the emergence of status orders.

2.1 Introduction

Since Veblen's (1899) *Conspicuous Consumption* and Weber's (1922) theoretical distinction between class and status, social status has been a core topic for the social sciences. Scholars who study vertical differentiation among individuals or groups stress the ubiquity of status orders and their importance for the organization of social life (Frank 1985; Gould 2002; Tilly 1998; Ridgeway 1991, 2014). Status theories have been used to explain a broad range of social phenomena, such as the influence of status characteristics on interactions in task-oriented groups (Ridgeway 1991), peer relations in schools and universities (Cillessen and Rose 2005; Faris and Felmlee 2014; Moody et al. 2011; Torlò and Lomi 2017), or strategic behavior in markets and organizational fields (see Sauder, Lynn, and Podolny 2012).

Most research on status implicitly assumes that the mechanisms undergirding status orders are homogeneous across contexts. In contrast, some scholars have stressed that status processes are highly dependent on properties of the environment in which they take place (Lynn, Podolny, and Tao 2009; Martin 2009b; McFarland et al. 2014; Podolny 2010; White 2008). Moreover, a growing body of empirical research suggests that the degree to which status recognition plays a role varies in intensity depending on contextual conditions, such as the uncertainty encountered by actors navigating their social environment (Dahlander and McFarland 2013; Lynn 2014; McFarland et al. 2014).

I build on this scholarship and advance our theoretical and empirical understanding of status orders by considering how contextual characteristics shape the distribution of actors' status ascriptions and the consequences of status for close social relationships. Using the school setting as a strategic research site (Merton 1987), I study the nexus between close relationships and status ascriptions and how it is affected by uncertainty as an external amplifier of status processes.

Theoretically, this article mobilizes considerations of network-theoretic approaches to status (Gould 2002; Lynn 2014; Mayhew and Levinger 1976; McFarland et al. 2014; Podolny 2010) and of accounts that highlight the importance of cognitive heuristics for the structure of social networks (Brashears 2013; Kilduff and Krackhardt 2008). In particular, I discuss two contextual conditions for *elevated uncertainty*, which has emerged as an important factor influencing the strength of status processes (Dahlander and McFarland 2013; Lynn 2014; McFarland et al. 2014; Podolny 2001, 2010). First, I argue that larger contexts exhibit higher uncertainty and should therefore show steeper status orders (Blau 1968, 1994; Mayhew 1973; Mayhew and Levinger 1976; McFarland et al. 2014). Second, I propose that more demographically diverse settings will foster status recognition among actors due to elevated uncertainty triggered by concerns for trust and in-group solidarity (following McFarland et al. 2014; Smith et al. 2016).

Empirically, this article uses data from three large-scale studies conducted in Western Europe that contain information on friendship networks and status ascriptions of more than 23,000 students at the classroom level (CILS4EU, (Kalter et al. 2016; Kalter, Kogan, and Dollmann 2019) and at the grade level (Kroneberg, Ernst, and Gerth 2016; Kroneberg et al. 2019, forthcoming). By applying multiple network analyses to this collection of data sets, I identify structural tendencies in students' status ascriptions and friendship networks (Lusher, Koskinen, and Robins 2013) that indicate the presence of status orders and analyze contextual variation in these tendencies with meta-regressions (An 2015). Finally, to ensure that the associations between contextual characteristics and estimates from network models can be interpreted substantially (see Martin 2020), I perform a simulation-based assessment of network estimates.

The article makes two contributions to the sociological study of status orders. First, I develop an integrative account that focuses on the structure of both close relationships and status ascriptions. Empirically, this allows me to study how status ascriptions are intertwined with close relationships, to investigate how they differ in their distributional logics, and to sidestep possible limitations of inferring status from close ties (as recently demonstrated by Vörös et al. 2019). The results suggest that status ascriptions are distributed more unequally among students than friendships and, most importantly, that status ascriptions react differently to changes in contextual conditions. For instance, larger classrooms and grades show more inequality in the distribution of status ascriptions but not in the distribution of friendship nominations. These findings illustrate that incorporating status ascriptions as networked processes in the empirical study of status is crucial for a deeper understanding of status orders.

Second, the study advances recent scholarship that aims to specify the scope conditions for status processes by considering how close relationships and status ascriptions react toward elevated uncertainty (Dahlander and McFarland 2013; Lynn 2014; McFarland et al. 2014; Podolny 2001, 2010). Lacking a direct measurement of status ascriptions, most previous work could not show whether and in what ways uncertainty affects both the structure of status ascriptions and their interrelation with close relationships. My results indicate that in larger classrooms and grades, status ascriptions are focused on a smaller set of students, and status is more closely tied to the formation of friendships in these contexts. These findings underline the context-sensitivity of status processes and suggest that uncertainty plays an important role in shaping status orders. Rather than being a universal characteristic of adolescent societies, elites of popular actors who form an exclusive circle in close relationships tend to emerge in specific contexts where elevated uncertainty amplifies status processes.

2.2 Theory and past research

Relational theories of social status have a long tradition in sociology (Berger et al. 1972; Chase 1980; Fararo and Skvoretz 1986; Gould 2002; Homans 1950; Martin 2009b; Mazur 1985; McMahan 2017; Podolny 2010; Ridgeway 1991; White 1992; Whyte 2012 [1943]). In general, proponents of these theories conceptualize status orders as a concatenation of individual acts of (psychological) deference marked by complex endogenous dynamics (Torlò and Lomi 2017: 30). Relational approaches to status build on this notion and infer status orders from patterns in observed relational behavior (Borkenhagen and Martin 2018; Burris 2004; Dong et al. 2015; Martin 2009; McMahan 2017; Ridgeway and Erickson 2000), the display of public status signals (Podolny 2010; Rossman, Esparza, and Bonacich 2010), or the structure of social networks (Ball and Newman 2013; Lazega et al. 2012; McFarland et al. 2014; Torlò and Lomi 2017).

The current study adds to these accounts by examining how status ascriptions and close social relationships are interrelated. Building on theoretical ideas put forward by McFarland et al. (2014), I investigate how contextual characteristics connected to uncertainty affect the interplay between status orders and friendships in the school setting—a research site that has proven to be well-suited to deepen the understanding of status processes (Adler and Adler 1998; Cillessen and Rose 2005; Coleman 1961; Faris and Felmlee 2014; Milner 2013; Moody et al. 2011; Rodkin et al. 2006; Veenstra et al. 2010). The network-ecological approach proposed by McFarland et al. outlines that some peer ecologies "are rank-ordered caste systems and others are flat, cliquish worlds" (2014: 1088) depending on ecological moderators which affect the fitness of certain tie-formation mechanisms. Against this backdrop, I study the role of uncertainty for the relational anatomy of status orders.

The remainder of the article is structured as follows: I review three status processes identified in the literature (preferential attachment, rank-ordering, and status homogeneity) and subsequently discuss contextual characteristics that should lead to higher uncertainty and therefore more pronounced status processes. Finally, I test the derived theoretical expectations in the school setting.

Preferential attachment

Preferential attachment is the tendency of actors with high status to experience further status gains in the future—also known as the "Matthew effect" (Merton 1968). As Martin pointed out, preferential attachment alone can lead to stark inequality in the distribution of ties among actors (Martin 2009b: 64-67). Furthermore, preferential attachment is a well-documented property of networks that can be observed in scientific co-authorships and citations (Barabâsi et al. 2002; Eom and Fortunato 2011; Newman 2001c), attention on social media platforms, e.g., followers on Twitter (Myers et al. 2014) and likes on Instagram (Ferrara, Interdonato, and Tagarelli 2014).

If preferential attachment would be the only organizational principle of status orders, we would expect a "winner-takes-it-all" situation in which one actor receives all status ascriptions (Gould 2002: 1149).[6] Yet as Gould (2002) pointed out, this situation is empirically rare. Gould's explanation for the absence of winner-takes-all situations is that actors prefer at least some degree of reciprocity when they grant psychological deference. This acts as a ceiling on inequality and establishes a counterbalance to the preference for associating with high-status actors. When one considers close relationships and status ascriptions separately, it becomes clear that a preference for reciprocity is inscribed into close relationships and can quickly lead to tension if it is violated by one of the participants of a relationship (Gould 2003). In contrast, status ascriptions do not presuppose reciprocity and can even flow between actors independent of personal acquaintance (Martin 2009b). Therefore, I expect that preferential attachment in status ascriptions is less hampered by reciprocity in comparison to preferential attachment in close relationships

In summary, preferential attachment can explain why status ascriptions are focused on an elite of actors, although winner-takes-all situations are relatively rare. This phenomenon is empirically connected to, yet conceptually distinct from, rank-orders and status homogeneity

[6] Gould (2002: 1157; 1174) provides a formal argument for this notion and demonstrates that even small differences in individuals' quality lead to a winner-takes-all equilibrium if self-reinforcing status attributions are the only guiding principle for status ascriptions.

in close relationships. These processes focus on how the structure of social relationships is affected by status ascriptions.

Ranked orders in close ties

The second status process under consideration builds on the widely held conviction that status shapes social relationships (Adler and Adler 1998; Anderson 1999; Collins 2004; Martin 2009; McFarland et al. 2014; Milner 2013; White 1992; Whyte 2012 [1943]). In empirical studies, this assumption has led to the common practice of inferring status orders from hierarchical structures in positive ties, such as friendships or liking ties (Davis 1970; McFarland et al. 2014; McMahan 2017; for a critical review, see Vörös, Block, and Boda 2019).[7] Thereby, scholars assume that if an actor A likes another actor B less than B likes A, a status difference in favor of A is implicitly established. Furthermore, if there is an asymmetry between actor B and actor C, where B likes C less than C likes B, this also induces a status difference in relation to A, resulting in a transitive order with A at the top, B in the middle, and C at the bottom (e.g., Davis 1970).[8] Following this scholarship, I assume that hierarchical structures in close social

[7] These accounts build on an understanding of status orders as dominance orders that are an outcome of a concatenation of antagonistic encounters in which one actor dominates another actor (Chase 1980; Fararo and Skvoretz 1986; Mazur 1985; for a review of the conceptual origins of dominance orders see Martin 2009b: Ch.4). Thereby, a hierarchy forms over a succession of antagonistic encounters resembling a (perfectly transitive) pecking order recognized by all members of a context in a theoretical ideal case.

[8] For an example imagine the following: Annabelle, Betty and Christine are students at the Average Middle School. Annabelle and Betty regularly spend time together but it is mostly Betty who asks Annabelle whether she wants to play after school and who runs over to Annabelle as soon as she sees her on the schoolyard. Although they are considered to be friends among their classmates, it is clear that Annabelle has more say in this relationship than Betty. When she is not hanging out with Annabelle, Betty sometimes talks to Christine, who is very fond of Annabelle and Betty. Unfortunately, her affection is not returned and as soon as Betty sees Annabelle, she leaves Christine alone. For the other

relationships are indicative of the presence of a status order (McFarland et al. 2014). If status plays a decisive role in a context, we should observe social relationships arranged in the form of a hierarchical tree.

Status homogeneity in close ties

As a third status process, I consider the tendency of actors to form close ties with others who have a similar status. A recurring finding in previous research is that actors' close relationships or coalitions are segregated along the lines of status—for instance, children and adolescents tend to form friendship cliques composed of similar-status individuals (Adler and Adler 1998; Coleman 1961; Milner 2013), and organizations that share a similar status have an elevated likelihood to collaborate with each other (Podolny 2010).

Podolny (2010) argued that this phenomenon can partially be explained by status homophily—the preference to associate with others similar in status—, e.g., due to high-status actors' fear that associations with low-status actors could damage their social standing. Whereas status homophily implies that actors of similar status select each other as interaction partners, the reversed causal direction is also possible: due to an actor's close relationship with a high-status actor, she rises in the status order. The underlying notion of "basking in reflected glory" assumes that actors benefit from associations with entities of high status, such as prestigious football clubs or other popular actors, because their social standing is indirectly elevated through the association (Cialdini et al. 1976; Dijkstra et al. 2010). Both mechanisms should lead to close ties segregated according to status differences, resulting in cliques of actors with similar social standing in the broader network ecology.

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students in the classroom, it is evident that Annabelle has the highest status, Betty has a middle position and Christine is at the bottom of this small hierarchy.

To summarize, previous scholarship has identified three status processes that contribute to the anatomy of status orders: preferential attachment in status attributions, rank-ordering, and status homogeneity in close relationships. Whereas these status processes seem to be present in a broad range of empirical settings, the next section will discuss contextual moderators that should amplify them.

Uncertainty as a contextual moderator of status processes

The idea that contexts characterized by higher uncertainty also exhibit more pronounced status processes has already guided research on organizational fields (Dahlander and McFarland 2013; Lynn 2014; Podolny 2010). More fundamentally, several theories of social status build on the assumption that status recognition is a cognitive heuristic which reduces uncertainty and helps actors to navigate complex social environments (Fiske 2011; Lynn et al. 2009; Podolny 2001; Ridgeway 2019; Ridgeway and Erickson 2000). Moreover, the link between networks and uncertainty also surfaces in the work of scholars who investigate the cognitive representation of close social ties and conclude that humans rely on simplification in the management of their relationships (Brashears 2013; Brashears and Quintane 2015; Kilduff and Krackhardt 2008). A similarity of these different branches of literature is that they propose a relationship between the limited cognitive capabilities of actors and the need to simplify a large amount of information in uncertain environments.

If uncertainty is high, actors have to process more information before they can adjust their behavior in interactions. Categorizing others on a vertical dimension is a helpful tool to cope with such increased complexity; therefore, status recognition should be more important for behavior in settings marked by high levels of uncertainty (McFarland et al. 2014; Podolny 2010). In a similar vein, Ridgeway (1991) has proposed that status recognition is useful cognitive devices to reduce uncertainty about how to behave correctly in face-to-face interactions of task groups. This claim is consistent with neuropsychological studies (Fiske

2011) and supported by evidence from social-psychological experiments (Ridgeway and Correll 2006; Ridgeway and Erickson 2000). For the case of organizations, Podolny (2010) found evidence for the notion that uncertainty exacerbates status processes, e.g., by illustrating that the decoupling of quality and status is more pronounced for the trade of assets involving higher uncertainty in the investment-banking sector. Closest to the current study, McFarland et al. (2014) reported evidence for more rank-ordering in friendships among students in larger schools and in schools with more demographic heterogeneity in terms of racial and age composition. They argued that these patterns are indicative of more pronounced status recognition due to elevated uncertainty and anonymity in larger schools.

Following this literature, I expect that status processes will be exacerbated by conditions of higher uncertainty. If the environment an actor tries to navigate in is marked by more uncertainty, status recognition should become more useful as a cognitive heuristic which reduces complexity. Hence, in line with network-ecological theory (McFarland et al. 2014), characteristics of the school context affect which kind of behaviors and ties are selected, retained or dissolved among adolescents as they vary in fitness across settings and over time. Based on the general framework outlined so far, the next section will derive theoretical expectations for the school setting. In particular, I consider the size and the demographic composition of classrooms and grades as potential moderators for status processes among students.

Size and uncertainty

Previous classical and contemporary studies considered the size of a social system as an influential factor for various social processes (Blau 1968, 1994; Mayhew 1973; Mayhew and Levinger 1976; Michels 1915; Simmel 1950). A recurring theoretical argument in these studies is that size exacerbates the uncertainty encountered by participants of a context, because the density of interactions among them decreases. Mayhew and Levinger (1976) formalized this theoretical consideration and argued that humans' limited capacity to process information explains why context size changes the frequency and quality of encounters. Likewise, Blau (1968, 1994) claimed that larger organizations develop more pronounced hierarchies to cope with coordination problems tied to an increased size.

McFarland et al. (2014) translated these theoretical considerations to the school setting and argued that larger schools should lead to greater uncertainty and anonymity among students with consequences for the structure of students' friendship networks. Connecting these arguments to the idea that uncertainty fuels status processes, I expect that larger contexts will exhibit higher levels of uncertainty and therefore show intensified status processes.

Hypothesis 1. Larger classrooms and grades show more pronounced preferential attachment in status ascriptions, more rank ordering in friendships, and higher status homogeneity in friendship choices compared to smaller classrooms and grades.

Previous literature on the school setting provides first evidence in support of this hypothesis. Adler and Adler (1998) studied an elementary school and compared it to a school researched by Kless (1990). They concluded that smaller grades lack one stratum of the status hierarchy that they had observed at their research site.[9] The authors described elsewhere that this "wannabe" stratum—composed of students who look up to the highly popular kids—shows pronounced status-seeking behavior (Adler and Adler 1998: 81–84; 94–95). Furthermore, Neal et al. (2016) reported that classroom size is associated with decreasing accuracy in

[9] Adler and Adler (1998: 75, footnote 5) note: "For every age level, within each gender group, and in every school with a population over eighty students per grade, the social system was composed of four main strata: the high, wannabe, middle and low ranks." Footnote 5: "Kless (1992): …For schools with a population of under eighty students per grade (such as Kless studied), that stratum [wannabe] tended to disappear, being replaced with only scattered individuals or not replaced at all."

schoolchildren's perceptions of their classmates' relationships (see Cappella, Neal, and Sahu 2012). This finding can be interpreted as indicating that students face higher uncertainty in larger classrooms and are therefore less accurate in their perception of others' relationships. Furthermore, McMahan (2017) and McFarland et al. (2014) reported evidence for more rank-ordering in friendship networks in larger grades and schools using the AddHealth data set.

Demographic diversity, uncertainty, and group boundaries

In addition to context size, previous scholarship has suggested that demographic diversity might be another amplifier of status processes among students. As McFarland et al. (2014) argued, settings with higher compositional heterogeneity exhibit more uncertainty. This would increase concerns for group boundaries and trust among context members.[10] As salient group boundaries trigger status recognition, perceptions of dissimilarity should lead to more rank ordered social relationships (McFarland et al. 2014: 1092–1093). Indeed, demographic characteristics such as gender or race often provide the basis for status recognition (Blau 1977a; Ridgeway 2019) and inter-group conflict (for ethnicity see e.g., Horowitz 1985).

To this argument, one could add that increased uncertainty in itself—i.e., irrespective of an increase in the salience of group boundaries—should suffice to amplify status processes, because the heuristic usefulness of status recognition is increased in uncertain contexts (Fiske 2011; Lynn et al. 2009; Podolny 2001; Ridgeway 2019; Ridgeway and Erickson 2000). To put

[10] This assumption is supported by empirical evidence. For instance, Dinesen, Schaeffer, and Sønderskov (2019) concluded in a recent meta-analysis that previous research—on average—established a weak negative association between neighborhoods' ethnic diversity and generalized trust. Likewise, studies of friendship networks in the school setting found that a higher share of minority students is linked to more ethnic homophily—the tendency to form friendships with others who have the same ethnic background (Smith et al. 2016; Kalter and Kruse 2014). Similarly, McFarland et al. (2014) reported that racially more diverse schools exhibit more racial homophily in friendships. In summary, these studies point to elevated concerns for trust and group boundaries in more diverse settings.

these ideas to an additional test, I will evaluate the hypothesis that classrooms and grades with more heterogeneous compositions in terms of ethnicity and gender will show more pronounced status processes among students.

Hypothesis 2. Demographically more diverse classrooms and grades show more pronounced preferential attachment in status ascriptions, more rank ordering in friendships, and higher status homogeneity in friendship choices compared to less diverse classrooms and grades.

While McFarland et al. (2014) reported a positive association between schools' racial heterogeneity and the degree of rank ordering in friendships, their results were less consistent for gender and age heterogeneity—so that the "complex relations between types of composition found warrant further detailed study of their own" (McFarland et al. 2014: 1110).

In addition to this mixed empirical evidence, there are also theoretical arguments that call for further examination. Most importantly, scholars have stressed that status struggles related to dominance and hierarchy are more prevalent among socially close individuals (Faris and Felmlee 2014; Gould 2003; Martin 2009b) and that many status processes take place within close-knit groups (Blau 1964; Homans 1950; Whyte 2012 [1943]). If group boundaries are more salient due to a higher demographic heterogeneity, this could have the counterintuitive effect of decreasing status struggles between members of different groups: students who rarely interact might have no reason to engage in status competition with each other. Hence, the notion that demographic diversity promotes status processes requires further empirical testing.

2.3 Data and measurements

Testing my hypotheses requires data on multiple types of networks and a large number of contexts that vary in size and demographic composition. I gained access to three different data sets that meet these criteria. Analyzing all three of them allows for a more rigorous evaluation of the robustness of findings. The data sets include friendship and status ascription networks among students at the classroom and the grade level. Classes and grades have particular organizational structures in European secondary schools. In contrast to schools in the United States, where students switch classes between subjects, European classes tend to be stable units, where students typically stay with the same classmates for most subjects and often spend the whole school day together, especially from grades 5 to 9. School grades are assemblages of these stable classes.

Data sources

The Children of Immigrants Longitudinal Survey in Four European Countries (CILS4EU) data contains rich individual-level and sociometric information of 18,716 students nested in 958 classes located in Germany, Sweden, England, and the Netherlands. The survey was conducted between October 2010 and June 2011, and schools were selected with a probability adjusted to their size (Kalter et al. 2016). After excluding cases with missing sociometric information, the initial analysis sample comprises 17,705 students.[11]

Additionally, two regional German data sets with grade-level information are used to test whether the proposed associations between contextual moderators and the intensity of status processes also hold in larger networks. The two studies—"Friendship and Violence in

[11] Note that although 1011 students do not enter the analyses, 94.5% of the students are included, since they answered the network questions. This share is almost identical to the AddHealth data (see McFarland 2014: 1095–1096, who report that 95% of the survey participants completed the sociometric part of the questionnaire).

Adolescence" (FVA, Kroneberg et al. 2016) and "Social Integration and Boundary Making in Adolescence" (SOCIALBOND, Kroneberg et al. 2019, forthcoming)—were conducted at schools in urban areas in North Rhine-Westphalia, Germany's most densely populated federal state. The data sets of both studies contain information about 39 grades and include 2630 and 3017 students, respectively. Due to high data quality, almost all students were able to be included in the analyses (n=2603 and n=2999, respectively).

Table 2.1 provides detailed information on the three data sets. Each survey asked students to answer a variety of sociometric items, with their classroom or grade as a boundary for nominations. The students received a list with the names of all members of their classroom or grade, linked to a unique identification number. They were asked to use this list to answer the network questions by indicating the respective student's assigned number. From this sociometric information, networks were constructed with directed ties for friendship and status ascriptions.

Status ascription networks

While previous studies often measured status as some form of individual score—e.g., how many popularity nominations a student receives—similar to van der Ploeg, Steglich, and Veenstra (2019), here status ascriptions are examined as a network.[12] This approach allows me

[12] Although researchers agree on the presence of status orders in school, they pursue different strategies to measure and analyze them. Status is either measured as sociometric status in the friendship network (e.g. Moody et al. 2011; Smith and Faris 2015), a score of popularity nominations granted by peers (Ahn, Garandeau, and Rodkin 2010; Fujimoto, Snijders, and Valente 2017; Sijtsema et al. 2009), as awards for athletic or academic achievement (Faris and Felmlee 2014), or as a score composed of different sociometric items (e.g. LaFontana and Cillessen 2002; Pál et al. 2016; for a critical discussion, see Rubineau, Lim, and Neblo 2019). A concept closely related to social status is perceived social status or "social standing" (Cillessen and Rose 2005). The literature on social standing argues that popularity and likability among peers are different dimensions of social standing (for a review, see Kornbluh and Neal 2016). Still, scholars contributing to the literature on popularity in the school context use similar

to detect structural configurations which are indicative of the shape and importance of status processes—such as preferential attachment—in a particular context.

To construct these networks, I rely on popularity nominations, which were surveyed by asking students to name up to five classmates in the CILS4EU data ("Who are the most popular students in this class?"), while both grade-level data sets (the FVA and the SOCIALBOND data sets) allowed naming a maximum of ten students. In addition, one grade-level data set (FVA) allowed self-nominations. I constructed directed networks from the popularity nominations and deleted self-nominations (for a similar approach, see van der Ploeg, Steglich, and Veenstra 2019). I interpret popularity nominations as *indirect status ascriptions,* because students are asked to indicate the consensus on who is popular among most students in a classroom or grade rather than their own opinion on who should be popular or whom they regard as popular (see, e.g., Ridgeway 2019 for a similar distinction).

Friendship networks

Friendship was measured in slightly different ways in each of the three surveys. In the CILS4EU survey, researchers asked students to indicate up to five best friends in the classroom ("Who are your best friends in class?"). The FVA data set includes an item that reads, "Who are your best friends in your grade?", where the number of possible nominations was limited to five students. The SOCIALBOND survey employed the same question but allowed for up to ten nominations. Reciprocal as well as asymmetric friendship nominations are used in all analyses. This is in line with previous studies and helps to avoid underestimating existing friendship ties, especially where nominations were restricted to students' five best friends (Boda

measures as researchers trying to understand social status (e.g., Berger and Dijkstra 2013; Rodkin et al. 2013).

and Néray 2015; McFarland et al. 2014; Smith et al. 2016). Descriptive information on both tie types is provided in appendix A.

Context size

Context size was measured by the number of students who participated in the sociometric part of the survey ("network size"). An alternative operationalization is the number of students who officially attend the class or grade. These two measures are highly correlated (CILS4EU: 0.85; FVA: 0.96; SOCIALBOND: 0.94). The main analyses used network size as the context size measure, and I include a report on how results differ if the official number of students is used instead.

Demographic composition

To capture the demographic diversity of a context, I calculated the inverse Hirschmann-Herfindahl index (HHI) for gender and ethnic origin (following McFarland et al. 2014). Ethnic origin was assigned based on the parents' country of birth. If only one parent was born abroad, that parent's country of birth was assigned. If both parents were born outside of the host country, the mother's country of birth was assigned (see Dollmann, Jacob, and Kalter 2014). Minority students therefore either immigrated themselves (1st generation) or are the children of immigrants (2nd generation). My analyses of the CILS4EU data use aggregated variables, encompassing the 5 largest ethnic groups in each country as well as two residual categories for western and non-western countries of origin (CILS4EU, 2016). In the grade-level data sets, ethnic origin is measured based on the country of origin.

Control variables

Class membership is included in the analyses of the grade-level data sets to account for the greater frequency of face-to-face contact within classrooms (Mastrandrea, Fournet, and Barrat

2015). I also include gender in all analyses due to its significance for social relations in adolescence. Moreover, ethnic origin is included to control for tendencies towards ethnic homophily in friendships and other types of nominations (Kruse et al. 2016; Moody 2001; Mouw and Entwisle 2006; Smith et al. 2016; for negative ties see Boda and Néray 2015; Wittek et al. 2020). Table 2.1 gives an overview of the different data sets and measures.

Table 2.1. Information on data sets

	CILS4EU	FVA	SOCIALBOND
Students	18,716	2630	3017
Students with valid network information	17,705	2603	2999
Contexts	958 classes in 457 schools	39 grades	39 grades
Number of students who participated in the survey	19.54 SD: 5.62 Range: [2;40]	66.74 SD: 38.11 Range: [15;156]	75.56 SD: 32.28 Range: [21;157]
Number of students who officially attend the class or grade	22.98 SD: 5.55 Range: [5;40]	85.49 SD: 45.72 Range: [21;179]	98.00 SD: 39.47 Range: [41;215]
Share female	0.50 SD: 0.21 Range: [0;1]	0.44 SD: 0.11 Range: [0.20;0.60]	0.46 SD: 0.08 Range: [0.20;0.61]
HHI female	0.44 SD: 0.12 Range: [0;0.50]	0.47 SD: 0.05 Range: [0.32;0.49]	0.48 SD: 0.04 Range: [0.32;0.50]
Share migrant	0.42 SD: 0.29 Range: [0;1]	0.53 SD: 0.18 Range: [0.12;0.90]	0.61 SD: 0.20 Range: [0.25;0.96]
HHI ethnic	0.56 SD: 0.19 Range: [0;0.84]	0.61 SD: 0.13 Range: [0.19;0.80]	0.76 SD: 0.13 Range: [0.44;0.93]
Grade	9th Grade	7th Grade	7th Grade
Average age	14	13	13
Network level	Class	Grade	Grade

Data collection	October 2010 till June 2011	September 2013 till December 2013	September 2018 till January 2019
Location of schools	Germany, Sweden, England, the Netherlands	Germany; Ruhr Area	Germany; Area around Cologne
Response rate students	85%	79%	76%
Survey method	Paper and pencil	Audio supported computer assisted self interviews	Audio supported tablet assisted self interviews
	MEASURES		
	CILS4EU	FVA	SOCIALBOND
Friendship nominations	Who are your best friends in class? (max. 5)	Who are your best friends in your grade? (max. 5)	Who are your best friends in your grade? (max. 10)
Status ascriptions	Who are the most popular students in this class? (max. 5)	Who are the most popular students in your grade? Please name up to ten classmates. You can also include yourself in the list (max. 10)	Who is popular among most students in your grade? (max.10)

2.4 Methods

I use a three-stage procedure to study whether status processes in students' status ascriptions and friendships are exacerbated by contextual moderators (for previous research using a similar analytical strategy, see McFarland et al. 2014; Smith et al. 2016). In the first step, exponential random graph models (ERGMs, Lusher et al. 2012) are estimated for each context and summarized by meta-analyses (Snijders and Baerveldt 2003). In a second step, I use multivariate meta-regressions to analyze which characteristics account for variation in status processes between contexts (An 2015). In a third step, a simulation-based assessment of network models is carried out to examine the links between contextual moderators and status processes in greater detail (for similar approaches see, Kruse et al. 2016; Snijders and Steglich 2015) and to offer a robustness check for how ERGM parameters relate to more basic measures of network structure (Martin 2020). For readers who are not interested in a detailed description of the analytical setup and who would like to move directly to the results, I briefly summarize the analytical strategy in the next section.

The analytical strategy in a nutshell

Network models allow researchers to detect structural tendencies indicative of theoretical concepts—such as homophily or social cohesion—while taking into account the opportunity structure for the formation of ties and other endogenous network processes (Robins 2011; Snijders 2011). I leverage such models to examine whether students' status ascriptions and friendships show network structures indicative of status processes in a particular class or grade. These processes—preferential attachment, hierarchization, and status homogeneity—are captured by parameters from network models, which are compared across contexts via meta-analytical techniques (An 2015).[13] This allows me to test the theoretical expectations that larger and demographically more diverse settings exhibit amplified status processes. Finally, networks are simulated from model results to examine whether the estimated status processes show a link with global measures of network structure and are substantially shaped by contextual characteristics. The following sections provide a more detailed description of this analytical strategy.

[13] The interpretation of ERGM parameters as indicative of relational preferences was recently critiqued by (Martin 2020). I discuss my application of ERGMs against the background of Martin's concerns at the end of the methods section.

Exponential random graph models (ERGMs)

Friendship and status ascription networks of each school are modeled with exponential random graph models (ERGMs).[14] The dependent variable for ERGMs is the global structure of a given network. The independent variables are count statistics for local structures, such as the number of transitive triangles. ERGM coefficients indicate whether a particular local structure occurs more often in the observed network than a random allocation of ties would suggest, conditional on all other local structures included in the model specification (Lusher et al. 2012; for an introduction, see e.g., Robins 2011). A strength of this method is that it allows researchers to dissect the global structure of networks with a generative model, which provides parameters for local tie-formation processes while taking into account other related factors. This is desirable, because as e.g., Goodreau, Kitts, and Morris (2009: 105) highlight, “there is rarely a neat correspondence of process and pattern, and statistical methods are needed to tease apart micro-level foundations of structure.”

In the current study, ERGMs allow me to estimate the extent to which friendship and status ascription networks show structures indicative of status processes, above and beyond other endogenous network mechanisms (e.g., reciprocity or transitivity). Furthermore, ERGMs provide ways to model tie configurations that involve individual characteristics (e.g., gender), as well as interdependencies between different tie types (entrainment effects).

A note on the application of ERGMs to model status ascriptions

Using ERGMs to model the structure of status ascriptions is a new way of approaching this type of data and warrants further justification. One could object that ERGMs are designed to model social networks such as friendships or cooperation and that they are not suited to model

[14] The analysis was carried out in R. The ergm package was utilized to conduct the ERGM analysis (Hunter et al. 2008). The mvmeta package was applied to aggregate ERGM parameters and to run the meta-regressions (for an application, see An 2015; Gasparrini, Armstrong, and Kenward 2012).

status ascriptions, which are more relational cognitions than relationships (for a typology of tie-types see Borgatti, Everett, and Johnson 2013: Ch. 1). Yet the assumptions underlying ERGMs—for instance, the non-independence of dyads—are also important for the study of self-organizing, networked processes, such as the granting of status among members of a context. As stressed by many scholars of social status (Fararo and Skvoretz 1986; Gould 2002; Lynn et al. 2009; Manzo and Baldassarri 2014; Torlò and Lomi 2017), an actor's acts of deference and her status ascriptions are influenced by others' deference, e.g., students are influenced in their perception of who they think is popular by their peers' opinions on who is popular. ERGMs offer a way to take these interdependencies into account and to model status processes such as preferential attachment, as well as other mechanisms that are simultaneously shaping the network of status ascriptions. Furthermore, previous studies applied ERGMs to networks such as advice-seeking (Brennecke and Rank 2016), leadership ascriptions (Kalish and Luria 2013), or attributions of power and influence (Kreager et al. 2017). Although these tie types are also not social relationships, applying ERGMs to them led to new insights on how these networked processes are organized.

In summary, the ERGM framework is well-suited to model status ascriptions, because it allows taking relational interdependency into account, provides parameters for the tie-formation mechanisms of interest, and can be extended to study contextual moderators of status processes. Furthermore, it permits a simulation-based exploration of the role of contextual characteristics for status orders.

Model specifications

In the analyses of friendship and status ascription ties, the applied model specifications aim at capturing the structural characteristics of these two different types of networks. The specification for friendship follows previous research (Moody 2001; McFarland et al. 2014; Smith et al. 2016; Kruse et al. 2016). As this study is the first to model status ascriptions as a dependent network in the ERGM framework, this part of the analyses required a systematic search for a converging and well-fitting specification.[15] More precisely, I identified key structural characteristics of status ascriptions by estimating a variety of specifications and followed an iterative procedure to provide results that show a balance between the number of converging networks under a particular specification and the average goodness of fit of the models.[16]

Endogenous network effects

To account for the density of a network, the edges term is included in all models and can be viewed as an intercept term (Smith et al. 2016: 1240). Also, to capture the tendency to reciprocate nominations, the mutual term is added to all specifications. Additional structural effects were entered to take configurations between triads of students into account. In the models of friendship relations, I added the "geometrically weighted edgewise shared partner" (GWESP*)* term. This term models transitive closure, i.e., the tendency of actors to become friends with friends (Hunter, 2007). The likelihood of a tie between two actors increases with each additional edgewise shared partner, but the magnitude of this increase is mitigated by each additional one. This decreasing effect of each additional shared friend is modeled by the GWESP alpha term, which was fixed to one. Together the two GWESP terms reflect students' tendency to befriend each other if they share a friend and account for a stronger likelihood of a friendship between two students as the number of common friends increases, whereby each additional shared friend contributes less to the overall likelihood of a friendship.

[15] For a similar approach in a longitudinal network analysis, see van der Ploeg, Steglich, and Veenstra (2019), who analyze popularity nominations as a "matrix of status ascriptions" to predict bullying behavior.

[16] The selection of ERGM terms is partially oriented towards Kreager et al.'s (2017) specifications, who analyzed networks of perceived influence and power among prison inmates.

To account for triadic patterns of tie formation in status ascriptions, a geometrically weighted version of the incoming non-edgewise shared partner (GWNESP-ISP) and the transitive non-edgewise shared partner (GWNESP-OTP) parameters were included. The former term models the absence of a status ascription between students who nominate the same students as popular. The GWNESP-OTP is based on a count statistic that captures the occurrence of triads in which A sends a popularity nomination to B and B sends a popularity nomination to C but there is no ascription of status between A and C (for details, see appendix C). The corresponding alpha terms of these parameters were also set to a fixed value of one. These geometrically weighted transitive terms were introduced into the ERGM framework to ease problems with model degeneracy and goodness of fit (Hunter 2007). In this study, they are also used to derive parameters for status processes net of local triadic structures characteristic of friendships and status ascriptions. Taking nested dyadic as well as triadic configurations into account is crucial to ensure correct inference about networks' structures (Anderson, Butts, and Carley 1999; Faust 2007; Goodreau et al. 2009; Lusher et al. 2013; McFarland et al. 2014). I subsequently outline how the three status processes under investigation—preferential attachment, hierarchy, and status homogeneity—are measured within the ERGM framework.

Preferential attachment

The geometrically weighted indegree term (GWIDEG) is added to all specifications and captures the degree to which actors with many nominations tend to receive additional ones. This term is an extension of a previously proposed alternating k-star and models the indegree distribution of an observed network with geometric weights (Hunter 2007). As Levy (2016) points out, the substantial interpretation of geometrically weighted degree terms is not trivial. Positive values are often interpreted as a tendency towards centralization or preferential attachment, i.e., that some nodes receive a high number of indegrees whereas most nodes receive few indegrees. Levy (2016) reported that positive values indicate the dispersion of edges but not centralization, whereas previous accounts tended to equate a dispersed distribution of edges with centralization (e.g., Peng 2015: 253). Studying status attributions among prison inmates, Kreager et al. (2017) interpreted a negative value of the GWIDEG parameter as indicative of the (positively) skewed shape of the indegree distribution of power/influence networks, with a small number of actors receiving large amounts of recognition while most received little or none. In line with this view, I will interpret negative values of the GWIDEG term as indicative of preferential attachment.[17]

Hierarchy

To measure the second status process under investigation, the hierarchical tau statistic is added when modeling friendship networks (as in McFarland et al. 2014).[18] The idea behind this statistic is to count triads pointing to a hierarchical network structure such as a chain of command or a dominance order. Based on the MAN triad census (Wasserman and Faust 1994), the tau statistic considers the number of different triadic configurations and weights them according to their contribution to a global score reflecting how hierarchical a network looks in

[17] Hunter (2007) shows that the GWD term (θ_S) "may be thought of as a sort of anti-preferential attachment model term." Therefore, negative values should, in turn, indicate preferential attachment. I tested this assumption by running simulations in the Shiny-app provided by Levy (2016). Setting the GWD term to negative values, the alpha term to one, and the number of nodes as well as the density of the networks to the empirical averages of the status ascription networks in the data sets under study, the simulations produced highly positively skewed degree distributions. Holding all other parts of the simulation setting constant, stronger negative values of GWD resulted in increasingly skewed degree distributions. These additional analyses further support the interpretation of a negative GWIDEG term as indicative of a skewed and thus unequal distribution of indegrees in a class or grade.

[18] I would like to thank James Moody for his advice regarding the implementation of this model term. The statistic was incorporated as follows: first, the change in the global tau score of the observed network is calculated for a hypothetical change of each dyad. Second, the resulting matrix of changes in the tau score is added in the model specification by using the edgecov() term. Details and code are available upon request.

general. Triads suggestive of local hierarchy are positively weighted, whereas triads pointing to triadic closure and thus clustering without ranking are weighted negatively (for details, see McFarland et al. 2014: 1096–1097, 1116).[19] Based on the global tau score, I include a matrix that entails the dyad-wise values of how the global tau score of the observed network would change if a dyad showed a different configuration than the observed one. This statistic thereby captures whether the hypothetical presence or absence of a tie between two actors increases or decreases the overall degree of hierarchization. This allows to assess whether the network exhibits hierarchical structures, controlling for the opportunity structure and other endogenous processes such as reciprocity or triadic closure.

Status homogeneity

The third status process considered here is status homogeneity—the tendency for actors with a similar status to befriend each other. In the case of continuous actor attributes, the ERGM framework usually measures homogeneity in reversed difference scores. Therefore, to test whether friendships between students of different popularity among their peers are less likely than friendships among students of similar popularity, a term capturing the absolute difference in relative popularity is included in ERGMs for friendship networks (as in Smith et al. 2016: 1240). At this point, the analysis adopts the more common operationalization of popularity as a score (e.g., Dijkstra et al. 2013). The score inserted in the absolute difference term consists of the share of all granted popularity nominations in an entire class or grade that a particular

[19] Imagine a scenario in which a student A sends a friendship to another student B, who sends a friendship nomination to C. Also, A is sending a friendship nomination to C but receives no nomination herself. This suggests that C is at the top of a local hierarchical structure, because C is “avoiding” a friendship with A and B while receiving nominations from these two students. The score reflects how many of such local hierarchical structures are present in a network and weights egalitarian structures (e.g., A, B, and C share reciprocal friendships) negatively.

student received. A negative value of the term indicates that an increase in the popularity difference between two students makes the occurrence of a friendship between them less likely.

Entrainment effects

To model whether the friendship and status ascriptions depend on each other, so-called entrainment effects are included in the analysis. These effects describe the tendency for ties in one type of network to co-occur with ties from a different type of network among the same set of actors (Harrigan and Yap 2017: 128; Robins and Pattison 2006). Here, entrainments effects are used to account for the association between likability and popularity found in previous studies (Kornbluh and Neal 2016; Vörös et al. 2019). Two entrainment effects are added: one to the model specification for status ascriptions and one to the model specification for friendship networks. The coefficients for these effects substantially indicate whether a status ascription between two students is more likely if they share a friendship tie and vice versa. A significant negative coefficient would suggest that tie types do not co-occur, e.g., that status ascriptions are rare between friends. In contrast, a significant positive estimate would indicate that tie types tend to overlap, for instance that friends also tend to nominate each other in status ascriptions.

Further controls

To control for gender differences, female activity and popularity terms were entered into all models. These terms capture whether females send or receive more ties than males do. Moreover, the same-gender effect is present in all specifications in order to capture the tendencies for ties to occur within same-gender rather than within cross-gender dyads. A term counting dyads between students who share the same ethnic group membership is included to account for ethnic homophily. Likewise, models for the grade-level data sets contain same class terms to model the tendency of ties to cluster within classrooms.

Meta-analysis and meta-regression

The second step of the analytical strategy is to investigate whether estimates of tie-formation processes vary across classes and grades. Meta-analytical techniques allow analysts to obtain averaged parameters and weight them by their standard errors as well as by their variance-covariance matrix (An 2015: 48–49; Snijders and Baerveldt 2003). This is necessary to account for the interdependency of estimates in the ERGM framework (An 2015; McFarland et al. 2014).

In addition, meta-regressions are used to investigate whether larger and demographically more diverse settings show stronger status processes compared to smaller, less diverse ones. Meta-regressions allow the inclusion of moderators such as context size to investigate whether they contribute to variation in tie-formation mechanisms across contexts (following McFarland et al. 2014; Smith et al. 2016; Wittek et al. 2020).[20]

Potential pitfalls of ERGMs

In line with previous literature (Lusher, Koskinen, and Robins 2013; McFarland et al. 2014; Moody 2001; Smith et al. 2016), the current study interprets ERGM parameters as indicative of micro-level tie-formation mechanisms. Yet interpreting parameters from network models is seldom straightforward (Block 2015; Block et al. 2018; Desmarais and Cranmer 2012; Levy 2016; Martin 2018). In a recent comment on Stivala (2020), Martin (2020) addresses a number of potential pitfalls when interpreting ERGM estimates. Among other aspects, Martin critiques the understanding of ERGM parameters as direct operationalizations of theoretical constructs—such as actors' relational preferences—irrespective of the strong assumptions baked into the models. In particular, he warns that specifications which include complex geometrically

[20] Multivariate fixed effects meta-analyses and meta-regression are estimated by the generalized least square approach (An 2015).

weighted terms and characteristics of network participants can lead to serious misinterpretations of individual ERGM estimates (Martin 2020: 6–7).

To avoid this, the current study takes a number of precautions. First, I estimated a variety of model specifications. As suggested by Martin (2020: 13–14), I started with simple specifications only including basic structural terms to detect potential interdependencies of purely structural terms with terms that take actors' attributes into account. Results of these specifications qualitatively point in the same direction as the specifications reported in the main text (analyses available upon request). Second, I examined which networks showed degeneracy issues. As shown in appendix B, this analysis suggests that the results are robust to the drop out of networks from the estimation process. Third, I used a simulation-based approach to assess the correspondence between patterns identified by ERGM parameters with more basic, global measures for network structure (similar to Kruse et al. 2016; Snijders and Steglich 2015). Finally, appendix E offers a simulation-based analysis of the link between size and inequality in status ascriptions without the involvement of ERGM estimates (cf., Bearman, Moody, and Stovel 2004).

2.5 Results

To study network structures indicative of status processes and their variation across classrooms and grades, ERGMs were estimated for each context and tie type. The CILS4EU data surveyed multiple—on average two—classes per school. Following Kruse et al. (2016), I combined these classes into one network. A term for cross-class nominations was set to minus infinity in the CILS4EU data set to prevent between-classroom nominations during the estimation processes; this was necessary to realistically capture the networks' structure, because the CILS4EU survey only allowed for within-classroom nominations. Since ERGMs have issues with convergence and goodness of fit—especially in smaller and sparser networks—this procedure led to more information entering the models. For the other two data sets, ERGMs were estimated for each grade separately.[21]

The results only rely on ERGMs with a sufficient model fit and goodness of fit. In appendix B, I discuss the selection criteria I employed following previous studies and provide details on how schools and grades with converging ERGMs vary in size and demographic composition compared to contexts with non-converging ERGMs (see table B1).

Average tendencies in status ascription and friendship networks

Tables 2.2 and 2.3 report multivariate meta-analyses for ERGMs with status ascription and friendship networks as dependent variables. Before discussing estimated parameters for the three status processes, I provide a rough overview of general structural tendencies in status ascriptions and friendship networks.

Across all data sets, the negative edges, positive same-class and same-gender parameters suggest that status ascriptions are relatively sparse and granted more often within classrooms or among students having the same gender. These average tendencies are shared by friendship networks (see table 2.3). Similarly, status ascriptions tend to be reciprocated except in the FVA data set, in which they show a tendency towards asymmetry. A notable difference between status ascriptions and friendship networks is that friendships are more often formed within ethnic groups than between them, given all other model terms. In contrast, status ascriptions

[21] To assess whether summarizing classes into larger networks changes the results, I repeated all analyses for the CILS4EU data set at the single classroom level. The results of this robustness check are reported in appendix D. Results regarding status processes are substantially similar to the combined classroom level. I decided to report the results combining classrooms of a school into a larger network in the main text, because these analyses are based on more information from the initial sample of networks. Whereas over 50% of the combined classroom networks produced reliable estimates (see table B1), less than 40% of the networks at the single classroom level lead to converging and well-fitting ERGM estimates (see table D4).

only show a slight tendency towards ethnic homophily in the classroom-level data. Furthermore, whereas boys and girls do not differ in the number of friendship nominations they send and receive, there is a clear tendency of girls sending more but receiving fewer status ascriptions than boys.

Regarding transitive structures, the geometrically weighted non-edgewise shared partner terms considerably improved convergence and GOF for status ascriptions in two data sets (see appendix C). The remaining data set showed problems with these terms, but a satisfactory trade-off between degeneracy and goodness of fit was obtained by including the geometrically weighted edgewise shared partners term, which was also used to capture triadic closure in friendship networks. Concerning the interplay between status and friendship, the meta-analysis reveals a significant link between the two tie types: friendship nominations significantly co-occur with popularity nominations and vice versa. This is in line with previous findings by Vörös et al. (2019).

Estimates indicative of status processes

To capture preferential attachment—the tendency of actors who already have many nominations to receive even more—the geometrically weighted indegree term (GWIDEG) was included in all models. It shows a negative sign in status ascriptions but a positive sign in friendship networks. In line with previous literature (Hunter 2007; Kreager et al. 2017; Levy 2016), my interpretation of this pattern is that preferential attachment is present in status ascriptions but not in friendships.

The second status process, hierarchy in close ties, was measured by the hierarchical tau score statistic. All data sets show a positive tendency for triads with hierarchical structures in friendship ties (albeit only at the 10% alpha level in the FVA data set).

Table 2.2. Meta-analysis of ERGMs for status ascriptions

	CILS4EU			FVA			SOCIALBOND		
	beta	s.e.	Q	beta	s.e.	Q	beta	s.e.	Q
Edges	-0.76***	0.01	832.65***	-4.34***	0.03	120.66***	-3.19***	0.04	456.27***
Mutual	1.76***	0.03	1259.17***	-0.93***	0.05	70.46***	1.43***	0.06	113.109***
GWIDEG	-3.29***	0.02	650.48***	-1.32***	0.05	369.44***	-3.76***	0.04	111.77***
GWESP				0.76***	0.01	239.08***			
GWNESP -OTP	-0.26***	0.004	763.71***				-0.13***	0.01	64.92***
GWNESP -ISP	0.05***	0.003	1190.30***				0.05***	0.01	457.06***
Same class				0.89***	0.02	289.40***	1.59***	0.03	411.37***
Activity female	0.06***	0.01	526.22***	0.42***	0.02	118.68***	0.26***	0.03	113.86***
Popularity female	-0.11***	0.02	397.45***	-0.65***	0.04	112.54***	-0.32***	0.05	86.84***
Same gender	0.13***	0.01	507.78***	0.39***	0.02	58.90**	0.35***	0.04	74.86***
Same ethnic group	0.02*	0.01	397.52***	-0.01	0.01	55.20***	-0.06**	0.03	27.36
Friendship entrainment	1.18***	0.02	665.80***	1.92***	0.03	113.32***	1.42***	0.04	97.76***
AIC	3639.52			1965.23			2457.90		
N	259 schools			30 grades			33 grades		
GOF	92%			87%			85%		

Table 2.3. Meta-analysis of ERGMs for friendship networks

	CILS4EU			FVA			SOCIALBOND		
	beta	s.e.	Q	beta	s.e.	Q	beta	s.e.	Q
Edges	-5.37***	0.02	883.48***	-5.61***	0.07	82.41***	-5.28***	0.03	129.44***
Mutual	1.98***	0.02	587.97***	2.42***	0.05	61.54***	1.98***	0.03	108.62***
GWODEG	2.85***	0.04	849.43***	1.07***	0.13	40.17***	1.60***	0.09	84.65***
GWIDEG	1.39***	0.03	516.71***	0.50***	0.08	31.27***	1.15***	0.07	50.92*
GWESP	0.89***	0.01	880.51***	0.74***	0.01	47.88***	0.86***	0.01	173.80***
Same class				1.05***	0.03	203.13***	0.53***	0.01	178.39***
Activity female	-0.07***	0.02	472.21***	-0.06	0.05	47.52**	-0.01	0.03	54.88**
Popularity female	0.11***	0.03	470.03***	0.06	0.08	47.24**	0.05	0.05	49.41*
Same gender	0.51***	0.01	767.94***	0.89***	0.03	45.85*	0.58***	0.02	154.30***
Same ethnic group	0.12***	0.01	549.04***	0.28***	0.02	61.06***	0.14***	0.03	114.38***
Popularity entrainment	1.25***	0.02	755.90***	1.79***	0.03	106.10***	1.47***	0.03	83.07***
Hierarchical Tau score	0.01***	0.003	1366.84***	0.01†	0.006	60.11***	0.03***	0.003	118.97***
Difference in popularity	-0.03***	0.001	713.15***	-0.16***	0.01	130.80***	-0.06***	0.003	137.75***
AIC	1689.59			384.21			268.59		
N	318 schools			28 grades			37 grades		
GOF	95%			94%			91%		

Finally, status homogeneity—the tendency of close ties to occur among status-similar actors—is also present in all data sets. The negative term for the absolute difference in relative status indicates that students with a larger difference in status are less likely to share a friendship tie.

In sum, the meta-analyses yield evidence for the presence of network structures indicative of all three status processes. The main goal of this article is to study contextual variation in these micro-mechanisms. The Cochrane's Q statistic suggests significant contextual variation for all parameters reflecting status processes, which justifies the application of meta-regressions (see Smith et al. 2016). The next section reports results of meta-regressions that examine context size and demographic diversity as potential moderators for status processes.

Meta-regressions

Do some school contexts exhibit more network structures indicative of status processes than others, depending on their size and demographic composition? To answer this question, I estimated bivariate meta-regressions as well as full models, including all contextual characteristics (cf. McFarland et al. 2014: 1107–1108). Tables 2.4 and 2.5 report how all parameters in a respective specification respond to contextual moderators.

Contextual variation in other tie-formation processes

Before discussing how the relational anatomy of status orders varies across contexts, it is worthwhile to point out that my analyses replicate important findings identified by previous studies on contextual variation of tie-formation mechanisms in friendship networks (Goodreau, Kitts, and Morris 2009; McFarland et al. 2014; Kalter and Kruse 2014; Smith et al. 2016). As shown in table 2.5, the first commonality is that clustering in friendships—measured by the GWESP statistic—tends to be more pronounced in larger settings (Goodreau et al. 2009; McFarland et al. 2014). This tendency holds in two of the analyzed data sets and is interpreted by McFarland et al. (2014) as students' search for more social support as they encounter elevated uncertainty and anonymity in larger contexts. The same finding was already reported by Goodreau et al. (2009: 114–115), who concluded: "If persons generally prefer some level of social closure, they must exert more effort in larger populations to create it." Similarly, the tendency to reciprocate friendship ties is amplified in larger classrooms and grades in all three data sets.[22] This finding is also in line with McFarland et al. (2014) and further corroborates their argument that uncertain environments foster closure in friendship relations. The second similarity to previous results is that friendship networks in European schools tend to exhibit higher levels of ethnic homophily in more ethnically diverse contexts (Smith et al. 2016; Kalter and Kruse 2014).[23]

Contextual variation in status processes

I now turn to the moderating role of contextual characteristics for status processes. To give an easily accessible overview of the main results, table 2.6 summarizes the results regarding status processes reported in tables 2.4 and 2.5.

In line with the theoretical notion that larger contexts exhibit more uncertainty, which should amplify status processes, all three data sets show stronger estimates of preferential attachment in status ascriptions in larger classrooms and grades. This is not the case for friendship nominations, corroborating the idea that close ties react differently to elevated uncertainty compared to status ascriptions: friendship formation does not show a degree distribution indicative of preferential attachment net of other model parameters, even in larger settings with presumably more uncertainty.

[22] However, this association is only significant in the bivariate meta-regression for the SOCIALBOND data set (see table 2.5, third panel).

[23] Also, in U.S. schools, racial homophily is more pronounced in contexts with higher compositional diversity (Goodreau, Kitts, and Morris 2009; McFarland et al. 2014).

Table 2.4. Meta-regression for ERGM estimates in status ascriptions

Classroom level		Size		Composition			
		Larger		*Higher Ethnic Heterogeneity*		*Higher Gender Heterogeneity*	
CILS4EU	Main	Bivar.	Full.	Bivar.	Full.	Bivar.	Full.
Edges	-0.75***	-0.05**	-0.05**	-0.11***	-0.13***	-0.09***	-0.09***
Mutual	1.65***	0.003	-0.002	0.15***	0.14***	0.07*	0.07*
GWIDEG	-3.26***	-0.09***	-0.07**	-0.04	-0.04†	-0.14***	-0.10***
GWNESP -OTP	-0.26***	0.04***	0.04***	-0.01*	-0.005	0.003	-0.003
GWNESP -ISP	0.06***	-0.03***	-0.03***	0.04***	0.04***	0.001	0.004
Activity female	0.07***	-0.05***	-0.05***	0.005	0.01	0.02	0.04*
Popularity female	-0.12***	0.05**	0.04**	-0.02	-0.03	-0.002	-0.02
Same gender	0.13***	0.01	0.004	-0.02	-0.01	0.10***	0.09***
Same ethnic group	-0.01	-0.002	-0.0001	-0.01	0.005	0.04**	0.02†
Friendship entrainment	1.20***	-0.05***	-0.05***	0.10***	0.09***	-0.01	0.01

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Grade level		Size		Composition			
		Larger		*Higher Ethnic Heterogeneity*		*Higher Gender Heterogeneity*	
FVA	Main	Bivar.	Full.	Bivar.	Full.	Bivar.	Full.
Edges	-4.10***	-0.16***	-0.12***	0.05†	-0.01	-0.14*	-0.06
Mutual	-0.83***	-0.35***	-0.36***	0.002	-0.01	0.05	0.13
GWIDEG	-1.54***	-0.49***	-0.31***	0.34***	0.29***	-0.37***	-0.20
GWESP	0.67***	-0.01	0.01	0.05**	0.04***	-0.03	-0.04
Same class	0.86***	0.21***	0.14***	-0.13***	-0.07**	0.19***	0.10*
Activity female	0.47***	-0.03	-0.05†	0.001	-0.01	-0.05	-0.02
Popularity female	-0.68***	0.04	0.07	-0.01	0.02	-0.04	-0.08
Same gender	0.43***	0.04	0.01	-0.10***	-0.11***	0.05	-0.05
Same ethnic group	0.06*	-0.01	-0.08***	-0.08***	0.02	-0.01	0.04
Friendship entrainment	1.90***	0.05	0.06†	0.16***	0.15***	-0.04	-0.05

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Grade level		Size		Composition			
		Larger		*Higher Ethnic Heterogeneity*		*Higher Gender Heterogeneity*	
SOCIALBOND	Main	Bivar.	Full.	Bivar.	Full.	Bivar.	Full.
Edges	-3.17***	-0.28***	-0.32***	-0.06	-0.18***	-0.10*	-0.04
Mutual	1.27***	-0.36***	-0.33***	0.51***	0.05	-0.08	0.02
GWIDEG	-3.76***	-0.20***	-0.17***	0.22***	0.15***	0.08	0.06
GWNESP -OTP	-0.12***	0.02***	0.01*	-0.03***	-0.01*	0.01*	0.01
GWNESP -ISP	0.05***	0.02***	-0.01	0.05***	0.04***	0.01†	0.02***
Same class	1.51***	0.32***	0.27***	-0.13***	-0.04	0.28***	0.21***
Activity female	0.32***	0.05***	0.06*	-0.08**	-0.03	-0.27***	-0.26***
Popularity female	-0.40***	-0.07†	-0.06	0.10**	0.06	0.25***	0.23***
Same gender	0.41***	0.07*	0.04	-0.11***	-0.04	-0.11**	-0.12**
Same ethnic group	0.003	-0.03	0.016	0.05*	0.08**	0.11**	-0.09
Friendship entrainment	1.33***	-0.12***	-0.08*	0.12***	0.07†	-0.04	-0.07†

Table 2.5. Meta-regression for ERGM estimates in friendship networks

Classroom level		Size		Composition			
		Larger		*Higher Ethnic Heterogeneity*		*Higher Gender Heterogeneity*	
CILS4EU	Main	Bivar.	Full.	Bivar.	Full.	Bivar.	Full.
Edges	-5.28***	-0.18***	-0.18***	-0.04	-0.05*	-0.01	0.01
Mutual	1.96***	0.06**	0.05**	-0.04*	-0.04†	0.01	-0.004
GWODEG	2.76***	0.34***	0.34***	-0.04	-0.02	0.03	-0.01
GWIDEG	1.35***	0.01	0.02	0.03	0.03	-0.03	-0.03
GWESP	0.87***	0.02***	0.02***	-0.002	-0.001	0.01	0.002
Activity female	-0.06**	-0.03*	-0.03†	0.03†	0.02	-0.07**	-0.06**
Popularity female	0.10**	0.06*	0.04	-0.05	-0.04	0.12**	0.10*
Same gender	0.52***	0.02***	0.02**	0.02†	0.02†	0.01	0.01
Same ethnic group	0.15***	-0.00	0.003	0.09***	0.09***	-0.002	-0.005
Popularity entrainment	1.27***	0.01	0.01	0.05***	0.05**	0.02	0.02
Hierarchical Tau score	0.02***	-0.01***	-0.01***	0.01†	0.005	0.002	0.005
Difference in popularity	-0.03***	-0.003***	-0.003***	0.002**	0.002*	-0.001	-0.001

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Grade level		Size		Composition			
		Larger		*Higher Ethnic Heterogeneity*		*Higher Gender Heterogeneity*	
FVA	Main	Bivar.	Full.	Bivar.	Full.	Bivar.	Full.
Edges	-5.51***	-0.25***	-0.31***	-0.07	-0.11	0.04	0.22†
Mutual	2.34***	0.13*	0.13*	-0.13*	-0.17**	0.04	-0.03
GWODEG	1.04***	-0.08	-0.03	-0.05	-0.03	-0.17	-0.13
GWIDEG	0.54***	-0.18*	-0.13	-0.01	0.09	-0.18	-0.08
GWESP	0.72***	-0.01	-0.01	0.01	0.002	0.00	0.01
Same class	0.96***	0.30***	0.32***	0.03	0.04	0.13**	-0.08
Activity female	-0.04	-0.03	-0.04	-0.04	0.01	-0.02	0.01
Popularity female	0.06	0.01	0.02	-0.05	-0.07	-0.005	0.002
Same gender	0.90***	0.05	0.03	0.04	0.06†	0.01†	-0.02
Same ethnic group	0.30***	-0.003	0.02	0.06*	0.05*	-0.05†	-0.07*
Popularity entrainment	1.79***	0.16***	0.14***	0.09*	0.06	0.09†	-0.005
Hierarchical Tau score	0.01†	-0.01†	-0.02*	0.01	-0.001	0.01	0.01
Difference in popularity	-0.16***	-0.05***	-0.03**	-0.01	0.03***	-0.04***	-0.01

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Grade level		Size		Composition			
		Larger		*Higher Ethnic Heterogeneity*		*Higher Gender Heterogeneity*	
SOCIALBOND	Main	Bivar.	Full.	Bivar.	Full.	Bivar.	Full.
Edges	-5.20***	-0.08**	-0.07†	0.02	0.03	-0.06	-0.02
Mutual	1.91***	0.13***	0.04	-0.20***	-0.17***	0.10*	0.06
GWODEG	1.51***	0.01	-0.01	-0.09	-0.14	0.05	-0.01
GWIDEG	1.08***	0.01	-0.05	-0.07	-0.12	0.11	0.15
GWESP	0.83***	0.04**	0.04**[24]	-0.0002	0.01	0.03†	0.02
Same class	0.53***	0.02	0.02	0.001	0.01	0.02	0.02
Activity female	-0.01	-0.001	0.02	0.02	0.02	-0.09†	-0.01*
Popularity female	0.08	-0.04	-0.09	-0.04	-0.06	0.10	0.14
Same gender	0.62***	-0.04*	-0.01	0.07***	0.07***	-0.06†	0.02
Same ethnic group	0.22***	-0.04*	0.002	0.12***	0.13***	0.03	0.02
Popularity entrainment	1.55***	0.03	0.08*	0.06†	0.10**	-0.02	-0.05
Hierarchical Tau score	0.03***	-0.004	-0.003	0.01*	0.01*	0.01**	0.01**
Difference in popularity	-0.07***	-0.03***	-0.03***	0.01***	-0.003	-0.01***	-0.004

[24] This association turns insignificant if the number of students who officially attend a grade is used as measure for context size.

Table 2.6. Summary table of moderator effect patterns on status processes

	Status Ascriptions			**Friendships**		
	Size	Composition		Size	Composition	
Micro-Mechanism	*Larger*	*Higher Ethnic Heterogeneity*	*Higher Gender Heterogeneity*	*Larger*	*Higher Ethnic Heterogeneity*	*Higher Gender Heterogeneity*
Classroom Level						
Preferential attachment	++		++			
Hierarchy in friendships	NA	NA	NA	--		
Status homogeneity in friendships	NA	NA	NA	++	--	

	Status Ascriptions						**Friendships**					
	Size		Composition				Size		Composition			
Micro-Mechanism	*Larger*		*Higher Ethnic Heterogeneity*		*Higher Gender Heterogeneity*		*Larger*		*Higher Ethnic Heterogeneity*		*Higher Gender Heterogeneity*	
Grade Level	F	S	F	S	F	S	F	S	F	S	F	S
Preferential attachment	++	++	--	--	+		+					
Hierarchy in friendships	NA		NA		NA		--			++		++
Status homogeneity in friendships	NA		NA		NA		++	++	--	-	+	+

Note: + denotes a significant positive relation; - denotes a significant negative relation. Repetition of a sign (i.e., ++/--) denotes significance in models entailing all contextual characteristics. Single sign indicates a significant bivariate relation. Results are reported separately for the grade level (F = FVA data set; S = SOCIALBOND data set).

A parsimonious explanation for these differences is that actors value reciprocity and equality in close relationships, as pointed out by Gould (2002), but do so less in status ascriptions. The distribution of friendship nominations is thereby limited by a ceiling on inequality, whereas stronger levels of inequality are possible in status ascriptions.

Regarding rank ordering in friendships, a larger size is not associated with an increase of the hierarchical tau score parameter. This differs from McFarland et al. (2014), who reported a significant relationship between size and hierarchical structures in friendships on the school level using the AddHealth data set. Possible reasons for this difference will be discussed in the concluding section.

Estimates of the third status process under investigation, status homogeneity in friendships, are more pronounced in larger classrooms and grades, as theoretically expected. In sum, context size significantly amplifies structures indicating preferential attachment in status attributions and status homogeneity in friendships, whereas rank ordering in friendships is not more pronounced in these contexts.

The second contextual characteristic that should show a link with status processes is the demographic composition of classrooms and grades. According to McFarland et al.'s (2014) theoretical arguments, I expected that more diverse settings marked by higher ethnic and gender diversity show more pronounced status processes. The assumed mechanisms behind this association are that concerns for group boundaries and the overall level of uncertainty should be higher in more diverse settings. Salient group boundaries should provide fertile ground for status rankings, and higher uncertainty should increase the usefulness of cognitive heuristics such as status recognition (cf., McFalrand et al. 2014).

As table 2.6 reveals, I only find mixed evidence for this idea. While gender heterogeneity—with a higher value indicating a more balanced composition between male and female students—is associated with more preferential attachment in status ascriptions on the classroom level, there is no strong evidence that this is also the case on the grade level. Hierarchy in friendship nominations is positively associated with gender heterogeneity in one of the grade-level data sets, but not on the classroom level. Similarly, estimates of status homogeneity increase with higher gender heterogeneity in bivariate models on the grade level, yet not on the classroom level. In comparison, McFarland et al. (2014: 1109) reported that gender heterogeneity dampens hierarchical patterns in friendships on the school level and has no effect on the classroom level. Taken together, these findings suggest that the role of gender heterogeneity for status processes is not straightforward and deserve further attention.

Regarding the influence of ethnic heterogeneity on status processes, the evidence is even less conclusive: only one association points in the expected direction, namely the link between ethnic heterogeneity and hierarchy in the SOCIALBOND data set. In all other cases, we see no or even a negative association between ethnic heterogeneity and estimates of status processes. In contrast, McFarland et al. (2014: 1109) found *more* hierarchical structures in friendships on the school level in contexts with higher racial heterogeneity. Possible explanations for this discrepancy are considered in the conclusion.

To summarize, my analyses across the three data sets found consistent evidence for the notion that preferential attachment and status homogeneity are elevated in larger settings. In contrast, there is no evidence suggesting that hierarchy in friendships is more pronounced in larger contexts. Furthermore, more diverse contexts do not necessarily show more network structures indicative of status processes.

To elaborate on the role of contextual moderators for status processes, the next section offers a simulation-based assessment of the most consistent associations found in the meta-regression analysis: the link between context size, preferential attachment in status ascriptions, and status homogeneity in friendships.

A simulation-based exploration of network models

So far, the analyses showed a significant link between context size, preferential attachment in status ascriptions, and status homogeneity in friendships across all data sets. Yet it is unclear whether the association with context size is substantial or merely statistically significant but negligible in magnitude.

Also, as recently pointed out by Martin (2020), ERGMs with complex model specifications can lead to a misinterpretation of nested parameters. A way to address these concerns is to study how changes in parameters, which are intended to reflect processes of tie formation, affect the overall structure of simulated networks (for a similar approach see e.g., Snijders and Steglich 2015; McFarland et al. 2014: 1102–1103).

Global measures

To investigate whether the increase of estimated preferential attachment in status ascriptions is substantial in larger settings, I choose the skewness of the indegree distribution as a measure for global inequality in the distribution of status (in line with, e.g., Moody 2004; Moody et al. 2011). Positively skewed indegree distributions can be interpreted as unequal, with a few individuals receiving many indegrees, while the majority receives none or only a few indegrees (Fisher 2018: 57; Moody et al. 2011: 103).

To measure how important the amplification of status homogeneity in larger settings is for the overall structure of friendship networks, I use the alpha index of network segregation proposed by Moody (2001).[25] This measure has the advantage that it is substantially

[25] The alpha index is calculated based on the formula provided by Moody (2001: 692–693). Alpha = AD/BC, with A being the number of dyads who share a friendship and in which both students belong to the same status category. B is the number of friendship dyads with students belonging to different categories. C is the number of dyads who do not share a friendship and in which students belong to the same status category. D is the number of dyads who do not exhibit a friendship tie and in which students belong to different status categories. Please note that the formula can also be written as Alpha = (A/C)

interpretable as the odds of a tie between actors belonging to the same category—e.g., two actors who have the same gender—relative to the odds of a tie between students who do not belong to the same category (Moody 2001: 692).[26] Since the index is designed for categorical variables—and an individual's status was measured as a continuous score, consisting a student's received status attributions relative to all status attributions granted in a context—I divided the percentage of received status ascriptions into quartiles. In sum, alpha captures the odds of a friendship between students who are in the same quartile of the status ranking relative to the odds of a friendship between students who are further apart in their contexts' status ranking.

Table 2.7. Empirical distribution of global measures

Skewness status ascriptions	Mean	SD	Median	Min.	Max.
CILS4EU	1.52	1.08	1.52	-0.15	3.21
FVA	1.66	1.12	1.56	0.13	3.51
SOCIALBOND	2.20	0.74	1.97	0.88	4.47
Status segregation friendships	Mean	SD	Median	Min.	Max.
CILS4EU	1.71	0.97	1.56	0.233	13.81
FVA	1.81	0.63	1.67	0.82	4.14
SOCIALBOND	1.37	0.40	1.27	0.95	3.24

/ (B/D). In this version, it is easier to see that alpha represents the odds of a friendship between two students who belong to the same status quartile relative to the odds of a friendship between two students who belong to different status quartiles.

[26] Although less common than categorical measures (Bojanowski and Corten 2014), measures for network segregation in continuous actor attributes exist. One example is Moran's I, which is a measure for spatial autocorrelation but can also be used to detect network segregation (de la Haye et al. 2011). I decided not to use these measures, because Moody's alpha allows a substantial interpretation as well as a comparison of absolute values, which is an advantage in judging differences between simulation scenarios.

Table 2.7 provides an overview of the empirical distribution of these measures. In line with the notion that status orders operate in the school setting, status ascriptions are—on average—positively skewed, and friendships are segregated along status rankings in all data sets. However, the wide ranges of the measures and their moderate to large standard deviations indicate considerable variation across contexts.[27]

How strongly do contextual moderators shape the structure of status order?

Based on the network models reported in tables 2.4 and 2.5, I run simulations to answer the counterfactual question: how strongly would the overall structure of status orders change if an average-sized context showed status processes similar to estimates of smaller or larger contexts? Figures 2.1 and 2.2 summarize global measures for inequality and status segregation of simulated networks and show their links with parameters indicative of status processes. The size of simulated networks is held constant across scenarios and within data sets (see McFarland et al. 2014: 1102–1103). Only parameters reflecting status processes are changed across scenarios (x-axis). These scenarios range from simulations for contexts two standard deviations below the average-sized context (-2) to simulations for contexts which are two standard deviations larger than average (2). The baseline effect of network size on networks' global characteristics (Anderson et al. 1999) is thereby accounted for, and simulation results should reflect the association of size with status processes, net of other aspects that change with network size, such as a lower density of larger networks.[28]

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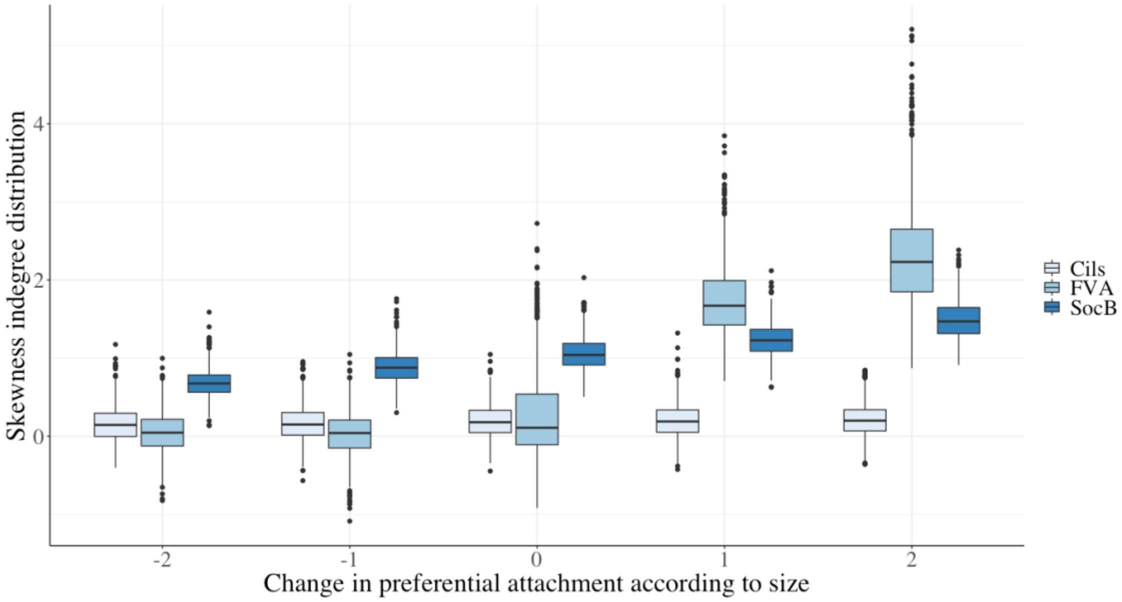
[27] The aim of the subsequent simulations is not to realistically reproduce observed levels of inequality in status ascriptions or status segregation in friendships. Rather, the empirical distribution of global measures provides a backdrop against which it becomes easier to assess whether changes across simulation scenarios are substantial.

[28] Since measures connected to the degree distribution are mechanically linked to size (Anderson, Butts, and Carley 1999), appendix D provides a robustness check with additional simulation-based analyses which compare random to observed networks without the involvement of ERGM estimates. In sum, the

Figure 2.1. Inequality in simulated status ascriptions based on ERGM estimates



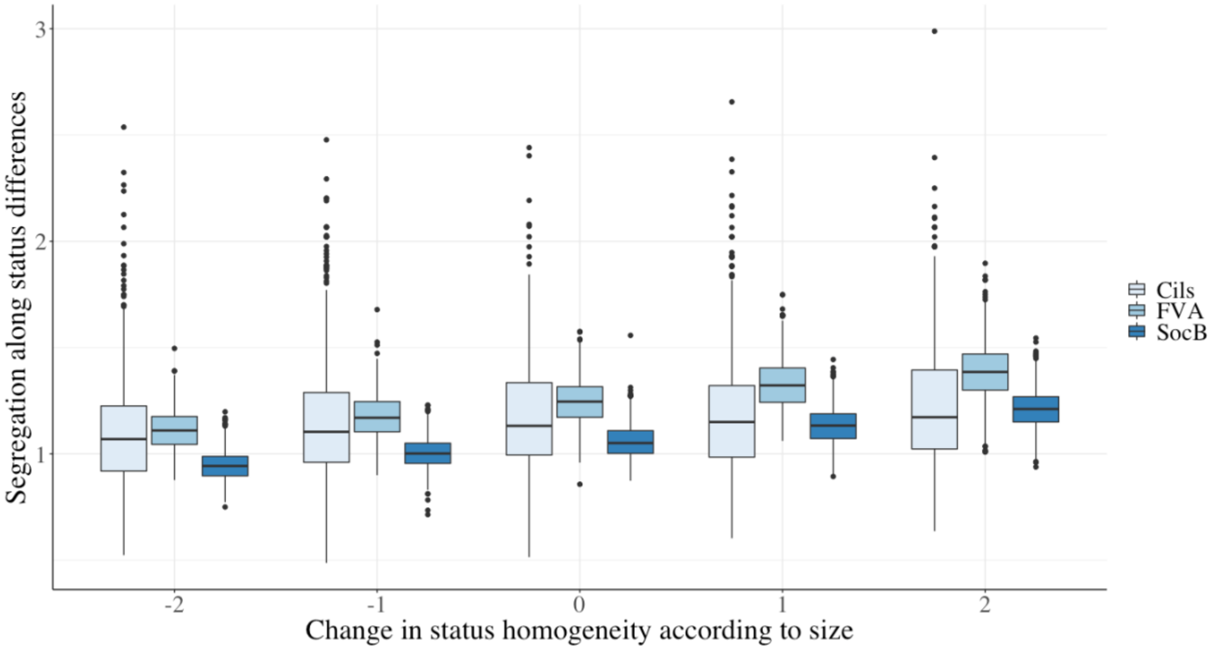
We now turn to the simulation-based exploration of network models. As figure 2.1 shows, the estimated increase in preferential attachment in larger networks substantially affects the global inequality of simulated status ascriptions, even if context size and the composition of the student body is fixed to average values.[29] The increase in the median skewness in status ascriptions on the classroom level is only modest (CILS4EU: 0.14 to 0.20), but the magnitude of the increase is substantial on the grade level (FVA: 0.05 to 2.23; SOCIALBOND: 0.68 to 1.47). For example, simulations for the FVA data show an increase of the median inequality in status ascriptions

findings provide evidence for the notion that the link between inequality and context size is more pronounced in observed status ascriptions than randomness would suggest, while this is not the case for friendship nominations.

[29] The networks all have a fixed size adjusted at the mean network size in the respective data set. Actor attributes are assigned according to a sample from the networks entering the ERGM analysis. The aim of these constraints was to inform the simulation process with an average network of constant size. 1,000 networks are simulated based on the mean parameters reported in table 2.4 for each boxplot. Only the GWIDEG parameter is changed across the different simulation scenarios. It is adjusted according to its estimated value in networks up to two standards deviations below and two standards deviations above the average size of the analysis sample. Simulations in figure 2.2 were obtained analogously.

with the size of roughly two empirical standard deviations (see table 2.7) across scenarios (from -2 to 2).

Figure 2.2. Status segregation in simulated friendship networks based on ERGM estimates



Regarding status segregation, the simulated friendship networks in figure 2.2 only show slightly higher values for classroom level networks across scenarios (CILS4EU: 1.07 to 1.17). In comparison, differences are more pronounced on the grade level (FVA: 1.11 to 1.38; SOCIALBOND: 0.94 to 1.21). Also, compared to the empirical spread in status segregation, the difference across scenarios is small on the classroom level, yet noticeable on the grade level: for the FVA data set, simulations yield a difference of about half an empirical standard deviation across scenarios. For the SOCIALBOND data set, this difference amounts to around one empirical standard deviation.

In summary, the simulation-based exploration of network models illustrated that changes in parameters indicative of status processes suffice to produce considerable variation in the global structure of simulated status orders. Furthermore, the simulations indicate that the moderating role of size seems to be more important on the grade level than on the classroom level.

2.6 Discussion and conclusion

This article examined how contextual characteristics connected to uncertainty shape status processes in the school setting. Most previous work has either focused on close social relationships to infer underlying status orders (Ball and Newman 2013; McFarland et al. 2014; Smith and Faris 2015) or has studied how individuals' behavior is linked to their standing among peers (Cillessen and Rose 2005; Faris and Felmlee 2014; Kornbluh and Neal 2016; Moody et al. 2011; Rodkin et al. 2006, 2013; Veenstra et al. 2010). Building upon a growing stream of research which highlights that network mechanisms vary across contexts (Goodreau et al. 2009; McFarland et al. 2014; Simpson 2019; Smith et al. 2016), I demonstrated that status processes in status ascriptions and friendships react differently to contextual pressures and should be studied simultaneously to better understand the organizing logics of status orders.

Most importantly, the results indicate that both 1) preferential attachment in status ascriptions and 2) status homogeneity in close ties are more pronounced in larger classrooms and grades. Moreover, the simulation-based exploration of the estimated network models suggests that the association between size and status processes is not only significant but also substantial in terms of magnitude. These findings provide more specific network-analytical evidence for the notion that context size is crucial for status orders (Blau 1968; Mayhew 1973; Mayhew and Levinger 1976; McFarland et al. 2014). They also serve to question the idea that a "leading crowd" (Coleman 1961: 34) is a ubiquitous feature of social life in schools. More broadly, this investigation speaks to literature that stresses that status orders and other network processes show starkly different dynamics across contexts (Goodreau et al. 2009; Martin 2009b; McFarland et al. 2014; White 2008).

The current study contributes to a network-ecological perspective (McFarland et al. 2014) by demonstrating how a focus on multiple types of ties can yield novel insights. The analyses revealed that the structural features of status ascriptions and friendships respond differently to contextual moderators. In larger settings, status orders among adolescents show more inequality in status ascriptions, while friendships are more segregated along the lines of status. These results suggest that status ascriptions are more strongly focused on an elite of students, and that status differences are more salient in larger peer ecologies. While these findings could be of interest to scholars who study how status processes affect students' behavior (Berger and Dijkstra 2013; Faris and Felmlee 2014; Kornbluh and Neal 2016; Veenstra et al. 2010), they could also inform the decisions of policy makers. In addition to the extensively discussed beneficial effects of smaller learning environments on academic achievement (e.g., Finn and Achilles 1999), my results suggest that limiting class and grade sizes could make status dynamics in school less severe and promote a more egalitarian climate among students.

While the general notion that inequality and status recognition intensifies in larger settings is in line with classic and contemporary accounts on status (Blau 1968; Mayhew 1973; Mayhew and Levinger 1976; McFarland et al. 2014), some of my findings deviate from previous research and are therefore worth discussing in more detail. First, whereas McFarland et al. (2014) found a significant association between rank ordering in friendships and context size, the data sets studied here do not show this association. One possible explanation is that schools vary more strongly in their size than grades.[30] Increased hierarchy in friendships may only appear in the presence of size differences greater than the differences in the data sets used in this analysis.

Another reason could be that the U.S. and the European school systems differ in their organizational features, leading to more status recognition in U.S. schools. For instance, the U.S. system places a larger emphasis on extracurricular activities, which probably fuel status processes by creating an elite of cheerleaders or football players particularly visible among a

[30] The authors report a mean of 643.10 students and a standard deviation of 494.51 for the 129 contexts they used in their school-level analysis (McFarland et al. 2014: 1113). By calculating how large schools are one standard deviation above or below the mean, one can deduce that schools with over 1,000 students as well as schools with less than 140 students were part of the sample. For a comparison with the data used in my analyses, see table 2.1.

larger peer audience (for evidence from ethnographic work, see Eder 1995; Eder and Enke 1991; Eckert 1989; Milner 2013). Finally, the insensitivity of the tau statistic to context size could point to limits of inferring status ascriptions from asymmetrical structures in close relationships, as argued by Vörös, Block, and Boda (2019).

Second, my results show no consistent link between status processes and demographic heterogeneity. While McFarland et al (2014) found that more racial heterogeneity is associated with more rank ordering in friendships, my analyses found an association between ethnic heterogeneity and elevated hierarchization in friendships in only one of the three data sets under study. This could be due to the different role of race in U.S. society compared to ethnicity in European countries (see Wimmer & Lewis 2010; Smith et al. 2016). If uncertainty is the main driver of status processes, it could be that ethnic heterogeneity in Western Europe does not increase uncertainty, since ethnic boundaries are often less salient than racial boundaries. While ethnic homophily in friendships is higher in more ethnically diverse settings (see table 2.5), this does not necessarily imply that uncertainty is higher among students.

Recent studies illustrate that the importance of ethnicity for social networks seems to depend on more scope conditions than the ethnic composition of the student body, such as students' identification with their ethnic group (Boda 2018; Kruse and Kroneberg 2019; Leszczensky and Pink 2019). Moreover, the role of composition for inter-group processes varies for natives and minority students (Smith et al. 2016). Taken together, there is reason to re-consider the assumption that more ethnic diversity is linked to more concerns for group boundaries and elevated uncertainty in future studies.

Limitations and avenues for further research

In summary, the current study offers new insights on how tie-formation mechanisms linked to status orders are affected by contextual moderators in multiple tie types. Thereby, the results contribute to a stream of research which studies status from a relational perspective (Faris and

Felmlee 2014; Lynn et al. 2009; Manzo and Baldassarri 2014; Martin 2009a; McFarland et al. 2014; McMahan 2017; Podolny 2010; Ridgeway 2019; Sauder et al. 2012; Smith and Faris 2015; Torlò and Lomi 2017; Vörös et al. 2019) and, more specifically, to the discussion on the scope conditions for the emergence of status orders (Martin 2009a, 2009b; McFarland et al. 2014; Sauder 2006). These contributions notwithstanding, there are obvious limitations of this study which point towards promising avenues for future research.

One such limitation is the cross-sectional nature of the analysis. Previous research found that status systems are marked by individual mobility, while global properties of status systems in schools seem to remain constant over time (Moody et al. 2011; Smith and Faris 2015). However, these studies analyzed data sets which only include information on friendship ties. The cross-sectional results presented here indicate that friendship networks show different structural variability across contexts compared to status ascriptions. Therefore, a possible extension could be to study individual trajectories and global stability in multiple tie types simultaneously.

A longitudinal perspective could also be leveraged to study whether the observed link between context size and status homogeneity in friendships is due to selection or influence (Steglich, Snijders, and Pearson 2010). The models presented in this article cannot disentangle whether friendships are more often initiated based on students' status in larger classrooms and grades, or whether students rise more strongly in the status ranking due to being friends with high-status actors in larger settings. Multiplex longitudinal network models capturing the co-evolution of different tie types, such as stochastic actor-oriented models, could be an important analytical tool to advance our understanding of the longitudinal developments of status systems and how status homogeneity can be decomposed into selection and influence dynamics (Fujimoto, Snijders, and Valente 2017; Lomi and Torló 2014; van der Ploeg et al. 2019; Torlò and Lomi 2017).

Another limitation of the presented analyses is that they are geared at comparisons within data sets of relatively homogeneous contextual units, such as classes or grades. However, the simulation-based exploration demonstrated that size plays a larger role for status processes in grades compared to classrooms. Therefore, future research could examine whether the moderating role of size for status orders becomes stronger as the average size of contexts increases, and whether it decreases again after a certain threshold. If environments become too large for actors to know a large proportion of context members, this could also lead to the mitigation of some status processes. While the data sets studied here do not provide sufficient ranges in size to study this question, comparing status orders across empirical settings—for instance, a comparison between the school setting and status orders in science or organizational fields—could lead to new insights and probe the generalizability of the results presented in this article.

In summary, this study illustrates that taking multiple tie-types into account is a fruitful avenue for future research. The results indicate that status ascriptions respond differently to contextual moderators compared with more widely studied friendship networks. Whereas friendships become more segregated along the lines of status and exhibit higher levels of closure, status ascriptions tend to centralize on an elite of actors in larger, more uncertain contexts. These differences point to a profound difference between relational processes characteristic of reciprocal, cost-intensive relationships in contrast to evaluative ties, which can be granted without notice by the evaluated person. While close relationships thereby remain relatively egalitarian, evaluative ties show increasing inequality as contextual uncertainty rises.

Chapter 3

The development of stratification and segregation in a new scientific field. A study of collaboration among scientists in neuroblastoma research between 1975 and 2016*

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This chapter was published in *Social Networks*.

Wittek, M., Bartenhagen, C., & Berthold, F. (2023). The development of stratification and segregation in a new scientific field: A study of collaboration among scientists in neuroblastoma research between 1975 and 2016. *Social Networks, 72*, 80-107.

* We would like to thank Richard Benton, Katharina Burgdorf, Lothar Krempel, and Tom Snijders for their valuable comments on parts of this work.

Abstract

Using a new data set on scientific collaboration in neuroblastoma research over a period of 41 years, we study how the structure of collaboration ties in an evolving scientific field changes over time. Guided by concepts from the sociology of knowledge and status theories, we highlight the importance of a field's size and age for processes of stratification and segregation within it. Our findings suggest that stratification becomes stronger and diversifies as the field of neuroblastoma research expands. Moreover, we find that the occurrence of collaboration between researchers with a similar status becomes more likely as the field matures. While previous work has primarily examined established fields, our study focuses on how scientific fields change their structure over time. More broadly, this chapter demonstrates the potential analytical merits of adopting a dynamic and relational perspective on the developmental trajectories of organizational and cultural fields.

3.1 Introduction

Both previous and recent research shows that accumulation dynamics shape the structure of scientific collaboration and perpetuate inequality in the distribution of recognition and resources within scientific communities (Allison et al. 1982; Blau 1994; Bol et al. 2018; Bourdieu 1988; Burris 2004; Cole and Cole 1973; Eom and Fortunato 2011; Gondal 2018; Hagstrom 1971; Lynn 2014; Merton 1968).

We contribute to this line of work by studying how stratification and segregation shape scientific collaboration networks throughout the evolution of a new scientific field. The empirical setting of our study is a specialized community of cancer researchers who began to investigate neuroblastoma—the most common solid cancer in childhood (Maris 2010)—in the second half of the 1970s. Consequently, our theoretical framework draws on insights from the sociology of knowledge (Chubin 1976; Cole and Cole 1973; Crane 1972; Mullins 1972), status theories (Gould 2002; Podolny 2010; Ridgeway and Correll 2006), and a growing body of research that applies network analysis to study the structure of coauthor or citation networks (Dahlander and McFarland 2013; Ferligoj et al. 2015; Foster et al. 2015; Friedkin 1978; Gondal 2011; Kronegger et al. 2012; Lynn 2014; Ma et al. 2020; Moody 2004; Shwed and Bearman 2010; Stark et al. 2020).

Sociologists have identified the Matthew effect—a tendency of actors with a large stock of resources and recognition to accumulate even more of these assets—as an important factor for the social organization of scientific communities (Cole and Cole 1973; Crane 1972; Merton 1988, 1968). Thereby, preferential attachment can be regarded as a special case of the Matthew effect and describes a process by which actors with many network ties tend to attract more ties over time (Barabâsi et al. 2002; Barabási and Albert 1999). While scientometric, sociological, and network-scientific studies persistently report a concentration of coauthorships among an elite of scholars (Barabâsi et al. 2002; Leydesdorff and Wagner 2008; Moody 2004; Newman

2001a), less systematic attention has been paid to the question of how inequality in the distribution of network partners changes as scientific fields mature.

Furthermore, although canonical works suggest that scientific fields exhibit different forms of social organization at the outset compared to during their later stages (Chubin 1976; Crane 1972: 85–98, 115–128; Mullins 1972), no network-analytical study to date has examined how accumulation dynamics operate through multiple channels throughout a network's evolution.

Moreover, our investigation of the structure of a new scientific field that has gradually transformed over more than 40 years also contributes to a stream of literature that emphasizes the role of contextual characteristics for network structure (Martin 2009; McFarland et al. 2014; Simpson 2019; White 2008). As McFarland et al. (2014: 1112) note, not only do the preconditions for processes of tie formation vary between contexts, they also change over time. Yet, thus far only a few sociological studies have examined changes in network mechanisms as a context matures (Lewis and Kaufman 2018; Schaefer and Kreager 2020). We address this research gap by studying changes in the structure of collaboration networks in a new scientific field.

To guide our analysis, we build upon the assumption that members of a nascent scientific specialty develop their careers by mobilizing new members (Chubin 1976; Frickel and Gross 2005; Mullins 1972). Established actors thereby acquire more resources as a field gains legitimacy and in turn receives more external funding (Alberts et al. 2014; Laudel 2006). Consequently, senior scientists are able to integrate new researchers into their teams and strengthen their position in the community (Bourdieu 1988; Frickel and Gross 2005; Lazega et al. 2006; Mullins 1972).

Moreover, status theories suggest that status recognition affects collaboration dynamics in organizational fields and helps actors to navigate complex social environments (Lynn 2014; Podolny 2010; Sauder et al. 2012). Similarly, status construction theory highlights that status beliefs reduce situational uncertainty and ease coordination problems (Ridgeway 1991;

Ridgeway and Correll 2006; Ridgeway and Erickson 2000). Following these literatures, we argue that the presence of a larger number of authors in a field increases uncertainty, which elevates the importance of status recognition for coauthor choices (cf., McFarland et al. 2014).

Both streams of literature lead us to the expectation that inequality in the distribution of coauthorships increases throughout the evolution of scientific fields. Furthermore, we propose that a diversification of accumulation dynamics accompanies this trend: as a field grows, we expect years of experience, productivity, and seniority to factor into scientists' popularity as coauthors. In addition, we hypothesize that status homogeneity—the tendency to collaborate with others similar in status—increasingly structures scientific collaboration in later stages of a field. At the same time, mentor-apprentice ties between early career researchers and established scientists should retain their relevance for scientific collaboration.

To test our theoretical arguments, we apply exponential random graph models (ERGMs; Lusher et al. 2013) to a coauthor network based on abstracts submitted to the Advances in Neuroblastoma Research (ANR) conferences between 1975 and 2016 (Berthold et al. 2019). This manually collected data source is well suited for studying how a scientific specialty evolved because, initially, neuroblastoma was a new topic addressed by only a small number of researchers (Martynov et al. 2020). While previous studies examined entire scientific disciplines (Moody, 2004; Newman, 2001a), national research communities (Ferligoj et al. 2015; Kronegger et al. 2011, 2012; Lazega et al. 2006), or collaboration within a single university (Dahlander and McFarland 2013; Rawlings et al. 2015; Stark et al. 2020), we focus on the long-term trajectory of a scientific field organized around a demarcated, well-defined research topic that was not diluted by other topics throughout the four decades under observation.

Our findings indicate that the concentration of collaboration on an elite of researchers becomes stronger as neuroblastoma research matures. Also, we find that collaboration is increasingly segregated according to researchers' productivity and experience over time.

3.2 Theory

Social scientists have firmly established the belief that social processes affect knowledge production (Bourdieu 1988; Chubin 1976; Crane 1972; Frickel and Gross 2005; Knorr 1999; Latour 1987; Lazega et al. 2006; Merton 1988, 1968; Mullins 1972). Scientific fields resemble *invisible colleges* (Crane 1972) marked by interorganizational collaboration and regular communication among researchers. Likewise, scientific specialization revolves around clusters of researchers connected by workshops, conferences, and informal social meetings (Chubin 1976; Mullins 1972). Moreover, the growing size of research teams—for instance, in high energy physics (Newman 2001b, 2001c)—makes modern science an increasingly social activity (Leahey 2016; Wuchty et al. 2007).

Concerning stratification in science, Merton (1968) noted the self-reinforcing nature of accumulation dynamics many years ago and coined the term "Matthew effect", which describes that well-known scholars gain more resources and recognition over time by benefitting from initially small relative advantages. For the case of network ties, this claim has since been supported by many studies analyzing coauthorships or citations and is usually called "preferential attachment" in network-analytical applications (Barabâsi et al. 2002; Eom and Fortunato 2011; Newman 2001a). While an accumulation of coauthorships by an elite of researchers is often viewed as an average tendency—persistently shaping the structure of scientific collaboration—contemporary and earlier theoretical accounts suggest that the structure of organizational (Hannan and Freeman 1993; Padgett and Powell 2012), cultural (Baumann 2001; Becker 2008; Bourdieu 1993, 1984; White and White 1993), and scientific fields (Chubin 1976; Crane 1972; Frickel and Gross 2005; Jurgens et al. 2018; Kuhn 1970; Munoz-Najar Galvez et al. 2019) changes over time. In the present study, we elaborate on these dynamic perspectives on the structural configurations of various fields and derive theoretical expectations for the developmental trajectory of a developing scientific specialty in the next section.

Inequality in a developing scientific field

Our first theoretical expectation concerns the question of whether a new scientific field exhibits different levels of stratification throughout its evolution. Previous work suggests that scientists first have to allocate resources to make new epistemic claims that are credited by a peer audience (Boardman and Ponomariov 2007; Chubin 1976; Frickel and Gross 2005). Also, scientists need to mobilize collaborators such as PhD students and postdocs to generate a high output of well-cited publications, thus allowing them to acquire more resources and to stabilize their position in a new field of inquiry (Griffith and Mullins 1972; Latour and Woolgar 1986; Lazega et al. 2016, 2006; Li et al. 2013).[31]

In terms of the structure of scientific collaboration, these processes produce "hub-spoke structures" (Martin 2009b), with senior scientists acting as hubs and younger researchers as spokes. These constellations induce stratification in the number of publications since the leader of a research group is usually named as a coauthor on all the papers that a group produces. In contrast, PhDs and postdocs tend to work on a small set of papers as primary investigators (see, for example, Knorr 2009: Ch. 9). Moreover, leaders often function as representatives of their group—for instance, by promoting the group at conferences or by contacting leaders of other research groups (Griffith and Mullins 1972: 961; Knorr 2009: 222–224; Lazega et al. 2016, 2006). This role allows them to forge collaborations between groups, which increases leaders' privileged access to coauthor ties (see, for example Hâncean et al. 2021).

[31] While we draw upon empirical findings stemming from the stream of science and technology studies (STS), we would like to point out that the usage of network-theoretic concepts in this tradition differs from our focus on collaborative networks (Venturini et al. 2019). According to the STS perspective, networks can be composed of entities such as documents, laboratories, and other parts of scientific infrastructure as well as human persons (Foster et al. 2015; Knorr 1999; Latour 1987; Shi et al. 2015). In comparison, sociologists of science and researchers using social network analysis tend to study social networks among persons—e.g., networks of collaborations or citations among scholars (Chubin 1976; Crane 1972; Dahlander and McFarland 2013; Gondal 2011; Mullins 1972; Rawlings et al. 2015; Stark et al. 2020).

Regarding the global trajectory of a field, we argue that the overall inequality in collaboration is likely to increase as an area of scientific inquiry grows. This should be the case because collaborations between research groups—often initiated by senior scientists (Latour and Woolgar 1986)—increase in maturing scientific specialties (e.g., Mullins 1972), and the structure of laboratories changes due to new funding sources (Alberts et al. 2014; Laudel 2006). If new entrants collaborate in the same way as previous field members, inequality should remain stable. Yet, we expect that the balance between scientists with tenured positions and early career researchers shifts as a field grows.

As more external funding is channeled into a new field of inquiry, funding agencies mainly offer programs that provide short-term employment for PhDs and postdocs. In contrast, the number of tenured positions does not increase proportionally because universities and research facilities are reluctant to create costly long-term positions (Laudel 2006; Münch 2014). As Alberts et al. (2014) point out in regard to US biomedical research: although the field experienced rapid growth from the 1980s onward, the career prospects of early career researchers worsened decisively as the influx of new funding "has led to an enormous growth in 'soft money' positions, with stagnation in the ranks of faculty who have institutional support" (Alberts et al. 2014: 5775). Consequently, we expect that established scientists employ a larger staff of early career researchers if more external funding opportunities emerge and that collaborations will concentrate on a smaller proportion of the field. Thus, in turn, we expect a nascent scientific field to exhibit less inequality in the distribution of coauthorships than a mature field.

This expectation can also be derived from another stream of literature concerned with the ubiquity of status processes in markets, organizational fields, and interaction in task-oriented groups (Borkenhagen and Martin 2018; Gondal 2018; Ma et al. 2020; Podolny 2010; Ridgeway 1991, 2019; Sauder et al. 2012). What is common to different usages of status as a theoretical concept is a definition of status as prestige, respect, recognition, and (psychological) deference received by others (Fiske 2011; Gould 2002; Podolny 2010; Ridgeway 2019).

In line with Podolny (2010), we assume that actors use status signals as cues to reduce uncertainty, thus allowing them to navigate complex fields.[32] Likewise, status construction theory suggests that status beliefs emerge from a concatenation of micro-interactions due to actors' need to reduce situational uncertainty. In particular, status beliefs allow actors to solve the problem of coordinating behavior, which is necessary to achieve group goals (e.g., Ridgeway and Correll 2006: 6). As uncertainty increases, status should play a more prominent role in actors' behavior because the heuristic usefulness of status categorizations increases as environments or situations become more complex (Blau 1968; Fiske 2011; Mayhew 1973; McFarland et al. 2014; Podolny 2010; Ridgeway 2019).

Regarding cooperation in science, most fields initially consist of a small set of actors. Therefore, it is still feasible to monitor the actions of others in detail. As a field matures, new actors enter and it becomes more difficult, or even impossible, to keep track of what others are doing. To retain their capacity to navigate the field—in other words, to decide whom they should collaborate with or whom they should cite—actors tend to apply filters to the relational information they receive (Brashears 2013; Brashears and Quintane 2015; Lynn 2014; Mayhew 1973; Mayhew and Levinger 1976).

Consequently, we expect more inequality in the distribution of coauthorships over time because a growing field increases uncertainty, which in turn amplifies the influence of status recognition on the formation of coauthor ties.

[32] The notion that actors use cognitive heuristics to store and represent relational information is well supported by empirical evidence (Brashears 2013; Carnabuci et al. 2018; Krackhardt and Kilduff 1999). Perceiving others on a vertical dimension plays a crucial role in social cognition and shapes interaction across a variety of settings (Anderson, Hildreth, and Howland 2015; Berger, Cohen, and Zelditch 1972; Fiske 2011; McMahan 2017; Ridgeway 1991).

Hypothesis 1. Inequality in the distribution of coauthorship ties increases as a scientific field matures and grows.

In summary, we expect rising inequality in the distribution of coauthorships due to a shrinking proportion of actors who manage to mobilize additional researchers and resources (Alberts et al. 2014; Chubin 1976; Frickel and Gross 2005; Laudel 2006; Mullins 1972), and due to the increasing importance of status as a cognitive heuristic shaping social interaction in uncertain environments (Podolny 2010; Ridgeway and Erickson 2000).

Diversification of accumulation dynamics

In addition to a trend towards more stratification in coauthor ties, we also consider different channels through which actors manage to attract coauthors. A scientist's prominence as a collaborator might result from their ability to offer others resources to conduct studies, a reputation for technical expertise in a particular research area, the skill to spark interest for new topics, or experience in writing academic papers and applying for funding (Blau 1994; Dahlander and McFarland 2013; Griffith and Mullins 1972; Knorr 1999; Lamont 2009; Merton 1968; Mullins 1972; Newman 2001a; Zuckerman 1968). Regarding the question of how multiple aspects structure the distribution of coauthorships, we expect accumulation dynamics tied to years of experience, productivity, and seniority to diversify throughout the evolution of a new scientific field.

Following accounts that stress the temporal unfolding of research communities, we expect that accumulation dynamics diversify because as actors develop their careers, they can draw upon multiple field-specific resources to mobilize additional collaborators (Chubin 1976; Cole and Zuckermann 1975; Frickel and Gross 2005; Griffith and Mullins 1972). In the early stages of a scientific endeavor, pioneering researchers primarily rely on their charisma and their ability to spark interest in new topics. In a comparison of different specialties, Griffith and Mullins

(1972: 961) highlight the role of leaders who are crucial in organizing the intellectual activities of a nascent specialty but who initially often lack tangible resources such as funding.[33]

Consequently, building and maintaining collaborations despite these unfavorable conditions should be the prime factor influencing researchers' prominence as coauthors during the genesis of a field.[34] Throughout its development, a field gains legitimacy, new external funding sources become available, and successful leaders of research groups forge their careers (Alberts et al. 2014; Laudel 2006). Thus, we expect field-specific resources such as years of experience, productivity, and seniority to gain importance for the acquisition of coauthorships over time.

Again, we can also build on status theories to arrive at this expectation (Gould 2002; Lynn et al. 2009; Podolny 2010; Ridgeway 2019; Ridgeway and Correll 2006). Ridgeway (2019) highlights that status characteristics influence interaction in task-oriented groups. Similarly, Podolny (2010) proposes that status signals guide collaborator choices in organizational fields. Following these accounts, we argue that the publications and years of experience a researcher has accumulated start to act as status markers as a field matures. As outlined by Ridgeway (2019), initially, the ascription of status to nominal characteristics, such as gender, is arbitrary and does not necessarily correspond with actors' contributions to group goals or their competence. Yet, even small differences in the ascription of status that align with nominal

[33] Furthermore, resources acquired in adjacent fields—e.g., previous academic positions or publications—are seldom sufficient to attract aspiring researchers because unorthodox scientific endeavors present much higher risks to the success of individuals' careers compared with work on established problems (Frickel and Gross 2005; Griffith and Mullins 1972; Latour and Woolgar 1986). As Latour (1987) observed, scientists who tackle new problems often face severe resistance from established scientific elites or an inadequate infrastructure for their research (see Bourdieu 1988; Frickel and Gross 2005).

[34] For instance, Mullins (1972) showed that the scientific specialty of phage work—which led to the new discipline of molecular biology—was initially driven by a small circle of charismatic leaders who managed to recruit students through informal social gatherings and workshops for their cause. Scientists only received more institutional support and started to build a stock of influential publications as phage work matured (Mullins 1972: 74).

characteristics can initiate a self-reinforcing dynamic whereby status beliefs spread and lead to persistent inequality in recognition and resources on the macro level (Grow et al. 2015; Mark et al. 2009; Ridgeway 1991, 2014).

In our case, we expect that the ascription of status is arbitrary at the beginning of a field but that a growing set of status markers crystalizes over time because researchers have to navigate an increasingly complex environment (Blau 1968; Fiske 2011; Mayhew 1973; Podolny 2010). While knowing, for instance, how many coauthors a scientist has worked with provides sufficient information to judge their status in the early stages of a new field, additional status markers such as years of experience, publications, or seniority should start to inform collaborator choices at later developmental stages.

Hypothesis 2. Accumulation dynamics diversify as a scientific field matures and grows.

Closure according to status differences, a consolidating elite

Besides more intense and diverse stratification, we also consider how status similarity between researchers affects collaboration during different periods of a field. Previous research suggests that actors' close relationships or coalitions are segregated along the lines of status—for example, adolescents tend to form friendship groups of similar-status individuals (Adler and Adler 1998; Coleman 1961; Milner 2013) and organizations sharing a similar status are more likely to collaborate (Podolny 2010). Additionally, scholars who studied status orders among university departments found that elite departments are more likely to exchange PhD students and to collaborate with other elite departments (Burris 2004; Gondal 2018; Han 2003; Ma et al. 2020).

Before increasing closure according to status differences emerges, we expect that researchers working in a nascent field primarily collaborate with others who are dissimilar in years of experience, productivity, and seniority. This tendency toward *status heterogeneity* should follow from the organizational logic of local research activities, which tend to be divided between experienced scholars and apprentices (Blau 1994; Knorr 1999; Latour 1987; Latour and Woolgar 1986; Lazega et al. 2006). Senior scientists offer new opportunities to conduct research within departments and primarily collaborate with PhD candidates and postdocs (e.g., Mullins 1972). Thus, scientists who hold many collaboration ties should work with others who hold fewer ties, especially if more external funding becomes available in a field and creates a larger scientific staff for leaders of established laboratories (Alberts et al. 2014; Laudel 2006). While these instances of local, status-dissimilar collaboration should not lose their significance over time, we expect more collaboration between status-similar senior scientists as a field matures according to status markers—i.e., increasing *status homogeneity*.

As Knorr (2009: 235–240) shows, leaders of research groups act as representatives and forge collaborations with other groups working on the same topics (see Chubin 1976; Griffith and Mullins 1972; Mullins 1972). Yet, this is only possible if a momentary consensus about relevant research areas and methods crystallizes (Koppman and Leahey 2016; Latour 1987; Lazega et al. 2016; Schwemmer and Wieczorek 2020; Shi et al. 2015; Shwed and Bearman 2010). Therefore, we expect more cases of status-similar collaboration as a field matures and senior scientists begin to form coauthor ties outside their local environments with leaders of other groups pursuing similar research.

In addition, we expect the formation of circles of authors who are status-similar due to increased status homophily in uncertain contexts.[35] In line with Podolny (2010), we argue that

[35] Please note that we use the term "status homogeneity" instead of "status homophily" because "homophily" has strong connotations of a social-psychological preference for similar others (McPherson et al. 2001). As Wimmer and Lewis (2010) point out, network segregation can originate in different sources such as the opportunity structure (Blau 1977a) or endogenous network mechanisms. Here, we remain agnostic as to the question of what drives status homogeneity in scientific networks and focus on changes over time. Furthermore, the methods we use cannot distinguish between influence and selection (Shalizi and Thomas 2011; Steglich et al. 2010). Therefore, we cannot determine whether

this stems from high-status actors' fear of being associated with low-status actors. As Podolny (2010, 24–39) highlighted, status "leaks" through social relationships, whereby the status of actors' collaborators rubs off on their own status. Corroborating this theoretical expectation, Podolny (2010, 76–102) finds that status homogeneity can be observed in the investment banking industry, particularly under greater uncertainty. Following this research, we argue that collaboration with low-status scientists sends negative signals within an academic community and that the balance between status-dissimilar and status-similar collaborations tends to shift in favor of status-similar collaborations as the field matures.

Hypothesis 3. Scientists who are dissimilar in their years of experience, productivity, and seniority collaborate at the outset of a field. This tendency weakens in the later stages of a field's development, and collaboration increasingly exhibits status homogeneity.

Overall, our theoretical expectations sketch a trajectory marked by the growing importance of accumulation dynamics for the structure of scientific collaboration. We argue that an elite of authors emerges as a field matures, based on the accumulation of coauthorship through multiple channels such as years of experience, productivity, and seniority. Also, senior scientists collaborate with status-similar researchers and their apprentices as a field ages.

The emerging field of neuroblastoma research

To test our theoretical expectations, we focus on the development of a specialized scientific community devoted to neuroblastoma research. Neuroblastoma represents the most common solid cancer in childhood (Maris 2010). A special characteristic of neuroblastoma is the vast diversity of possible tumor types and consequences for patients: while most infants with

actors of similar status select each other as collaborators or whether connections to high-status alters are elevating actors' status.

neuroblastoma may recover entirely with minimal treatment[36], children who are older than one year often die or face long-term health conditions due to high-dose chemotherapy, radiation, and immunotherapy (Brodeur 2003; Cheung and Heller 1991; Matthay et al. 1999).

Neuroblastoma is a malignant tumor of the sympathetic autonomic nervous system and was first described by R. Virchow in 1864 as a neoplasm originating from the organ adrenal medulla.[37] While research continued into the late 19th and early 20th centuries (Hutchison 1907; Pepper 1901)[38], scientists only started to develop a clearer consensus on how to classify and study neuroblastoma during the 1980s due to advances in the field of histopathology—the microscopic study of diseased biological tissues (Dehner 1988; Olson 1989; Shimada et al. 1984). Moreover, the first internationally accepted staging system was proposed by Evans et al. (1971), which paved the way for progress in research, diagnosis, and treatment.

Since then, those involved in researching and treating neuroblastoma have achieved higher survival rates among patients—especially for low- and intermediate-risk neuroblastoma—while also achieving earlier detection of the disease and providing more insights about its potential causes (Brodeur et al. 2003; Maris 2010). However, high-risk neuroblastoma still leads to very high mortality rates, and the molecular mechanisms underpinning the disease continue to be subject to research efforts (Ray 2019).

The scholars who have entered this community came from various disciplines such as medicine, biology, and chemistry (Martynov et al. 2020). In the first third of the field’s development, clinical researchers and biologists made up the majority of scholars participating in neuroblastoma research. From the 1990s onward, thought, the field experienced an influx of

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[36] Merely tumor resection and observation of the primary tumor sites (e.g., Maris 2010).

[37] The adrenal medulla is part of the adrenal glands, which lie above the kidneys and produce various hormones (e.g., Avisse et al. 2000).

[38] Marchand (1891) disclosed the common features of the sympathetic nervous system and the adrenal medulla. Pepper (1901) and Hutchinson (1907) described different biological prototypes.

bio-molecular and bio-chemical researchers as well as immunologists, which broadened the interdisciplinary scope of the community (Martynov et al. 2020).[39]

3.3 Data and measures

To study how the social organization of neuroblastoma research changed over time, we analyze information on abstracts submitted to the Advances in Neuroblastoma Research (ANR) conference series. The initial ANR conference was the first interdisciplinary meeting devoted explicitly to neuroblastoma and hosted by the Children's Hospital of Philadelphia in 1975. We consider 18 conferences until 2016, which all addressed neuroblastoma from the perspective of basic, translational, and clinical science without dilution by other topics (Berthold et al. 2019). The authors digitalized all the abstracts from 18 conferences documented in the conference proceedings books (for details, see Berthold et al. 2019). The resulting data set spans 41 years (1975-2016). We used the co-occurrence in abstracts of papers presented at the ANR to derive collaboration ties between researchers at each conference.

Following the idea that repeated interaction and communication among researchers is crucial for the emergence of a community (Chubin 1976; Crane 1972; Mullins 1972), we decided to only include researchers in our study who appeared as authors of abstracts for at least two conferences (~40% of the initial sample).[40]

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[39] This development was accompanied by literature that studied the genetic characteristics of neuroblastoma and has led to new forms of therapy and a better understanding of the disease on a molecular level (Brodeur 2003; Kaghad et al. 1997; Mossé et al. 2008).

[40] Focusing the analysis on authors who appeared at least twice in abstracts over the years under observation seemed reasonable to us in light of the general trend in scientific research toward more publications per author and the expansion of research teams (Wuchty, Jones, and Uzzi 2007). Whereas many authors who appear only once might be included in the paper but not attend the conference or contribute much to the actual paper, the likelihood of capturing a real collaboration between authors should be higher for the stable part of the sample.

Years of Experience

To measure the length of scientists' careers, we operationalized experience as years since the first occurrence of an author in our data set. Descriptive statistics on scientists who participated in the conference series at least twice are provided in appendix A.

Productivity

We accessed Clarivate's Web of Science database to capture scientists' research output during the period 1975-2017 and merged the obtained publications with our data set on conference participation.[41] Because the conference data did not provide full names for every author and some names and abbreviations were ambiguous, we followed a step-wise disambiguation strategy: in the first step, we identified authors who could not be unambiguously connected to publications via abbreviated names (123 out of 8460 authors). In the second step, we manually linked these authors with their publications under consideration of their institutional affiliations. To ensure a correct linkage, an experienced neuroblastoma scientist carried out an in-depth investigation and achieved unambiguous correspondence between authors and publications in nearly all cases.

We restricted our search to articles on the subject "neuroblastoma" and considered the headlines, abstracts, and keywords of published articles. Hence, the search according to subject was preferred over a purely title-based approached (Tal and Gordon 2017). We pursued this focused search strategy to avoid an overlap with adjacent research fields, as our aim was to capture publications within the scientific specialty of neuroblastoma research. Also, we excluded abstracts, meeting reports, presentations at satellite workshops, and reviews, as these carry different meanings and functions in research communities compared with peer-reviewed

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[41] Accessed July 17, 2017.

articles (e.g., Lamont 2009). This decision was motivated by our goal to obtain a homogeneous measure for researchers' publication output over a long period.

Seniority

We measured seniority by constructing a variable that indicates how often a researcher is listed as the last author on one of the papers presented. In a similar vein to the relative position of investment banks in advertisements announcing a new deal (Podolny 2010: 40–76), the positions of author names in publications and conference abstracts in science are unequally prestigious: in particular, the last position in publications is more prestigious than other positions, as this person represents—in many instances—the leader of a research group (Bennett and Taylor 2003; Costas and Bordons 2011; Knorr 1999; Latour and Woolgar 1986; Savitz 1999; Shapiro et al. 1994; Zuckerman 1968).[42]

Stratification

We use the skewness of the degree distribution of the collaboration network as a global measure for inequality at a given point in time. If a degree distribution is positively skewed, this is indicative of a small number of individuals having many ties, while the majority of individuals exhibit none or only a few ties (Fisher 2018: 57; Moody et al. 2011: 103). As additional measures for inequality, we repeated our analyses with the standard deviation and the Gini coefficient (Badham 2013; Snijders and Steglich 2015). Results for these measures are reported in appendix A.

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[42] Please note that last author positions are not necessarily prestigious in all disciplines or fields of scientific inquiry. Therefore, the measure for seniority we propose here might not be applicable to other settings such as the social sciences. However, previous studies illustrate that last author positions are linked to a division of labor between senior scientists and early career researchers in the disciplines neuroblastoma research is mainly embedded in, such as medicine, epidemiology, and biomedical research (Savitz 1999; Shapiro et al. 1994). Moreover, we did not consider shared last authorships, i.e., only the actual last author counted as the last author.

3.4 Methods and models

Exponential random graph models (ERGMS)

We use exponential random graph models (ERGMs) to study how neuroblastoma research changed its social structure (Lusher et al. 2013).[43] ERGMs allow us to test whether inequality in coauthorships intensified, accumulation dynamics diversified, and segregation along the lines of status amplified throughout the field's development.

The dependent variable for ERGMs is the global structure of a given network. The independent variables are count statistics for local structures, such as the number of dyads sharing the same characteristic—e.g., researchers who collaborate and work in the same country. ERGM coefficients indicate whether a particular local structure occurs more often in the observed network than a random allocation of ties would suggest, conditional on all other local structures considered by the model specification (Lusher et al. 2013; Robins 2011). A strength of this method is that it allows researchers to dissect the global structure of networks with a generative model, which provides parameters for local tie-formation processes while taking into account other related factors.

Another advantage of ERGMs is that they allow researchers to obtain random networks conditional on a particular model specification. Thus, global statistics capturing the structure in simulated networks can be calculated and compared with empirical values (e.g., Gondal and McLean 2013a, 2013b). We make use of this feature to assess which models are capable of reproducing observed levels of inequality. This procedure enables us to test Hypothesis 1—which states that inequality in the distribution of coauthor ties increases over time—because we account for the fact that many network measures are mechanically linked to a network's

[43] The analysis was carried out in R. The *ergm* package was utilized to conduct the ERGM analysis (Hunter et al. 2008). In addition, the *ergMargins* package was used to calculate average marginal effects (Duxbury 2019).

opportunity structure, size, or endogenous network tendencies (Anderson et al. 1999; Blau 1977b; Wimmer and Lewis 2010). Also, simulations help us to evaluate whether models including researchers' characteristics provide a better approximation of observed levels of stratification, which would point to a diversification of accumulation dynamics (H2).

To implement this part of our analytical strategy, we first calculate descriptive measures capturing stratification for each conference (18 conferences from 1975 to 2016). Subsequently, we simulate 1,000 random networks—based on parameters from different ERGMs—which had the same size, density, and node attributes as the corresponding empirical network. This provides us with a distribution of statistics stemming from simulated networks. Finally, we examine whether measures of empirical networks are substantially different from those we find in simulated networks (Gondal and McLean 2013a, 2013b; Snijders and Steglich 2015). While this procedure does not provide a formal test of statistical significance, it can tell us whether observed changes in network structure are substantial beyond basic network features such as changes in network density.

In addition, we compare average marginal effects (Duxbury 2021) in different years to further investigate a potential diversification of accumulation dynamics (H2) and to probe whether segregation according to status differences became a feature of network structure as neuroblastoma research matured (H3).

Model specifications

Table 3.1 provides an overview of the different model specifications we estimate to study the role of researchers' characteristics for network structure over time. All specifications include the edges term, which captures the density of a network and can be thought of as intercept term reflecting the overall probability of a tie (Smith et al. 2016: 1240). Furthermore, we added terms for homophily—the tendency of similar actors to form relationships (McPherson et al. 2001)—

on the country and the institutional level, because these foci are likely to shape collaborations (Dahlander and McFarland 2013; Feld 1981; Stark et al. 2020).

Table 3.1. Summary of exponential random graph model specifications

Model terms	M1	M2	M3	M4	M5
Edges	X	X	X	X	X
Same country	X	X	X	X	X
Same institution	X	X	X	X	X
Popularity according to experience		X	X		
Difference in authors' experience		X	X		
Popularity according to cumulated publications		X		X	
Difference in cumulated publications		X		X	
Popularity according to share last author positions		X			X
Difference in share last author positions		X			X
Reported in table	3	4	A2	A3	A4

Note: X signifies whether a term was included in the respective model specification.

M1 is a baseline specification that only includes the terms described above and helps us to assess whether changes in network density or other basic network properties can account for changes in global inequality. The full specification (M2) adds the main effects and the absolute differences for all characteristics to account for possible interdependencies of popularity and homogeneity as well as multicollinearity between characteristics (Bojanowski and Corten 2014; Lusher et al. 2013). Main effects reflect the popularity[44] of actors according to a specific attribute, which allows us to investigate a potential diversification of accumulation dynamics (H2), because the main effects of years of experience, cumulated publications, and last author

[44] Please note that the network is undirected. We use the term "popularity" to denote the main effect of an attribute because collaborations are based on researchers' mutual consent, i.e., instances of declined requests to collaborate are not recorded. Technically, main effects of nodal attributes combine popularity—the tendency to receive ties—and expansiveness—the tendency to send ties—in undirected networks (Goodreau et al. 2009; Lusher et al. 2013).

positions mirror whether researchers with a higher stock of these resources attract more collaboration partners.

To detect whether the balance between status heterogeneity and status homogeneity according to researchers' characteristics changes over time (H3), we use terms that indicate whether dissimilar dyads are more or less likely to exhibit ties. In the case of continuous attributes, the ERGM framework usually models homogeneity in reversed difference scores. Therefore, a significantly negative estimate for e.g., the "Difference in authors' experience" term reflects that scientists with similar years of experience are more likely to collaborate.

While the full specification (M2) entails all characteristics, we also estimate specifications that only add one characteristic to our baseline specification. M3 considers researchers' years of experience, M4 entails terms for authors' productivity, and M5 adds seniority. A comparison between M2 and M3 to M5 allows us to assess the role of researchers' characteristics for network structure in greater depth.

Average marginal effects (AMEs)

We calculate average marginal effects (AME) as proposed by Duxbury (2019, 2021) in order to compare estimates across model specifications and conferences. This allows us to overcome methodological challenges concerning the substantial interpretation of ERGM coefficients, and the comparability of estimates between models—which can be problematic due to, e.g., residual variation (Duxbury 2021; for similar problems in logistic regressions, see Mood 2010). In comparison to standard coefficients, AMEs are unaffected by scaling and offer a substantial interpretation in terms of absolute changes in tie probability. For example, if the AME for the "Popularity experience" term is 0.01, this would mean that the probability of scientists with a long experience to attract an additional tie is 1 percentage point higher than for scientists with less experience.

To ensure a valid comparison of effect sizes over time, we interpret AMEs in relation to the baseline probability to form a tie during a given conference. As Kreager et al. (2021: 59, footnote 12) recently noted: "AMEs differ from odds ratios in that they are on a probability scale and so their magnitudes should be interpreted relative to the baseline tie probability (i.e., network density)".[45] Therefore, we report AMEs that are divided by the baseline probability to form a tie during a given conference. These scaled AMEs can be interpreted as change of the baseline probability to form a tie if a network variable increases by one unit.

3.5 Results

Table 3.2 provides an overview of the collaboration network among neuroblastoma researchers. Whereas conferences in the first decade of the ANR series were still relatively small, with fewer than 100 authors, attendance at the conferences began to grow rapidly from the early 1990s onward. This growth was accompanied by the internationalization of the ANR series. Whereas the first eight conferences were held in Philadelphia (USA), the ANR expanded to Europe between 1998 and 2006. Then, in 2006, the conference organizers decided to rotate the ANR between the Americas, Europe, and Asia/Australia.

Parallel to the geographical expansion of the conference series, the mean degree centrality of the collaboration network increased. For instance, the early Philadelphia phase of the conference reached a maximum of—on average—13 submitted abstracts per author (1996), 20 years later this figure doubled at the ANR in Cairns in 2016. These trends are in line with

[45] In the example sketched above, an increase by 1 percentage point can have a different substantial interpretation depending on how likely it is for a tie to form in the first place. In the case of a sparse network—exhibiting a baseline probability of e.g., 0.02—an AME of 0.01 would increase the probability to form a tie by 50%, indicating a substantial effect of experience. However, if the network's baseline probability would be higher, e.g., 0.20, an AME of 0.01 would be less substantial, and suggest that the baseline probability to form a tie is only increased by 5%. This property of AMEs is crucial for our application since the network density of neuroblastoma researchers' collaborations varies strongly over time.

findings of a recent scientometric analysis of neuroblastoma research, which also reported the growth and proliferation of the field over time (Martynov, Klima-Frysch, and Schoenberger 2020, see also Berthold et al. 2019).

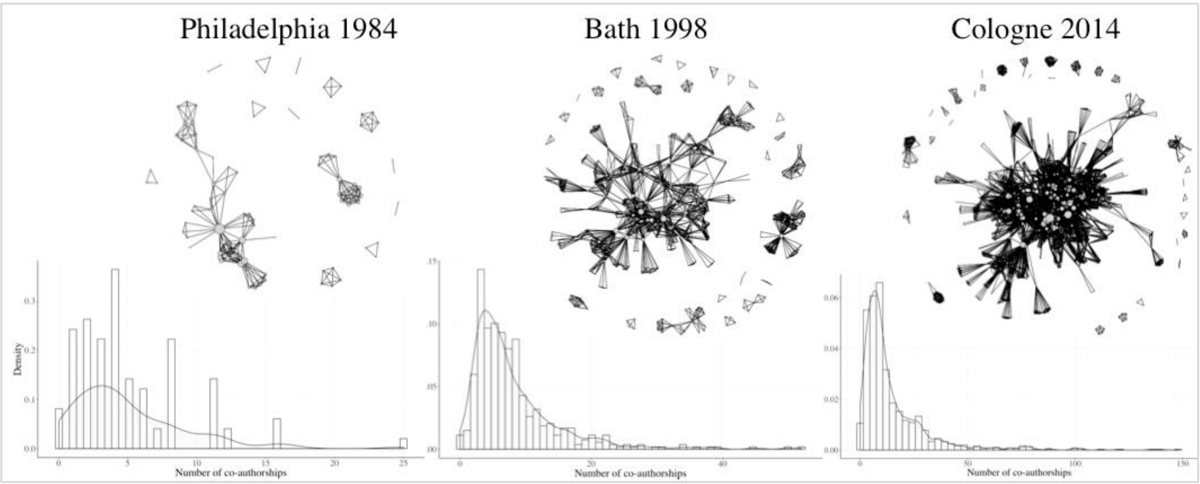
Besides the internationalization and growth of the community, the collaboration network exhibited another pattern that provides initial evidence for the emergence of a stratified order over time (H1). The skewness of the degree distribution increased over the years, meaning that collaboration ties were distributed increasingly unequally as the field matured.

This trend is depicted in figure 3.1, which shows the network at three exemplary time points (see table 3.2 for the complete history of the field). In the next section, we scrutinize the robustness of this descriptive trend and test our other theoretical considerations in the ERGM framework.

Table 3.2. Information on conferences and coauthor networks

Year	City of congress	Country of congress	Size[46]	Average degree centrality	Skewness of degree distribution	Standard deviation of degree distribution
1975	Philadelphia	USA	13	0.50	1.91	0.38
1979	Philadelphia	USA	36	1.92	0.04	1.00
1984	Philadelphia	USA	97	6.00	1.76	4.20
1987	Philadelphia	USA	114	5.82	1.63	6.70
1990	Philadelphia	USA	174	5.75	1.58	4.52
1993	Philadelphia	USA	262	8.84	2.17	8.03
1994	Philadelphia	USA	205	10.13	1.25	4.12
1996	Philadelphia	USA	470	12.89	3.30	11.07
1998	Bath	UK	507	11.75	2.56	6.88
2000	Philadelphia	USA	488	12.47	2.81	8.66
2002	Paris	France	641	11.96	2.83	7.30
2004	Genoa	Italy	920	12.66	2.73	7.20
2006	Los Angeles	USA	908	14.12	3.47	8.45
2008	Chiba	Japan	970	19.51	3.12	13.84
2010	Stockholm	Sweden	1184	21.90	3.23	16.85
2012	Toronto	Canada	1117	17.00	3.32	9.93
2014	Cologne	Germany	1197	23.27	3.32	16.64
2016	Cairns	Australia	955	26.69	2.98	19.29

Figure 3.1. The changing structure of the coauthor network at three time points



Note: Nodes in the sociograms depict researchers who participated at least twice in the ANR conference series; ties between them indicate that they appeared as coauthors on an abstract submitted to the ANR conference. Histograms are based on the distribution of coauthor ties in the relevant year. The x-axis denotes the number of coauthor ties per author and the y-axis the density of the distribution.

[46] Size refers to the number of authors who participated at least twice in the ANR conference series.

Table 3.3. Average marginal effects (AMEs) of baseline exponential random graph models (ERGMs) for collaboration network

Years	1979		1984		1987		1990		1993		1994	
	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME
Same country	-0.004	-0.094	0.094***	1.793	0.061***	0.996	0.075***	2.273	0.049***	1.594	0.080***	2.441
	(0.021)		(0.008)		(0.006)		(0.003)		(0.002)		(0.003)	
Same institution	0.110***	2.754	0.091***	1.739	0.095***	1.548	0.053***	1.597	0.055***	1.768	0.030***	0.931
	(0.017)		(0.008)		(0.009)		(0.003)		(0.003)		(0.003)	
Baseline probability	0.040		0.053		0.062		0.033		0.031		0.032	

Years	1996		1998		2000		2002		2004		2006	
	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME
Same country	0.039***	1.895	0.034***	2.121	0.030***	1.677	0.031***	2.276	0.022***	2.347	0.020***	1.911
	(0.001)		(0.001)		(0.001)		(0.001)		(0.0004)		(0.0004)	
Same institution	0.034***	1.656	0.027***	1.721	0.035***	1.971	0.025***	1.877	0.020***	2.107	0.024***	2.291
	(0.001)		(0.001)		(0.001)		(0.001)		(0.0003)		(0.0003)	
Baseline probability	0.021		0.016		0.018		0.013		0.009		0.010	

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Years	2008		2010		2012		2014		2016	
	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME
Same country	0.021***	1.704	0.021***	1.775	0.018***	2.012	0.023***	1.881	0.029***	1.630
	(0.0004)		(0.0003)		(0.0003)		(0.0003)		(0.0004)	
Same institution	0.026***	2.052	0.025***	2.089	0.021***	2.291	0.026***	2.089	0.036***	1.980
	(0.0004)		(0.0003)		(0.0003)		(0.0003)		(0.0005)	
Baseline probability	0.013		0.011		0.009		0.012		0.018	

Note: All continuous variables are z-standardized to enhance the comparability of estimates across models. Delta standard errors (Duxbury 2019) are reported in parentheses. Scaled AMEs are AMEs divided by the baseline probability and can be interpreted as relative changes in tie probability if a network variable increases by one unit. We multiplied scaled AMEs by 100 to provide a measure capturing the percentage change of the baseline probability in figure 3.3 and figure 3.4.

† $p < 0.10$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$ (two-sided)

Table 3.4. Average marginal effects (AMEs) of full exponential random graph models (ERGMs) for collaboration network

Years	1979		1984		1987		1990		1993		1994	
	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME
Same country	-0.004	-0.111	0.097***	1.836	0.065***	1.062	0.074***	2.258	0.045***	1.463	0.08***	2.353
	(0.021)		(0.008)		(0.006)		(0.003)		(0.002)		(0.003)	
Same institution	0.105***	2.643	0.091***	1.720	0.090***	1.470	0.054***	1.648	0.060***	1.938	0.03***	1.038
	(0.017)		(0.008)		(0.009)		(0.003)		(0.003)		(0.003)	
Popularity years of experience	0.001	0.034	-0.009**	-0.177	0.006*	0.091	0.002	0.065	0.005***	0.159	0.002	0.057
	(0.006)		(0.003)		(0.003)		(0.001)		(0.001)		(0.001)	
Difference in authors' years of experience	-0.007	-0.174	-9e-03	-0.018	-0.007*	-0.118	-0.005**	-0.140	-0.004***	-0.138	-0.005**	-0.147
	(0.009)		(0.004)		(0.003)		(0.002)		(0.001)		(0.002)	
Popularity cumulated publications	0.008	0.206	0.007	0.128	0.014***	0.227	0.007***	0.198	0.009***	0.278	0.005**	0.168
	(0.011)		(0.006)		(0.003)		(0.001)		(0.001)		(0.001)	
Difference in cumulated publications	-0.024	-0.595	0.005	0.085	0.006	0.093	0.002	0.064	-0.002*	-0.079	-0.001	-0.038
	(0.017)		(0.007)		(0.003)		(0.002)		(0.001)		(0.002)	
Popularity share last author positions	0.001	0.028	-0.008	-0.160	-0.013**	-0.210	-0.015***	-0.466	-0.005***	-0.170	-0.01***	-0.243
	(0.007)		(0.006)		(0.005)		(0.003)		(0.001)		(0.002)	
Difference in share last author positions	0.003	0.067	0.008	0.190	0.004	0.072	0.013***	0.389	0.001	0.039	0.007**	0.200
	(0.009)		(0.006)		(0.006)		(0.003)		(0.002)		(0.002)	
Baseline probability	0.040		0.053		0.062		0.033		0.031		0.032	

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Years	1996		1998		2000		2002		2004		2006	
	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME
Same country	0.037***	1.802	0.032***	2.035	0.029***	1.616	0.029***	2.184	0.021***	2.280	0.019***	1.853
	(0.001)		(0.001)		(0.001)		(0.001)		(0.0004)		(0.0004)	
Same institution	0.036***	1.744	0.028***	1.770	0.036***	1.990	0.025***	1.897	0.020***	2.090	0.023***	2.262
	(0.001)		(0.001)		(0.001)		(0.001)		(0.0003)		(0.0003)	
Popularity years of	0.0001	0.006	0.0007*	0.044	0.002***	0.126	0.002***	0.139	0.001***	0.086	0.001***	0.120
experience	(0.0003)		(0.0003)		(0.0003)		(0.0002)		(0.0001)		(0.0001)	
Difference in authors'	-0.004***	-0.184	-0.005***	-0.340	-0.004***	-0.243	-0.003***	-0.213	-0.002***	-0.164	-0.002***	-0.178
years of experience	(0.001)		(0.0004)		(0.0004)		(0.0003)		(0.0002)		(0.0002)	
Popularity cumulated	0.010***	0.462	0.006***	0.353	0.006***	0.334	0.003***	0.216	0.002***	0.195	0.003***	0.305
publications	(0.0003)		(0.0003)		(0.0004)		(0.0003)		(0.0002)		(0.0002)	
Difference in cumulated	-0.002***	-0.082	>0.0001	0.016	-0.002***	-0.081	-0.0004	-0.020	0.0002	0.017	-0.001***	-0.069
publications	(0.0004)		(0.0004)		(0.0004)		(0.0003)		(0.0002)		(0.0002)	
Popularity share last	-0.003***	-0.145	-0.002***	-0.151	-0.003***	-0.190	-0.0003	-0.024	-0.001***	-0.085	-0.001***	-0.121
author positions	(0.001)		(0.001)		(0.001)		(0.0003)		(0.0002)		(0.0002)	
Difference in share last	>0.001	0.026	0.002***	0.128	0.003***	0.160	0.001*	0.064	0.001**	0.068	0.001*	0.066
author positions	(0.001)		(0.001)		(0.001)		(0.0004)		(0.0002)		(0.0003)	
Baseline probability	0.021		0.016		0.018		0.013		0.009		0.010	

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Years	2008		2010		2012		2014		2016	
	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME
Same country	0.020***	1.620	0.019***	1.633	0.017***	1.894	0.022***	1.794	0.028***	1.571
	(0.0004)		(0.0003)				(0.0003)		(0.0004)	
Same institution	0.026***	2.072	0.025***	2.163	0.021***	2.295	0.026***	2.115	0.037***	2.020
	(0.0004)		(0.0003)				(0.0003)		(0.001)	
Popularity years of experience	0.001***	0.109	0.001***	0.120	0.0004***	0.046	0.001***	0.099	0.003***	0.145
	(0.0001)		(0.0001)				(0.0001)		(0.0002)	
Difference in authors' years of experience	-0.002***	-0.178	-0.002***	-0.187	-0.001***	-0.114	-0.002***	-0.129	-0.003***	-0.142
	(0.0002)		(0.0002)				(0.0002)		(0.0002)	
Popularity cumulated publications	0.004***	0.345	0.005***	0.380	0.003***	0.345	0.005***	0.365	0.006***	0.343
	(0.0002)		(0.0001)				(0.0001)		(0.0002)	
Difference in cumulated publications	-0.001***	-0.072	-0.002***	-0.131	-0.001***	-0.084	-0.001***	-0.104	-0.002***	-0.110
	(0.0002)		(0.0001)				(0.0001)		(0.0002)	
Popularity share last author positions	-0.001***	-0.080	-0.0004*	-0.045	-0.0004*	-0.060	-0.0004*	-0.031	-0.002***	-0.102
	(0.0002)		(0.0002)				(0.0002)		(0.0003)	
Difference in share last author positions	-0.0004	-0.015	-0.0005*	-0.042	0.0003	0.035	-0.0005*	-0.043	-0.001	-0.038
	(0.0003)		(0.0002)				(0.0002)		(0.0004)	
Baseline probability	0.013		0.011		0.009		0.012		0.018	

Note: All continuous variables are z-standardized to enhance the comparability of estimates across models. Delta standard errors (Duxbury 2019) are reported in parentheses. Scaled AMEs are AMEs divided by the baseline probability and can be interpreted as relative changes in tie probability if a network variable increases by one unit. We multiplied scaled AMEs by 100 to provide a measure capturing the percentage change of the baseline probability in figure 3.3 and figure 3.4.
† $p < 0.10$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$ (two-sided)

ERGM results overview

We now turn to the results of exponential random graph models. Table 3.3 reports estimates of the baseline specification. All tables report the average marginal effects and their corresponding delta standard errors (Duxbury 2019, 2021).[47]

The full models reported in table 3.4 additionally entail researchers' characteristics—i.e., their years of experience, productivity, and seniority. Furthermore, we estimated models only adding one characteristic to the baseline specification to investigate how estimates change if characteristics are considered independently or simultaneously (reported in tables A2, A3, and A4). We compare selected average marginal effects from these models with AMEs stemming from full models in figures 3.3 and 3.4.

Figure 3.2 visualizes the properties of simulated networks obtained from models reported in table 3.3 and table 3.4. Boxplots show the distribution of simulated values, while triangles depict empirical values in each year. The upper panel of the figure allows us to assess whether inequality increased above and beyond basic network tendencies such as institutional and country homophily or changes in size and density. In addition, the bottom panel provides information on whether adding researchers' characteristics provides better predictions for observed levels of inequality. Before we discuss our results, we provide details on the goodness of fit of our models.

Goodness of fit (GOF)

We assessed the goodness of fit (GOF) of all models by simulating networks from estimated ERGMs and comparing their degree, edgewise-shared partner, and geodesic distance statistics

[47] As pointed out by Duxbury (2021: 8). "While rescaling does not alter conclusions about the direction and significance of noninteraction coefficients, it does affect coefficient magnitude." In our case, the direction and significance of AMEs are identical with those of coefficients. However, due to the networks' differing sizes, significance and direction should only be interpreted with caution.

with the observed statistics in the corresponding network (Hunter et al. 2008). We decided to report the share of statistics with a t-ratio smaller than 2 for the degree distribution, the distribution of edgewise-shared partners, and the occurrence of geodesic distances.[48] Hence, we focus on a comparison between our baseline model specification and full models. In addition, we report plots depicting the GOF for networks' degree distributions. This allows us to explore which model specification better accounts for actors holding many collaborations. GOF analyses are reported and discussed in appendix A.

In summary, results indicate that the GOF for edgewise-shared partners and geodesic distances was insufficient, irrespective of the model specification. In contrast, the fit for the degree distribution was noticeably better in full models, especially in the later stages of the field's development. These findings corroborate our theoretical expectation that the importance of researchers' characteristics for the distribution of collaboration ties increases over time.

The remainder of the results section will proceed as follows. First, we discuss the results of simulations to map changing stratification in coauthorships. Second, we turn to the questions of whether accumulation dynamics diversified and status homogeneity increased over time.

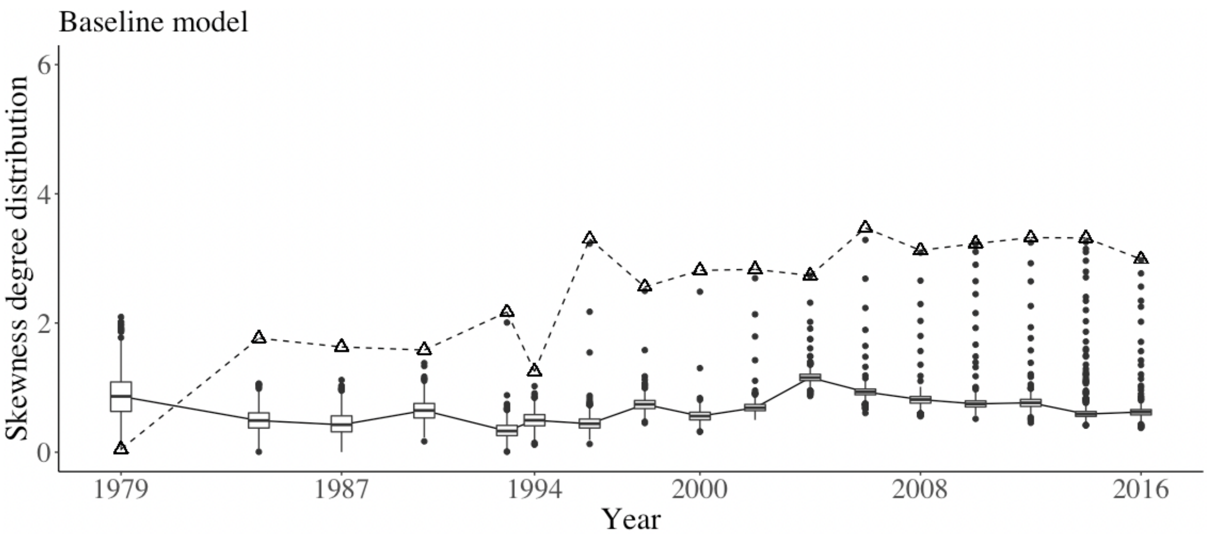
Rising inequality in coauthor ties

We simulated 1,000 networks for each conference from baseline models. Simulated networks had the same number of nodes and the same densities as observed networks. Thus, they tell us whether an unequal degree distribution could also have been a by-product of basic network

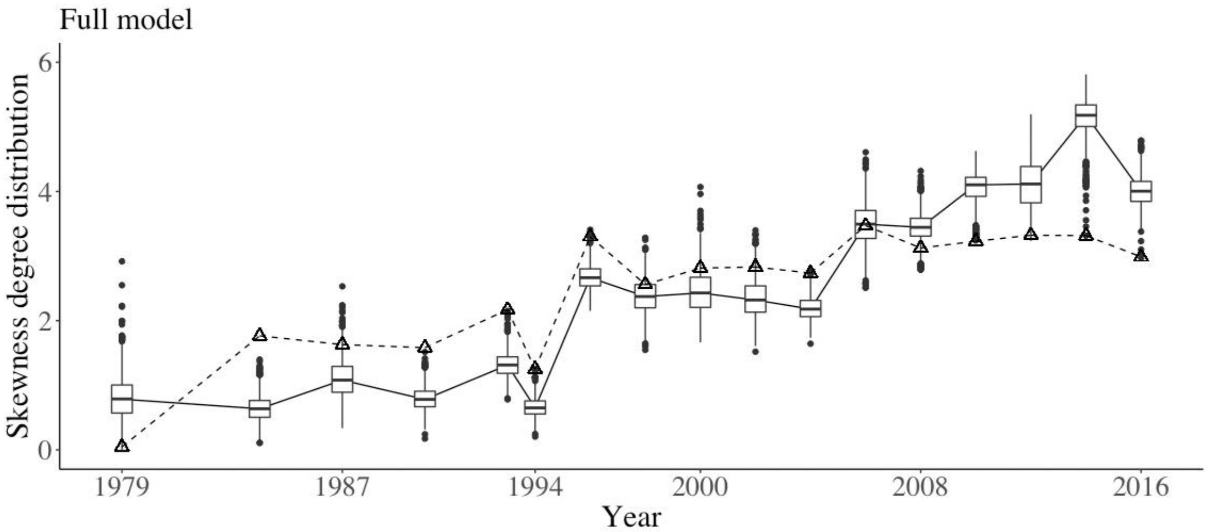
[48] Previous accounts either report GOF plots that depict the fit of all statistics of these three network properties, tables with selected statistics (e.g., Gondal and McLean 2013b), or aggregate t-ratios across network properties (e.g., Smith et al. 2016). While the first two strategies are feasible when researchers analyze a single network or a small set of networks, studies that report models for many networks must strike a balance between an in-depth report of models' GOF and an aggregation of the fit of simulated statistics. We decided to aggregate t-ratios separately for all three network properties (figure A1) and additionally report individual GOF plots for the degree distribution (figure A2).

properties such as changes in the average size of research teams. Figure 3.2 summarizes the skewness in simulated networks in box plots and shows how empirical values—depicted by triangles—differed from simulated values.[49] While simulated networks stemming from baseline models indicated a mild trend toward more inequality, empirical values differed starkly from 1996 onward and experienced a jump in inequality after the first 20 years of the community's history. Another, smaller, increase in inequality was visible after 2004. Overall, these results are in line with our first theoretical expectation that inequality in the distribution of coauthor ties increases as a scientific field matures and grows (H1).

Figure 3.2. Predicting inequality in coauthor ties over time



[49] We repeated this analysis with the standard deviation (e.g., Snijders and Steglich 2015) and the Gini coefficient (Badham 2013) as additional measures for inequality. The results for different measures were qualitatively similar and are reported in appendix A (figures A3 and A4).



Note: Each box plot represents the distribution of skewness values calculated in simulated networks obtained from network models reported in tables 3.3 and 3.4. Boxplots in the upper panel show simulated values for networks generated according to our baseline model specification (see table 3.3). The bottom panel reports simulated values generated from the full models that include researchers' characteristics (table 3.4). We simulated 1,000 networks for each year and specification. Triangles indicate empirical values, i.e., the observed skewness of the degree distribution in a particular year. The dashed line connects empirical values, while the straight line follows the medians of simulated values.

Furthermore, a comparison between the upper and the bottom panel provides further evidence for our second hypothesis. While simulations obtained from baseline models were not sufficient to approximate the empirical trend in inequality, full models substantially improved our predictions, especially in the later stages of the field's development. A similar tendency is visible if we compare the fit of degree distributions between baseline and full models over time (see figure A2 in appendix A). In the next section, we provide a more detailed picture of how researchers' characteristics mold network structure over time.

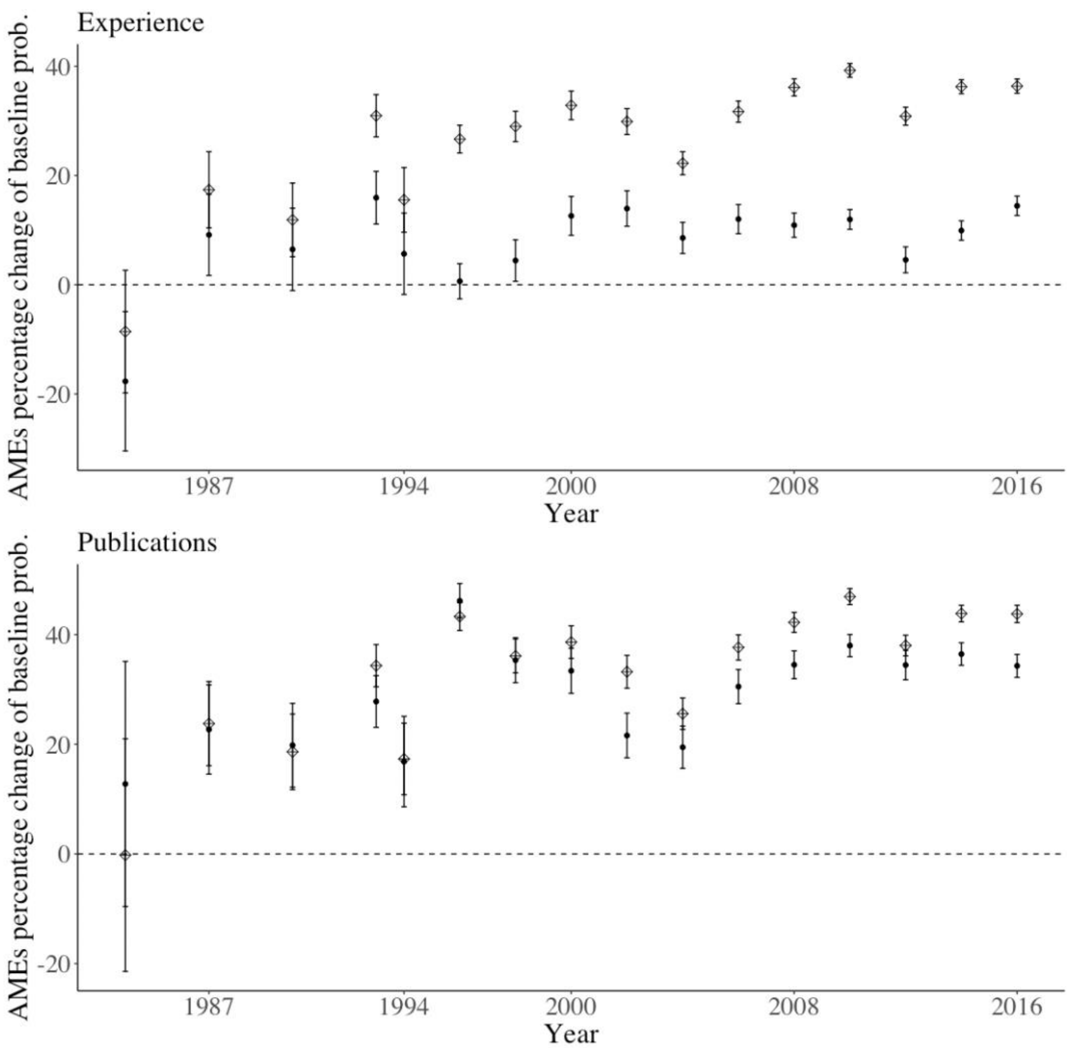
Diversification of accumulation dynamics

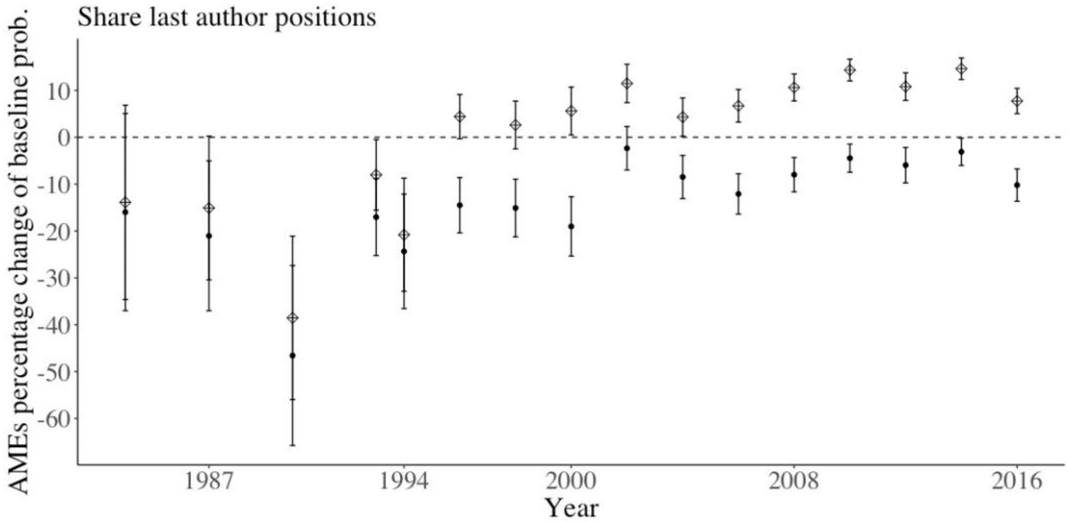
Here, we consider whether a scientist's prominence as a coauthor was linked to a variety of characteristics as the field matured (H2).

Figure 3.3 depicts selected average marginal effects (AMEs) and their corresponding confidence intervals stemming from full models (table 3.4) and from models only adding one characteristic to the baseline specification (reported in table A2 for years of experience, table A3 for productivity, and table A4 for seniority). AMEs from full models are represented by dots, while diamonds visualize AMEs obtained from simpler models.

The results of specifications that add only one characteristic to the baseline specification indicate that researchers with one standard deviation more years of experience and last author positions exhibited significantly more coauthorships than their peers in the second half of the field's development. For instance, in 1994, researchers with one standard deviation more years of experience showed a 15.5% higher probability of engaging in an additional collaboration relative to the baseline probability of forming a tie during this year.

Figure 3.3. Popularity according to researchers' characteristics over time





Note: Dots represent scaled AMEs and their 95% confidence intervals for main effects derived from full models in table 3.4. Diamonds depict coefficients from model specifications that only include one of the researchers' characteristics in addition to the baseline specification. These models are reported in appendix A (tables A2, A3, and A4).

From 1996 to 2006, one standard deviation more experience elevated the baseline probability by more than 22%, and, from 2008 to 2016, by at least 31%.[50]

Similarly, productivity and seniority showed a rising association with more coauthor ties from 1996 onward. Yet, for seniority, AMEs obtained from full models show that including multiple characteristics simultaneously changes this picture: the AMEs for last author positions showed negative values in all years in M2 (table 3.4). This pattern points to fewer coauthorships held by senior researchers after accounting for their experience and productivity.

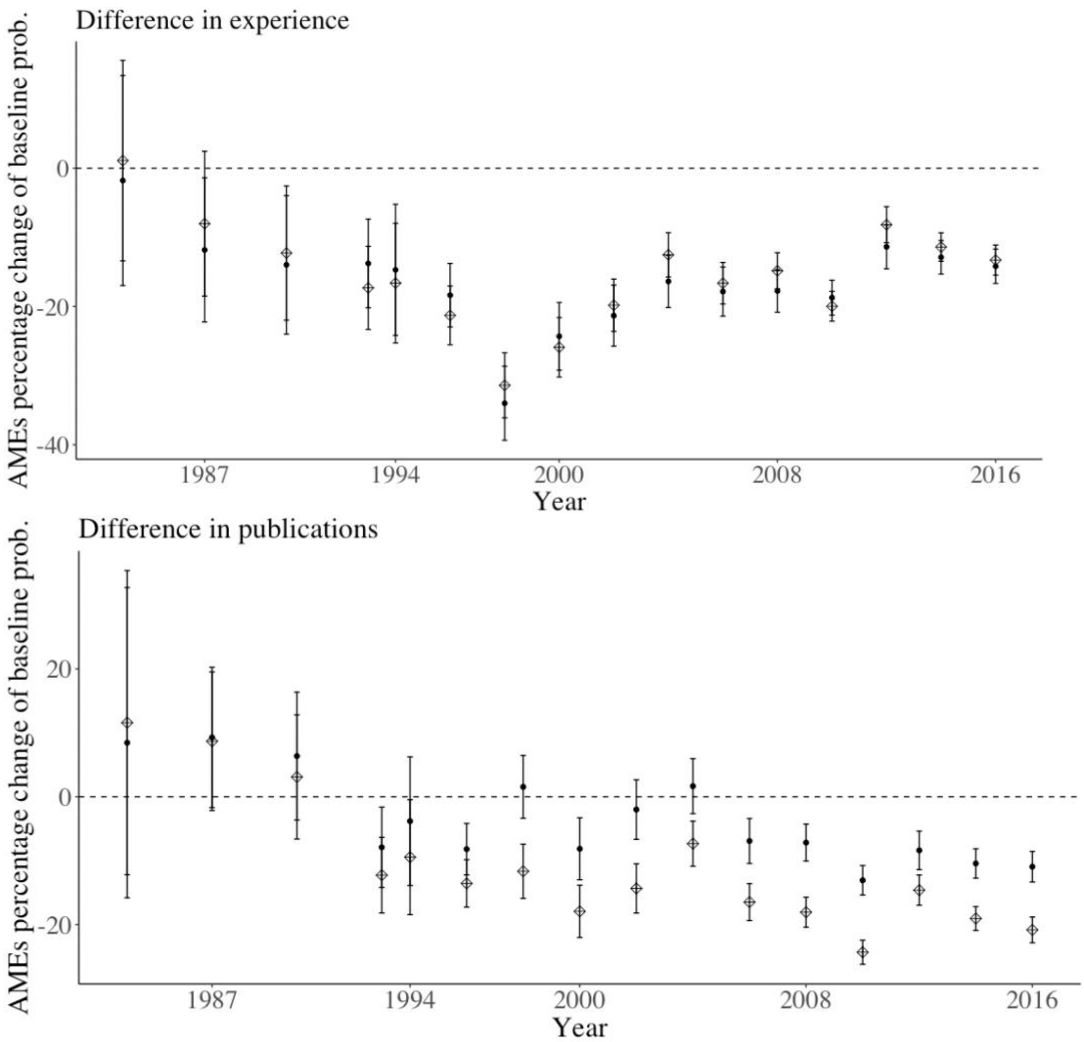
[50] These are AMEs for the specification which only included years of experience as researcher characteristic (M3, reported in table A2 and depicted as diamonds in figure 3.3). The corresponding numbers from full models are as follows: 1994: 6%; 1996-2006: at least 1%; 2008-2016: at least 5% (M2, reported in table 3.4 and depicted as dots in figure 3.3). While these numbers indicate a decreased importance of experience once other characteristics are considered, a time trend towards rising AMEs in the second half of the field's development is still visible in figure 3.3.

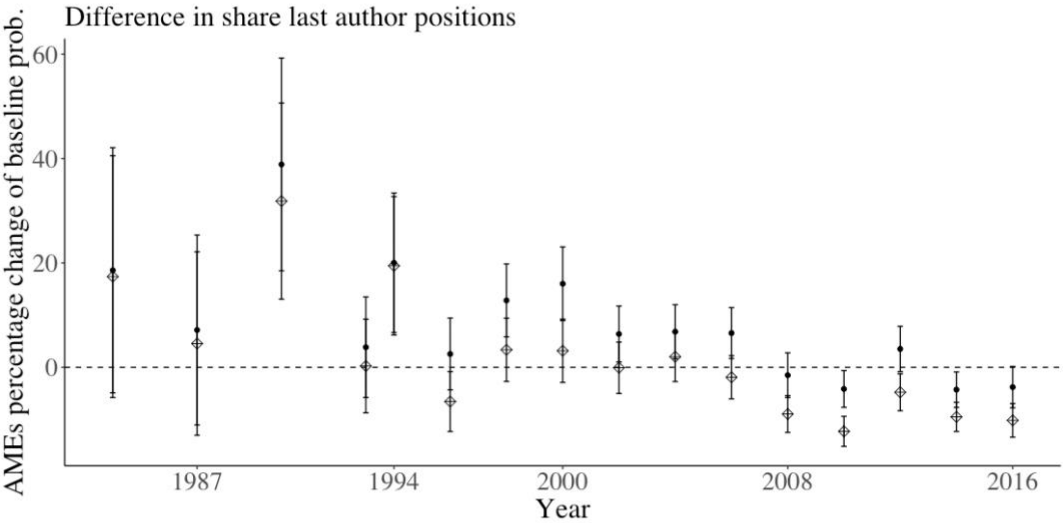
Status homogeneity over time

In this section, we test our third theoretical expectation that new scientific fields are mainly characterized by status-dissimilar collaborations, whereas later stages of a field should additionally display circles of coauthors who are status-similar (H3). We included model terms that capture whether a one standard deviation difference in years of experience, productivity, or seniority changes two scientists' likelihood of collaborating.

Figure 3.4 shows how the tendency to affiliate with others of similar status in terms of years of experience, publications, and share of last author positions changed over time. Consistent with the notion that a field is less marked by closure along differences in status at its outset, average marginal effects showed a decreasing trend.

Figure 3.4. Homogeneity according to researchers' characteristics over time





Note: Dots represent scaled AMEs and their 95% confidence intervals for z-standardized difference scores derived from our full models in table 3.4. Diamonds depict AMEs from model specifications that only include one of the researchers' characteristics in addition to the baseline specification. These models are reported fully in appendix A (tables A2, A3, and A4).

Here, decreasing AMEs mean that collaborative ties between status-dissimilar partners became less likely as the field matured. For instance, a one standard deviation difference in publications showed positive AMEs from 1984 to 1990. Subsequently, the results indicate that a one standard deviation difference in publications reduced scientists' baseline probability to collaborate by 7% to 18% between 1993 and 2004. In the third stage of the field's development (2006-2016), baseline probabilities to collaborate were reduced by 15% to 24% for researchers with dissimilar publication records.[51]

In a similar vein, differences in years of experience decreased scientists' probability to collaborate but started to structure collaboration networks earlier than scientists' publication records. Also, a curvilinear trend is visible: AMEs decreased until 1998—indicating elevated importance of differences in experience for tie-formation—and increased afterward.

[51] These are AMEs for the specification that only added accumulated publications to the baseline specification (M4, reported in table A3 and depicted as diamonds in figure 3.4). The corresponding numbers from the full models are as follows: 1993-2004: 1.6%-8%; 2006-2016: 7%-12% (M2, reported in table 3.4 and depicted as dots in figure 3.4).

For the simple model specification (M5), AMEs for differences in seniority showed a similar trend as differences in publications indicating that a tie between dissimilar researchers became less likely over time. In addition, AMEs for seniority are relatively small and only show negative values during a late stage of the field's development. Between 2008 and 2016, scaled AMEs suggest a reduction of the baseline probability between 5% and 10% (M5, reported in table A4). The corresponding values for the full model specification range from 1.5% to 4% (M2, reported in table 3.4).

In summary, our results suggest that status-similar collaborations became more likely over time. However, collaborations between early career researchers and established scientists probably retained their relevance for scientific work in neuroblastoma research. The analyses presented here did not investigate whether high-degree nodes are connected to low-degree nodes (assortativity). Instead, we provided estimates for status homogeneity net of other model terms and the opportunity structure to form ties. Moreover, the large AMEs for institutional homophily could partially point to the persisting importance of mentor-apprentice ties parallel to the trends toward status homogeneity according to researchers' attributes. We will further discuss this aspect in the concluding section of the article.

Additional analyses

In addition to ERGMs, we also estimated stochastic actor-oriented models (SAOMs, Snijders et al. 2010), which we report in appendix B. Due to the rapidly changing size of the network, a violation of the assumption that actors have a sense of all potential collaboration partners (Ripley et al. 2019), and issues with model fit and convergence, we were unable to make comparisons across the entire history of the field using SAOMs. Nevertheless, the results from longitudinal network models show overall consistency with the results reported in the main text, which further strengthens our confidence that the new patterns we detected with our analyses are not a mere by-product of the network's changing size and density or other basic network tendencies such as homophily according to social foci (Anderson et al. 1999; Feld 1981).

3.6 Discussion

How do stratified orders in new scientific fields evolve? To address this question, we analyzed a unique data set spanning 41 years of scientific collaboration in neuroblastoma research. We integrated previous accounts that assume a link between the importance of status and the amount of uncertainty exhibited by social environments (Lynn 2014; Mayhew 1973; McFarland et al. 2014; Podolny 2010; Ridgeway 2019; Ridgeway and Erickson 2000) with research highlighting the role of various resources in mobilizing collaboration partners (Chubin 1976; Frickel and Gross 2005; Griffith and Mullins 1972; Knorr 1999; Latour and Woolgar 1986; Lazega et al. 2016, 2006; Li et al. 2013). Thus, we derived hypotheses about the developmental trajectory of a growing field. We expected increasing inequality in the distribution of coauthorships, a diversification of accumulation dynamics, and rising segregation along status differences. Our results supported our hypotheses.

We found increasing inequality in the distribution of coauthorships, suggesting the formation of an elite of authors at the center of the network. Simulations obtained from network models enabled us to confirm that this trend is substantial (Gondal and McLean 2013a; Snijders and Steglich 2015). Regarding our expectation that circles of status-similar authors accompany a mentor-apprentice model of collaboration over time, we found a trend toward more status homogeneity according to researchers' experience and productivity. Yet, we would like to point out that our ERGM analysis focused on researchers' characteristics and did not investigate whether actors with many ties collaborate with actors holding few ties (assortativity). In comparison, results of SAOM suggest that, independent of their attributes, researchers with many coauthor ties tended to collaborate with others who hold fewer ties in most periods. This finding supports the idea that a mentor-apprentice model of collaboration was simultaneously present to status homogeneity according to researchers' attributes (for details, see online appendix B). Furthermore, the large estimates for institutional homophily in ERGMs and SAOMs can be interpreted as suggestive evidence for a persisting relevance of local interaction among senior scientists and early career researchers.

In spite of the insights we have provided, we also acknowledge several limitations that should be addressed in further research. While our data set is a comprehensive documentation of collaboration in neuroblastoma research, it lacks fine-grained information regarding individual researchers. For instance, we were unable to establish how researchers' gender affects collaboration (Bozeman and Gaughan 2011; Holman and Morandin 2019; Main 2014) and could not account for the funding that individuals managed to accumulate (Bol et al. 2018). Likewise, we had no information about scientists' activities before they engaged with neuroblastoma research, such as their educational careers or their disciplinary background. Therefore, we focused on the link between field-specific resources and the structure of collaborations because previous accounts suggest that scientists can seldom import resources from adjacent fields into new fields of inquiry (Bourdieu 1988; Griffith and Mullins 1972; Latour 1987). Additional information would have allowed us to study how the allocation of coauthorships differed over time—depending on who entered the field—instead of the linear trend towards more diversification that we tested here. Future research could expand our efforts by studying non-linear trajectories of the diversification of accumulation dynamics in scientific communities.

Similarly, further research could investigate which network mechanisms are dominant in producing the observed trend toward more inequality in the distribution of coauthor ties. Our analyses established that the trends towards more stratification and segregation are substantial and are connected to researchers' accumulated status in terms of experience, productivity, and seniority. Yet, further studies could utilize future advancements in longitudinal network modelling to deepen our understanding of how network mechanisms interact with one another to produce different global outcomes.[52]

Another limitation was that we had no information on the content of the research conducted by the scientists in our study. Therefore, we did not investigate how changes in the social structure of neuroblastoma research were accompanied by shifts in knowledge production (Chubin 1976; Cole and Zuckermann 1975; Griffith and Mullins 1972; Knorr 1999; Latour and Woolgar 1986; Mullins et al. 1977). However, it is noteworthy that the structural changes towards more stratification and segregation according to status differences that we observed took place roughly in the second half of the field's history. This later stage in the field's history was also characterized by an influx of researchers with a background in molecular biology (Brodeur 2003; Martynov et al. 2020) and a steady internationalization of the community (Berthold et. al 2019). These new members widened neuroblastoma research's interdisciplinary scope and promoted the field in more countries. Simultaneously, new insights were produced from the late 1990s onward, such as a deeper understanding of the disease's genetic mechanisms (Brodeur 2003; Mossé et al. 2008; Ray 2019) and improved treatment strategies (Maris 2010; Matthay et al. 1999). Whether advancements in scientific knowledge are linked to changes in stratification and segregation along status differences in coauthor networks are exciting questions for further research.

A further problem was that we could not consider the role of institutions to its full extent. As previous research shows, academic institutions often have a distinct status of their own and

[52] Our initial analytical approach was to apply SAOMs and to simulate how global levels of inequality and segregation change if parameters for researchers' characteristics are manipulated (cf., Adams and Schaefer 2016; Snijders and Steglich 2015). The rapid growth of the network, a violation of the assumption that actors consider all potential collaboration partners (Ripley et al. 2019), and issues with model fit and convergence, forced us to abandon this strategy. We hope that new developments in modeling large networks with SAOMs will solve these issues (for details, see appendix B).

this affects the success and collaborative choices of the individuals affiliated with them (Burris 2004; Gondal 2018; Hagstrom 1971; Han 2003; Lazega et al. 2006; Ma et al. 2020). Moreover, large institutes tend to offer researchers more resources to conduct their research and play a key role in understanding the formation of collaboration among scientists (Latour and Woolgar 1986; Lazega et al. 2006).

Furthermore, as we focused on one particular scientific field, we cannot separate general developments in science from trends that are specific to the community of neuroblastoma researchers. For instance, the reported diversification of accumulation dynamics could be due to an overall trend toward the economization and increasing stratification of knowledge production over the last few decades (Evans 2008; Fochler et al. 2016; Jones et al. 2008; Leahey and Barringer 2020; Lok 2016; Münch 2014; Münch and Baier 2012). Further research should therefore compare the trajectories of different fields to help us understand what changes typically occur as fields mature and what developments are common across fields, for example, due to macroeconomic trends (Ramage et al. 2020; Stark et al. 2020).

Despite these limitations, our study contributes to a better understanding of how stratified orders emerge in new scientific fields. Our theoretical considerations provide a relational and dynamic view of inequality and segregation in emerging scientific fields. Moreover, we propose a complementary perspective to studying individual trajectories (e.g., Azoulay et al. 2010; Costas and Bordons 2011; Hâncean et al. 2021; Li et al. 2013; Petersen et al. 2014), macrotrends within and across scientific disciplines (Evans 2008; Foster et al. 2015; Jones et al. 2008; Leahey 2016; Moody 2004; Münch 2014; Shi et al. 2015; Wuchty et al. 2007), or the micro-interactional antecedents for knowledge production (Latour and Woolgar 1986; Parker and Hackett 2012) by focusing on long-term changes in the overall structure of scientific collaboration in demarcated fields of research. Finally, we have shown how our theoretical considerations apply to empirical settings by mapping how the structure of collaboration changed among neuroblastoma researchers.

Chapter 4

The emergence of status orders in Hollywood filmmaking. Evolution of a cultural Field, 1920 to 2000

Co-authored with Katharina Burgdorf, Faculty of Social Sciences, University of Mannheim.

Abstract

How do status orders emerge in cultural fields? Our study sheds new light on this question by investigating the interplay of networks, status, and culture among Hollywood filmmakers from 1920 to 2000. Information on artistic references and collaborations of more than 13,000 filmmakers retrieved from the Internet Movie Database (IMDb) allows us to examine long-term changes in the social organization of this cultural field. Our findings suggest that the distribution of social recognition—measured by filmmakers' prominence in collaborative ties and artistic references—became more stratified as the field grew and matured. Furthermore, collaborations increasingly exhibited segregation according to filmmakers' artistic status during the New Hollywood era (1960-1985). This period was characterized by the rising prominence of a new generation of filmmakers who established film as an art form in the U.S. This chapter shows that contextual characteristics, such as a field's size and institutional environment, can foster or impede stratification and segregation in collaborative networks among cultural producers.

4.1 Introduction

Various fields of cultural production, such as literary writing, making music, and academia, are marked by an unequal distribution of recognition, esteem, and material resources (Bourdieu 1993; Crossley 2009; Faulkner 1983; Lena and Pachucki 2013; Merton 1968; Newman 2001a). In addition, cultural fields are often characterized by closed circles of status similar actors who interact and collaborate (Bourdieu 1988, 1993; Cattani, Ferriani, and Allison 2014; Lena and Pachucki 2013; Ma et al. 2020). While previous studies offer rich insights on how actors' field position and networks shape their individual trajectories (e.g., Faulkner 2017; Borkenhagen and Martin 2018; Jones 2001; Lutter 2015), we know less about how status inequalities in cultural fields emerge in the first place or change over time.

We examine the contextual characteristics for long-term changes in the social structure of one of the most influential fields of cultural production in the world: Hollywood filmmaking (Baumann 2007). Past studies stressed the importance of social networks for cultural production (Becker 2008; Bottero and Crossley 2011; Crossley 2019; Lena 2012; Phillips 2013) and highlighted that social recognition structures artistic fields (Bourdieu 1983, 1993; Dowd et al. 2002; Lena and Pachucki 2013; Pachucki 2012). Our investigation of Hollywood filmmaking synthesizes these streams of literature and offers the first network-analytical study that maps long-term changes in the interplay of networks and status in a cultural field. In particular, we trace during which periods Hollywood was characterized by a stratified order, and socially-closed cultural elites among filmmakers.

Our research goes beyond accounts that focus exclusively on individual-level outcomes or treat inequality and segregation as given, time-constant properties of cultural fields. Previous research showed that having access to collaboration partners or advantageous network positions is crucial for individuals' economic and cultural success (Burt 2004; Ferriani, Cattani, and Baden-Fuller 2009; Lutter 2014, 2015; Uzzi and Spiro 2005; Vedres and Cserpes 2020, 2021). Yet, less systematic attention has been devoted to the question of how the network structure of cultural fields comes about in the first place and changes over time (Mohr et al. 2020). A reason for this research gap is that collecting complete network data for an entire cultural field was impossible before large digital data sources became widely available—e.g., databases of scientific publications (Barabâsi et al. 2002; Moody 2004; Newman 2001a) or artistic contributions (Lena 2004; Rossman et al. 2010; DeVaan, Vedres, and Stark 2015). While analyzing how positional characteristics of individuals or project teams affect their outcomes is already methodologically challenging, modeling the structure of large networks is still in its infancy and riddled with technical problems such as model degeneracy, high requirements of computational power, and non-comparability of estimates across network models (Snijders 2011; Hunter 2007; Duxbury 2021; Martin 2020).

The mobilization of a vast dataset that includes collaborations and references among more than 14,000 U.S. American filmmakers over 80 years and recent advances in network analysis (Duxbury 2021) allow us to overcome these methodological challenges and shed light on the origins of stratification in artistic fields. Moreover, this data source enables us to investigate the social correlates of major artistic developments identified by film history scholars, such as the turn from a studio based-system of filmmaking to the New Hollywood era marked by a more artistic style of filmmaking (Baumann 2001; Biskind 1999; Bordwell, Staiger, and Thompson 1985; King 2002).

Our results indicate that the distribution of social recognition changed as the field of Hollywood filmmaking matured. More filmmakers entered the industry, and an elite of writers and directors formed, attracting disproportional shares of collaborative ties and artistic references. These findings resonate with previous accounts that relate the size of a context to its inequality in social recognition (Blau 1968; Mayhew 1973; Mayhew and Levinger 1976; McFarland et al. 2014). In addition, our findings suggest that artistic status influenced collaborations more strongly during the New Hollywood era of the 1960s and 1970s. This period saw the downfall of the studio system and a shift in the perception of Hollywood films from entertainment products to artworks in their own right (Baumann 2001, 2007; Becker 2008; Faulkner 2017).[53] We find that during the New Hollywood period, filmmakers of similar artistic status tended to form collaborative ties more often than status dissimilar filmmakers, while this tendency was less pronounced or absent in other periods.

Methodologically, our article shows the fruitfulness of applying computational tools to answer longstanding sociological questions (Edelmann et al. 2020; Lewis 2021; McFarland, Lewis, and Goldberg 2016), as we combine the analysis of an extensive process-produced data set with expectations derived from sociological theory and detailed consideration of Hollywood's historical development (Mohr et al. 2020). In addition, our results are of interest to proponents of social network analysis and scholars who develop relational theories of social status. While the majority of applications of network models are still limited to analyzing relatively small networks among children, adolescents, or students, our investigation illustrates that it is possible and worthwhile to analyze larger social systems with network models such as exponential random graph models (ERGMs; Lusher and Robins 2013). Finally, our research highlights that the interplay between status and networks requires time to evolve and can change depending on the institutional environment in which a network is embedded. These findings present a challenge for existing status theories, which often implicitly assume that status orders crystalize quickly and exhibit a stable structure over time (Gould 2002; Lynn, Podolny, and Tao 2009; Manzo and Baldassarri 2014; Ridgeway 2019; Smith and Faris 2015).

[53] The term "studio system" refers to the Golden Age of Hollywood (1920s-1960s) and describes the power oligopoly of the Big Five (Paramount Pictures, 20th Century Fox, Metro-Goldwyn-Mayer (MGM), Warner Bros., RKO Pictures) and Little Three studios (Universal Studios, Columbia Pictures, United Artists). It was characterized by the long-term employment of creative personnel and studios' unified ownership (vertical integration) of distribution and exhibition.

4.2 Status orders in cultural fields

Previous sociological work suggests that cultural fields are marked by an unequal distribution of social recognition and material resources (Bourdieu 1993; Cattani and Ferriani 2008; Lena and Pachucki 2013; Lutter 2015). While inequality is often viewed as an average tendency—persistently shaping the structure of cultural fields—contemporary and earlier theoretical accounts suggest that the structure of organizational (Hannan and Freeman, 1993; Padgett and Powell, 2012), cultural (Baumann, 2001; Becker, 2008; Bourdieu, 1993, 1984; White and White, 1993), and scientific fields (Chubin, 1976; Crane, 1972; Frickel and Gross, 2005; Jurgens et al., 2018; Kuhn, 1970; Munoz-Najar Galvez et al., 2019) changes over time. In the present study, we draw upon these dynamic perspectives and study the emergence of status inequalities in the cultural field of Hollywood filmmaking.

Our first theoretical considerations concern the question of whether a cultural field exhibits different levels of stratification in social recognition throughout its evolution. By social recognition we mean filmmakers' prominence in collaboration and artistic reference networks. In the following, we build on previous scholars concerned with cultural fields (Becker 2008; Bourdieu 1993) and relational theories of status orders (Gould 2002; Podolny 2010) to argue that a field's size and maturity amplify inequality in the distribution of collaboration partners and artistic references.

Increasing inequality in collaborations

The first relational process under study is collaborative work, which is a constitutive of all labor in the arts and culture, including music (Becker 2008; Faulkner 1983, 2017; Lena 2012; Phillips 2013; Vedres 2017; Vedres and Cserpes 2020), theater and musicals (Serino, D'Ambrosio, and

Ragozini 2017; Uzzi and Spiro 2005), video games (DeVaan, Vedres, and Stark 2015), and films (Baumann 2007).[54]

Previous work on filmmaking suggests that collaborations facilitate the gathering of resources and information which allows filmmakers to manufacture artworks that are recognized and credited by an audience of peers (Cattani and Ferriani 2008; Lutter 2015).[55] Moreover, collaboration with high-status individuals increases filmmakers' odds of accumulating symbolic resources such as prizes (Ebbers and Wijnberg 2010; Rossman, Esparza, and Bonacich 2010; Rossman and Schilke 2014). These benefits of collaborating with others should, in turn, facilitate further collaborations. This accumulation of a large stock of resources (including collaborators) by a small number of actors is commonly referred to as the Matthew effect (Bol, de Vaan, and van de Rijt 2018; Bothner et al. 2010; Merton 1968; Snijders and Steglich 2015). Just as the Matthew Effect produces an elite among scientists (Crane 1972; Eom and Fortunato 2011; Merton 1968; Newman 2001c), we expect that a small number of filmmakers accumulated high numbers of collaborators over time.

In addition, we argue that the cycles of accumulation which link resources to collaborations and vice versa (for scientific fields, see Latour and Woolgar 1986) depend on the developmental stage of a cultural field. The beginning stage of cultural fields is typically characterized by a small avant-garde that pursues new artistic endeavors and is marked by a high turnover of

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[54] Outside of art worlds, the structure and consequences of collaboration continue to attract great interest in organizational sociology (Kilduff and Krackhardt 2008; Powell et al. 2005), the sociology of science (Blau 1994; Crane 1972; Moody 2004), science and technology studies (Evans 2008; Knorr 1999; Latour 1987), and the study of political movements (Wang and Soule 2012).

[55] Often, resources are materials and tools such as pigments in classical painting (White and White 1993), cameras in photography or instruments in music (Becker 2008; Faulkner 1983, 2017). While some fields depend less on tangible resources—e.g., literary writing and poetry (Bourdieu 1993; Dubois 2018)—filmmaking is an art form that requires a lot of resources such as cinematic equipment and money to pay for large teams of personnel (Baumann 2007; Bordwell, Staiger, and Thompson 1985).

members and a local mode of cultural production (Becker 2008; Lena 2012). Moreover, resources are scarce in nascent fields that exhibit little institutionalization, legitimation, or acclaim by public or critical audiences (Baumann 2007; Dubois 2018). Taken together, the lack of a stable community and potential access to funding and equipment during the early stages of Hollywood filmmaking should have made it harder for filmmakers to build a large number of collaborators. Only as more filmmakers entered the field, production companies emerged (Bordwell, Staiger, and Thompson 2015; Cattani et al. 2008; Mezias and Mezias 2000; Schatz 1996), and an infrastructure of film distributors and cinemas developed (Bordwell et al. 1985). We expect that as field size increased more artists managed to forge long-term careers. Thereby, a new elite formed at the field's center, characterized by a small number of filmmakers who collaborated with many others.

This hypothesis can also be derived from a second stream of literature concerned with status orders in markets, organizational fields, and interactions in task-oriented groups (Borkenhagen and Martin 2018; Gondal 2018; Ma et al. 2020; Podolny 2010; Ridgeway 2019; Sauder, Lynn, and Podolny 2012). These theories define status as prestige, respect, recognition, and (psychological) deference received by others (Fiske 2011; Gould 2002; Manzo and Baldassarri 2014; Podolny 2010; Ridgeway 2019; Torlò and Lomi 2017). Following Podolny (2010), we assume that cultural producers derive information from status signals to reduce uncertainty when navigating cultural fields.[56] If uncertainty rises, status should play a more pronounced role for behavior since the heuristic usefulness of status recognition is greater in environments or situations that exhibit more uncertainty (Blau 1968; Fiske 2011; Mayhew 1973; McFarland

[56] The idea that humans draw upon cognitive heuristics to store and represent relational information is well supported by empirical evidence (Brashears, 2013; Carnabuci et al., 2018; Krackhardt and Kilduff, 1999). Perceiving others on a vertical dimension plays a crucial role in social cognition and shapes interaction in a variety of settings (Anderson, Hildreth, and Howland, 2015; Berger, Cohen, and Zelditch, 1972; Fiske, 2011; McMahan, 2017; Ridgeway, 1991).

et al. 2014; Podolny 2010). To retain their capacity to navigate the field—for instance, to decide whom they should collaborate with—humans tend to apply filters to the relational information they receive (Brashears, 2013; Brashears and Quintane, 2015; Dahlander and McFarland, 2013; Lynn, 2014; Mayhew, 1973; Mayhew and Levinger, 1976; McFarland et al., 2014).

In Hollywood filmmaking, only a few artists participated in the field in its first decades (Bordwell et al. 1985). Under these conditions, it is highly likely that artists were able to detailly monitor the actions of their peers. As the filmmaking industry matured, new filmmakers entered the field, and we assume that it became more difficult, or even impossible, to keep track of what others were doing. The field grew in size, and uncertainty about the proficiency of one's collaborators increased. Therefore, we expect to see a heightened reliance on the one trait filmmakers could consider: the status of potential collaboration partners. Consequently, we expect more inequality in the distribution of collaborations over time because a growing field increases uncertainty, which in turn amplifies the effect of status recognition on the structure of networks.

Hypothesis 1. Inequality in the distribution of collaboration ties among cultural producers increases with a field's size and maturity.

Increasing inequality in artistic references

The second relational process we consider is artistic referencing. References among artists surface in artworks and are intelligible to other artists or informed outsiders such as critics or connoisseurs. Repeating the ideas of others is an important way to signal one's own position in a cultural field (Bourdieu 1993). Jazz musicians who imitate others' musical phrases, styles of playing (Berliner 2009) or selection of compositions (Phillips 2013), rap musicians who sample tracks by fellow artists or repeat samples used by other musicians (Lena 2004; Lena and

Pachucki 2013), and literary writers who refer to peers' books in their own texts (Bourdieu 1993) are all instances of artistic referencing.

Here, we build on previous studies that conceptualize Hollywood filmmakers' referrals to other movies as artistic referencing (Bioglio and Pensa 2018; Spitz and Horvát 2014). These references can take several forms, such as dialogue sequences or exact camera settings that one film borrows from another. According to scholars of film history, references can include "quotations, the memorialization of past genres, the reworking of past genres, homages, and the recreation of 'classic' scenes, shots, plot motifs, lines of dialogue, themes, gestures, and so forth from film history" (Carroll 1982: 52). Biguenet (1998) characterizes them as a "direct reference by title or the inclusion of an actual clip from another film, a similarity to a famous character or a repetition of a classic shot, an imitation of a well-known scene or an allusion to an entire film genre." An example would be the final scene of Steven Spielberg's *Raiders of the Lost Ark* (1981). It includes a wide shot of aisles and wooden boxes stored in a warehouse, which is a reference to the final scene of Orson Welles' *Citizen Kane* (1941), see figure 4.1.

Figure 4.1. Example for artistic references in filmmaking

Citizen Kane (Orson Welles, 1941)

Raiders of the lost Ark (Steven Spielberg, 1981)

While past studies scrutinize the positive effects of collaborations on the accumulation of material and symbolic resources, such as career success or awards (Lutter 2015; Rossman et al. 2010), we know little about the role of artistic references in filmmaking careers. However, accounts from other cultural fields, such as music, indicate that references among artists are associated with higher chances to succeed (Lena 2004, 2006; Lena and Pachucki 2013; Phillips 2013).

Unlike collaborations, artistic references rarely occurred during the early stages of Hollywood. The so-called Golden Age of Hollywood (1920-1960) was marked by the dominance of film studios and a primarily commercial understanding of filmmaking (Bordwell et al. 1985). Throughout a transformation from the studio system to more artistic filmmaking in the 1960s (King 2002), filmmakers increasingly referenced each other.

During this time, *auteurism* inspired a new generation of filmmakers. Auteurism is a template for filmmaking which originated in French film criticism and continues to imply an artistic understanding of filmmaking. In particular, auteurism stresses the role of the individual filmmaker as the creative engine behind a film. American film critic Andrew Sarris formulated the auteur theory in 1962 (Sarris 1962, 1968) which provided a tool for critics and academics to assess the artistic value of films and included a list of consecrated auteurs.[57] According to auteurism, instead of being interchangeable—as in the previous studio system (1920-1960)—the director constitutes the author of a film and shapes its story and style.

In general, sociologists have demonstrated that critics and legitimating institutions, such as museums or art schools, foster processes of canonization and consecrate selected art works (Film: Baumann 2001, 2007; Allen and Lincoln 2004; Hicks and Petrova 2006; Watson and Anand 2006; Jazz: Lopes 2009; Literature: Corse and Westervelt 2002; Impressionism: White and White 1993; for a comparative account, see Lena 2020). The creation of a canon demarcates a subgroup of the art form that artists and critical or public audiences can refer to as representative of their role model for legitimate art (DiMaggio 1992). In the case of Hollywood,

[57] As Sarris (Sarris 1962: 563) describes it: “At the moment, my list of auteurs runs something like this through the first twenty: Ophuls, Renoir, Mizoguchi, Hitchcock. Chaplin, Ford, Welles, Dreyer, Rosselini, Murnau, Griffith, Sternberg, Eisenstein, von Stroheim, Buñuel, Bresson, Hawjs, Lang, Flaherty, Vigo [...]”.

identifying “sacred” works and demarcating them from “the profane” allowed artists and critics to dismiss other films as a different kind of cinema, thereby establishing the artistic integrity of “real” cinema. (Baumann 2001: 416).[58]

The canonization of filmmakers by early 1960s film critics entailed a call for a new filmmaker generation to study their consecrated peers and ancestors carefully. Many young filmmakers were exposed to auteur theory through their film school education during the 1960s and articulated their career strategies as imitations or emulations of these stars (see Pye and Myles 1979). For instance, filmmaker John Milius reported his admiration for established auteurs in an interview from 1994: “We wanted to be like Tom Ford, Howard Hawks, Orson Welles but we never thought we could be.” (quoted in Pye and Myles 1979). Moreover, the emerging critical discourse around auteur theory and the rise of film school departments were indicative of Hollywood’s legitimation process and the field’s increased maturity (Baumann 2007). We expect that these institutional changes were necessary conditions for filmmakers to develop referencing as a novel aesthetic practice.

In addition to the increasing prevalence of references, we also expect that the distribution of references became increasingly unequal as the field formed a consensus on who’s work should be regarded as artistically valuable and should, thus, be referenced disproportionally. While critics and institutions contributed to the initial formation of a film canon, filmmakers fostered

[58] Film scholar Noel Carroll (Carroll 1982: 52) describes the interplay between critics and filmmakers as follows: “During that period, a canon of films and filmmakers was forged. An aggressive polemic of film criticism, often called auteurism, correlated attitudes, moods, viewpoints, and expressive qualities with items in the putative canon. These associations became available to contemporary filmmakers, who were able to lay claim to them by alluding to the original films, filmmakers, styles and genres to which certain associations or assignments were affixed in the emerging discourse about film history. Thus, Body Heat, a film based on references to film history, a film that tells us that for this very reason it is to be regarded as intelligent and knowing, a film that demands that the associations which accrued to its referents be attributed to it and that it be treated with the same degree of seriousness as they were.”

canonization whenever they used references. Considering the accumulation of attention on a small subset of cultural producers leads us to the expectation that a rising number of filmmakers who used references is linked to increased inequality in the distribution of artistic references as a canon of highly acclaimed artists formed. Note that only because filmmakers used *more* references, this does not necessarily imply rising *inequality* in the distribution of references. Without a process of canonization, we would expect no noticeable increase in the inequality of the distribution of artistic references as they should spread among a larger proportion of filmmakers without concentrating on a cultural elite.

As outlined above, larger fields exhibit more uncertainty and make it harder for field participants to process information about others (Mayhew 1973). Consequently, cognitive heuristics—such as status recognition—are more consequential for actors' perceptions of each other (McFarland et al. 2014; Podolny 2010). In the case of Hollywood, the film industry faced a severe economic crisis during the 1950s and 1960s, driven by legal pressures, demographic changes in audiences, and the advent of TV (Baumann 2007). During this time, fewer filmmakers participated in the field, and it took several decades before the industry regained its economic strength. We expect that the associated influx of filmmakers between 1960 and 2000 led to more inequality in the distribution of artistic references. In general, previous scholarship on cultural fields indicates that cultural fields exhibit more artistic referencing and the formation of a canon of consecrated art works once a field gained legitimacy (Allen and Lincoln 2004; Baumann 2007; Bourdieu 1993; Dubois 2018; Lopes 2009).

Hypothesis 2. Artistic referencing becomes a widespread practice after a field gains legitimacy. Subsequently, inequality in the distribution of artistic references among cultural producers increases with a field's size and maturity.

The advent of artistic status in Hollywood filmmaking

So far, we have considered how the distribution of social recognition in the form of collaborations and artistic references changed over time. While we have hereby discussed collaborations and artistic references independent of each other, we subsequently argue that the re-orientation of cultural producers towards artistic criteria during the New Hollywood period also affected the interplay between collaborative ties and artistic references. In particular, we expect that cliques of artists with a similar artistic status emerge after Hollywood's transformation into an art world (Baumann 2007).

Status homophily—the tendency to collaborate with status-similar others—may result from actors' fear to associate with others who hold a lower status because public display of a connection would endanger their reputation (Podolny 2001). More broadly, reasons for network homophily are that persons with similar traits and characteristics tend to understand each other better, often communicate more easily, and find each other more likable and predictable (Blau 1977b; Byrne et al. 1971; McPherson et al. 2001; Wimmer and Lewis 2010). In the case of status homophily, the reversed causal direction is also plausible as status and collaborations change over time actors might gain or lose status based on their former collaboration partners' status (Dijkstra et al. 2010; Torlò and Lomi 2017).

An example for homophilous collaboration in cultural production are collaborations among scientists. Several studies demonstrated that scientists with similar traits are more likely to collaborate (Dahlander and McFarland 2013; Kossinets and Watts 2009; Main 2014; Moody 2004; Stark et al. 2020). Moreover, scientists not only tend to collaborate with others who share salient socio-demographic characteristics, such as gender and age but also with others who hold a similar organizational status (Ma et al. 2020). While collaborations tend to span geographic and institutional boundaries, they often remain within the same university rank—i.e., status-similar researchers tend to collaborate more often than status-dissimilar researchers (Jones, Wuchty, and Uzzi 2008).

As in science, filmmaking careers are embedded in collaborative contexts that shape rewards and recognition (Rossman et al. 2010; Cattani et al. 2014). We argue that sharing a similar artistic status—reflected by the volume of artistic references a filmmaker attracts—became a socially relevant trait during the New Hollywood era as an artistic status order crystallized throughout the field's artistic legitimation process (Bauman 2007a, see H2). This legitimation process induced a crisp distinction between art and non-art that could then guide filmmakers' decision-making when choosing a collaborator (see Gieryn (1983) for a similar distinction between science vs. non science).

A collaboration between filmmakers of similar artistic status potentially provides several advantages: first, filmmakers secure their status by avoiding collaborations with others who have a lower status than themselves (Podolny 2010). Second, connections to other filmmakers high in artistic status allow filmmakers to be perceived as artistically sophisticated by peers and audiences and to construct artistic rather than commercial identities (Goldberg and Vashevko 2013; Zuckerman et al. 2003). Third, collaborating with status similar artists creates a bond against the commercial demands of producers. As in other creative contexts, filmmaking is characterized by the dilemma between commercial vs. artistic interests (see Becker 2008; Baker and Faulkner 1991). This is reflected in the conflict of the producer's interest to make a film on time with a limited budget, and the director's interest of creating a work of art. Fourth, status-similar collaborations support realistic expectations on the collaborative process and outcome. When two filmmakers of high artistic status collaborate, they can tacitly assume that they both share an interest in creating a work of art rather than a commercial product. Both kinds of filmmaking—artistic and commercial—employ different aesthetic conventions that smooth or hinder the collaborative process (Becker 2008).[59]

[59] One could argue that status homophily is unlikely because auteur theory stresses the role of the individual filmmakers as the sole mastermind behind a film. Consequently, filmmakers are potentially confronted with a dilemma: if two auteurs collaborate, who will be seen as the creator of the film? Yet,

We argue that the changing institutional environment of Hollywood filmmaking fostered the emergence of an artistic status order which in turn shaped filmmakers' collaborations. The collapse of the studio system during the 1950s offered filmmakers more freedom in choosing whom to collaborate with. At the same time, critics, as well as institutions, fueled a novel understanding of filmmaking as a mode of artistic expression.[60] While artistic status might have already played a role during the studio era, we assume that the grip studios held over the production of films and filmmakers' creative process did not permit the emergence of a strong artistic status order among filmmakers. As Bourdieu (1993) pointed out, increasing autonomy of a cultural field from economic constraints paves the way for field-specific standards of evaluation and a social organization centered around the idea of art for its own sake. This leads us to our third hypothesis.

Hypothesis 3. Artistic status increasingly shapes collaborations among cultural producers as a field gains artistic legitimacy. Consequently, cultural producers with a similar amount of received references tend to collaborate more often than dissimilar ones.

In addition, we expect a decreased importance of artistic status for collaborations in the decades after New Hollywood as this period was marked by an institutional environment which was less supportive for the ideal of artistic filmmaking. The unforeseen success of New

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despite the ideals of auteur theory, filmmaking remained a collaborative effort involving many different professional roles from directors to writers, cinematographers, and editors. Though the literate interpretation implies the combination of writers and directors, many filmmakers split these roles while still identifying as auteurs. For example, Martin Scorsese counts as an auteur, but he collaborated with writer Paul Schrader several times. Taken together, we expect that auteurs continued to collaborate with others and that artistic status influenced their collaboration choices.

[60] A Supreme Court decision in 1948 ruled that Hollywood studios had to cease long-term employment contracts and allow filmmakers to freely engage in collaborations with other studios.

Hollywood films “The Godfather” (1972) and “Jaws” (1975) rang in the era of blockbusters. This era was characterized by an increasing re-commercialization of movies. The auteur identity served as a marketing tool to promote films (Baker and Faulkner 1991) and a star and celebrity culture increasingly influenced Hollywood’s public perception. Due to the renewed economic success of Hollywood, production companies gained more power over creative decisions. One sign for this development was the introduction of sequels and the tendency to produce several films based on previous successes casting the same stars repeatedly. Like major record labels that tried to establish an assembly line of commercial successes (Lena 2012; Phillips 2013), production companies aimed to decrease risks by re-furbishing former blockbusters. Also, filmmaking became increasingly expensive and involved larger casts and more technology during this period. In sum, we expect that these developments are linked to a decreased importance of artistic status among filmmakers during the Blockbuster era. More broadly, we expect that collaborative networks in cultural fields are less structured by an artistic status order if the institutional environment of the field becomes detrimental to an artistic orientation (cf., Bourdieu 1983, 1993).

Hypothesis 4. The role of artistic status for collaborations among cultural producers decreases during periods which offer less institutional support for an artistic ideal of cultural production.

4.3 Data

We use information on collaborations and references as listed in the Internet Movie Database (IMDb), a rich data repository, which includes all films and their associated crew and cast over the course of the entire history of filmmaking. IMDb is a crowd-sourced platform where a community of film enthusiasts submits, edits, and updates information. Unless the information is submitted by users with a proven track record, IMDb publishes new data entries only after screening them for consistency and correctness. We are not the first to draw on this exceptional source for scientific purposes. Several studies have relied on the IMDb and confirmed the validity of its entries with regard to information on casts, crews, and genres (Zuckerman et al. 2003; Sorenson and Waguespack 2006; Cattani and Ferriani 2008; Cattani et al. 2014; Max Wei 2020), user ratings (Keuschnigg and Wimmer 2017), acting credits (Rossman et al. 2010), and artistic references (Bioglio and Pensa 2018; Spitz and Horvát 2014).

We discuss data quality aspects in a separate analysis (see appendix A). Since we focus on filmmakers in this study, we only include writers and directors in our sample. We limit the sample to filmmakers who participated in the production of a film during at least three different years.[61] We do not consider artists with other professional roles, such as actors or composers. Moreover, we exclude the following genres: news, talk-show, gameshow, reality-tv and adult movies as these genres follow different organizational logics compared with filmmaking. Details on the selection of our analytical sample are provided in appendix A.

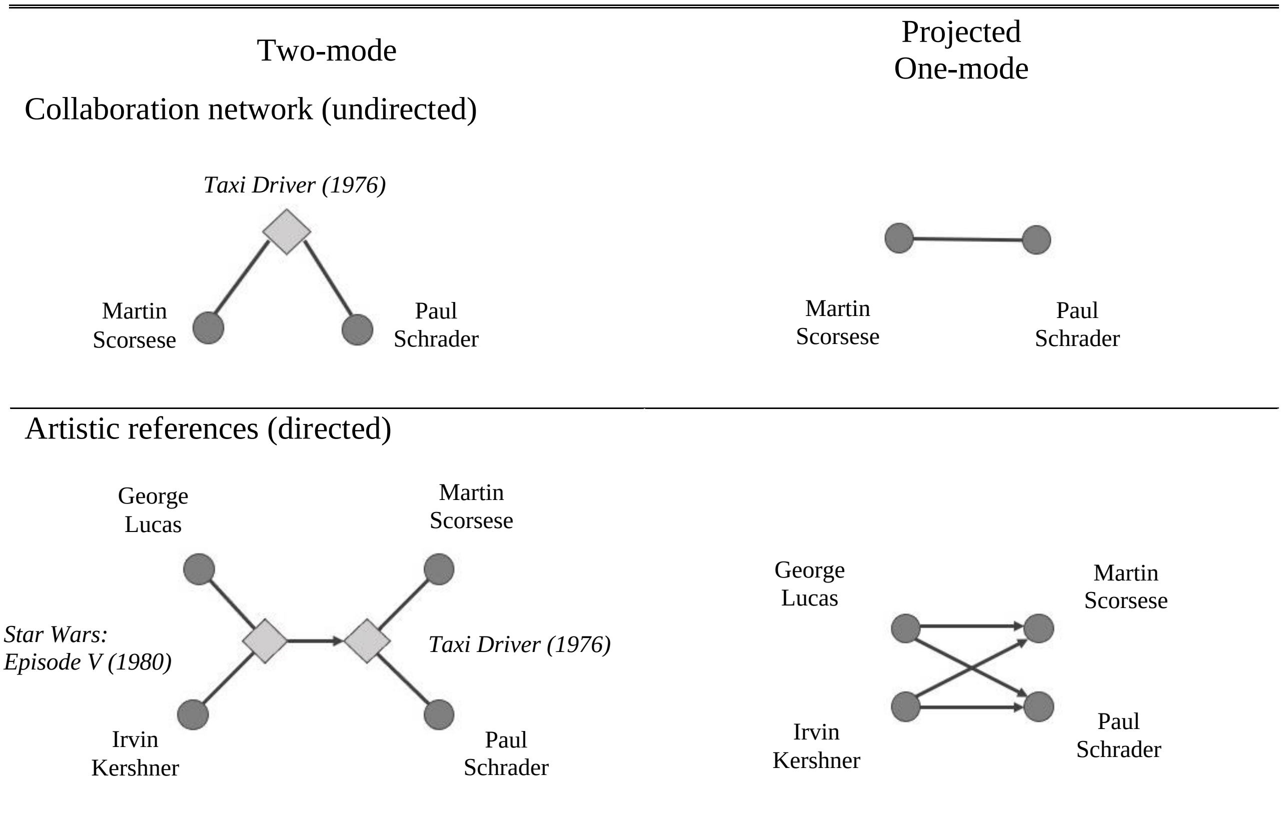
[61] A high proportion (61%) of filmmakers drops out of the industry after only one project. We focus on filmmakers that were active in at least three different years because these filmmakers are more likely to contribute to the field's development.

4.4 Measures

Collaboration networks

We used the co-occurrence of filmmakers in IMDb entries for particular films to derive collaboration ties between filmmakers. Since realizing a film usually takes several years, we decided to aggregate collaboration ties stemming from multiple years into windows. A similar approach was previously pursued by De Vaan et al. (2015) who applied network analysis to study collaborations among game developers. We report analyses for three-year windows, because three years are close to the overall average production time of a film (Follows 2018).[62] For instance, the window from 1930 until 1932 contains collaboration ties among filmmakers who collaborated either in 1930, 1931, or in 1932.

Figure 4.2. Operationalization of collaboration and artistic reference networks



[62] https://stephenfollows.com/how-long-the-average-hollywood-movie-take-to-make/

Artistic reference networks

To measure artistic references, we collected all information from the section on "connections" to other films in IMDb. There is considerable variation in the types of connections listed in the IMDb: they range from active ones, such as "references," to passive ones, such as "version of" or "remade as" (Spitz and Horvát 2014). We only consider titles that are listed as "references" because we seek to show to what extent filmmakers were paying homage to previous works in film history. We are less interested in remakes or spoofs of earlier films. According to the IMDb's stated definition a film includes a reference if it "references or pays homage to a previous title (i.e., a still, poster, or artifact; mentioned by name; scene discussed by characters; dialog quoted in non-spoofing way)".

Thereby, we also coded a reference if filmmakers reference works of their peers from previous periods. For instance, Quentin Tarantino's film *Pulp Fiction* (1994) references Francis Ford Coppola's *The Godfather Part II* (1974). As Coppola is an active member of the film industry in the period from 1993 to 1995, an artistic reference is established from Tarantino to Coppola although *The Godfather Part II* was produced in a previous period.

Stratification

We use the skewness of the degree distribution of the collaboration networks and of the indegree distribution of the artistic reference networks as a global measure for inequality during a given period. If a degree distribution is positively skewed, this is indicative of a small number of individuals having many ties, while many have none or only a few ties (Fisher 2018: 57; Moody et al. 2011: 103).

Artistic status

In addition to the question of how artistic references are distributed among filmmakers, we also consider homogeneity in artistic status among filmmakers. This implies the question whether filmmakers with a similar volume of artistic references are more likely to collaborate. To measure segregation according to artistic status, we first computed a score for each filmmaker that summarizes all references she received from other filmmakers who participated in a focal window. Next, we z-standardized these scores for each window to account for the increasing number of references over time.

Experience

To account for filmmakers' experience in the industry, we calculated how many years a filmmaker participated in Hollywood filmmaking. Thereby, we use the year when a filmmaker released her first film as the starting point of her career and subtracted it from the focal year. Subsequently, we z-standardized the accumulated years of experience to account for time trends in the length of careers.

Productivity and resources

To capture filmmakers' ability to harness resources from production companies and to successfully finish film projects, we calculated the number of films a filmmaker made in a particular period. Also, we derived the crew size—which includes composers, costume designers, cinematographers, and further production personnel—for each film a filmmaker was involved in and averaged the crew sizes for each window. Thereby, we account for the fact that filmmakers involved in projects with larger crews have more access to resources such as funding and participate in economically more profitable films (for a similar approach, see Rossman et al. 2010). We z-standardized these measures as they show time trends.

4.5 Methods and Models

Exponential random graph models (ERGMS)

We use exponential random graph models (ERGMs) to measure changes in the social structure of Hollywood filmmaking (Lusher et al., 2013).[63] These network models allow us to test whether inequality in collaborations and artistic references intensified over time, and whether artistic status played a more prominent role for collaboration networks during the New Hollywood era.

The dependent variable for ERGMs is the global structure of a given network. The independent variables are count statistics for local structures, such as the number of dyads sharing the same characteristic—e.g., filmmakers who collaborate and have a similar artistic status. ERGM coefficients indicate whether a particular local structure occurs more often in the observed network than a random allocation of ties would suggest, conditional on all other local structures considered in the model specification (Lusher et al., 2013; Robins, 2011). An advantage of this method is that it allows researchers to study the global structure of networks with a generative model, which models multiple local tie-formation processes simultaneously (e.g., Goodreau, Kitts, and Morris 2009).

Another strength of ERGMs is that they allow researchers to simulate networks from a particular model specification. Consequently, global statistics that capture the structure of simulated networks can be compared with empirical values (e.g., Gondal and McLean, 2013a, 2013b). Our analytical strategy uses this possibility to assess which models are capable of reproducing observed levels of inequality. This procedure enables us to test Hypothesis 1 and 2—stating that inequality in the distribution of collaborations and artistic references increases

[63] The analysis was carried out in R. The ergm package was utilized to conduct the ERGM analysis (Hunter et al. 2008).

with field size—because we account for the mechanical link between a network's size and density with graph level indices (Anderson et al., 1999). Thereby, we can assure that observed trends in inequality are not a mere by-product of the overall probability of tie formation.

We implement this part of our analytical strategy by calculating descriptive measures capturing the stratification of ties in each period (27 periods from 1921 to 2000). Subsequently, we obtain 1,000 random networks—based on parameters from a baseline ERGM specification—which had the same size, and density as the corresponding observed network. This yields a distribution of graph-level statistics stemming from simulated networks. Finally, we investigate whether measures of empirical networks are substantially different from those we find in simulated networks (Gondal and McLean, 2013a, 2013b; Snijders and Steglich, 2015). This procedure does not provide a test of statistical significance. However, it indicates whether empirical changes in network structure point to substantial differences and allows us to test Hypothesis 1 and 2.

Model specification

To test Hypothesis 3 and 4—increased importance of artistic status for collaborative ties during the New Hollywood era and decreasing importance during the Blockbuster era—we included a term in our model specification that captures homogeneity according to artistic status. In particular, the "Difference in artistic status term" in table 4.2 reflects whether filmmakers who are dissimilar in their volume of received artistic references are more or less likely to exhibit a collaborative tie. For instance, a statistically significant and negative coefficient for this term would indicate that filmmakers who display a difference of one standard deviation in artistic status are more likely to collaborate—i.e., the presence of homogeneity according to artistic status. To control for the possibility that filmmakers with a higher artistic status also maintain more collaborations in general, we included the "Popularity according to artistic status" term (see table 4.2). Thereby, we obtain a measure of status homogeneity net of differences in sociability—i.e., overall expansiveness and popularity of nodes (for a similar approach regarding ethnic and racial homophily, see Goodreau et al. 2009, Wimmer and Lewis 2010).

In addition to the terms for artistic status, we estimated several model specifications including various terms for endogenous network processes and decided to report a specification that worked for all periods. We followed an iterative procedure similar to the one described in Wimmer and Lewis (2010: 625) and considered terms for endogenous network processes, such as the GWDEG, GWESP, and GWNSP terms for the degree distribution and triadic structures. As the inclusion of most terms for higher-order structures led to degeneracy issues in several periods, we decided to estimate a simpler model specification that allowed for comparisons between all periods. This approach offers a straightforward interpretation of the role of actors' attributes for network structure. In contrast, higher-order terms can complicate interpretation, as Martin (2020) recently pointed out. While including more endogenous network processes would be desirable, network models currently often show problems with degeneracy and model fit when estimated for large networks (cf., Stark et al. 2020, Lewis and Kaufmann 2018). As Hypothesis 3 and 4 are concerned with homogeneity according to artistic status, we are confident that the analytical strategy we pursued here is sufficient because it accounts for the networks' opportunity structure and considers multicollinearity between measures of artistic status and filmmakers' career outcomes (for a similar line of argumentation, see Rubineau et al. 2019).

Our final specification includes the edges term, which accounts for the networks' density and captures the baseline probability for forming a tie (cf., Smith et al. 2016). In addition, we included terms that allow us to account for popularity[64] and homogeneity according to filmmakers' productivity, experience, and resources.

[64] As we had no information on aspirational collaborations, the network is undirected. Consequently, we use the term "popularity" here because we assume that collaborations are based on filmmakers' mutual agreement. Methodologically, main effects for actors' characteristics combine popularity—the

We measured homogeneity according to productivity, experience, and resources by including absolute difference scores. This is a common way to account for homogeneity in continuous attributes in the ERGM framework (cf., Smith et al. 2016: 1240). For instance, the "Difference in experience" term in table 4.2 estimates whether two filmmakers who showed a difference of one standard deviation in experience were more or less likely to collaborate given all other terms in the specification. A statistically significant and negative "difference in experience" term would indicate that filmmakers with a similar experience showed a higher likelihood of collaborating than filmmakers who were dissimilar in experience. These terms consider the *difference* in experience, productivity, and resources. Thus, negative values indicate the presence of homogeneity, while positive values indicate heterogeneity.

In addition to terms that measure homogeneity, we also added terms that consider how filmmakers' popularity as collaborators is linked to the volume of films they already produced (productivity), their career length (years of experience), and their access to resources (average crew size). These main effects of our set of control variables reflect whether a filmmaker is more often chosen as a collaboration partner if she exhibits more productivity, experience, or resources. For example, the "Popularity according to experience term" in table 4.2 measures whether one standard deviation more years of experience in the industry are associated with a higher or lower likelihood of attracting additional collaboration ties. Here, statistically significant and positive values indicate a higher likelihood of attracting additional collaboration partners.

Including these control variables is crucial as they allow us to consider the role of artistic status for network structure net of other factors that are probably correlated with high artistic

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tendency to receive ties—and expansiveness—the tendency to send ties—in undirected networks (Goodreau et al., 2009; Lusher et al., 2013).

status—i.e., it is likely that highly referenced filmmakers also exhibit longer careers, more films, and larger crew sizes.

In our interpretation of ERGM estimates, we compare the direction and statistical significance of ERGM coefficients in different periods. In addition, we calculate average marginal effects (AMEs) introduced by Duxbury (2021) to account for changes in Hollywood filmmaking's size and composition. Similar to AMEs for logistic regressions, they allow us to compare the relative magnitude of coefficients within model specifications and between different periods (Mood 2010). We discuss AMEs in relation to the baseline probability to form a tie in a given window which allows us to make comparisons of effect sizes over time. As Kreager et al. (2021: 59, footnote 12) pointed out recently: "AMEs differ from odds ratios in that they are on a probability scale and so their magnitudes should be interpreted relative to the baseline tie probability (i.e., network density)." This property of AMEs is crucial for our application since the network density of filmmakers' collaborations varies strongly over time.

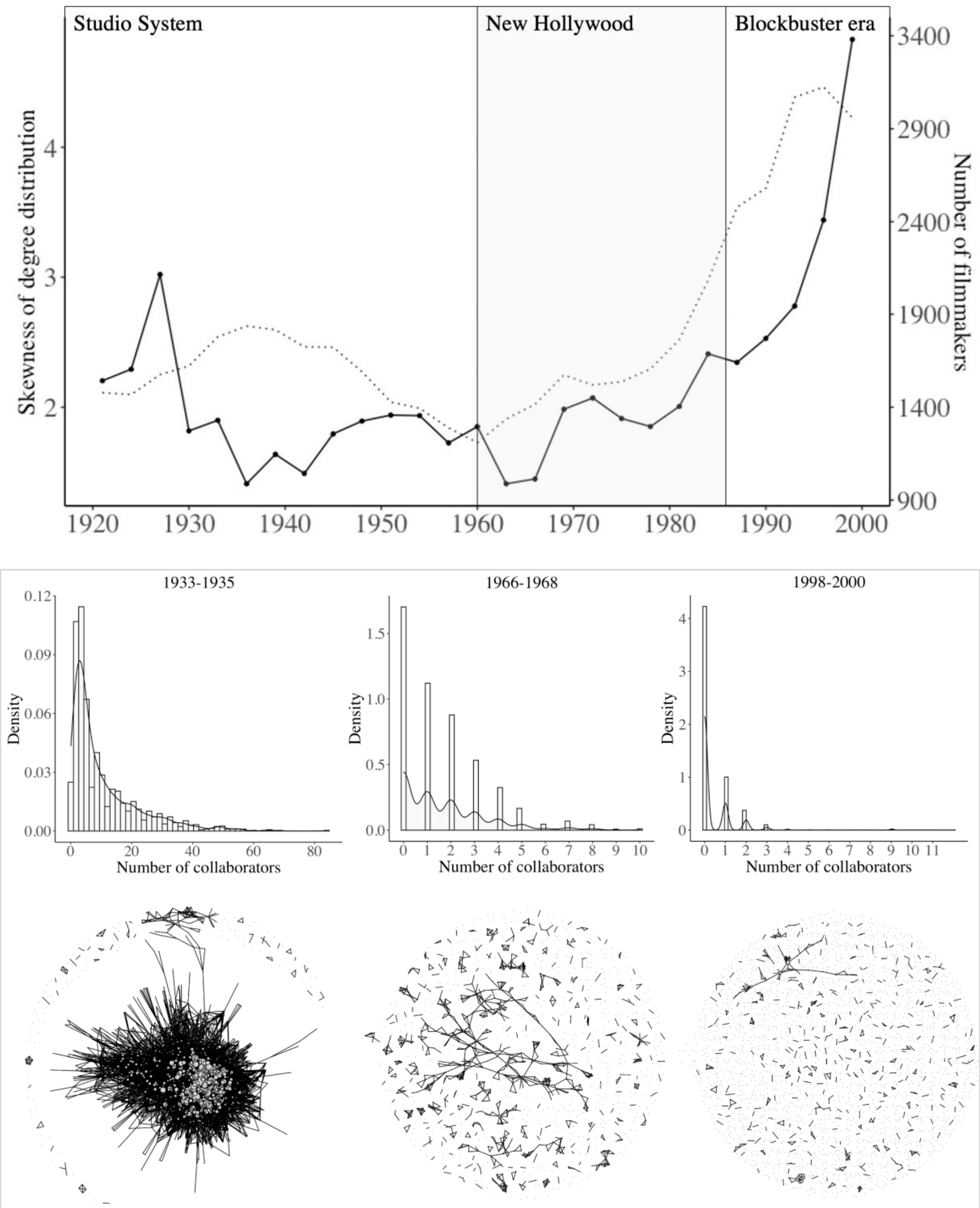
4.6 Results

Table 4.1 displays the number of collaborations and artistic references among filmmakers over time. Whereas the first two decades showed an increase in the number of filmmakers, the New Hollywood era exhibited a decrease in size due to the economic crisis of the industry and the collapse of the studio system. However, the field regained in size throughout the 1960s. A new dynamic is visible from 1984 onward: during the Blockbuster age, the number of filmmakers rapidly increased due to the unprecedented economic success of films. Regarding the practice of artistic referencing, our descriptive results are in line with the expectation that referencing needed time to evolve. The share of filmmakers who referred to the work of others lies below 27% until 1966. Subsequently, the share of referencing filmmakers rises until 1989; here it reaches the highest value of 44%, corroborating our expectation that artistic referencing became a widespread practice among filmmakers during the New Hollywood era. The pattern also illustrates that the share of referencing filmmakers did not increase further during the Blockbuster era and that around one-fifth of filmmakers already engaged in referencing before the dawn of auteur filmmaking (see 1933-1960).

Table 4.1. Information on collaboration and artistic reference networks

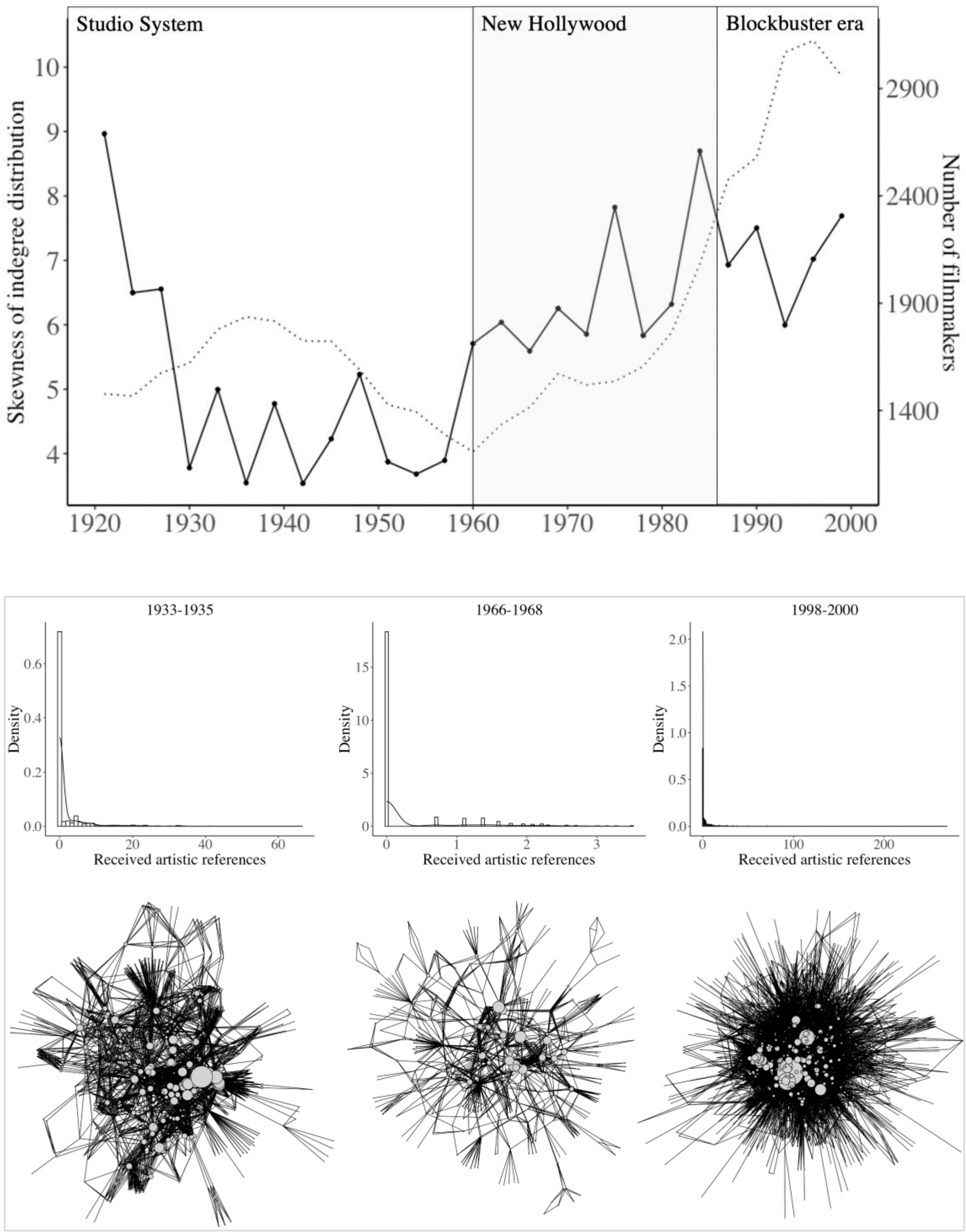
Years	Size	Mean # of films	SD of # films	Mean # of collab.	SD of # collab.	Mean # of references	SD of # references	Share referencing
1921-1923	1478	4.86	6.92	10.97	12.11	0.07	0.46	0.01
1924-1926	1468	5.90	8.38	15.62	17.69	0.14	0.81	0.03
1927-1929	1576	6.40	9.82	20.88	24.59	0.31	1.41	0.05
1930-1932	1622	5.42	8.54	19.26	20.80	0.99	2.92	0.11
1933-1935	1779	4.83	6.97	21.77	23.86	1.62	4.94	0.18
1936-1938	1837	4.82	6.74	22.54	21.37	1.86	4.45	0.20
1939-1941	1817	4.38	5.46	17.85	17.13	3.30	9.11	0.26
1942-1944	1725	4.05	4.99	16.92	15.62	1.85	4.38	0.22
1945-1947	1723	3.41	4.53	11.91	10.75	1.96	5.01	0.21
1948-1950	1591	3.43	4.91	10.72	10.25	1.40	4.21	0.20
1951-1953	1428	3.22	4.69	9.73	9.61	1.32	3.31	0.18
1954-1956	1394	2.74	3.82	7.61	6.87	1.10	2.72	0.21
1957-1959	1289	2.18	3.10	6.61	6.14	0.84	2.32	0.20
1960-1962	1209	2.07	3.33	4.81	4.84	0.94	2.88	0.21
1963-1965	1336	2.06	3.49	4.16	4.18	0.86	2.62	0.25
1966-1968	1416	1.94	2.75	3.49	3.68	0.92	2.98	0.27
1969-1971	1573	1.71	2.04	2.98	3.44	0.80	2.69	0.26
1972-1974	1520	1.55	1.86	2.54	3.05	0.96	3.23	0.30
1975-1977	1537	1.54	1.46	2.68	3.25	1.20	4.43	0.30
1978-1980	1606	1.40	1.33	2.14	2.74	1.54	4.97	0.38
1981-1983	1764	1.34	0.82	2.02	2.79	1.87	6.18	0.40
1984-1986	2084	1.42	0.95	1.78	2.64	2.65	9.68	0.44
1987-1989	2477	1.44	1.02	1.71	2.49	2.42	8.34	0.44
1990-1992	2579	1.42	1.02	1.98	4.35	2.25	7.92	0.40
1993-1995	3069	1.42	1.28	1.38	2.32	3.04	10.86	0.38
1996-1998	3124	1.42	1.14	1.16	2.17	2.99	11.34	0.38
1998-2000	2959	1.44	1.03	0.95	2.01	3.58	12.69	0.38

Figure 4.3. Inequality in collaborations and field size over time



Note: The straight line in the upper panel indicates the skewness of the degree distribution of collaboration networks over time. The dotted line represents changes in field size measured as the number of filmmakers. In the bottom panel, nodes in the sociograms are filmmakers who participated in the production of a film during at least three different years; ties between them indicate that they worked on the same film. Histograms are based on the distribution of collaboration ties. The x-axis denotes the number of collaborations per filmmaker and the y-axis the density of the distribution.

Figure 4.4. Inequality in artistic references and field size over time



Note: The straight line in the upper panel indicates the skewness of the indegree distribution of artistic reference networks over time. The dotted line represents changes in field size measured as the number of filmmakers. In the bottom panel, nodes in the sociograms are filmmakers who participated in the production of a film during at least three different years; a tie indicates an artistic reference between two filmmakers. Histograms are based on the distribution of artistic reference ties. The x-axis denotes the number of references per filmmaker and the y-axis the density of the distribution. To ease interpretability of the sociograms, we only depicted the largest component of artistic reference networks.

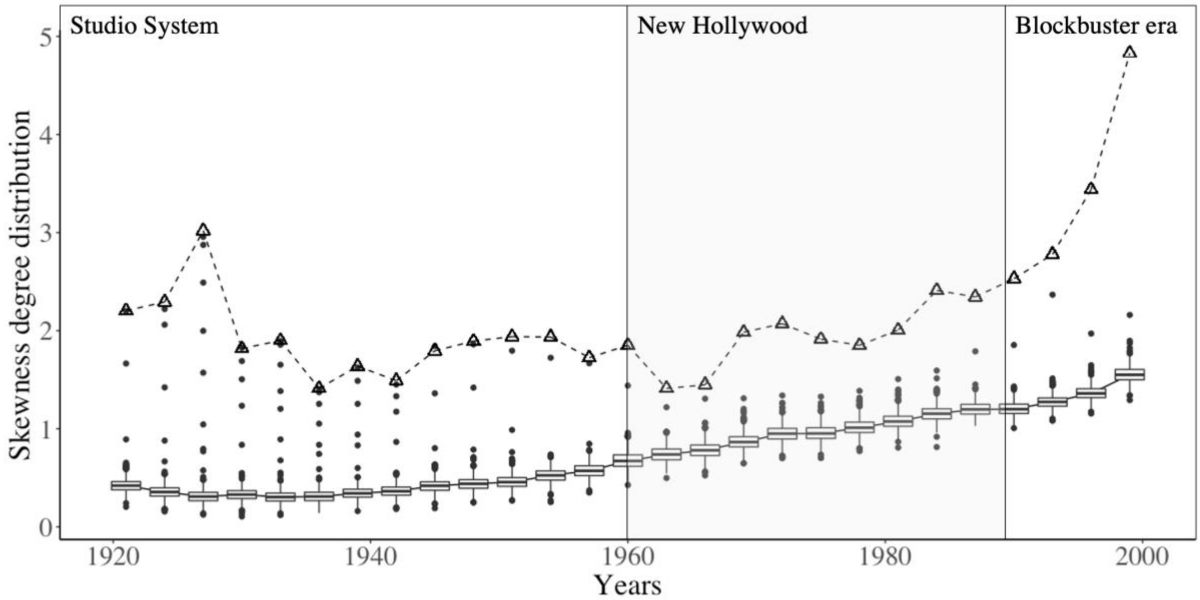
Inequality in Hollywood's social organization descriptive trends

We now turn to the question of how social recognition was distributed among filmmakers during different historical phases of the field. Figures 4.3 and 4.4 summarize changes in the stratification of collaborative ties and artistic references over time (straight lines) and trends in field size (dotted lines). Furthermore, we visualize the degree distribution and sociograms of collaboration and artistic reference networks during three exemplary periods in the figures' bottom panels.

The results indicate that stratification in social recognition increased over time and was associated with a corresponding increase in field size. In line with our first and second hypothesis, we observe more skewness in the distribution of collaboration partners and received artistic references as more filmmakers entered the industry. While this trend is consistent for both network types, the periods 1960-1962 and 1963-1965 are an interesting exception: although the number of filmmakers was quite low during these periods, we see a steep increase in the inequality in artistic references in comparison to the time before. A possible explanation is that these periods constitute the onset of the New Hollywood era in which artistic standards of evaluation played a prominent role in filmmakers' creative process. Therefore, it makes sense that artistic references exhibit a jump in inequality expressing the new artistic style of filmmaking and the emergence of a cultural elite during these periods.

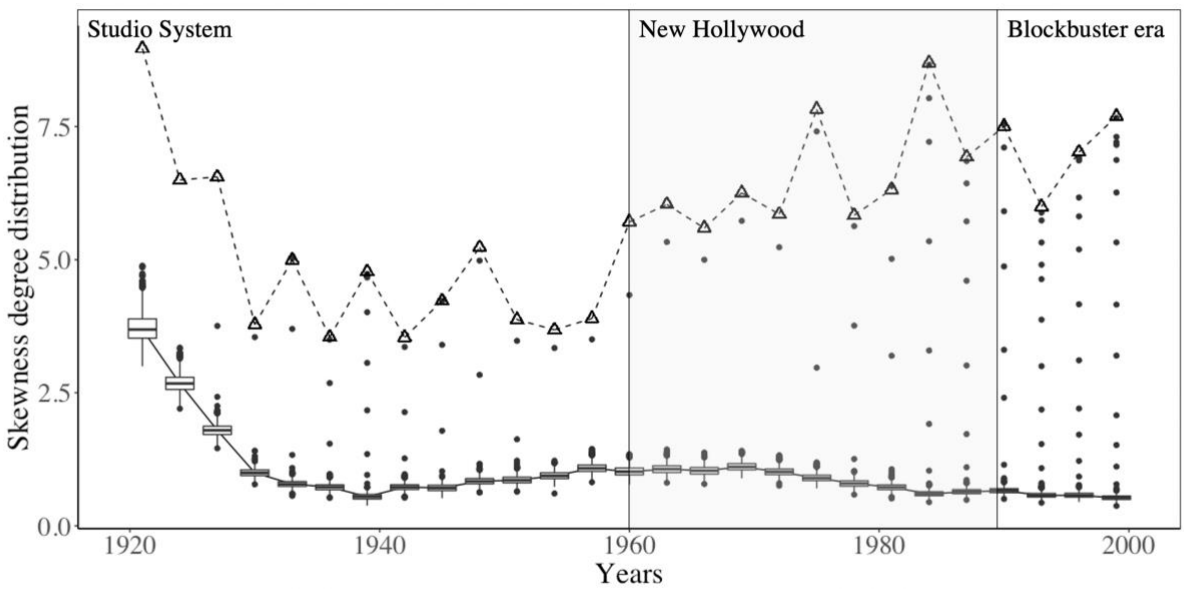
Our descriptive findings provide preliminary support for our theoretical expectations concerning the social structure of filmmaking. Yet, we cannot rule out that the link between inequality and size is a mechanical byproduct of network density. We, thus, account for this possibility in the next section.

Figure 4.5. Simulated inequality vs. empirical inequality in collaboration ties over time



Note: Each box plot represents the distribution of skewness values calculated in simulated collaboration networks obtained from baseline network models only including the edges term. We simulated 1,000 networks for each period. Triangles indicate empirical values, i.e., the observed skewness of the degree distribution in a particular period. The dashed line connects empirical values, while the straight line follows the medians of simulated values.

Figure 4.6. Simulated inequality vs. empirical inequality in artistic references over time



Note: Each box plot represents the distribution of skewness values calculated in simulated artistic reference networks obtained from baseline network models only including the edges term. We simulated 1,000 networks for each period. Triangles indicate empirical values, i.e., the observed skewness of the degree distribution in a particular period. The dashed line connects empirical values, while the straight line follows the medians of simulated values.

Inequality in Hollywood's social organization: Simulation results

We simulated 1,000 networks for each period from baseline exponential random graph models only considering the density and size of empirical networks. These simulated networks can tell us whether an unequal degree distribution could also have been a by-product of basic network properties, such as the baseline probability of ties in combination with the networks' opportunity structure. Figures 4.5 and 4.6 summarize the skewness in simulated networks in box plots and show how empirical values—depicted by triangles—differed from simulated values.

While simulated collaboration networks indicate a trend toward more inequality, empirical values show much higher inequality. These results suggest that the rising inequality in the distribution of collaboration partners is substantial beyond the increases in skewness we would expect from the networks' changing densities and opportunity structure.

Likewise, trends in the distribution of artistic reference networks differ noticeably from simulated values. The increase in inequality from the 1960s onward supports our hypothesis that artistic referencing centralized on a novel cultural elite during the New Hollywood era. However, the periods in the time from 1921-1929 also show high values and inequality stabilized at high levels during the Blockbuster age.

In sum, simulations support our expectations that inequality in social recognition increased over time and covaried with the size of Hollywood filmmaking (H1 and H2). Yet, we also discovered that the 1920s saw strong inequality in artistic references, which could point to early artistic filmmaking prior to the dawn of the studio era. Next, we turn to the results of network models to assess the role of artistic status for collaborations.

Table 4.2. Exponential random graph model (ERGM) estimates for collaboration ties over time

Years	1921-1923	1924-1926	1927-1929	1930-1932	1933-1935	1936-1938	1939-1941	1942-1944
Edges	-4.57***	-4.24***	-3.90***	-3.98***	-4.07***	-3.85***	-4.06***	-4.31***
Popularity according to average crew size	0.59***	0.61***	0.49***	0.49***	0.62***	0.52***	0.52***	0.62***
Difference in average crew size	-1.27***	-1.07***	-1.27***	-1.21***	-1.17***	-1.25***	-1.77***	-1.28***
Popularity according to number of films	0.60***	0.65***	0.65***	0.70***	0.73***	0.70***	0.61***	0.61***
Difference in number of films	-0.30***	-0.47***	-0.40***	-0.58***	-0.48***	-0.46***	-0.41***	-0.35***
Popularity according to experience	0.16***	0.13***	0.05***	0.05***	0.03**	0.01	0.06***	0.06***
Difference in experience	-0.11***	-0.15***	-0.13***	-0.1***	-0.1***	-0.12***	-0.08***	-0.09***
Popularity according to artistic references	0.24***	0.10***	0.13***	0.24***	0.21***	0.25***	0.22***	0.16***
Difference in artistic references	-0.31***	-0.07***	-0.14***	-0.20***	-0.25***	-0.33***	-0.21***	-0.23***
GOF	0.37	0.51	0.56	0.40	0.43	0.31	0.33	0.36

Years	1945-1947	1948-1950	1951-1953	1954-1956	1957-1959	1960-1962	1963-1965	1966-1968
Edges	-4.35***	-4.5***	-4.35***	-4.41***	-4.81***	-4.91***	-4.89***	-5.04***
Popularity according to average crew size	0.49***	0.56***	0.59***	0.45***	0.59***	0.64***	0.51***	0.49***
Difference in average crew size	-1.71***	-1.60***	-1.54***	-1.92***	-1.47***	-2.25***	-2.59***	-2.71***
Popularity according to number of films	0.57***	0.55***	0.54***	0.46***	0.50***	0.54***	0.49***	0.39***
Difference in number of films	-0.32***	-0.3***	-0.32***	-0.2***	-0.29***	-0.34***	-0.31***	-0.25***
Popularity according to experience	0.07***	0.09***	0.03**	0.12***	0.15***	0.07***	0.19***	0.13***
Difference in experience	-0.10***	-0.07***	-0.16***	-0.26***	-0.29***	-0.18***	-0.19***	-0.21***
Popularity according to artistic references	0.20***	0.18***	0.28***	0.20***	0.06*	0.16***	0.16***	0.2***
Difference in artistic references	-0.29***	-0.24***	-0.39***	-0.28***	-0.13**	-0.17***	-0.37***	-0.27***
GOF	0.27	0.21	0.26	0.27	0.31	0.31	0.34	0.58

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Years	1969-1971	1972-1974	1975-1977	1978-1980	1981-1983	1984-1986	1987-1989	1990-1992
Edges	-5.50***	-5.24***	-5.29***	-5.23***	-5.62***	-6.02***	-6.11***	-5.89***
Popularity according to average crew size	0.57***	0.63***	0.46***	0.38***	0.38***	0.37***	0.17***	0.26***
Difference in average crew size	-2.49***	-3.44***	-3.62***	-3.69***	-3.47***	-3.38***	-2.9***	-3.92***
Popularity according to number of films	0.47***	0.53***	0.42***	0.49***	0.35***	0.39***	0.43***	0.48***
Difference in number of films	-0.36***	-0.44***	-0.25***	-0.42***	-0.14***	-0.18***	-0.31***	-0.4***
Popularity according to experience	0.18***	0.26***	0.20***	0.28***	0.27***	0.16***	0.27***	0.21***
Difference in experience	-0.19***	-0.37***	-0.24***	-0.32***	-0.34***	-0.27***	-0.37***	-0.34***
Popularity according to artistic references	0.20***	0.12**	0.02	0.07	-0.09	0.04	-0.08	0.09
Difference in artistic references	-0.27***	-0.35***	-0.11	-0.31***	-0.24**	-0.28***	-0.22*	-0.41***
GOF	0.52	0.60	0.55	0.52	0.58	0.63	0.77	0.77

Years	1993-1995	1996-1998	1998-2000
Edges	-6.35***	-6.64***	-6.69***
Popularity according to average crew size	0.31***	0.27***	0.25***
Difference in average crew size	-3.81***	-3.04***	-3.36***
Popularity according to number of films	0.66***	0.53***	0.48***
Difference in number of films	-0.62***	-0.44***	-0.38***
Popularity according to experience	0.24***	0.14*	0.22**
Difference in experience	-0.27**	-0.2	-0.19
Popularity according to artistic references	-0.17	0.00	0.00
Difference in artistic references	-0.07	-0.24	-0.37
GOF	0.68	0.61	0.66

Note: All continuous variables are z-standardized to enhance the comparability of estimates across models. † $p < 0.10$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$ (two-sided).

Table 4.3. Average marginal effects scaled at the baseline probability of a tie in a particular period

Years	1921-1923	1924-1926	1927-1929	1930-1932	1933-1935	1936-1938	1939-1941	1942-1944
Popularity according to average crew size	0.57***	0.59***	0.47***	0.47***	0.60***	0.51***	0.51***	0.60***
Difference in average crew size	-1.23***	-1.03***	-1.22***	-1.16***	-1.13***	-1.22***	-1.71***	-1.25***
Popularity according to number of films	0.58***	0.63***	0.62***	0.67***	0.71***	0.68***	0.59***	0.59***
Difference in number of films	-0.29***	-0.45***	-0.38***	-0.56***	-0.46***	-0.45***	-0.39***	-0.35***
Popularity according to experience	0.16***	0.13***	0.05***	0.05***	0.03**	0.01	0.06***	0.06***
Difference in experience	-0.11***	-0.14***	-0.12***	-0.1***	-0.1***	-0.12***	-0.08***	-0.09***
Popularity according to artistic references	0.23***	0.10***	0.13***	0.23***	0.20***	0.24***	0.21***	0.16***
Difference in artistic references	-0.30***	-0.06**	-0.13***	-0.19***	-0.24***	-0.32***	-0.2***	-0.23***
GOF	0.37	0.51	0.56	0.40	0.43	0.31	0.33	0.36

Years	1945-1947	1948-1950	1951-1953	1954-1956	1957-1959	1960-1962	1963-1965	1966-1968
Popularity according to average crew size	0.48***	0.55***	0.58***	0.44***	0.58***	0.62***	0.50***	0.49***
Difference in average crew size	-1.68***	-1.57***	-1.50***	-1.88***	-1.43***	-2.19***	-2.54***	-2.67***
Popularity according to number of films	0.56***	0.54***	0.53***	0.45***	0.49***	0.52***	0.48***	0.39***
Difference in number of films	-0.31***	-0.30***	-0.31***	-0.20***	-0.29***	-0.33***	-0.30***	-0.25***
Popularity according to experience	0.07***	0.09***	0.03**	0.12***	0.14***	0.07***	0.18***	0.13***
Difference in experience	-0.10***	-0.07***	-0.16***	-0.25***	-0.29***	-0.17***	-0.18***	-0.21***
Popularity according to artistic references	0.19***	0.18***	0.27***	0.19***	0.06*	0.16***	0.16***	0.19***
Difference in artistic references	-0.29***	-0.24***	-0.38***	-0.28***	-0.12**	-0.17***	-0.36***	-0.27***
GOF	0.27	0.21	0.26	0.27	0.31	0.31	0.34	0.58

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Years	1969-1971	1972-1974	1975-1977	1978-1980	1981-1983	1984-1986	1987-1989	1990-1992
Popularity according to average crew size	0.57***	0.63***	0.46***	0.38***	0.38***	0.37***	0.17***	0.26***
Difference in average crew size	-2.46***	-3.39***	-3.58***	-3.66***	-3.46***	-3.37***	-2.88***	-3.91***
Popularity according to number of films	0.46***	0.52***	0.42***	0.48***	0.35***	0.39***	0.43***	0.48***
Difference in number of films	-0.35***	-0.43***	-0.25***	-0.42***	-0.14***	-0.18***	-0.31***	-0.4***
Popularity according to experience	0.18***	0.26***	0.20***	0.27***	0.27***	0.16***	0.27***	0.21***
Difference in experience	-0.19***	-0.37***	-0.24***	-0.32***	-0.34***	-0.27***	-0.37***	-0.34***
Popularity according to artistic references	0.20***	0.12**	0.02	0.07	-0.09	0.04	-0.08	0.09
Difference in artistic references	-0.26***	-0.35***	-0.11	-0.31***	-0.24**	-0.28***	-0.22*	-0.41***
GOF	0.52	0.60	0.55	0.52	0.58	0.63	0.77	0.77

Years	1993-1995	1996-1998	1998-2000
Popularity according to average crew size	0.31***	0.27***	0.25***
Difference in average crew size	-3.82***	-3.04***	-3.37***
Popularity according to number of films	0.66***	0.53***	0.48***
Difference in number of films	-0.62***	-0.44***	-0.38***
Popularity according to experience	0.24***	0.14*	0.22**
Difference in experience	-0.28**	-0.20	-0.19
Popularity according to artistic references	-0.17	>0.00	>0.00
Difference in artistic references	-0.07	-0.24	-0.37
GOF	0.68	0.61	0.66

Note: All continuous variables are z-standardized to enhance the comparability of estimates across models. † $p < 0.10$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$ (two-sided).

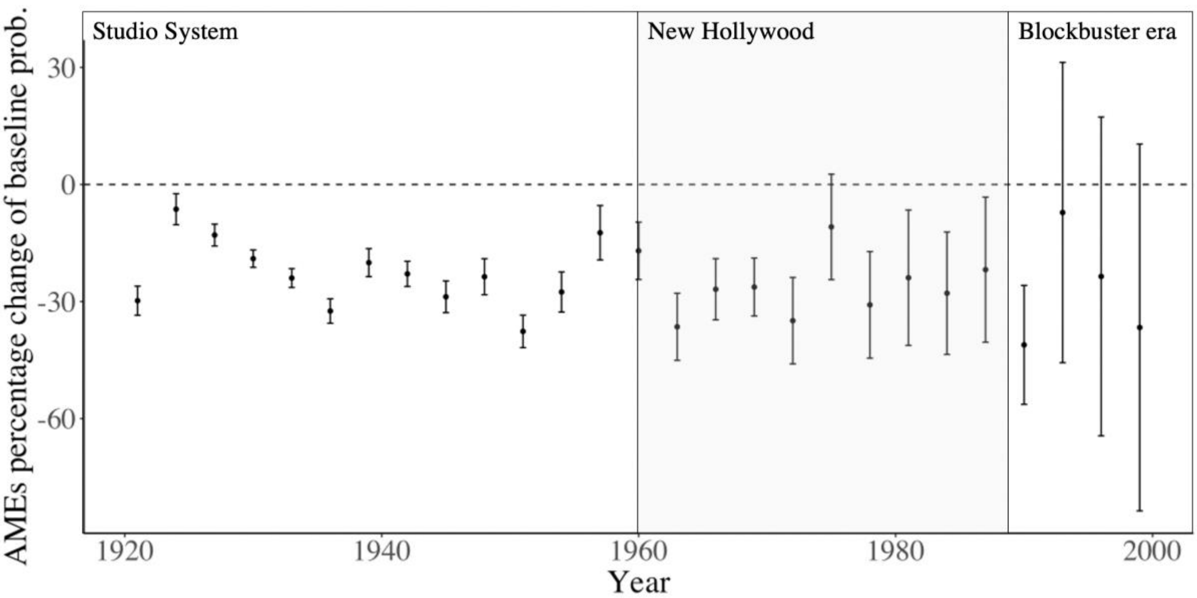
The role of artistic status for filmmakers' collaboration networks over time

We estimated exponential random graph models (ERGMs; Lusher, Koskinen, and Robins 2013) to investigate the role of artistic status for the formation of collaborations. Details on the goodness of fit of models are provided in the appendix. We include two terms to capture the impact of artistic status. First, an absolute difference term estimates the extent to which filmmakers' similarity in artistic status affected collaboration. This term denotes whether a collaborative tie between two filmmakers became more or less likely if the difference in their artistic status—i.e., how many references they received by their peers—increased by one standard deviation given all other terms in the model. Second, we account for the popularity of filmmakers as collaborators according to their artistic status. While table 4.2 reports ERGM coefficients, table 4.3 reports average marginal effects (AMEs) divided by the baseline probability of a tie in a given period. AMEs allow for a more intuitive interpretation as they report the percentage change in the baseline probability for a one unit change in a given network variable (cf., Kreager et al. 2021). For instance, the baseline probability of forming a tie increased by 16% in the period 1921-1923 for a filmmaker who had one standard deviation more years of experience in the industry than the average filmmaker.

Regarding the question of how artistic status segregated the network, our results indicate that peers' appreciation of artistic status substantially structured filmmakers' collaborations in almost all periods. The smaller the AME value displayed in figure 4.7, the more filmmakers tended to form collaborations with status-similar others. The values for artistic status are of similar magnitudes as scaled AMEs for experience and productivity. For example, during the period 1963-1965 an increase by one standard deviation in the difference in artistic status decreased the probability of a tie between two filmmakers by 36% in comparison to the baseline probability (see figure 4.7). While homogeneity according to artistic status was already present during the studio system era, AMEs decreased and stabilized around 30% during New Hollywood. Interestingly, whereas we expected a clearer discontinuity in our third hypothesis

(H3), we observe a rather smooth downward trend in AMEs for the role of differences according to artistic status for collaborations. This suggests that the transformation towards artistic filmmaking was less abrupt than often assumed and portrayed in historical accounts (e.g., Baumann 2007).

Figure 4.7. Homogeneity according to filmmakers' artistic status over time



Overall, the results provide suggestive evidence in support of our expectation that collaboration networks were less marked by artistic status homogeneity during the Blockbuster era (H4). This conclusion is based on a careful analysis of statistical and substantive significance of AMEs in the context of exponential random graph models. On the one hand, it is apparent from figure 4.7 that the magnitude of AMEs does not differ noticeably between the New Hollywood and the Blockbuster era. On the other hand, in the last three of the Blockbuster era periods, the estimates for homogeneity according to artistic status become statistically insignificant. While statistical insignificance does generally not imply substantive irrelevance, there is reason to believe that the AMEs are also substantively unimportant in these periods and point to the decreased importance of artistic status for collaboration. In particular, as AMEs are scaled at the baseline probability, even small initial values can become very large if the network has a low density. This is especially the case for the Blockbuster era, as the number of filmmakers increased, but the average number of films per filmmaker decreased (table 4.1). Hence, even small values are amplified in the scaled version of the AMEs. This is desirable as it allows for a comparison of effect sizes over time, but it also means that statistically insignificant effects should be interpreted as substantially insignificant as even small deviations of AMEs from zero can show noticeable magnitudes in scaled AMEs. Another potential reason for the increasing statistical uncertainty in the last three periods could be that artistic status retained its relevance for a subset of auteur filmmakers but became less important for the majority of filmmakers.

Taken together, the results mostly support our theoretical expectations. Inequality in the distribution of social recognition was especially pronounced during periods in which the field was large (H1 and H2). Yet, strong inequality in artistic references was already present at the outset of the field—although only a small share of filmmakers (less than 6%) used references before 1930. This finding could point to the importance of Hollywood's institutional environment as early filmmaking was less controlled by the studio system which possibly allowed filmmakers to reference each other more freely according to their own artistic standards of evaluation. Regarding the formation of cultural elites (H3 and H4), our findings are less straightforward. On the one hand, we see a trend towards more homogeneity according to artistic status in collaboration networks. On the other hand, this trend is more gradual than we expected based on the literature that describes the transformation of Hollywood into an artworld (e.g., Baumann 2007). Moreover, we find that the role of artistic status may not have ceased completely during the Blockbuster age, which could point to a differentiation of the field into artistic filmmaking and mainstream productions.

4.7 Discussion

Our results provide evidence that status orders in cultural fields emerge as field size increases and that artistic status becomes more important for collaboration as a cultural field gains legitimacy. To arrive at these conclusions, we analyzed 80 years of Hollywood film history and information on more than 13,000 filmmakers captured in the IMDb database. We derived networks of collaboration and artistic references to investigate whether this cultural field became more stratified and segregated during its development.

Our article contributes to several literatures. We synthesized past research that highlighted the role of individuals' network position for their creative and economic success (Becker 2008; Bottero and Crossley 2011; Crossley 2019; Lena 2012; Phillips 2013) with scholarship on status recognition in cultural fields (Bourdieu 1983, 1993; Dowd et al. 2002; Lena and Pachucki 2013; Pachucki 2012). This allowed us to map long-term changes in the link between artistic status orders and networks with a vast, process-produced data source for the first time. We expected that changes in size are associated with increasing inequality in the distribution of social recognition captured by filmmakers' prominence as collaboration partners and the volume of artistic references they receive. Furthermore, we discussed the role of artistic status for collaborations and argued that collaboration networks should show segregation into status-similar circles of artists during the New Hollywood period. In general, our results support our hypotheses and illustrate that the development of the structure of artistic fields can be studied from a network analytical perspective (Bottero and Crossley 2011).

We showed field size to be linked with stratification in social recognition and demonstrated that changes in the networks' opportunity structure and density are not sufficient to account for the association between inequality and size (Anderson et al. 1999; Bearman, Moody, and Stovel 2004; Gondal and McLean 2013a; Snijders and Steglich 2015). These findings resonate with previous accounts which point to a relationship between network size and inequality (Mayhew 1973; Mayhew and Levinger 1976; McFarland et al. 2014). To model the structure of collaboration networks during different periods, we used exponential random graph models (ERGMs; Lusher and Robins 2013) and applied recent advances that allow credible comparisons between models (Duxbury 2021). Thereby, our study also makes a methodological contribution as most applications of network models are limited to relatively small networks among children, adolescents, or students and to short periods of time seldom longer than 10 years.[65]

In addition, results showed that collaborations were segregated along artistic status and that this tendency moderately increased during the New Hollywood era, while estimates retained their size but became insignificant during the Blockbuster age. These findings are of interest for scholars who study status orders, as an often-implicit assumption in status theories is that status orders crystallize relatively quickly out of micro-interactions and remain stable overt time (Gould 2002; Lynn et al. 2009; Manzo and Baldassarri 2014; Ridgeway 2019; Smith and Faris 2015). Also, the elevated importance of artistic status for collaborations after the collapse of the studio system and before the onset of the Blockbuster era is in line with historical perspectives on Hollywood (Baumann 2007; Bordwell et al. 1985; King 2002), and the notion that cultural fields exhibit artistic standards of evaluation more strongly if they are increasingly decoupled from the economic field (Bourdieu 1993). Yet, we also discovered that artistic references played a substantial role for collaborations in the early stages of Hollywood

[65] A caveat of our study is that we did not use genuine longitudinal network models, which allow for a separation of selection and influence effects (Snijders 2011; Steglich et al. 2010). For instance, stochastic actor-oriented models would have helped us to assess whether status-similar filmmakers collaborate or whether collaborating filmmakers become more status-similar over time (Torlò and Lomi 2017). We tried to apply these models, but model degeneracy, violation of model assumptions in large datasets, poor goodness of fit, and continuing problems with comparisons of effect sizes across models forced us to abandon SAOMs as our analytical strategy. We hope that future methodological developments will pave the way for longitudinal analyses of the presented dataset.

filmmaking which points to the emergence of an early artistic status order prior to auteur filmmaking.

We acknowledge several limitations that should be addressed in future research. Our dataset is a comprehensive documentation of the field of Hollywood filmmaking, yet it lacks some relevant information about filmmakers. For instance, we are unable to account for filmmakers' educational careers and socio-economic background. Likewise, we had no information on artists' income or occupations outside the film industry. Also, on the level of studios more information on e.g., box-office returns, the size of studios, and variation in the economic situation of studios would have been desirable (Cattani et al. 2008).

Furthermore, we focused on one particular cultural field. Therefore, we do not know whether our findings generalize to other fields of cultural production such as music, literature, or painting. It would be fascinating to compare collaborations and artistic references in multiple cultural fields to arrive at a more general perspective on how social systems organize the distribution of social recognition under different contextual conditions.

Chapter 5

Conclusion

5.1 A Comparative perspective on status and networks across domains

Throughout this dissertation, I proposed a general theoretical framework to study the interplay between status and social networks and applied this framework to three different empirical domains. Here, I summarize the substantial insights gained from the empirical applications and return to the overarching theoretical expectations developed at the thesis's beginning. In particular, this final chapter illustrates how the three domain-specific applications complement each other, discusses the limitations of my research, and outlines directions for further investigations of the status-network nexus.

The ubiquitous link between size and the role of status systems for networks

Comparing the empirical analyses of the school setting, the scientific field of neuroblastoma research, and the cultural field of Hollywood filmmaking, the most noticeable similarity between these domains is the link between context size and the distribution of social recognition. Larger contexts exhibit more inequality in the distribution of social recognition, and networks tend to be more strongly segregated according to actors' social status compared to smaller contexts. These findings corroborate the size-status proposition derived at the thesis's beginning.

While the theoretical expectation that context size amplifies status recognition already surfaced in previous literature (Mayhew 1973; Mayhew and Levinger 1976; McFarland et al. 2014; Michels 1915), no study to date investigated empirically how the size of contexts and other contextual antecedents affect the link between status and network structure across multiple domains. Also, previous accounts did not consider how different types of status shape different types of networks, although theory increasingly highlights that the content of relationships matters for network structure (Fuhse and Gondal 2022; Martin 2009b; Martin and Murphy 2020; White 2008).

In the next section, I will discuss the empirical applications in greater detail and sketch how future research could contribute to a general perspective on the role of reputation-based status orders for social networks.

5.2 Status in school

In the school setting, I found that students nominate a smaller share of their peers as popular in larger classrooms and grade levels. In addition, the results suggest that friendship networks are marked by status homogeneity, i.e., in larger contexts, students tend to form friendships with status-similar peers more often. These findings shed new light on the assumption that status systems operate similarly across contexts which is deeply rooted in many classic and contemporary studies concerned with social status in school. Scholars usually portray a highly popular group of students as an unavoidable part of the school experience (Coleman 1961; Ennett et al. 2006; Faris and Felmlee 2014; Haynie 2001; Kornbluh and Neal 2016; Logis et al. 2013; Moody 2001; Pál et al. 2016; Rambaran, Dijkstra, and Stark 2013; Rodkin et al. 2006; Sijtsema et al. 2009; Smith and Faris 2015). Many of these accounts build on Coleman's seminal book, *Adolescent Society*, in which Coleman briefly considers the possibility that status processes in school might vary across contexts or could even be absent (1961: 34): "What does it take to be in the 'leading crowd' in school? This question, of course, presumes that there *is* a leading crowd in the school. To be sure, when students were asked such a question, some, particularly in the smallest school, did object the idea that there was a leading crowd." Nevertheless, in his analysis, Coleman did not devote further systematic attention to these concerns and instead assumed the presence of a leading crowd in every school.

My investigation of the school setting suggests that it is fruitful to examine under which circumstances leading crowds form in the first place. Context size was the strongest predictor for a mode of social organization marked by inequality in the distribution of status ascriptions and segregation along status differences in students' friendship networks. In contrast to previous research, I did not find that students' friendships exhibit more hierarchization in larger contexts or that demographic diversity elevates status recognition (McFarland et al. 2014). Also, incorporating multiple types of ties, i.e., friendships and status ascription networks, revealed that friendship networks are not prone to exhibit more inequality in larger contexts. This finding is in line with the notion that inequality in personal ties is hampered by relationship content such as normative expectations (Gould 2003; Kitts and Leal 2021) and constraints on time and energy (Dunbar 2008; Martin and Murphy 2020). However, friendships become more segregated according to status differences as context size increases which illustrates that status recognition still leaves its mark on personal relationships and introduces salient group boundaries as reported by ethnographic studies (Adler and Adler 1998; Eckert 1989; Eder 1995; Milner 2013). These results indicate that while popularity tournaments are more pronounced in larger classrooms and grades, there is less evidence for the emergence of dominance-based status systems. This sheds doubt on the findings of previous research, which infers dominance orders by measuring the occurrence of hierarchical network structures in personal ties (Ball and Newman 2013; Davis 1970; McFarland et al. 2014) and speaks to scholars who are critical of this measurement strategy (Block 2015; Vörös, Block, and Boda 2019).

Taken together, my first empirical investigation suggests that scholars and policymakers alike should not take a status culture among adolescents for granted. Reducing the size of grade levels and classrooms could be a starting point to impede status recognition and could potentially also mitigate detrimental behavior connected to students' strive for status. For instance, previous research established a link between students' popularity and their bullying behavior and suggests that popular students partially gain and maintain their status by bullying others (Adler and Adler 1998; Faris 2012; Faris and Felmlee 2014; van der Ploeg, Steglich, and Veenstra 2019). Other research found that delinquency is more widespread among popular students (Kreager et al. 2011; Snijders and Baerveldt 2003) and that popular students engage in substance abuse more often than their less visible peers (Ennett et al. 2006; Moody et al. 2011). Hence, dampening the formation of popularity-based status systems in the school context by reducing classroom and grade-level sizes could also decrease the prevalence of these detrimental behaviors. However, I would like to highlight that this is an avenue for further research and that I did not study the relationship between status-motivated behavior and contextual characteristics in my thesis.

5.3 Status in science

The second empirical investigation revealed similar tendencies for scientific collaboration networks among neuroblastoma researchers: as the field attracted more researchers, the distribution of collaboration partners became increasingly unequal, and status-similar researchers—according to their publication output, seniority, and experience—tended to collaborate more often. This suggests that accumulation dynamics in scientific fields operate differently depending on the developmental stage of a field. While previous accounts from the sociology of science discuss how the social organization of scientific specialties changes over time (Chubin 1976; Crane 1972; Mullins 1972), network-analytical studies tend to assume that the Matthew effect and preferential attachment are generic features of scholarly activity (Burris 2004; Gondal 2011, 2018; Han 2003; Newman 2001c; Wang 2016). The analyses reveal that future research should re-evaluate this assumption.

In addition, it is noteworthy that the observed changes towards more stratification and segregation according to status differences took place roughly in the second half of the field's history. This later stage was also characterized by an influx of researchers with a background in molecular biology (Brodeur, 2003; Martynov et al., 2020) and a steady internationalization of the community (Berthold et al. 2019). These new members widened neuroblastoma research's interdisciplinary scope and promoted the field in more countries. Simultaneously, new insights were produced from the late 1990s onward, such as a deeper understanding of the disease's genetic mechanisms (Brodeur, 2003; Mossé et al., 2008; Ray, 2019) and improved treatment strategies (Maris, 2010; Matthay et al., 1999).

These advancements in scientific knowledge might be related to more funding and institutional support, which in turn changes the structure of scientific collaboration. As more external funding is channeled into a new field of inquiry, funding agencies mainly offer programs that provide short-term employment for PhDs and postdocs. In contrast, the number of tenured positions does not increase proportionally because universities and research facilities are reluctant to create costly long-term positions (Laudel, 2006; Münch, 2014). As Alberts et al. (2014) point out in regard to US biomedical research: although the field experienced rapid growth from the 1980s onward, the career prospects of early-career researchers worsened decisively as the influx of new funding "has led to an enormous growth in 'soft money' positions, with stagnation in the ranks of faculty who have institutional support" (Alberts et al., 2014: 5775).

To conclude, the investigation of status in science that my coauthors Frank Berthold, Christoph Bartenhagen, and I conducted carries potential implications for policymakers and scientists alike and suggests that field growth is a double-edged sword. On the one hand, more funding and positions become available and foster the production of new knowledge. On the other hand, inequality in the distribution of recognition increases, and socially-closed circles of established scholars evolve. This development probably contributes to a highly competitive environment for early-career researchers and can have undesirable outcomes such as decreasing research quality and labor market mismatches (for the case of biomedical research, see Alberts et al. 2014). Whether advancements in scientific knowledge are linked to changes in stratification and segregation along status differences in coauthor networks are exciting questions for further research. Our investigation of the antecedents for changing levels of stratification and segregation prepares the ground for inquiries which could scrutinize how much inequality is necessary for scientific progress and which levels of inequality might prove toxic.

5.4 Status in filmmaking

In the third empirical application, the analyses revealed that filmmaking showed higher levels of inequality in the distribution of social recognition during periods in which Hollywood attracted more filmmakers. Again, these findings are in line with the notion that larger contexts exhibit a stronger link between status recognition and network structure. Moreover, the results indicated that references among filmmakers became a status marker from the late 1960s onward. After the advent of the New Hollywood movement—which was devoted to an artistic ideal of filmmaking—the volume of references a filmmaker received from others began to play a substantial role for her prominence as a collaborator. Also, circles of status-similar filmmakers formed, suggesting the emergence of a cultural elite at the field's center.

Past studies stressed the importance of social networks for cultural production (Becker 2008; Bottero and Crossley 2011; Crossley 2019; Lena 2012; Phillips 2013) and highlighted that status recognition structures artistic fields (Bourdieu 1983, 1993; Dowd et al. 2002; Lena and Pachucki 2013; Pachucki 2012). Yet, the investigation of Hollywood filmmaking my coauthor Katharina Burgdorf and I conducted is the first network-analytical study that maps long-term changes in the social organization of an artistic field. Thereby, we contribute to several literatures.

First, most research on individuals' trajectories in artistic fields implicitly assumes the presence of a stable status order. Our investigation illustrates that this assumption should be scrutinized in future research. We argue that taking into account the developmental stage of an artistic field is crucial to understand better why some actors manage to forge successful careers while others find themselves at the fringes of the field.

Second, we contribute to a growing stream of research that stresses the importance of contextual characteristics for the structure of social networks (Lewis and Kaufman 2018; McFarland et al. 2014; Moody 2001). In particular, our research highlights that status orders need time to evolve and can change depending on the institutional environment they are embedded in. These findings present a challenge for existing status theories, which often implicitly assume that status orders crystalize quickly and remain stable over time (Gould 2002; Lynn, Podolny, and Tao 2009; Manzo and Baldassarri 2014; Ridgeway 2019; Smith and Faris 2015). We hope that future research will clarify under which circumstances status orders are stable and when they become fluid.

5.5 Towards a comparative theory of status and networks across domains

In Chapter 1, I outlined how different forms of status recognition—affectionate, popularity-based, and dominance-based status—carry different implications for the structure of personal and professional networks. Throughout the empirical investigations, I found little evidence for dominance-based status orders, and I argued that persons' likeability plays a minor role for the link between status and networks from a theoretical perspective. In contrast, all three empirical domains exhibited a popularity-based status system, especially if context size increased.

Consequently, the next step for future research would be to study whether the patterns found in the school setting, neuroblastoma research, and Hollywood filmmaking also hold in different domains. In terms of theory development, the investigations suggest that it is possible to build a general theory of how social systems produce reputation-based status orderings which leave their mark on social networks. Considering a unified conceptual space that is organized by the size of social systems and the consequences of status recognition for network structure generates new theoretical considerations because context size varies within and between domains.

Figure 5.1 illustrates how the investigation of more domains could complement the findings presented in this dissertation. The figure illustrates that as the size of domains rises (x-axis), actors' social networks are increasingly structured by their reputations in a twofold way. First, inequality in the distribution of network partners increases (y-axis). Second, status becomes a relevant trait for social distinction, and circles of status-similar actors evolve (z-axis).

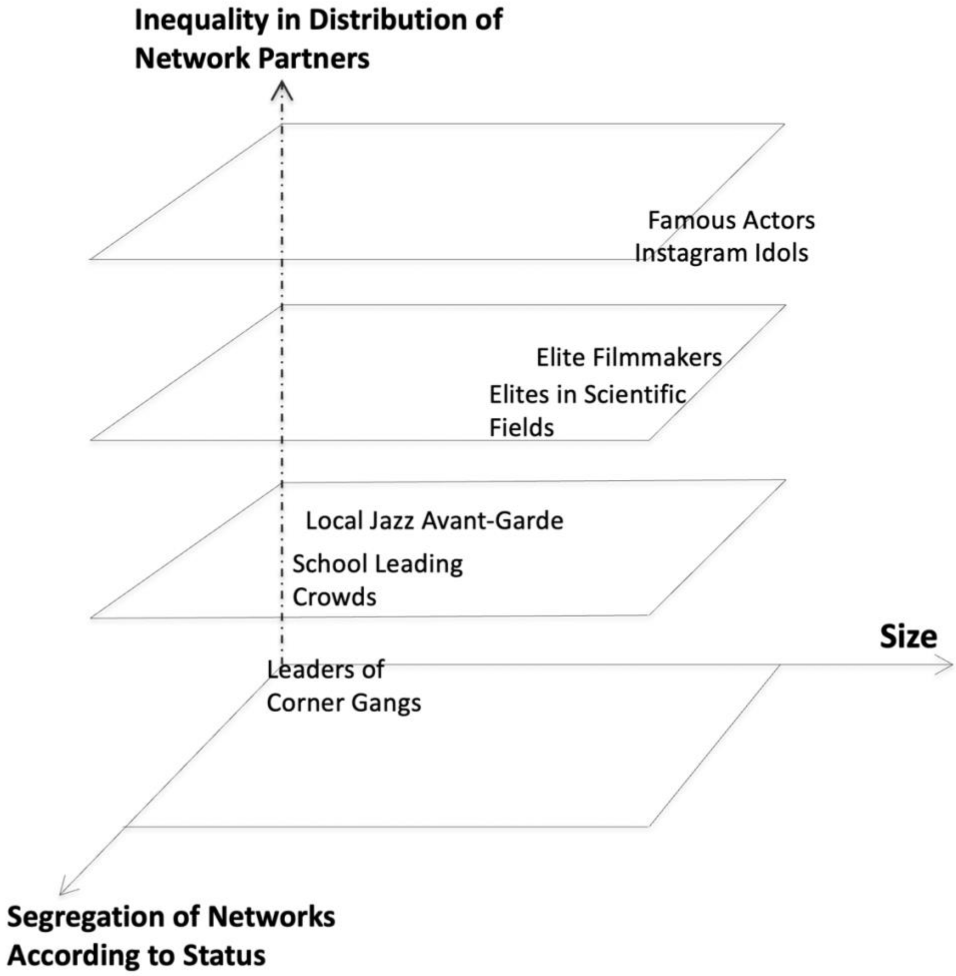
For instance, being the leader of a corner gang, as described in Whyte's (2012 [1943]) *Street Corner Society*, is tied to responsibilities, such as lending other members of the group money or organizing the group's activities. Although a status order was operational among the corner boys in Whyte's ethnography—e.g., members' status influenced their performance during bowling—the group did neither segregate into different cliques nor did members primarily aspire to befriend their leader Doc. Instead, Whyte's portrait of Doc gives the impression of a *primus inter pares*, similar to the "Big-Man" leaders in villages of pacific islanders who tend to be replaced if the group feels that they do not fulfill their roles as leaders (Martin 2009b: 216–231).

In line with the notion that small domains show a weak link between status and network structure, von Rueden et al. (2019) found that compared with kinship, reciprocity, and transitivity, status was less important for cooperation networks in the preindustrial society of the Tsimane.[66] In particular, the authors investigated the link between status and networks in the male population of a Tsimane village which encompassed 72-89 male adult individuals by using longitudinal network analysis. Although status was linked to the number of cooperation ties individuals managed to form and maintain, the authors found no evidence for selecting

[66] "The Tsimane live in small villages in the neotropics of central, low-land Bolivia. Their economy is based on swidden horticulture (plantains, manioc, rice and corn), hunting, fishing and fruit gathering" (von Rueden et al. 2019: 6).

status-similar others as cooperation partners. Also, their findings suggest that status was linked to individuals' contributions to group goals.[67]

Figure 5.1. Domain size and the role of status recognition for network structure



Please note that I do not suggest that status is unimportant in small social systems. Status can have numerous functions—e.g., status can ease coordination problems and in turn facilitate the achievement of group goals (Blau 1964; Carnabuci et al. 2018; Lazega 2001; Redhead et

[67] "Among the Tsimane, men who are respected and influential in community decision-making (i.e. high in status) were more likely to be nominated over time as sharing food or assisting in hunting, fishing or horticultural labour" (von Rueden et al. 2019: 4).

al. 2019; Ridgeway and Correll 2006; Ridgeway and Erickson 2000). Yet, I argue that *social networks* are less marked by status in smaller domains.

Switching to the second plane depicted in figure 5.1, I sketched larger social systems such as grade levels in schools or local music scenes. These aggregates of approximately 100-500 persons tend to exhibit groups of status-similar actors and some form of local stardom. Think of the cool student everyone wants to hang out with (Adler and Adler 1998; Coleman 1961) or the hip jazz pianist who is esteemed by a small circle of peers (e.g., Berliner 2009). These systems already display moderate levels of stratification and segregation, and status leaves a stronger imprint on social networks than in smaller social systems. However, as my investigation of the school setting illustrated: there can be noticeable variation within domains. Some school grade levels had a student body that was smaller than 50 students. In these grades, I found less pronounced segregation according to status differences and lower levels of inequality in the distribution of popularity nominations compared with larger grade levels.

The third plane of figure 5.1 depicts quite large domains. Here status recognition becomes even more consequential for persons' networks. In a scientific field or a broader field of cultural production encompassing ca. 500-5,000 participants, reputations are crucial for social survival in the field and produce drastic patterns in terms of stratification and segregation. For example, a tenured leader of a research group at the center of a scientific field enjoys a powerful position in a semi-public environment (Blau 1994; Lamont 2009; Latour and Woolgar 1986). Attracting hundreds of coauthors and collaborating with other internationally-renown scientists (Lamont 2009; Latour and Woolgar 1986, also see Chapter 3) is a qualitatively different experience than being the leader of a small corner gang who is primarily esteemed by other gang members (Anderson 1999; Whyte 2012 [1943]).

On the last plane in figure 5.1, I sketched some extremely large domains with sizes beyond 5,000 persons. Empirical examples for very skewed distributions of recognition in large domains are followers on Twitter (Myers et al. 2014) or likes on Instagram (Ferrara, Interdonato, and Tagarelli 2014). Famous actors, Pop Stars, or influencers on social media platforms illustrate how system size can starkly amplify status differences among persons. As the recognition of thousands of fans is focused on a small set of idols, the stratification and segregation of social networks should be strongest in these large settings. As described in sociological studies of celebrities or public figures (Ferris 2007; Fine 1996, 2014; van de Rijt et al. 2013), reputations develop a self-reinforcing dynamic detached from local interaction in these domains and sometimes decouple completely from a person's private life.

A historical perspective on networks and status orders

In addition to comparing social systems of varying sizes that are embedded in contemporary societies, another fruitful alley for future investigations could be to consider how the dramatic growth of human groups in the last 10,000 years influenced the relationship between status orders and network structure. As Mann (2012) highlighted: before the emergence of civilization—often loosely defined by a combination of urbanization, scripture, and increasing division of labor—humans lived in relatively small groups that seldomly exceeded 500 persons. A combination of irrigation-based agriculture and new technologies such as the plow, the domestication of animals, and the wheel allowed humans to produce enough food to maintain larger settlements, and the first major cities evolved around 7,500 BC.[68]

Mann (2012) argues that fixed territories, geographical boundaries, and increased sizes of settlements introduced several significant changes in the social organization of human groups. While smaller societies made up of bands of gatherer-hunters, early agriculturalists, or nomadic pastoralists showed relatively egalitarian social structures, the first civilizations—located in Mesopotamia, the Indus valley, and the yellow river valley region in nowadays China—all

[68] For instance, the largest city of early antiquity, the Sumerian city of Uruk—located in nowadays southern Iraq—encompassed approximately 40,000 persons in the timespan 3500-2700 BC (Crawford 2013; Matthiae and Lamberg-Karlovsky 2003).

exhibited strong stratification, i.e., a division of human groups into ruling elites and ordinary people.

Describing these developments through a network-analytical lens, one could argue that throughout history, social networks increasingly entailed types of ties marked by exploitation, serfdom, or patronage (Martin 2009b) in addition to ties of kinship and cooperation. Following the theoretical framework developed in this dissertation and the empirical results indicating that larger social systems show networks that are stratified and segregated according to status differences, I assume that the emergence of ruling elites in the first civilizations can partially be explained by the decoupling of persons' reputations from local interaction. Whereas positions of leadership got ascribed to individuals that contributed to the goals of a group in smaller social aggregates such as bands of gatherer-hunters or villages (for supportive evidence from contemporary small-scale societies, see Redhead et al., 2019; von Reuden et al., 2019; Homans 1950), the first major cities carried the potential for the creation of God-like social positions. As context size increased, status recognition became more important for network structure and fostered stratification and segregation in larger human aggregates after the advent of the first civilizations (for similar lines of argumentation, see Michels 1915; Mayhew 1973; Mayhew and Levinger 1976; McFarland et. al 2014). Testing these expectations goes beyond the scope of this dissertation.

However, future research could consider how the role of status for network structure changed throughout history. While this task is extremely challenging—as only indirect information on how reputations evolved in the past exists—previous research in the network-oriented branch of historical sociology demonstrated that it is possible to gain insights into the relational structure of past social formations (Bearman 1993; Erikson and Bearman 2006; Gondal and McLean 2013a; Gould 1995; Hillmann 2008; Padgett and Ansell 1993; White and White 1993; Wurpts, Corcoran, and Pfaff 2018).

In sum, future research could build on the comparative view on status systems and social networks that I proposed here. Studying more domains and integrating insights from various literatures on status is, in my opinion, a promising path for a deeper understanding of the emergence of social order. While many empirical studies treat categories generated by societies—such as differences along socioeconomic dimensions or membership in ethnic groups—as starting point for their investigations, I believe that sociology should also be capable to explain how social categories emerge in the first place (cf., Abbott 2016; Goldberg 2012; Guilbeault, Baronchelli, and Centola 2021; White 2008). Regarding the role of social status, studying the outcomes of status orders—like individuals' career, health, or educational outcomes—is an important endeavor and will continue to inform scientific and public discourses. Yet, the investigations presented here demonstrate that status orders change depending on the developmental stage, size, and other contextual characteristics of social systems. Incorporating these insights in accounts concerned with the consequences of status could prove fruitful to explain better under which circumstances status affects persons' outcomes.

5.6 Limitations

In closing, I would like to point out a number of limitations of my research, which may point to additional avenues for future work. One problem of the empirical applications is that they could not dissect the underlying mechanisms for the link between context size and status recognition. The general framework argued that size increases uncertainty, i.e., actors have to process more information in a larger context (Mayhew and Levinger 1976). Consequently, actors tend to apply status recognition as simplifying cognitive heuristic guiding their interactions with others more often in larger contexts, and networks should exhibit structures indicative of an underlying status order (McFarland et al. 2014). Yet, the data sets under study did not offer direct information on actors' experienced uncertainty. Thereby, I could not explore the role of uncertainty for status recognition to its full extent.

In general, as criticized by Lynn et al. (2009: 765), "despite the recognition that uncertainty is important, the actual dynamics around uncertainty itself are not well specified. Uncertainty is usually hypothesized to affect a given status-related outcome, but the reasons why are often vague; the reader is generally instructed to believe that outcome *X* is the result of actors coping with uncertainty." Moreover, the term "uncertainty" probably means something qualitatively different in different settings. For instance, uncertainty about product quality encountered in markets is likely to follow other empirical regularities than uncertainty felt by students in the school setting.

Moreover, future research should use more fine-grained data than I had at my disposal to understand further what drives the empirical patterns I presented in this dissertation. As, e.g., McElreath (2020) pointed out, observing a particular distributional shape can result from different processes producing the same pattern on the aggregate level. For instance, a skewed distribution of social recognition in larger contexts can originate from different processes or a mixture of processes. While a rise in cognitive uncertainty and the increased heuristic usefulness of status recognition is one explanation, it could also be the case that actors in larger settings have more opportunities to gather resources, which allows them to offset cycles of accumulating status and resources alike. The latter explanation is probably less relevant in the school setting, but my coauthors and I discussed it comprehensively in the investigations of neuroblastoma research and Hollywood filmmaking. While we tried to control for the allocation of resources in these domains, the data sets did not include sufficient information on funding in neuroblastoma research or financing projects in Hollywood filmmaking.

A third explanation for the link between status, network structure, and size that I considered at the outset of my engagement with the topic is that reputations develop self-reinforcing dynamics through communication about absent actors in larger settings. In contrast to face-to-face encounters, communication about absent actors is selective, simplifying, and lacks the potential for corrective experiences. I expected that the larger a context becomes, the higher the importance of communication about absent actors should be for the respective status system. Small contexts foster the formation of local status systems in which face-to-face encounters are the dominant way to create reputations. Large contexts favor the emergence of global status systems marked by high importance of communication about absent actors for the construction of reputations. Regarding the distribution of status, public attention focuses on a small number of actors. Moreover, global status systems should be marked by elevated status awareness among actors compared to that of local status systems, since communication about absent actors implies that actors are aware of their status evaluations of others.

As the used data sources lacked information on communication about absent actors, I could not test this explanation for the link between status and system size. Clarifying the role of communication for the creation of social objects such as reputations is a challenging and exciting interdisciplinary enterprise and could involve the study of conversations (e.g., Gibson 2005; McFarland et al. 2013), mixed-method approaches which complement findings from quantitative network-analytical methods with, e.g., in-depth interviews (Kreager et al. 2017; Small 2017), and a study of physiological processes undergirding spontaneous vertical categorization schemes (Fiske 2011; Zerubavel et al. 2015, 2018).

Another limitation of my study is that I did not consider all types of status discussed in Chapter 1 in all domains under study. As the investigated artistic and scientific collaboration networks were undirected, I could not test whether dominance orders are present in neuroblastoma research or Hollywood filmmaking. Also, I had no information on personal attraction and sympathy in these domains. Future research could complement the investigations presented here by combining behavioral data—which we derived from conference books and the internet movie database—with survey data, ethnographic observations, or other types of data.

A further limitation is that only size, maturity, and demographic characteristics were considered as contextual moderators of status dynamics. Another potential factor is the role of third parties that can fuel status competition. For instance, Eder (1995) describes how coaches instill competitive values in students during extracurricular activities. Another example of third-party interventions in a status system can be found in Sauder (2006), who studied the influence of a newly introduced newspaper ranking among law schools on status dynamics within the education system (Espeland and Sauder 2007). Also, Martin's (2009b, 2009a) work on dominance hierarchies suggests that scarce resources and a cadged context for interaction fuel the development of dominance-based status orders. Future research should explore the contextual conditions for the emergence of status orders more thoroughly than I was capable of in this study.

Moreover, I focused on personal and professional networks as these network types are studied by many researchers and play an important role in a broad range of settings, among them labor markets (Burt 2005; Coleman 1988; Erikson and Goldthorpe 2002; Lin 2002), organizational fields (Benton 2016; Padgett and Powell 2012; Powell et al. 2005; Wong, Gygax, and Wang 2015), schools and universities (Carbonaro and Workman 2016; Carolan 2018; Raabe, Boda, and Stadtfeld 2019; Stadtfeld and Pentland 2015; Torlò and Lomi 2017), or scientific communities (Barabâsi et al. 2002; Chubin 1976; Crane 1972; Dahlander and McFarland 2013; Merton 1968; Moody 2004; Mullins 1972; Newman 2001a; Rawlings et al. 2015; Stark et al. 2020). However, future research could broaden the scope to other types of networks such as negative ties (Harrigan, Labianca, and Agneessens 2020) or exchange networks (Gondal 2018; Gondal and McLean 2013a; Lomi and Bianchi 2021).

In conclusion, I hope that my thesis will speak to scholars who share my enthusiasm for a general, relational, and scientific sociological approach that explores how concatenations of interactions coalesce into a social reality that profoundly shapes our behavior, our relationships, and our perceptions of others and ourselves.

I. Appendix to Chapter 2

A. Descriptive information on networks

Table A1. Descriptive information on network characteristics

	CILS4EU			
Number Students: 17,705	Friendship		Popularity	
Number Networks: 906 classes				
	mean	sd	mean	sd
Density	0.19	0.08	0.12	0.06
Degrees per node	6.52	1.52	4.15	1.72
In-degrees per node	3.26	0.76	2.08	0.86
Skewness indegree distribution	0.20	0.57	1.28	0.61
Share reciprocity	0.67	0.13	0.19	0.14
	FVA			
Number Students: 2603	Friendship		Popularity	
Number Networks: 39 grades				
	mean	sd	mean	sd
Density	0.07	0.05	0.09	0.06
Degrees per node	6.68	1.14	8.07	2.38
In-degrees per node	3.33	0.57	4.03	1.19
Skewness indegree distribution	0.52	0.38	1.66	0.80
Share reciprocity	0.59	0.06	0.19	0.09
	SOCIALBOND			
Number Students: 2999	Friendship		Popularity	
Number Networks: 39 grades				
	mean	sd	mean	sd
Density	0.09	0.05	0.04	0.02
Degrees per node	12.05	1.92	4.71	1.56
In-degrees per node	6.02	0.96	2.36	0.78
Skewness indegree distribution	0.42	0.26	2.20	0.74
Share reciprocity	0.62	0.05	0.10	0.05

Note: All statistics are calculated as summaries of individual values. The interpretation is therefore, for instance, that an average student in the respective sample received 3.36 friendship nominations with a standard deviation of 2 (CILS4EU).

B. ERGMs: model fit, goodness of fit (GOF), and convergence

Only ERGM results with a satisfactory model fit entered the meta-analyses. Models in which the t-ratio of convergence exceeded 0.1 for any parameter estimated in the model were excluded. Furthermore, if one of the model's parameters had a standard error greater than 5 or ranged outside a [-10; 10] boundary, the whole model was excluded. Due to these criteria, a differing number of networks enter the meta-analyses.

I assessed the goodness of fit (GOF) of the models by simulating networks from estimated ERGMs and comparing their indegree, outdegree, edgewise-shared partner, and geodesic distance statistics with the observed network statistics in the corresponding network (Hunter et al. 2008). All ERGM results reported in the main text had a GOF of at least 85% of t-ratios smaller than 2 averaged across contexts. This can be regarded as satisfactory GOF (Lusher and Robins 2013).

Analysis of convergence

ERGMs often have degeneracy issues, and it is not unusual that many networks in a sample cannot be analyzed (e.g., Smith et al. 2016: 1258–1260). Therefore, I analyzed whether context entering the results in the main text differ significantly in their demographic composition or size. Taking into consideration how contexts with converging models differ from context prone to non-convergence is important to judge whether the results in the main text are robust.

In the following section, I report a set of linear probability regressions with contexts as the unit of analysis.[69] The dependent variable in all models is the convergence of a particular ERGM specification in a school or grade.[70] Meta-analyses of the converged ERGMs can be

[69] Please note that I combined classes surveyed in the same school into one network in the network analyses of the CILS4EU data, following Kruse et al. (2016).

[70] Although researchers usually prefer logistic regressions if the dependent variable is binary—here converged vs. not converged—I opted for the linear probability model, because some of the logistic

found for status ascriptions in table 2.2 and for friendships in table 2.3. These are the same ERGM estimates that later enter the meta-regressions (table 2.4 and 2.5). Characteristics of contexts are included as independent variables. Moreover, I added a row including the percentage of converged ERGMs for each tie type and data set.

Friendship networks showed the highest convergence rates in two of the three data sets, whereas popularity networks showed higher dropout rates. The size of a context significantly predicts convergence in two of the three data sets. This means that schools and grades analyzed in the main text are significantly larger than contexts not entering the analyses. The demographic composition of contexts is not consistently associated with convergence.

Taken together, while the dropout of contexts is systematic, it does not threaten the substantial interpretation of my main results. If context size is still significantly associated with network structures indicative of status processes after several small contexts are missing in the analysis, this would only present a problem if they show stronger status processes than the small and medium-sized contexts remaining in the analysis. The meta-regressions in the main text suggest the opposite.

regressions showed convergence issues in the grade-level data sets. This was possibly due to the high share of contexts with converging ERGMs for some tie types. The lack of information on the dependent variable probably leads to degeneracy issues in these models. Furthermore, linear probability models have the advantage of easy interpretability with regard to the strength of coefficients. Therefore, they are well suited for assessing the composition of contexts entering the network analysis in the main text. The results of the logistic regressions producing reasonable estimates do not lead to different substantial interpretations (results available upon request).

Table B1. Linear probability models of convergence in ERGMs

	Status ascriptions		Friendship networks	
CILS4EU	beta	se.	beta	se.
Intercept	0.42***	0.05	0.51***	0.05
Network size	0.05*	0.02	0.07***	0.02
Share female	-0.06*	0.02	-0.06**	0.02
Share migrants	0.002	0.02	-0.001	0.022
Country (Ref. England)				
Germany	0.37***	0.06	0.25***	0.06
The Netherlands	0.14*	0.06	0.18**	0.07
Sweden	0.03	0.06	0.26***	0.06
N schools	456		456	
Percentage converged	57%		70%	
R^2	0.11		0.09	
	Status ascriptions		Friendship networks	
FVA	beta	se.	beta	se.
Intercept	0.77***	0.06	0.72***	0.07
Network size	0.24**	0.08	0.20***	0.08
Share female	-0.09	0.07	-0.002	0.08
Share migrants	0.01	0.07	-0.06	0.07
N grades	39		39	
Percentage converged	77%		72%	
R^2	0.24		0.25	
	Status ascriptions		Friendship networks	
SOCIALBOND	beta	se.	beta	se.
Intercept	0.85***	0.05	0.95***	0.04
Network size	0.09	0.06	0.07	0.04
Share female	0.15*	0.06	0.01	0.04
Share migrants	0.05	0.06	0.01	0.04
N grades	39		39	
Percentage converged	85%		95%	
R^2	0.26		0.11	

Note: All variables besides county of survey were z-standardized to ease interpretation. † $p < 0.10$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$ (two-sided).

Moreover, I claim that the dropout of small contexts even presents a conservative bias for the main results. If contexts with non-converging estimates would show converging ERGMs, these estimates would probably be similar to the estimates of the small contexts which already entered the analysis, thereby strengthening the associations with size reported in table 2.4 and 2.5.

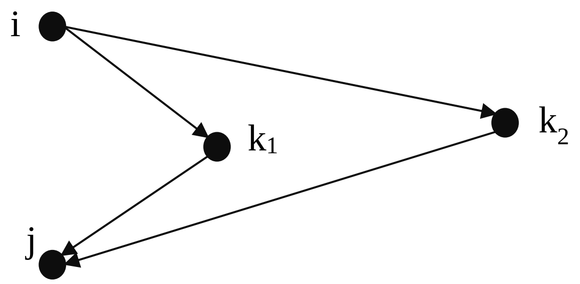
The demographic compositions of schools and grades showed far less pronounced associations with convergence. While there seems to be a small tendency of contexts with higher shares of females to show convergence issues in the CILS4EU, there is no significant association with the share of migrants across data sets and specifications.

In the CILS4EU data, German schools showed converging ERGMs more often than schools from England. This is probably due to the lower data quality of the network information in the English part of the sample, also discussed in Kruse et al. (2016). In summary, I am confident that the results in the main text are robust and probably present even slightly underestimated associations of status processes with context size.

C. ERGMs: discussion of GWNESP-OTP and GWNESP-ITP parameters

The GWNESP-OTP term counts triads in which i perceives k as popular and k perceives j as popular but there is no popularity nomination from i to j, and the GWNESP-OTP term also weights the occurrence of such configurations geometrically.

Figure C1. Graphical representation of the GWNESP-OTP term

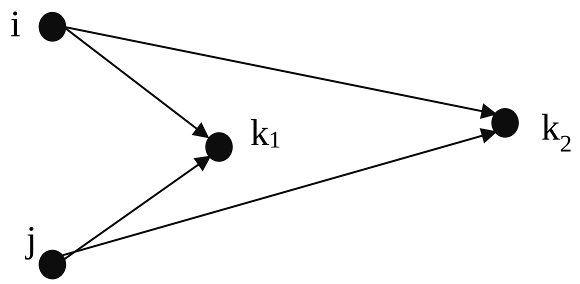


Here k_1 denotes the first shared partner and k_2 a possible additional shared partner. Further shared partners are omitted from the visualization of the term but in principle are included in the term's estimation process (up to k_n). The term weights these additional partners geometrically with a decreasing importance of each additional edgewise shared partner.

The ERGMs for status ascriptions reported in table 2.5 and 2.6 indicate that, given the overall model specifications, these structures are rather absent. This is indicative of a tendency towards consensus in status ascriptions, since if i perceives k as popular and k perceives j as popular it should be more likely that i also perceives j as popular.

Additionally, I added the incoming non-edgewise shared partner term (GWNESP-ISP). This term models the absence of a status ascription between two students who send a status ascription to the same students.

Figure C2. Graphical representation of the GWNESP-ISP term



The GWNESP-ISP term showed positive and significant parameter estimates in ERGMS for status ascriptions in all datasets (table 2.5 and 2.6). This could be interpreted as an agreement effect "forbidding" a tie between the two agreeing parties. Students who nominate the same other students as popular do not tend to ascribe status to each other. This could indicate that friends agree on who is popular but do not nominate each other as popular; note that the co-occurrence of friendship and popularity is already controlled in the model. These additional substantive interpretations of the terms have to be treated with caution. Given the interdependencies of ERGM parameters, which are similar to the dependencies of parameters in logistic regressions (Lusher et al. 2013), structures are nested within other structures included in the model. The geometrical weighting further complicates a substantial interpretation. To conclude, the GWNESP-OTP and GWESP-ITP parameters should be interpreted with great caution and mainly entered my analysis to achieve a satisfying goodness of fit. Nevertheless, their direction and significance make intuitive sense, and further research should clarify their interpretability, especially in light of other parameters entering a specification.

D. Robustness check: classroom level analysis without structural zeros for the CILS4EU data set

Table D1. Meta-analysis of ERGMs for status ascription and friendship networks

	Status ascriptions			Friendship networks		
CILS4EU	beta	s.e.	Q	beta	s.e.	Q
Edges	-0.75***	0.02	550.05***	-5.12***	0.03	783.63***
Mutual	1.39***	0.04	704.53***	2.01***	0.03	522.01***
GWODEG				2.69***	0.06	533.26***
GWIDEG	-3.00***	0.04	364.3***	1.23***	0.05	482.25***
GWESP				0.83***	0.01	865.50***
GWNESP -OTP	-0.23***	0.01	515.31***			
GWNESP -ISP	0.02***	0.00	526.15***			
Activity female	0.07***	0.02	366.72***	-0.05**	0.02	408.96***
Popularity female	-0.12***	0.03	274.06	0.07†	0.04	424.13***
Same gender	0.16***	0.02	377.83***	0.48***	0.01	664.07***
Same ethnic group	0.00	0.02	332.95***	0.15***	0.01	438.961**
Friendship entrainment	1.23***	0.02	545.75***			55.20***
Popularity entrainment				1.28***	0.02	723.48***
Hierarchical Tau score				0.02***	0.00	1250.27***
Difference in popularity				-0.03***	0.00	639.31***
AIC	2980.39			2910.06		
N	250 classrooms			332 classrooms		
GOF	94%			96%		

Note: ERGM coefficients are weighted by the variance-covariance matrix of all parameters estimated per model specification with a multivariate fixed-effects meta-analysis (An 2015); *s.e.* reports the standard error associated with this averaged ERGM coefficient. The GOF is reflected by the average share of convergence ratios <2;

† $p < 0.10$
* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$ (two-sided).

Table D2. Meta-regression for ERGM estimates in status ascriptions, single classroom level

		Size		Composition			
		Larger		*Higher Ethnic Heterogeneity*		*Higher Gender Heterogeneity*	
CILS4EU	Main	Bivar.	Full.	Bivar.	Full.	Bivar.	Full.
Edges	-0.74***	-0.15**	-0.15***	-0.14***	-0.15***	-0.07**	-0.03
Mutual	1.23***	0.14***	0.11*	0.10**	0.08*	0.11**	0.09*
GWIDEG	-3.03***	-0.29***	-0.28***	-0.02	-0.03	-0.12**	-0.04
GWNESP -OTP	-0.22***	0.03***	0.03***	-0.01	-0.002	-0.01	-0.02**
GWNESP -ISP	0.03***	-0.02***	-0.02***	0.04***	0.04***	0.01†	0.01*
Activity female	0.07***	0.002	0.01	0.02	0.01	-0.02	-0.03
Popularity female	-0.12***	-0.01	-0.02	-0.02	-0.01	0.03	0.05
Same gender	0.16***	0.06**	0.06**	-0.01	-0.01	0.06**	0.03
Same ethnic group	-0.02	0.02	0.02	0.01	0.04*	0.04*	0.03
Friendship entrainment	1.23***	0.005	-0.002	0.07**	0.07**	0.01	0.02

Note: All contextual moderators were z-standardized before they entered the meta-regression. The intercept therefore gives the ERGM parameter for a network of average size and demographic composition in the respective data set.

† $p < 0.10$
* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$ (two-sided).

Table D3. Meta-regression for ERGM estimates in friendship networks, single classroom level

		Size		Composition			
		Larger		*Higher Ethnic Heterogeneity*		*Higher Gender Heterogeneity*	
CILS4EU	Main	Bivar.	Full.	Bivar.	Full.	Bivar.	Full.
Edges	-4.95***	-0.32***	-0.33***	-0.05	-0.05	0.06*	0.08**
Mutual	1.99***	0.10***	0.10***	-0.03	-0.03	0.04	0.02
GWODEG	2.53***	0.39***	0.40***	0.06	0.08	0.02	-0.004
GWIDEG	1.13***	0.08	0.08†	-0.02	-0.03	-0.14**	-0.14**
GWESP	0.79***	0.06***	0.06***	0.004	-0.03	-0.02*	-0.02*
Activity female	-0.04	-0.03	-0.02	0.04	0.03	-0.06*	-0.06*
Popularity female	0.06	0.04	0.03	-0.07†	-0.05	0.11*	0.11*
Same gender	0.50***	0.02***	0.01	0.01	0.02	0.005	0.01
Same ethnic group	0.17***	-0.003	-0.005	-0.09***	0.09***	0.000	-0.015
Popularity entrainment	1.28***	0.05*	0.05*	0.02	0.02	0.02	0.02
Hierarchical Tau score	0.02***	-0.02***	-0.02***	0.001	0.004	-0.007	-0.004
Difference in popularity	-0.03***	-0.006***	0.006***	0.006	0.002	-0.001	-0.0014

Note: All contextual moderators were z-standardized before they entered the meta-regression. The intercept therefore gives the ERGM parameter for a network of average size and demographic composition in the respective data set.

† $p < 0.10$
* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$ (two-sided).

Table D4. Linear probability models of convergence in ERGMS

	Status ascriptions		Friendship networks	
CILS4EU	beta	se.	beta	se.
Intercept	0.23***	0.03	0.33***	0.03
Network size	0.05***	0.01	0.11***	0.02
Share female	-0.02	0.02	-0.03*	0.02
Share migrants	-0.01	0.01	0.01	0.02
Country (Ref. England)				
Germany	0.19***	0.06	0.12**	0.05
The Netherlands	-0.01	0.06	-0.01	0.07
Sweden	-0.03	0.06	0.03	0.05
N classes	906		906	
Percentage converged	28%		37%	
R^2	0.05		0.07	

Note: All variables besides county of survey were z-standardized to ease interpretation.

† $p < 0.10$
* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$ (two-sided).

E. Comparison between random and empirical networks

In addition to the simulation-based exploration of network models reported in the main text, this section compares random networks with observed networks. As Anderson et al. (1999) point out, graph level indices—here called global measures—for centralization and hierarchization are mechanically linked to size. Although the simulation procedure reported in the main text holds the size of simulated networks constant and thereby should correct for this methodological problem, the results presented here provide a further robustness check.

Figure E1 and E2 present box plots depicting inequality in the distribution of status ascriptions and friendships in simulated random networks with differing sizes and densities according to deciles (cf. Bearman et al. 2004: 62–67).[71]

Intuitively, the figures answer the question: how unequally would status ascriptions and friendships be distributed if they would be formed at random? As becomes clear from the figures, the inequality in status and in prominence as a friend would slightly increase in larger settings under this baseline scenario. To quantify this change in one of the data sets: the difference in the median skewness between the 1st and the 9th decile is 0.23 for status ascriptions and 0.22 for friendships for the FVA data set.

[71] To inform the simulations with realistic densities, I estimated OLS regressions with network density as dependent and network size as independent variables. Afterwards, predictions for each decile were derived and used as densities informing the simulations (1,000 networks per decile). Holding densities constant while increasing network size would have obscured the results, since it is a well-known feature of many networks that density decreases with a larger size. See also Bearman et al. (2004: 63) who inform their simulations by the number of nodes and network density. Results for the tenth decile are not reported, because predictions extrapolated towards empirically impossible values, i.e., regressions predicted negative densities for the tenth decile in some of the data sets.

Figure E1. Distribution of inequality in random status ascriptions

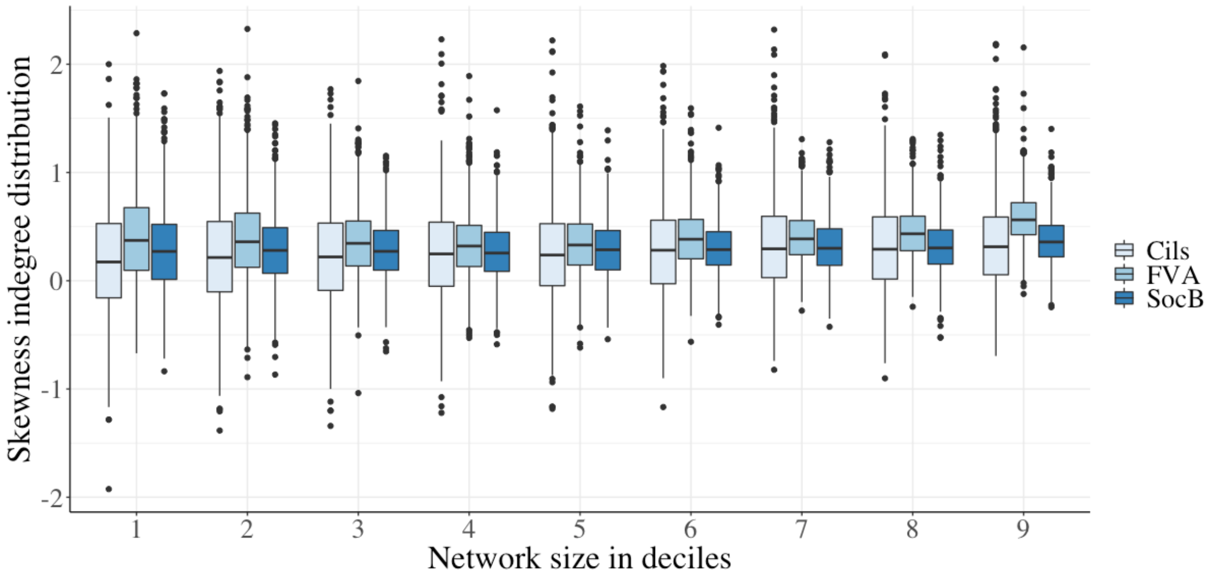
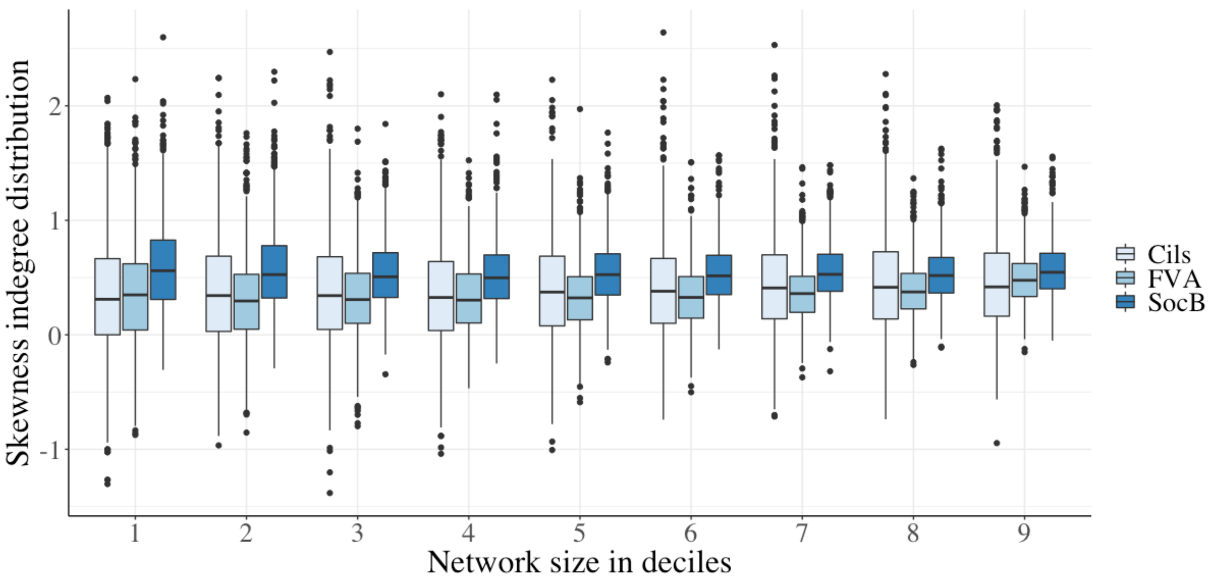


Figure E2. Distribution of inequality in random friendship networks



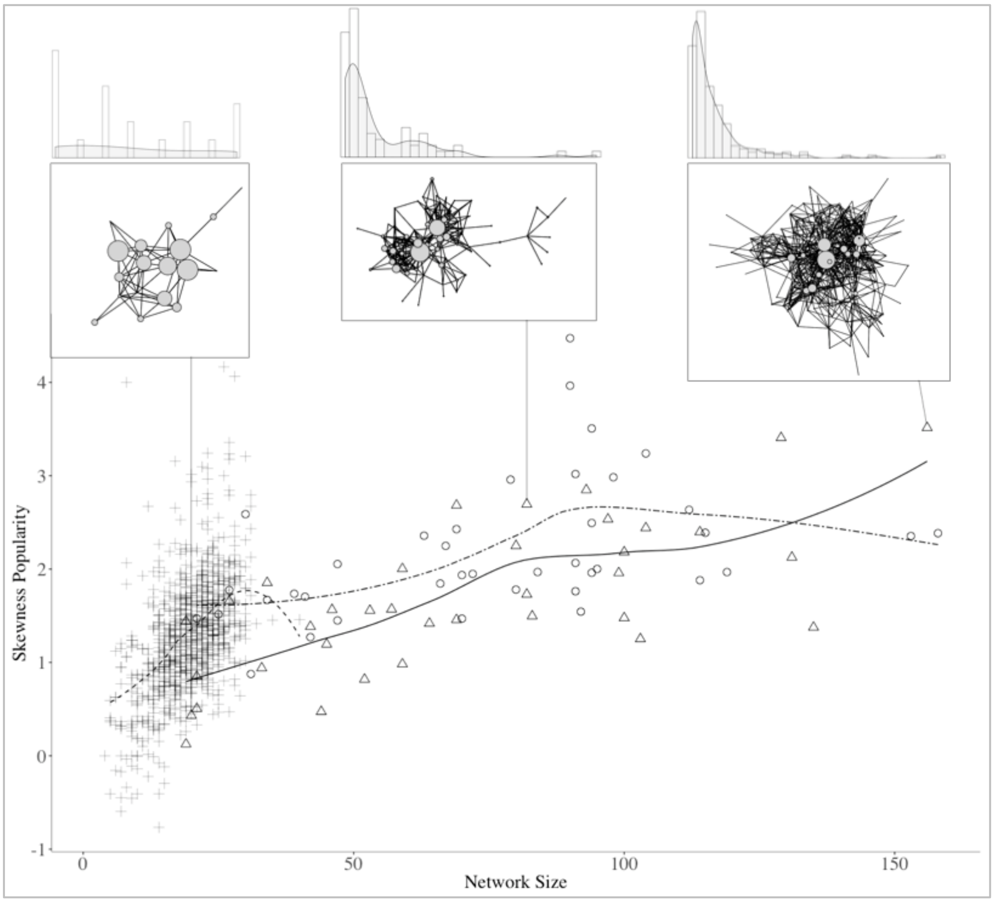
In conclusion, we would expect a small to moderate increase in inequality between small and large contexts in both tie types, even if students ascribed status and formed friendships randomly. In the next section, I turn to inequality in observed networks to assess whether patterns found in empirical networks can be accounted for by randomness.

Inequality according to size in observed networks

Figures E3 and E4 show the associations of context size with the degree of inequality in received status ascriptions and friendship nominations across all three data sets. Each cross represents a school class (CILS4EU), and each triangle or dot represents a grade (FVA and SOCIALBOND, respectively). A higher skewness (y-axis) indicates more inequality in the distribution of incoming nominations in the respective tie type.

Status ascriptions are distributed increasingly unequally within larger classes and grades. To illustrate the magnitude of the differences and to give a sense of the variability in network characteristics according to their size, the upper parts of the figures entail sociograms for three example grades.

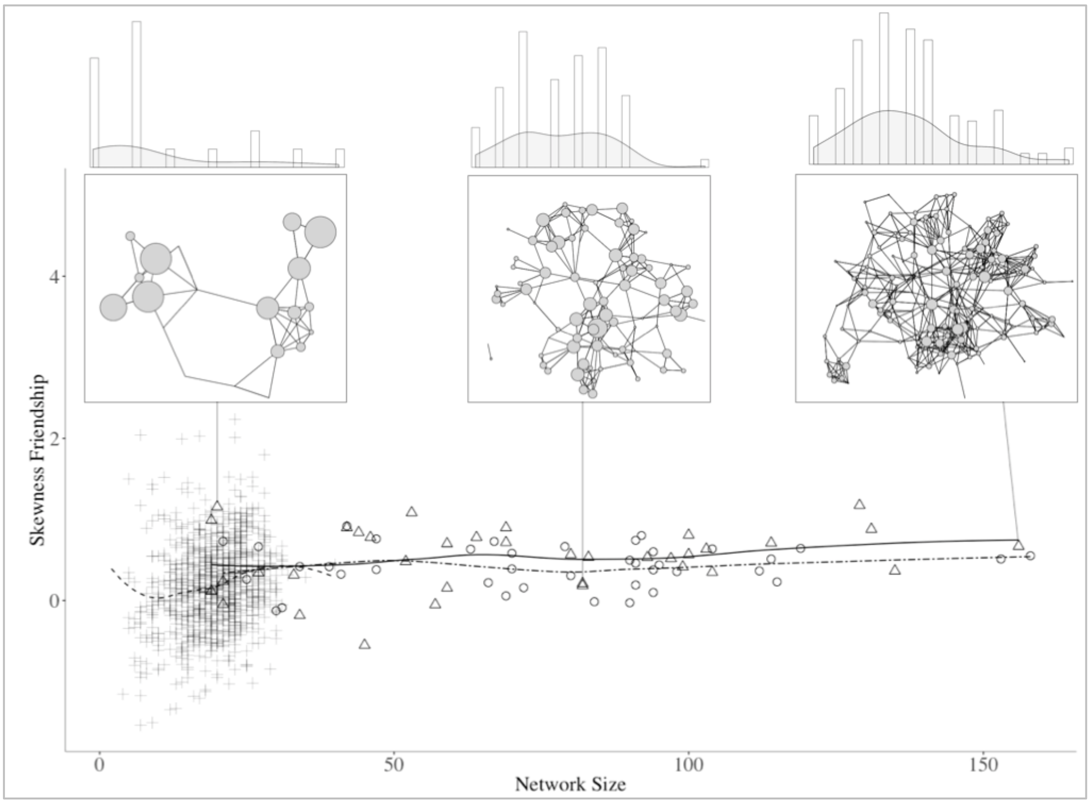
Figure E3. Skewness in status ascriptions and network size



Note: Crosses represent school classes (CILS4EU), triangles (FVA) and dots (SOCIALBOND) represent grades. Histograms are based on the percentage of received status ascriptions in three example grades.[72] Node size in the network visualizations is adjusted at the share of received indegrees. Lines are lowess curves for the respective data sets: dashed line (CILS4EU), straight line (FVA), double-dashed line (SOCIALBOND).

In contrast, friendships are only slightly more unequally distributed in larger networks, which is in line with previous findings (Moody et al. 2011).

Figure E4. Skewness in friendship and network size



Note: Crosses represent school classes (CILS4EU), triangles (FVA) and dots (SOCIALBOND) represent grades. Histograms are based on the percentage of received friendship nominations in three exemplary grades. Node size in the network visualizations is adjusted at the share of received indegrees. Lines are lowess curves for the respective data sets: dashed line (CILS4EU), straight line (FVA), double-dashed line (SOCIALBOND).

[72] It is notable that the most skewed class-level networks score even higher on the skewness measure than networks on the grade-level. This is probably due to the smaller "choice set" within classes leading to more extreme patterns in the allocation of nominations. I still assume that the skewness is a valid measure to compare between class networks with more or less inequality in nominations. However, it would be problematic to compare classes with grades; therefore, I perform all subsequent analyses separately for the three data sets.

Finally, table E1 and E2 capture how inequality varies across differently sized contexts, given a random formation of ties in comparison to observed networks. Table E1 illustrates that the median empirical skewness of status ascriptions is around 3 to 4 times higher than randomness would suggest. Furthermore, whereas the increase in skewness according to context size is small for random status ascriptions, a substantial trend towards more inequality with increasing context size is visible in observed status ascriptions. For instance, the difference between the 1st and the 9th percentile in the FVA data set is approximately 1.20, which is almost ten times the size of the difference obtained for the random scenario.

Table E1. Median skewness in random and observed status ascriptions according to size[73]

Status ascriptions	CILS4EU		FVA		SOCIALBOND	
Size in deciles	random	observed	random	observed	random	observed
1st	0.31	0.48	0.35	1.00	0.56	1.65
2nd	0.34	0.91	0.30	0.68	0.53	1.69
3rd	0.34	1.01	0.31	1.62	0.51	1.75
4th	0.33	1.13	0.30	1.01	0.50	2.25
5th	0.37	1.27	0.32	1.56	0.53	1.94
6th	0.38	1.30	0.33	1.46	0.51	2.97
7th	0.41	1.43	0.36	1.99	0.53	1.91
8th	0.42	1.45	0.37	2.53	0.52	2.25
9th	0.42	1.49	0.48	2.18	0.55	2.81

Note: Calculations are based on the random status ascriptions reported in figure E1 and on the empirical status ascriptions depicted in figure E3.

In comparison to status ascriptions, the values of inequality in empirical friendship networks are much closer at the values obtained for randomly generated friendship networks. Moreover, there is no substantial trend towards more inequality in random or observed friendship networks as context size increases. For instance, the 1st and the 9th percentile of network sizes observed

[73] Results for the difference in means are very similar and available upon request.

in the FVA data set yields a difference of 0.17, which has about the same magnitude as the increase in inequality according to network size than a random assignment of ties would suggest.

Table E2. Median skewness in random and observed friendship networks according to size

Friendship networks	CILS4EU		FVA		SOCIALBOND	
Size in deciles	random	observed	random	observed	random	observed
1st	0.17	-0.10	0.37	0.44	0.30	0.46
2nd	0.22	0.11	0.36	0.29	0.25	0.37
3rd	0.18	0.09	0.35	0.59	0.26	0.70
4th	0.22	0.16	0.32	0.63	0.25	0.22
5th	0.25	0.19	0.33	0.52	0.30	0.49
6th	0.27	0.12	0.38	0.72	0.30	0.15
7th	0.28	0.22	0.39	0.37	0.28	0.60
8th	0.28	0.44	0.43	0.52	0.30	0.41
9th	0.31	0.30	0.56	0.63	0.35	0.44

Note: Calculations are based on the random friendship networks reported in figure E2 and on the empirical friendship networks depicted in figure E4.

Taken together, these findings provide further evidence for the notion that global inequality in the distribution of ties is more pronounced in status ascriptions with increasing context size than under a random baseline scenario, while this is not the case for friendship nominations.

Robustness check, standard deviation of indegree distribution as measure for inequality

This section repeats the comparison between random and observed networks according to network size with the standard deviation as an additional measure for inequality in the distribution of status ascriptions and friendship ties. The results are qualitatively similar to the analyses presented above, which use the skewness as a measure for inequality. Firstly, observed standard deviations of status ascription ties are substantially higher than under a random scenario. Secondly, while the standard deviation is increasing with network size given a random allocation of size, this association is much stronger for the empirical status ascriptions (see table E3). Thirdly, distributional inequality in friendships is closer to the random scenario, and there is only a weak link between network size and inequality in empirical or observed friendships (see table E4).

Table E3. Median standard deviation in random and observed status ascriptions according to size

Status ascriptions	CILS4EU		FVA		SOCIALBOND	
Size in deciles	random	observed	random	observed	random	observed
1st	1.16	1.42	1.47	3.14	1.20	1.50
2nd	1.28	2.02	1.71	2.36	1.37	2.51
3rd	1.33	2.57	2.04	3.57	1.56	3.08
4th	1.36	2.66	2.13	3.46	1.59	3.92
5th	1.39	2.54	2.22	4.05	1.62	3.03
6th	1.40	2.68	2.25	6.75	1.64	5.24
7th	1.39	2.89	2.23	4.82	1.64	3.67
8th	1.40	3.02	2.13	7.68	1.65	4.58
9th	1.39	3.21	1.79	6.67	1.59	4.26

Note: The standard deviation of the indegree distribution was calculated for empirical networks and 1,000 randomly simulated networks for each size decile.

Table E4. Median standard deviation in random and observed friendship networks according to size

Friendship networks	CILS4EU		FVA		SOCIALBOND	
Size in deciles	random	observed	random	observed	random	observed
1st	1.42	1.19	1.39	1.86	1.97	2.68
2nd	1.53	1.57	1.63	1.74	2.22	2.73
3rd	1.62	1.65	1.89	1.70	2.52	2.96
4th	1.62	1.61	2.00	2.10	2.55	3.46
5th	1.67	1.77	2.06	2.14	2.59	3.10
6th	1.68	1.69	2.08	2.13	2.55	3.18
7th	1.68	1.92	2.05	2.13	2.54	3.34
8th	1.69	1.88	1.91	2.14	2.53	2.93
9th	1.69	1.97	1.56	2.23	2.32	3.52

Note: The standard deviation of the indegree distribution was calculated for empirical networks and 1,000 randomly simulated networks for each size decile.

II. Appendix to Chapter 3

A. Information on scientists' characteristics, assessment of goodness of fit (GOF), and robustness checks

Table A1. Information on scientists' characteristics

	Years of experience					Number of publications per year					Seniority—share of last author positions				
Year	Mean	SD	Median	Min.	Max.	Mean	SD	Median	Min.	Max.	Mean	SD	Median	Min.	Max.
1975	0	0	0	0	0	0.69	1.65	0	0	6	0.15	0.38	0	0	1
1979	1.22	1.89	0	0	4	1.78	3.10	0.50	0	16	0.27	0.39	0	0	1
1984	1.73	2.89	0	0	9	0.45	1.20	0	0	7	0.17	0.35	0	0	1
1987	2.86	3.56	3	0	12	2.17	2.86	2.17	0	12	0.14	0.32	0	0	1
1990	2.02	3.63	0	0	15	1.96	2.67	1	0	11	0.19	0.36	0	0	1
1993	3.00	4.08	3	0	18	4.27	5.13	3	0	24	0.17	0.35	0	0	1
1994	2.23	3.34	1	0	19	3.76	5.63	2	0	28	0.16	0.33	0	0	1
1996	3.49	4.42	2	0	21	5.10	6.81	3	0	40	0.13	0.30	0	0	1
1998	3.66	4.51	3.66	0	23	6.18	8.58	3	0	63	0.14	0.30	0	0	1
2000	4.30	4.81	2	0	25	7.96	11.33	4	0	88	0.12	0.28	0	0	1
2002	4.30	5.10	4.30	0	27	7.56	12.62	3	0	110	0.12	0.27	0	0	1
2004	4.14	5.26	2	0	29	6.99	12.91	2	0	113	0.12	0.28	0	0	1
2006	4.69	5.53	2	0	31	7.37	13.83	3	0	125	0.13	0.30	0	0	1
2008	5.53	5.96	4	0	29	8.42	15.54	3	0	137	0.11	0.27	0	0	1
2010	5.51	6.33	4	0	31	8.35	16.46	3	0	155	0.10	0.25	0	0	1
2012	5.86	6.51	4	0	33	9.20	18.71	2	0	170	0.12	0.28	0	0	1
2014	6.64	6.86	4	0	35	9.67	19.95	3	0	183	0.09	0.25	0	0	1
2016	8.99	7.18	6	0	37	13.17	23.96	5	0	201	0.10	0.25	0	0	1

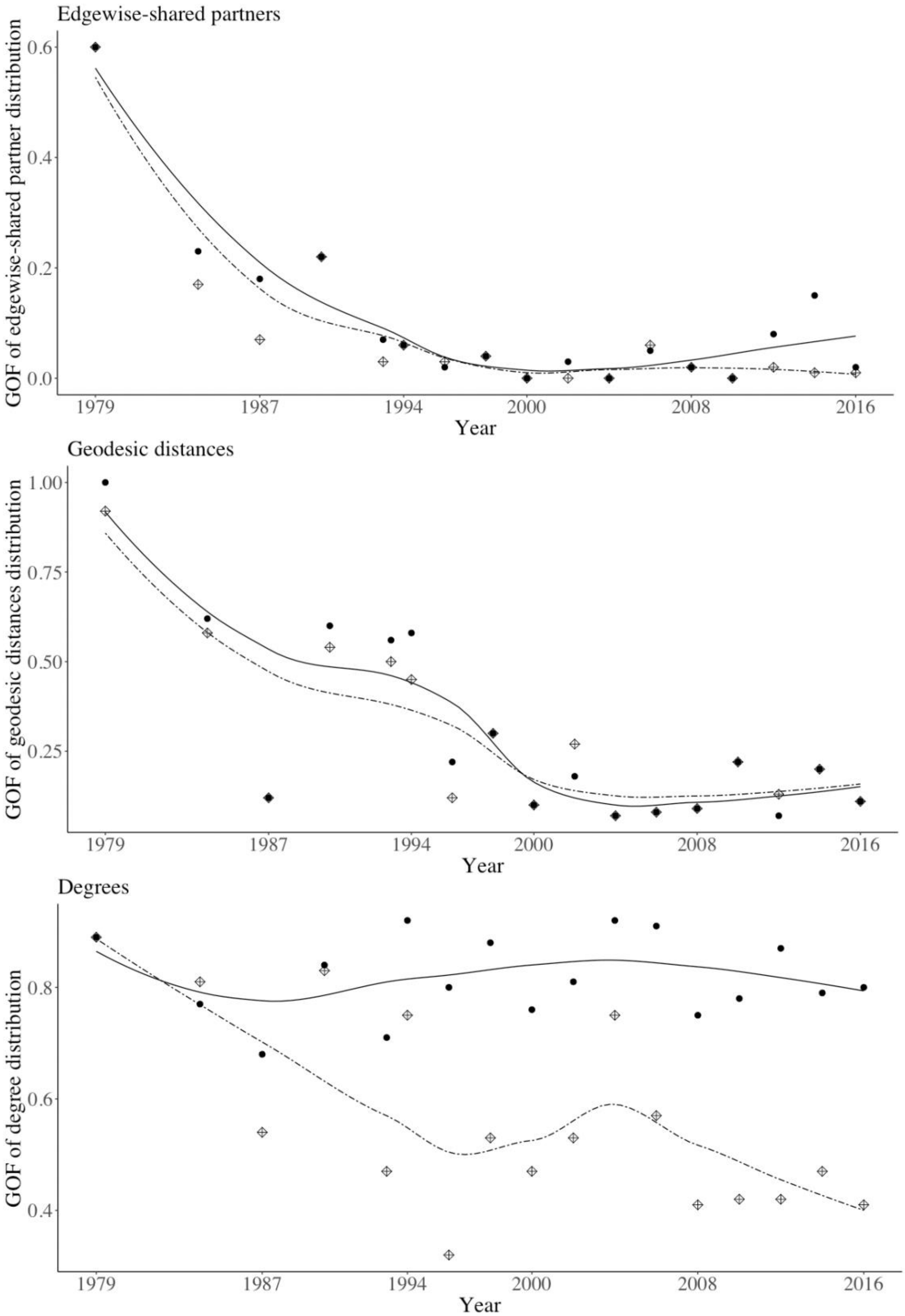
Goodness of fit (GOF): general trends

Figure A1 reports the share of simulated statistics for the distribution of edgewise-shared partners, geodesic distances, and degrees that showed a tolerable fit in relation to empirical statistics. Nearly all models showed an inappropriate GOF for geodesic distances and edgewise-shared partner statistics. Also, the fit for these network properties did not improve after adding researchers' characteristics to the models. In contrast, the fit for the degree distribution was improved by accounting for researchers' characteristics, especially during the second half of the field's development. This result is in line with our theoretical expectation that researchers' characteristics became more important for collaboration as the field matured (H2).

In addition, we would like to point out that an insufficient GOF for the distribution of edgewise-shared partners and geodesic distances is not unusual in large networks (similar issues are reported for SAOMs by Lewis and Kaufman, 2018: 1736, Stark et al., 2020: 458). We attempted to increase the GOF by adding geometrically weighted statistics—such as the GWDEG and GWESP terms (Hunter, 2007). Yet, these terms led to model degeneracy in several years.[74] Consequently, we decided to report specifications that worked for all conferences instead. While a high GOF is desirable, simpler specifications sufficiently addressed our research questions regarding the link between authors' attributes and the distribution of coauthorships. Moreover, terms beyond dyadic configurations introduce complex interdependencies among parameters and can complicate interpretation (Martin, 2020; Rubineau et al., 2019).

[74] While models that operate only on the dyad level use pseudo-maximum likelihood estimation, models that include terms beyond dyadic interdependence rely on Monte Carlo Markov Chains (Hunter et al., 2008). The latter simulation-based estimation procedure probably caused model instability in the networks under study. Also, please note that we do not report information on convergence t-ratios because these are only calculated if ERGMs are estimated by a simulation-based procedure.

Figure A1. Difference in goodness of fit (GOF) between baseline and full model specification



Note: Each diamond and dot displays the share of statistics with a t-value below 2. A higher share indicates better model fit. Diamonds represent the GOF calculated for baseline models reported in table 3.3. Dots depict the GOF derived for full models reported in table 3.4. Lines are loess curves to enhance interpretability (dotted lines for baseline models, straight lines for full models).

Goodness of fit (GOF): detailed discussion of fitting the degree distribution

Figure A2 further explores differences in the goodness of fit between baseline and full models for networks' degree distributions. Three major trends can be inferred from the figure.

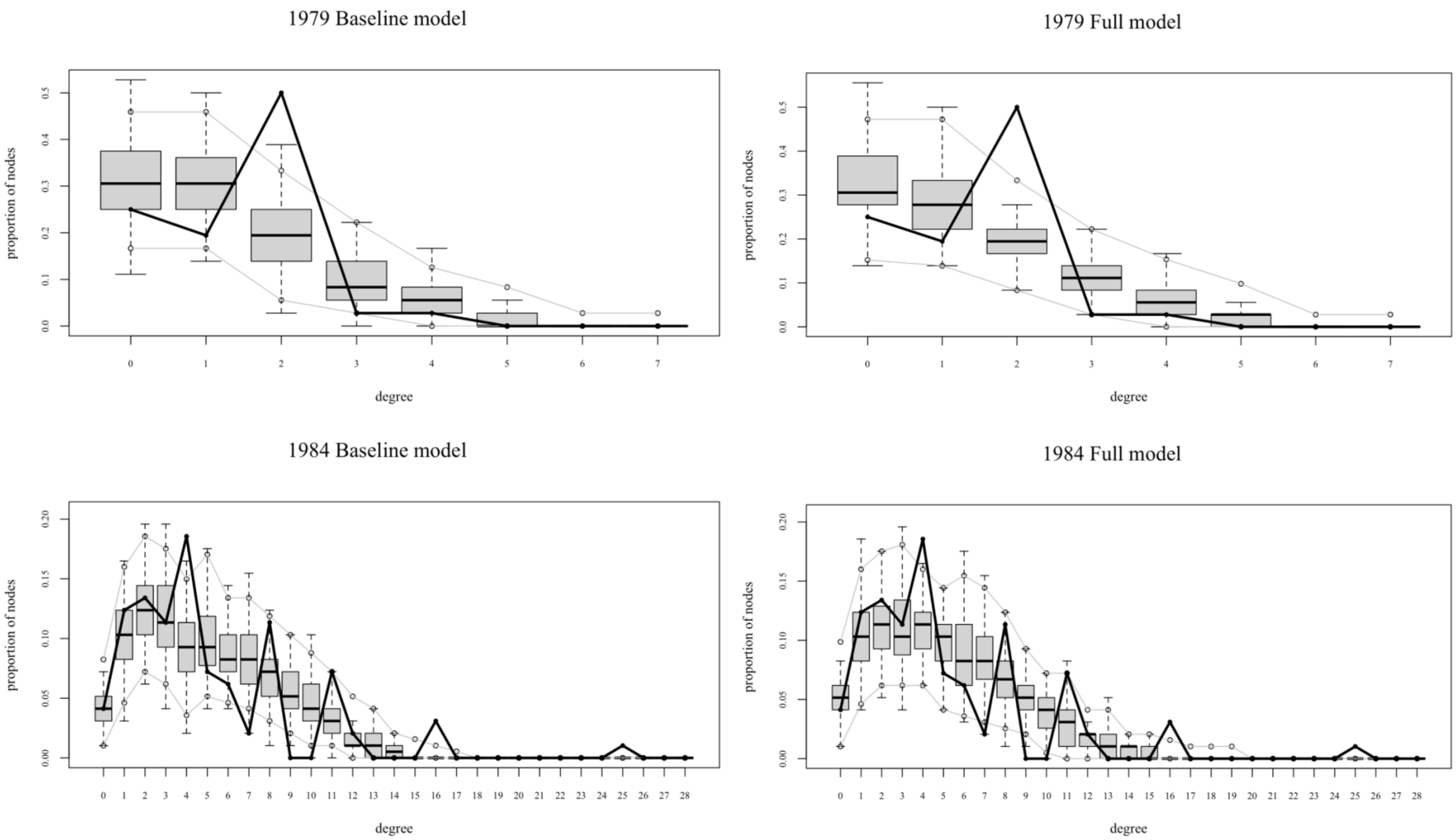
First, the difference between the simulated degree distributions produced by baseline models and full models becomes more pronounced over time. This is in line with the bottom panel of figure A1, which illustrates that the shares of well-approximated statistics started to differ noticeably from 1993 onward.

Second, simulated degree distributions from full models exhibit a higher skewness than the simulated degree distributions stemming from baseline models. This trend is especially visible during the last five conferences and further corroborates the notion that researchers' characteristics affected their prominence as collaborators. It also strengthens our interpretation of figure 3.3 in the main text, which shows that full models perform better in approximating the empirical skewness of the degree distribution.

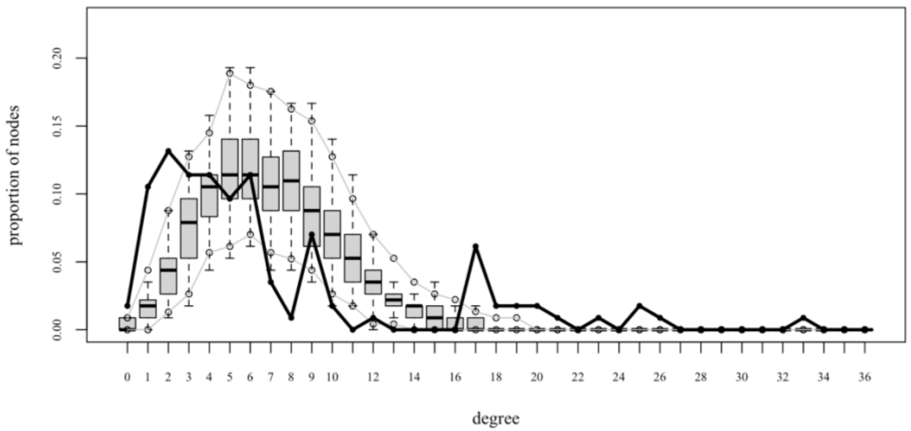
Third, figure A2 shows that full models increase the fit for nodes with a high degree. This trend is visible from 1996 onward: while the boxplots remain "flat" for high-degree nodes in baseline models, the range of simulated values is extended in full models, which is indicated by the empty dots representing the upper end of confidence intervals in this plot type. In the long tail of the degree distribution, simulated values of full models show a wider confidence interval and thereby cover empirical values more often than baseline models.

In summary, our additional GOF analyses for the degree distribution further support our substantial claims. Models including researchers' characteristics—i.e., years of experience, publications, and last author positions—improve the fit of the degree distribution, especially during the second half of the field's development, in comparison to baseline models. This points to an increased relevance of accumulation dynamics as the field grew and matured.

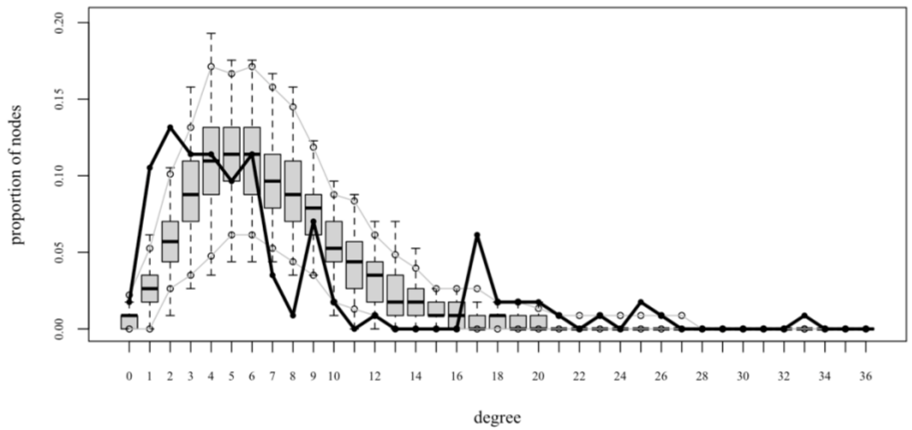
Figure A2. Goodness of fit (GOF) plots for the degree distribution



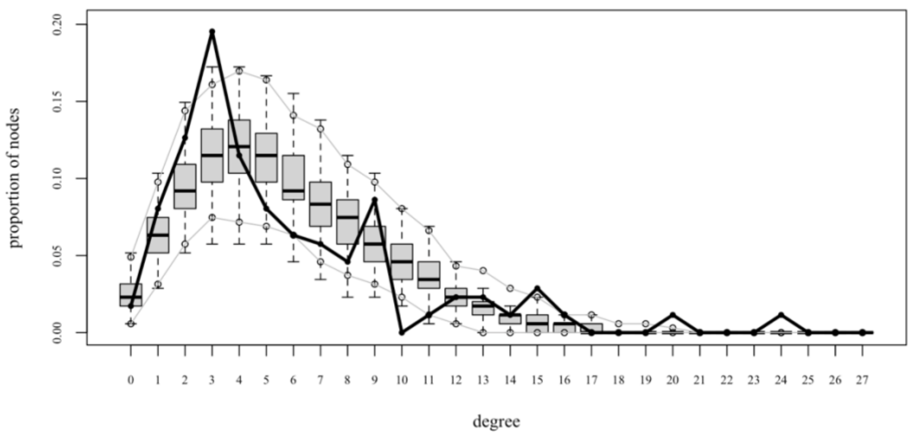
1987 Baseline model



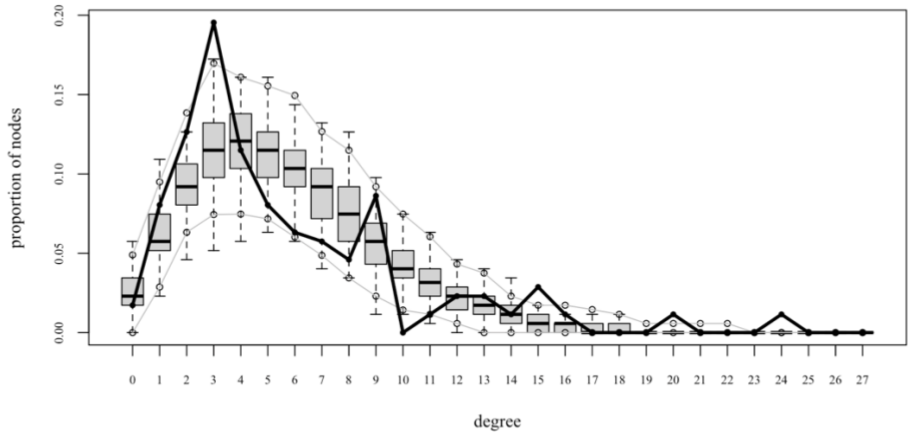
1987 Full model



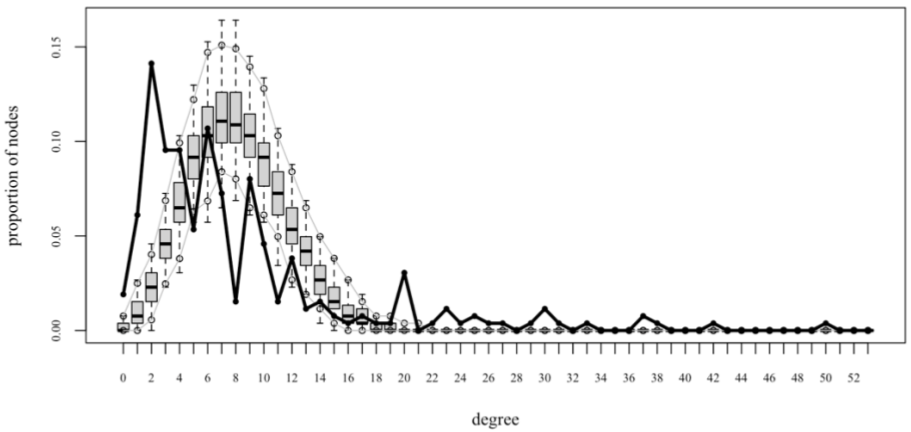
1990 Baseline model



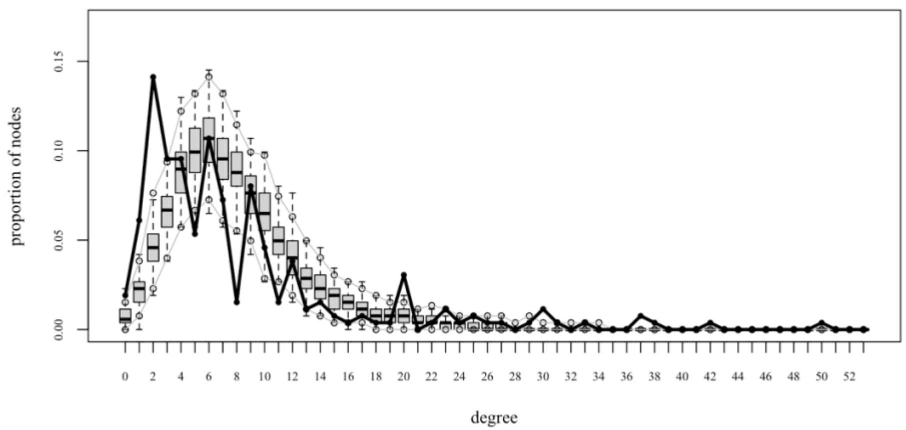
1990 Full model



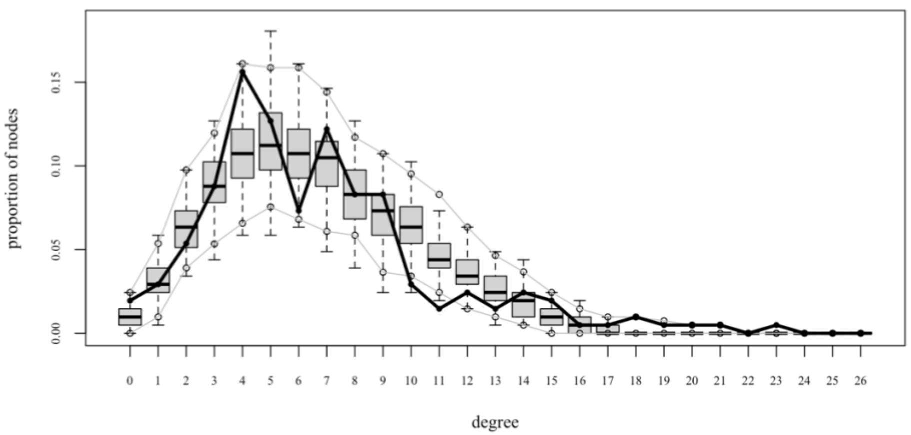
1993 Baseline model



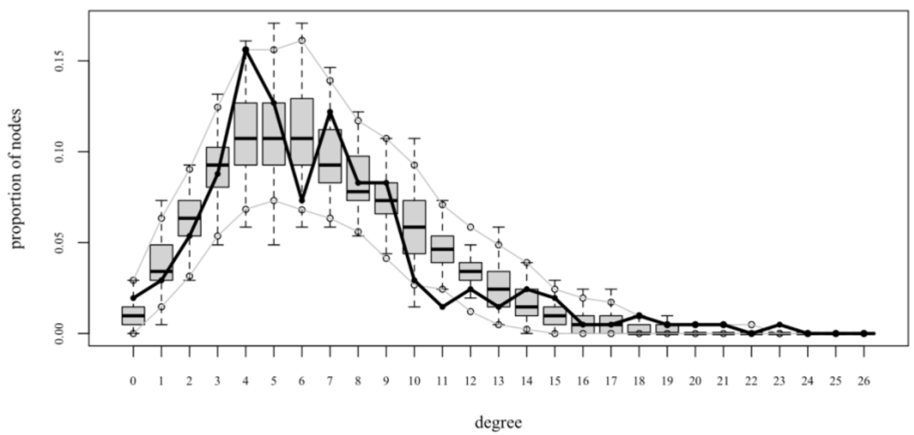
1993 Full model

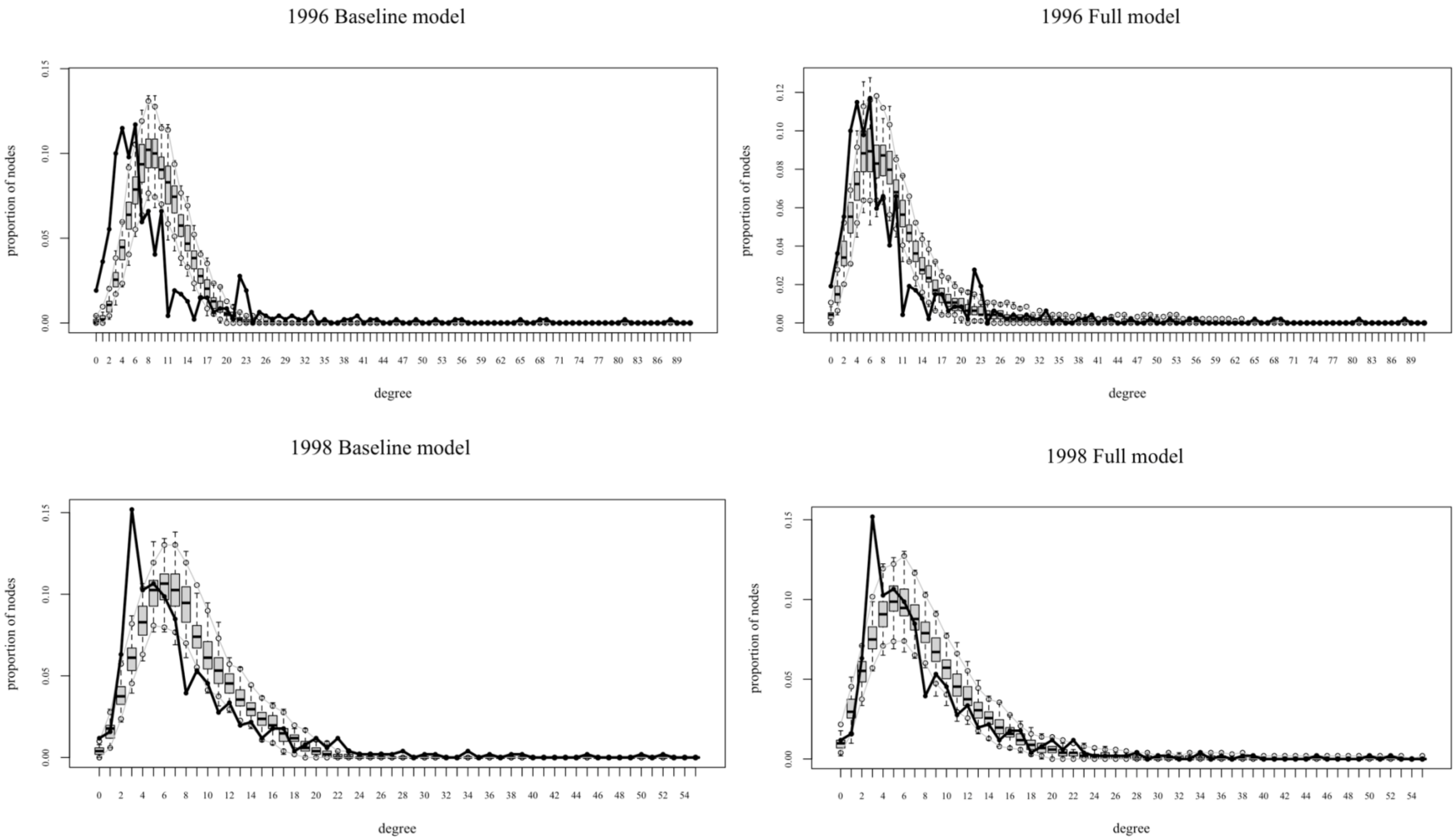


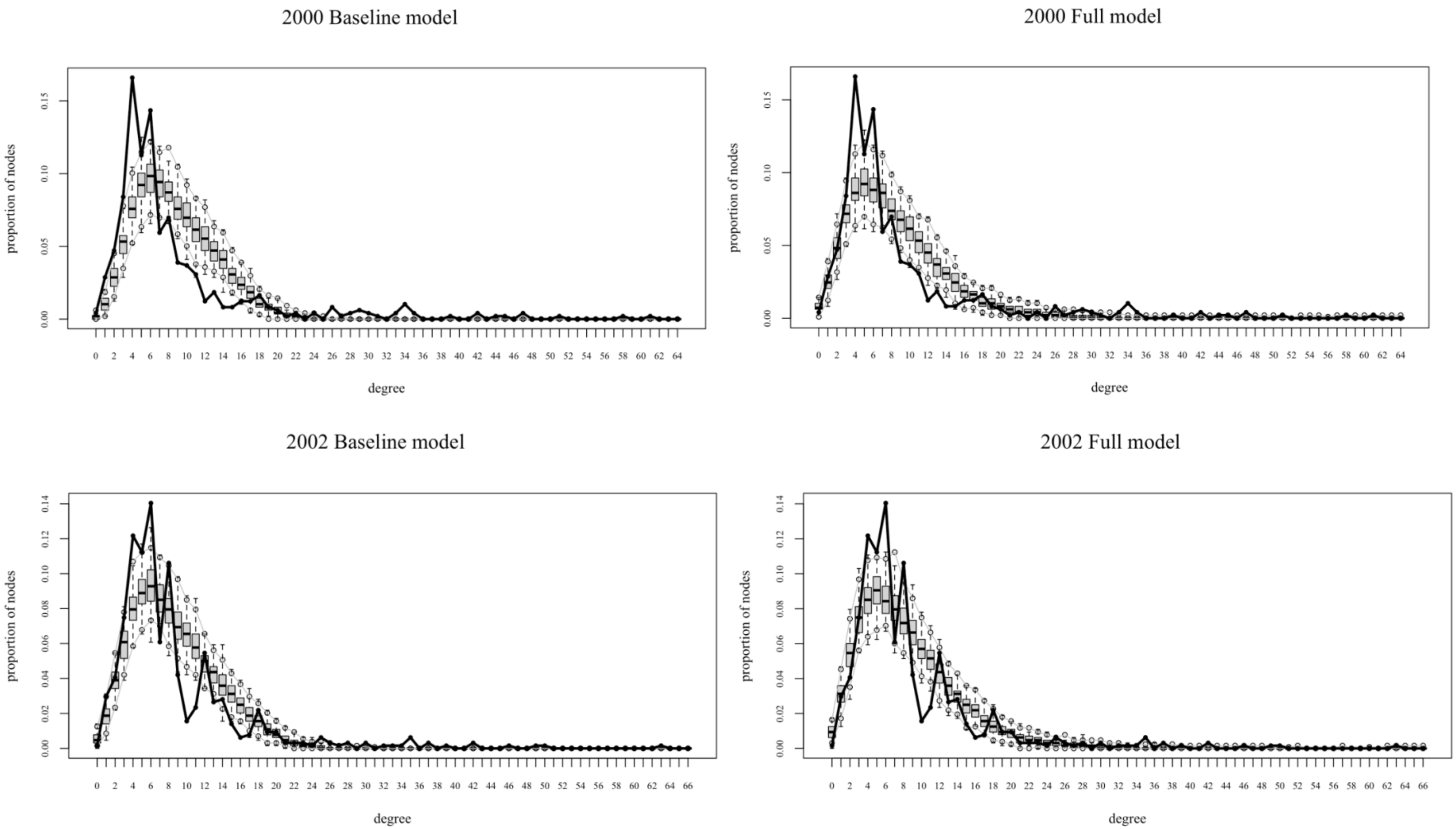
1994 Baseline model



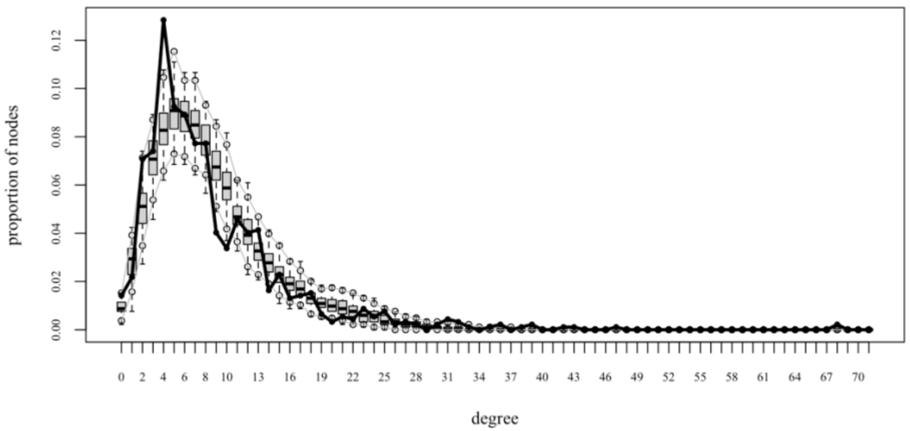
1994 Full model



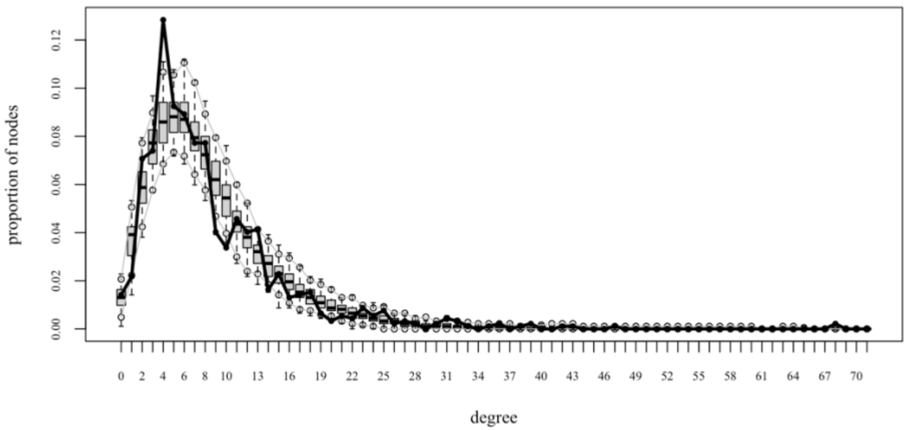

1996 Baseline model
proportion of nodes
degree
1996 Full model
proportion of nodes
degree
1998 Baseline model
proportion of nodes
degree
1998 Full model
proportion of nodes
degree


2000 Baseline model
2000 Full model
2002 Baseline model
2002 Full model
proportion of nodes
degree

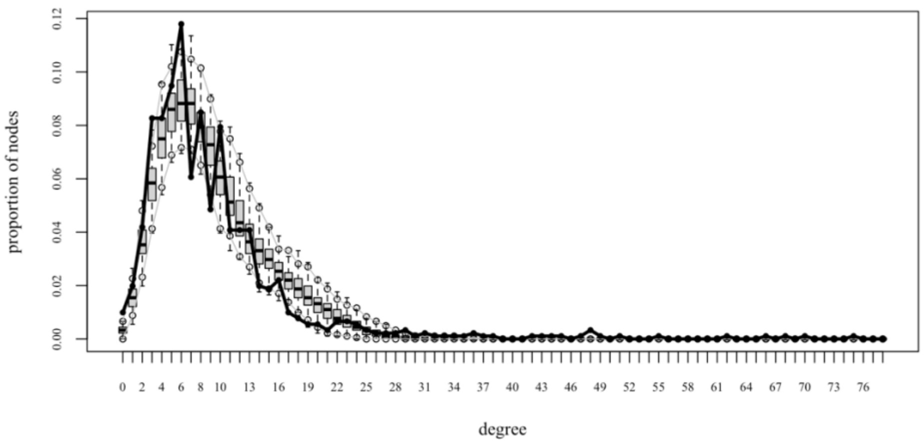
2004 Baseline model



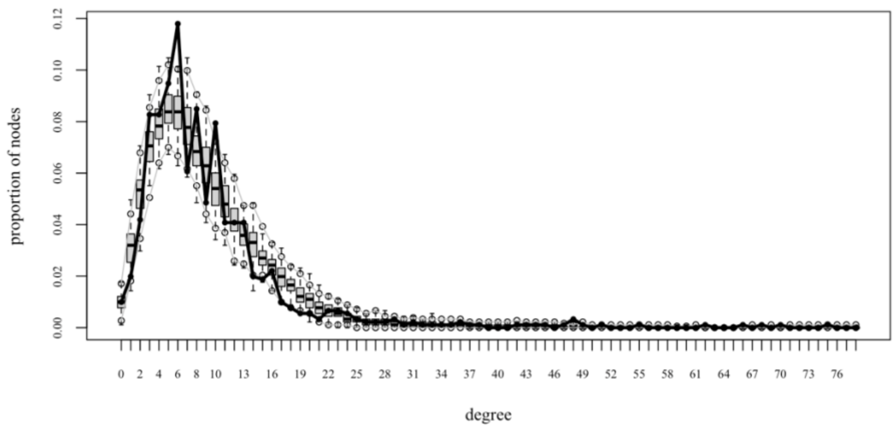
2004 Full model



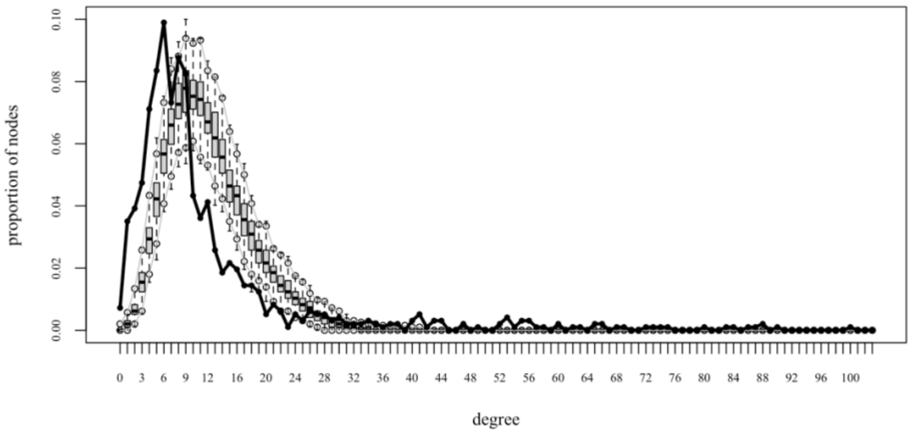
2006 Baseline model



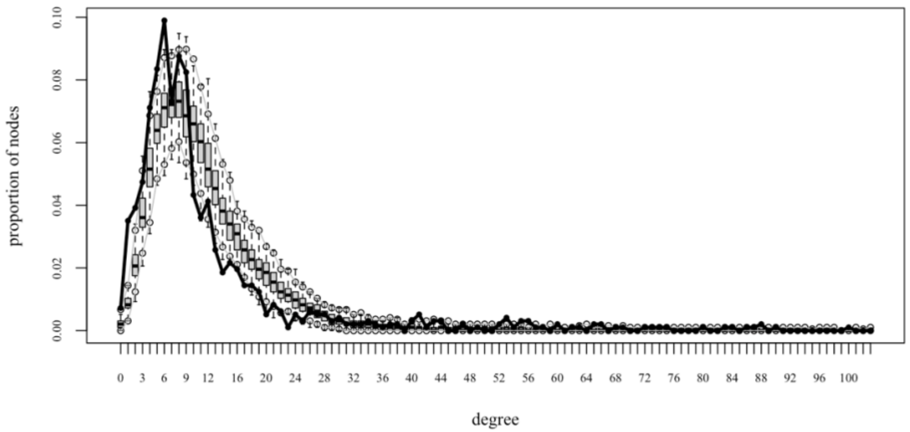
2006 Full model



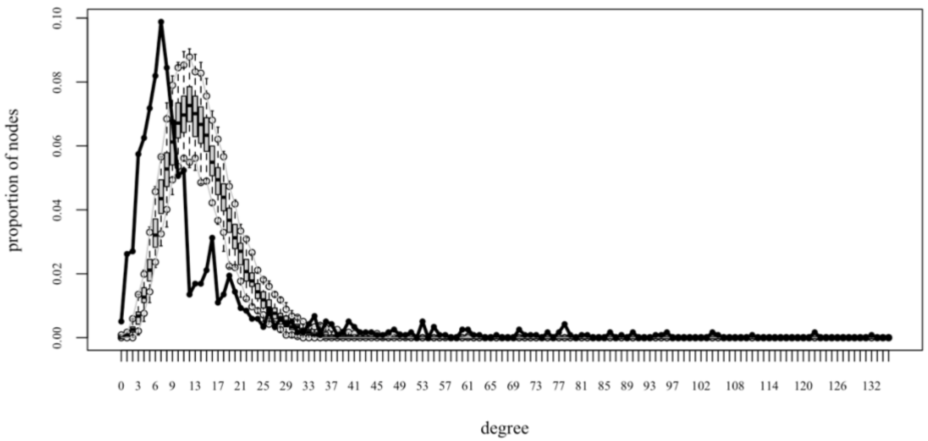
2008 Baseline model



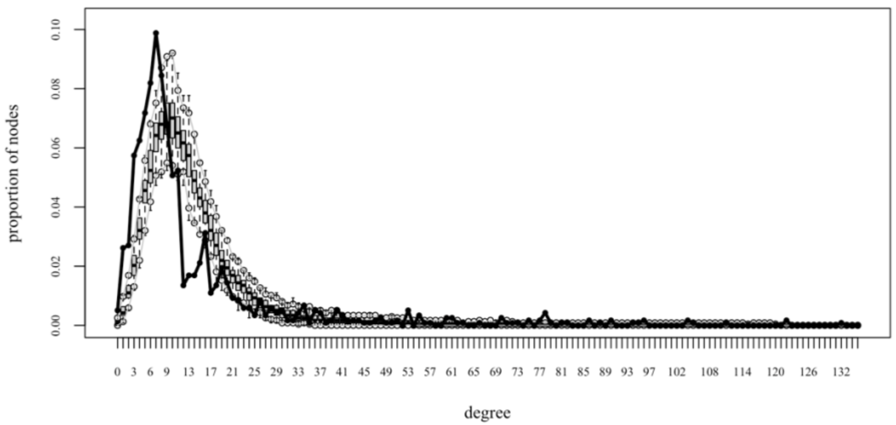
2008 Full model

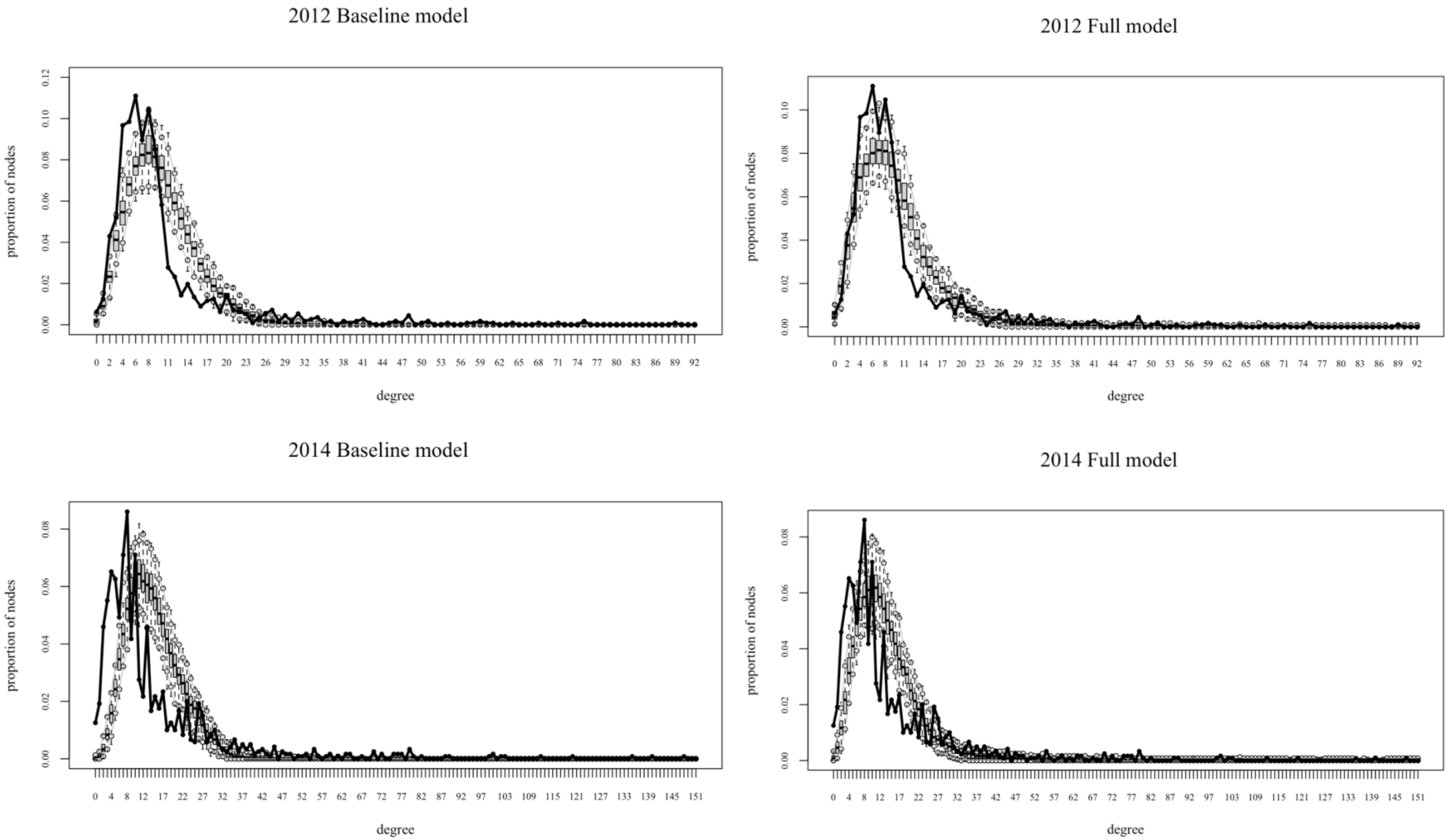


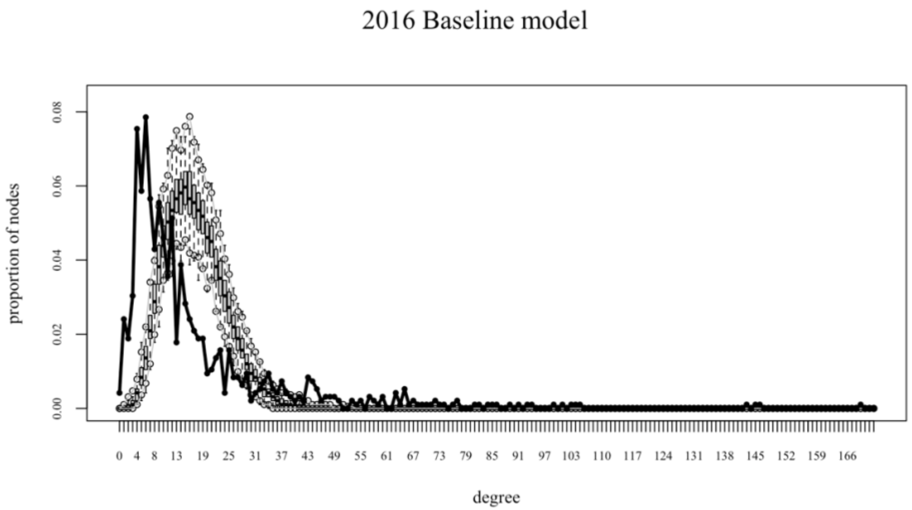
2010 Baseline model

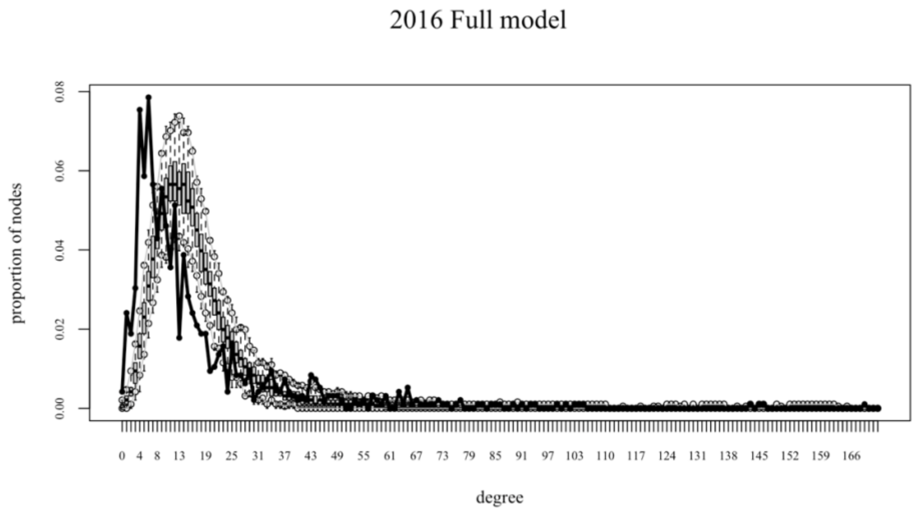


2010 Full model




2012 Baseline model
2012 Full model
2014 Baseline model
2014 Full model
proportion of nodes
degree


2016 Baseline model
proportion of nodes
degree


2016 Full model
proportion of nodes
degree

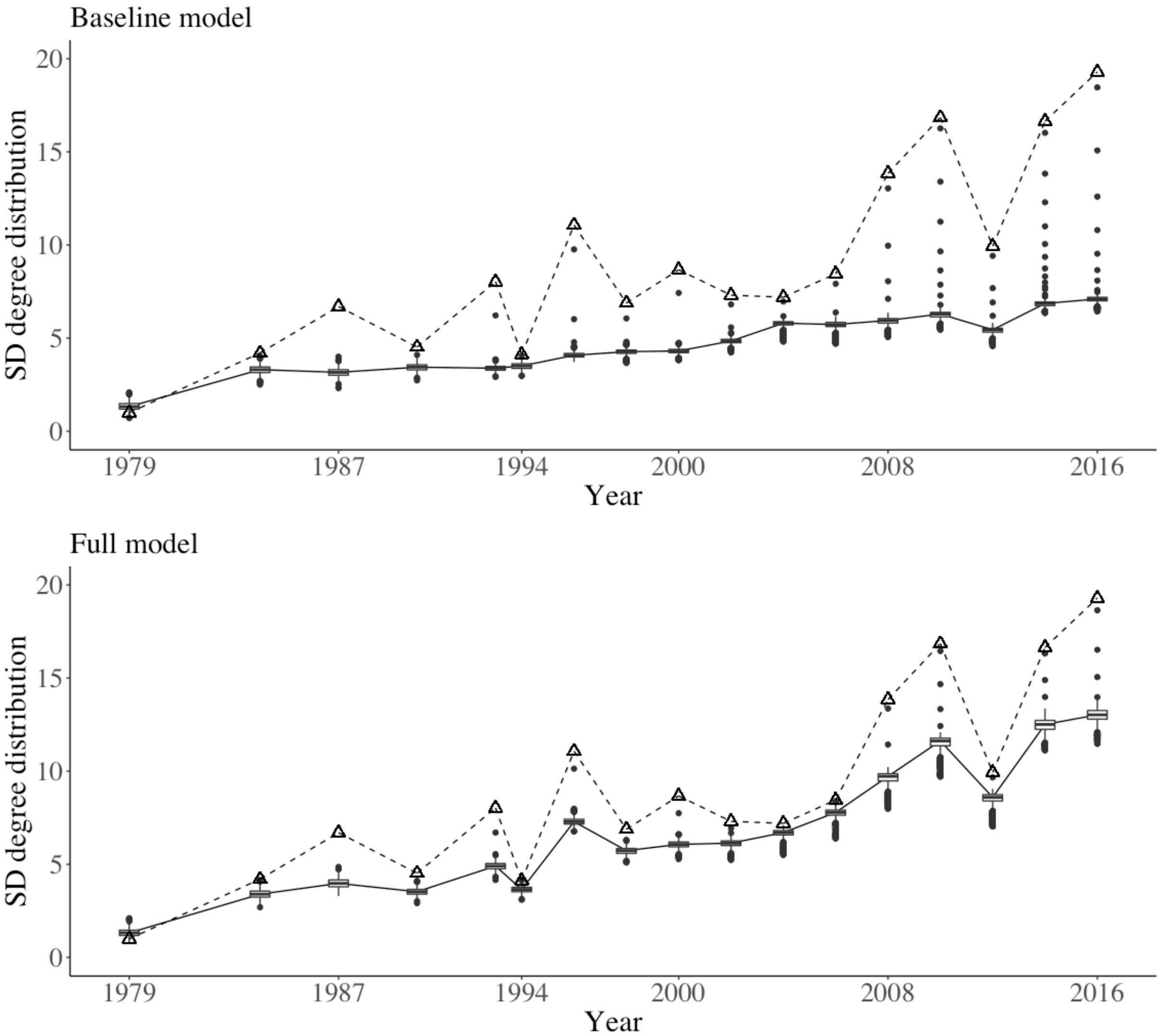
Trends in inequality and simulated values from network models

Here we report similar analyses as performed in Figure 2 in the main text. The only difference is that we used the standard deviation and the Gini coefficient as alternative measures for inequality in the network's degree distribution (Badham, 2013; Snijders and Steglich, 2015).

The results presented in figure A3 are in line with our results reported in the main text: inequality in empirical networks increased over time, and models including actor attributes simulated values that are closer to empirical values than simulated values from baseline models.

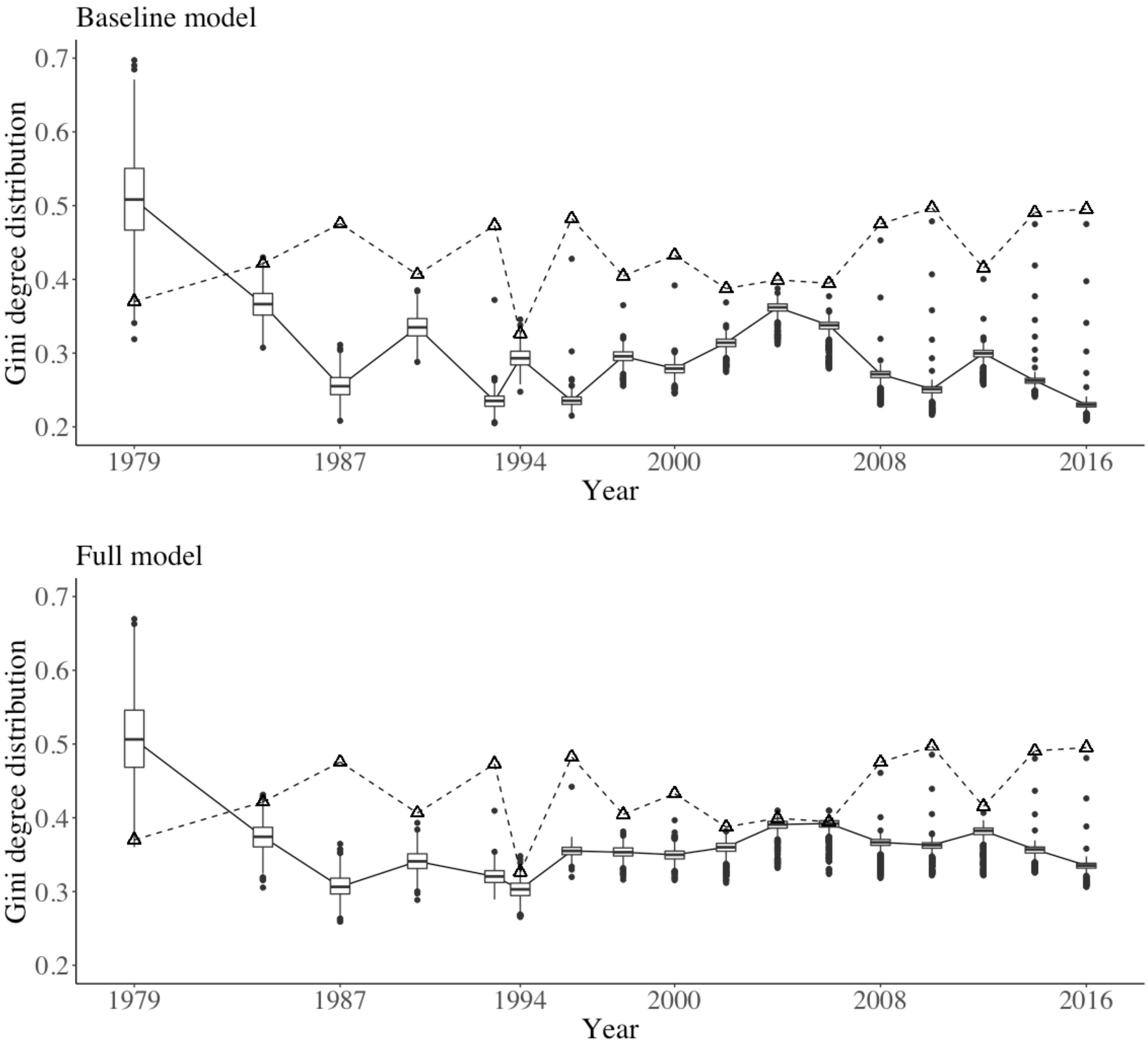
Results for the Gini coefficient are summarized in figure A4 and did not indicate a strong increase in inequality. Moreover, while full models were closer to simulating empirical values than baseline models, these differences were less pronounced in comparison with other measures for inequality. These findings are probably due to the fact that the Gini coefficient places equal emphasis on all percentiles of a distribution, whereas the skewness and the standard deviation are more sensitive to the top ranks of a distribution. While the Gini coefficient considers that most researchers did not have many collaborative ties from the outset of the field, the standard deviation and the skewness capture the advent of authors accumulating very large numbers of collaboration partners. Given that we are interested in the formation of elites rather than the uniform distribution of the total number of coauthor ties, we believe that the skewness and the standard deviation are better measures for our purpose.

Figure A3. Inequality in coauthor ties over time measured by the standard deviation



Note: Each box plot represents the distribution of standard deviations calculated in simulated networks obtained from network models reported in tables 3.3 and 3.4. Boxplots in the upper panel show simulated values for networks generated according to our baseline model specification (see table 3.3). The bottom panel reports simulated values generated from the full models that additionally include researchers' characteristics (table 3.4). We simulated 1,000 networks for each year and specification. Triangles indicate empirical values, i.e., the observed standard deviation of the degree distribution in a particular year. The dashed line connects empirical values, while the straight line follows the medians of simulated values.

Figure A4. Inequality in coauthor ties over time measured by the Gini coefficient



Note: Each box plot represents the distribution of Gini coefficients calculated in simulated networks obtained from network models reported in tables 3.3 and 3.4. Boxplots in the upper panel show simulated values for networks generated according to our baseline model specification (see table 3.3). The bottom panel reports simulated values generated from the full models that additionally include researchers' characteristics (table 3.4). We simulated 1,000 networks for each year and specification. Triangles indicate empirical values, i.e., the observed Gini coefficient of the degree distribution in a particular year. The dashed line connects empirical values, while the straight line follows the medians of simulated values.

Table A2. The role of experience for the collaboration network of neuroblastoma researchers in exponential random graph models (ERGMs)

Years	1979		1984		1987		1990		1993		1994	
	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME
Same country	-0.003	-0.076	0.094***	1.801	0.054***	0.874	0.074***	2.241	0.046***	1.481	0.079***	2.411
	(0.021)		(0.008)		(0.006)		(0.003)		(0.002)		(0.003)	
Same institution	0.108***	2.709	0.092***	1.755	0.096***	1.559	0.053***	1.605	0.058***	1.881	0.031***	0.937
	(0.017)		(0.008)		(0.009)		(0.003)		(0.002)		(0.003)	
Popularity years of experience	0.001	0.034	-0.004	-0.086	0.011***	0.174	0.040***	0.119	0.010***	0.309	0.005***	0.155
	(0.006)		(0.003)		(0.002)		(0.001)		(0.001)		(0.001)	
Difference in authors' years of experience	-0.009	-0.227	0.001	0.011	-0.005	-0.080	-0.004*	-0.123	-0.005***	-0.173	-0.005***	-0.162
	(0.008)		(0.004)		(0.003)		(0.002)		(0.001)		(0.001)	
Baseline probability	0.040		0.053		0.062		0.033		0.031		0.032	

Years	1996		1998		2000		2002		2004		2006	
	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME
Same country	0.037***	1.807	0.033***	2.083	0.030***	1.649	0.030***	2.213	0.021***	2.301	0.020***	1.893
	(0.001)		(0.001)		(0.001)		(0.001)		(0.0004)		(0.0004)	
Same institution	0.035***	1.677	0.027***	1.701	0.035***	1.965	0.025***	1.875	0.019***	2.089	0.023***	2.251
	(0.001)		(0.001)		(0.001)		(0.0005)		(0.0003)		(0.0003)	
Popularity years of experience	0.006***	0.267	0.005***	0.290	0.006***	0.328	0.004***	0.299	0.002***	0.223	0.003***	0.317
	(0.0003)		(0.0002)		(0.0002)		(0.0002)		(0.0001)		(0.0001)	
Difference in authors' years of experience	-0.004***	-0.213	-0.005***	-0.314	-0.005***	-0.259	-0.003***	-0.198	-0.001***	-0.125	-0.002***	-0.166
	(0.0004)		(0.0004)		(0.0004)		(0.0003)		(0.0002)		(0.0002)	
Baseline probability	0.021		0.016		0.018		0.013		0.009		0.010	

Years	2008		2010		2012		2014		2016	
	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME
Same country	0.021***	1.647	0.020***	1.672	0.017***	1.934	0.022***	1.824	0.029***	1.578
	(0.0004)		(0.0003)		(0.0003)		(0.0003)		(0.0004)	
Same institution	0.026***	2.078	0.026***	2.166	0.021***	2.286	0.026***	2.144	0.037***	2.066
	(0.0004)		(0.0004)		(0.0003)		(0.0003)		(0.0005)	
Popularity years of	0.005***	0.361	0.005***	0.393	0.003***	0.309	0.004***	0.363	0.007***	0.364
experience	(0.0001)		(0.0001)		(0.0001)		(0.0001)		(0.0001)	
Difference in authors'	-0.009***	-0.148	-0.002***	-0.200	-0.001***	-0.082	-0.001***	-0.114	-0.002***	-0.133
years of experience	(0.0002)		(0.0002)		(0.0001)		(0.0001)		(0.0002)	
Baseline probability	0.013		0.011		0.009		0.012		0.018	

Note: All continuous variables are z-standardized to enhance the comparability of estimates across models. Delta standard errors (Duxbury, 2019) are reported in parentheses. Scaled AMEs are AMEs divided by the baseline probability and can be interpreted as relative changes in tie probability if a network variable increases by one unit. We multiplied scaled AMEs by 100 to provide a measure capturing the percentage change of the baseline probability in figure 3.3 and figure 3.4.

† $p < 0.10$

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$ (two-sided)

Table A3. The role of productivity for the collaboration network of neuroblastoma researchers in exponential random graph models (ERGMs)

Years	1979		1984		1987		1990		1993		1994	
	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME
Same country	-0.005 (0.021)	-0.130	0.095*** (0.008)	1.807	0.065*** (0.006)	1.059	0.074*** (0.003)	2.258	0.046*** (0.002)	1.500	0.078*** (0.003)	2.385
Same institution	0.107*** (0.017)	2.684	0.090*** (0.008)	1.715	0.092*** (0.009)	1.488	0.055*** (0.003)	1.658	0.060*** (0.002)	1.920	0.033*** (0.003)	1.013
Popularity cumulated publications	0.009 (0.010)	0.226	-0.0004 (0.006)	-0.002	0.015*** (0.002)	0.238	0.006*** (0.001)	0.186	0.011*** (0.001)	0.343	0.006*** (0.001)	0.173
Difference cumulated publications	-0.025 (0.016)	-0.618	0.006 (0.006)	0.116	0.005 (0.003)	0.087	0.001 (0.002)	0.031	-0.004*** (0.001)	-0.123	-0.003* (0.0015)	-0.095
Baseline probability	0.040		0.053		0.062		0.033		0.031		0.032	
Years	1996		1998		2000		2002		2004		2006	
	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME
Same country	0.037*** (0.001)	1.796	0.032*** (0.001)	2.039	0.029*** (0.001)	1.608	0.029*** (0.001)	1.608	0.021*** (0.0004)	2.285	0.019*** (0.0004)	1.841
Same institution	0.036*** (0.001)	1.751	0.028*** (0.001)	1.793	0.036*** (0.001)	2.011	0.026*** (0.0005)	2.011	0.020*** (0.0003)	2.102	0.024*** (0.0003)	2.289
Popularity cumulated publications	0.009*** (0.0003)	0.433	0.006*** (0.0002)	0.361	0.007*** (0.0003)	0.386	0.005*** (0.0002)	0.386	0.002*** (0.0001)	0.256	0.004*** (0.0001)	0.377
Difference cumulated publications	-0.003*** (0.0004)	-0.136	-0.002*** (0.0003)	-0.117	-0.003*** (0.0004)	-0.179	-0.002*** (0.0003)	-0.179	-0.004*** (0.0002)	-0.073	-0.002*** (0.0002)	-0.165
Baseline probability	0.021		0.016		0.018		0.013		0.009		0.010	

Years	2008		2010		2012		2014		2016	
	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME
Same country	0.020***	1.622	0.019***	1.640	0.017***	1.895	0.022***	1.790	0.028***	1.563
	(0.0004)		(0.0003)		(0.0003)		(0.0003)		(0.0004)	
Same institution	0.026***	2.088	0.025***	2.158	0.021***	2.305	0.026***	2.125	0.036***	2.013
	(0.0004)		(0.0003)		(0.0003)		(0.0003)		(0.0005)	
Popularity cumulated publications	0.005***	0.422	0.006***	0.469	0.003***	0.380	0.005***	0.438	0.008***	0.438
	(0.0001)		(0.0001)		(0.0001)		(0.0001)		(0.0001)	
Difference cumulated publications	-0.002***	-0.181	-0.003***	-0.243	-0.001***	-0.146	-0.002***	-0.191	-0.004***	-0.208
	(0.0001)		(0.0001)		(0.0001)		(0.0001)		(0.0002)	
Baseline probability	0.013		0.011		0.009		0.012		0.018	

Note: All continuous variables are z-standardized to enhance the comparability of estimates across models. Delta standard errors (Duxbury, 2019) are reported in parentheses. Scaled AMEs are AMEs divided by the baseline probability and can be interpreted as relative changes in tie probability if a network variable increases by one unit. We multiplied scaled AMEs by 100 to provide a measure capturing the percentage change of the baseline probability in figure 3.3 and figure 3.4.

† $p < 0.10$

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$ (two-sided)

Table A4. The role of last authorships for the collaboration network of neuroblastoma researchers in exponential random graph models (ERGMs)

Years	1979		1984		1987		1990		1993		1994	
	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME
Same country	-0.004	-0.092	0.094***	1.791	0.064***	1.038	0.075***	2.280	0.049***	1.594	0.080***	2.432
	(0.021)		(0.008)		(0.006)		(0.003)		(0.002)		(0.003)	
Same institution	0.109***	2.741	0.092***	1.740	0.095***	1.538	0.052***	1.591	0.055***	1.769	0.031***	0.941
	(0.017)		(0.008)		(0.009)		(0.003)		(0.003)		(0.003)	
Popularity share last author positions	0.0004	0.004	-0.007	-0.139	-0.009	-0.151	-0.013***	-0.385	-0.0025*	-0.080	-0.007***	-0.208
	(0.007)		(0.006)		(0.005)		(0.003)		(0.0012)		(0.002)	
Difference share last author positions	0.002	0.052	0.009	0.174	0.003	0.046	0.011**	0.318	0.0001	0.003	0.006**	0.194
	(0.009)		(0.006)		(0.006)		(0.003)		(0.001)		(0.002)	
Baseline probability	0.040		0.053		0.062		0.033		0.031		0.032	

Years	1996		1998		2000		2002		2004		2006	
	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME
Same country	0.039***	1.895	0.034***	2.119	0.030***	1.676	0.031***	2.269	0.022***	2.348	0.020***	1.909
	(0.001)		(0.001)		(0.001)		(0.001)		(0.0004)		(0.0004)	
Same institution	0.034***	1.658	0.027***	1.725	0.035***	1.981	0.025***	1.890	0.020***	2.108	0.024***	2.295
	(0.001)		(0.001)		(0.001)		(0.001)		(0.0003)		(0.0003)	
Popularity share last author positions	0.0009	0.044	0.0004	0.026	0.0010*	0.056	0.002***	0.115	0.0004*	0.043	0.001***	0.067
	(0.0005)		(0.0004)		(0.0005)		(0.0003)		(0.0002)		(0.0002)	
Difference share last author positions	-0.001*	-0.066	0.0005	0.034	0.0006	0.032	>0.0001	-0.001	0.0002	0.020	-0.0002	-0.019
	(0.0006)		(0.0005)		(0.0006)		(0.0003)		(0.0002)		(0.0002)	
Baseline probability	0.021		0.016		0.018		0.013		0.009		0.010	

Years	2008		2010		2012		2014		2016	
	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME	AME	Scaled AME
Same country	0.021***	1.701	0.021***	1.777	0.018***	2.006	0.023***	1.877	0.029***	1.630
	(0.0004)		(0.0003)		(0.0003)		(0.0003)		(0.0004)	
Same institution	0.026***	2.059	0.025***	2.090	0.021***	2.309	0.026***	2.106	0.036***	1.981
	(0.0004)		(0.0003)		(0.0003)		(0.0003)		(0.0005)	
Popularity share last author positions	0.001***	0.106	0.002***	0.144	0.001***	0.108	0.002***	0.146	0.001***	0.077
	(0.0002)		(0.0001)		(0.0001)		(0.0001)		(0.0002)	
Difference share last author positions	-0.001***	-0.090	-0.001***	-0.123	-0.0004*	-0.048	-0.001***	-0.095	-0.002***	-0.102
	(0.0002)		(0.0002)		(0.0002)		(0.0002)		(0.0003)	
Baseline probability	0.013		0.011		0.009		0.012		0.018	

Note: All continuous variables are z-standardized to enhance the comparability of estimates across models. Delta standard errors (Duxbury, 2019) are reported in parentheses. Scaled AMEs are AMEs divided by the baseline probability and can be interpreted as relative changes in tie probability if a network variable increases by one unit. We multiplied scaled AMEs by 100 to provide a measure capturing the percentage change of the baseline probability in figure 3.3 and figure 3.4.

† $p < 0.10$

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$ (two-sided)

B. Stochastic Actor-Oriented Models

In addition to our main analytical strategy, we also analyzed the data set with stochastic actor-oriented models (SAOMs), which have been developed to capture dynamic social processes (Snijders, 2011). Detailed explanations can be found in Ripley et al. (2019) and Snijders et al. (2010). These models treat changes in collaboration ties as the result of a continuous-time Markov process in which actors "choose" whom to collaborate with based on an objective function. This actor-oriented approach in principle allows researchers to estimate parameters for theoretically assumed network mechanisms under consideration of endogenous network dynamics.[75]

A note of caution

Despite the numerous analytical advantages of SAOMs, certain methodological concerns ultimately forced us to abandon SAOMs as part of our primary analytical strategy. One of these concerns was related to a poor goodness of fit, an issue which seems to be impossible to circumvent in applications to large networks at the method's current developmental stage (Stark et al. 2020: 458, endnote 2; Lewis and Kaufman 2018: 1736–1737). Another problem was that SAOMs assume that actors are aware of all potential partners in the network (Ripley et al., 2019; Snijders et al., 2010). This assumption might be warranted for early stages of

[75] It is also possible to account for the longitudinal structure of the data set in the ERGMs framework by controlling for previous collaborations. We performed analyses that controlled for previous collaborations by considering whether dyads had a tie during earlier stages of the network, which is in line with previous studies (e.g., McFarland et al., 2014). These analyses showed very similar results compared with analyses reported in the main text and are available upon request. We decided to report models without controlling for previous collaborations because advancements in the interpretation of longitudinal network models raised doubts about whether an auto-regressive approach is valid for ERGMs (Block et al., 2018). Nevertheless, it is reassuring that our interpretation of the results remains qualitatively unchanged if we enter previous collaborations in our model specifications.

neuroblastoma research but it becomes problematic for later stages as the field quickly grew, encompassing more than 200 researchers from the early 1990s onward.

Therefore, we would like to emphasize that the reported network models should be interpreted only with the greatest caution regarding the substantial claims made in this article. However, we hope that these additional results will be informative for other researchers facing similar problems in their applications of network models to large data sets with changing sizes. Also, changes between models may still provide a qualitative indication of changes in network structure, e.g., if they are compared between periods with similar sizes.

Model specification

We included four parameters in all specifications. The so-called “degree activity effect” captures how popular a researcher is as a collaborator based on her previously accumulated number of coauthorships. A positive estimate indicates that preferential attachment is occurring, and scientists with many coauthor ties maintain and attract more ties over time. The second parameter, “degree homophily” (alias “assortativity”), measures whether authors with a similar number of coauthorships are more or less likely to collaborate. A significantly negative value for this parameter indicates a tendency for authors with many ties to collaborate with others who have fewer coauthorships. The third effect (“Experience of author”) depicts whether authors who have a long experience in the field are more attractive as collaborators: this is the case if the effect turns positive and significant. The fourth parameter is called “Similar experience” and measures whether researchers with similar years of experience are more likely to collaborate with each other than researchers with dissimilar years of experience. We would interpret a significantly positive estimate here as a sign of the presence of status homogeneity in the network. Likewise, we included a term capturing the network popularity of scientists according to their cumulated publications record (“Publications of author”) and a corresponding parameter indicating whether scientists with similar publication records are more likely to collaborate (“Similar number of publications”). Moreover, we add the “Share of last author positions” term to account for the accumulation of coauthorships that occurs due to being the leader of a research group, i.e., seniority. Likewise, we included a term that captures homogeneity according to seniority (“Similar share of last author positions”).

Control variables

Besides past coauthorship, experience, productivity, and seniority, many other factors are also influential in the formation of scientific collaboration. As highlighted by Wuchty et al. (2007), the average number of coauthor ties increased dramatically over time. To control for the number of ties, we included the “density” term, which is always part of SAOMs and which captures the density of the network. A negative term indicates that fewer ties are present than there would be if a random allocation of ties took place. Previous research illustrated that collaboration is—like many social relationships—bound to foci of activity (Feld, 1981). For instance, coauthorships are more prevalent among researchers in the same department (Dahlander and McFarland, 2013; Stark et al., 2020). To account for these foci of interaction we included a term capturing whether two authors are affiliated with the same institution (“same institution”) or country (“same country”). Moreover, we added the geometrically weighted edgewise-shared partner (GWESP) effect, which models transitivity—the tendency to collaborate with others who collaborate with one’s current coauthors—to further account for the local clustering of ties.

Table B1. Stochastic actor-oriented models SAOMs for collaboration network of neuroblastoma researchers

Periods	1975-1987	1984-1987	1987-1990	1990-1993	1993-1994	1994-1996	1996-1998	1998-2000
Density	-2.56***	-2.83***	14.18	-2.88***	10.15	-3.76***	-2.50***	-3.35***
	(0.41)	(0.24)	(8.62)	(0.16)	(11.13)	(0.82)	(0.22)	(0.13)
Geometrically weighted edgewise-shared partners (GWESP)	5.90***	3.60***	10.56**	4.10***	12.99 †	5.09***	4.98***	4.67***
	(1.00)	(0.25)	(4.23)	(0.20)	(6.88)	(0.46)	(0.35)	(0.14)
Degree activity (preferential attachment)	0.31***	0.19***	0.80 †	0.17***	0.87	0.28*	0.12***	0.11***
	(0.09)	(0.04)	(0.48)	(0.02)	(0.50)	(0.15)	(0.03)	(0.01)
Degree homophily (assortativity)	-0.97***	-0.49***	-3.23†	-0.48***	-3.55	-0.75**	-0.54***	-0.39***
	(0.25)	(0.10)	(1.73)	(0.05)	(2.20)	(0.30)	(0.09)	(0.03)
Same country	-3.03***	-2.36***	-3.40†	-2.08***	-2.52	-1.73***	-1.09***	-2.11***
	(0.67)	(0.35)	(1.63)	(0.30)	(2.19)	(0.35)	(0.13)	(0.15)
Same institution	1.08†	1.41***	-0.61	0.02	-0.62	-0.35	0.02	0.45***
	(0.64)	(0.37)	(1.38)	(0.26)	(1.31)	(0.44)	(0.14)	(0.11)
Experience of author	0.02	0.07 †	0.24*	0.06 †	-0.08	0.14*	-0.03	0.01
	(0.06)	(0.037)	(0.12)	(0.04)	(0.10)	(0.07)	(0.02)	(0.01)
Similar experience	0.08	0.43	1.66	0.83	-1.22	2.42**	0.18	0.12
	(0.56)	(0.31)	(1.47)	(0.60)	(1.49)	(0.80)	(0.30)	(0.27)
Publications of author (cumulative)	0.22**	0.01	0.35**	0.04	0.03	0.08**	0.07***	0.03***
	(0.08)	(0.13)	(0.13)	(0.04)	(0.06)	(0.03)	(0.01)	(0.01)
Similar number of publications	4.73***	0.42	2.34	0.44	-0.41	2.35***	1.67**	2.16***
	(1.89)	(0.78)	(1.51)	(0.40)	(1.56)	(0.66)	(0.64)	(0.40)
Share of last author positions	0.15	-0.21	-3.14	0.47*	-3.82	-0.16	0.44*	0.19
	(0.42)	(0.34)	(2.32)	(0.24)	(3.20)	(0.48)	(0.21)	(0.20)
Similar share of last author positions	0.24	-0.26	0.17	0.22	-2.45	-0.27	0.26	0.17
	(0.39)	(0.33)	(1.10)	(0.22)	(2.65)	(0.28)	(0.21)	(0.17)
Number of actors	158	152	240	323	364	531	708	721
Overall convergence ratio	0.16	0.17	0.14	0.17	0.15	0.17	0.17	0.14

Periods	2000-2002	2002-2004	2004-2006	2006-2008	2008-2010	2008-2012[76]	2012-2014	2014-2016
Density	-2.09***	-1.37***	-3.59***	-4.93***	-5.83***	-5.97***	-5.70***	-7.96***
	(0.29)	(0.21)	(0.11)	(0.14)	(0.42)	(0.18)	(0.74)	(0.51)
Geometrically weighted edgewise-shared partners (GWESP)	5.22***	5.86***	5.00***	4.43***	4.92***	4.99***	4.70***	5.17***
	(0.61)	(0.18)	(0.14)	(0.09)	(0.36)	(0.12)	(0.62)	(0.33)
Degree activity (preferential attachment)	0.17***	0.20***	0.10***	0.04***	0.04***	0.05***	0.04***	0.03***
	(0.17)	(0.02)	(0.01)	(0.004)	(0.004)	(0.003)	(0.01)	(0.003)
Degree homophily (assortativity)	-0.68***	-0.81***	-0.40***	-0.17***	-0.17***	-0.20***	-0.16***	-0.10***
	(0.20)	(0.04)	(0.03)	(0.01)	(0.01)	(0.008)	(0.04)	(0.01)
Same country	-1.60***	-1.89***	-1.70***	-1.51***	-1.28***	-0.98***	-1.36***	-0.61***
	(0.18)	(0.12)	(0.09)	(0.06)	(0.10)	(0.05)	(0.19)	(0.04)
Same institution	0.48***	0.26***	0.14*	0.26***	0.45***	0.34***	0.42***	0.51***
	(0.14)	(0.09)	(0.075)	(0.06)	(0.07)	(0.05)	(0.05)	(0.05)
Experience of author	0.05***	0.01	-0.02*	-0.01*	-0.007†	-0.007*	-0.01***	0.01***
	(0.01)	(0.01)	(0.01)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)
Similar experience of authors	1.02***	0.66*	0.49*	0.11	0.04	-0.02	-0.22	0.28**
	(0.32)	(0.28)	(0.23)	(0.14)	(0.10)	(0.09)	(0.22)	(0.11)
Publications of author (cumulative)	0.02*	0.03***	0.04***	0.02***	0.02***	0.01***	0.02***	0.004***
	(0.01)	(0.01)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Similar number of publications	0.87	0.76	3.69***	2.48***	3.02***	2.27***	3.24***	1.69***
	(0.74)	(0.71)	(0.49)	(0.28)	(0.24)	(0.20)	(0.63)	(0.23)
Share of last author positions	-0.18	0.10	0.79***	0.44***	0.52***	0.46***	0.45**	0.75***
	(0.23)	(0.22)	(0.14)	(0.11)	(0.14)	(0.09)	(0.18)	(0.15)
Similar share of last author positions	-0.38	-0.07	0.39***	-0.05	0.15	0.15†	-0.002	0.08
	(0.24)	(0.19)	(0.13)	(0.10)	(0.10)	(0.08)	(0.002)	(0.17)
Number of actors	814	1155	1257	1334	1517	1850	1585	1417
Overall convergence ratio	0.17	0.23	0.20	0.23	0.20	0.12	0.18	0.20

Note: Standard errors are reported in parentheses. † $p < 0.10$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$ (two-sided)

[76] It was not feasible to estimate a converging model for the period 2010 to 2012. However, defining a period, which entailed three conferences, allowed us to obtain converging estimates for the same model specification as for the other periods.

Results

We now apply SAOMs to investigate how their results relate to our findings reported in the main text.[77] We investigated the 18 conferences in 16 periods and ran our model specification separately for each of these periods. We chose this partitioning of the data because it allowed for converging estimates whereas longer periods often proved too complex for the model (cf., Stark et al. 2020: 444). All presented models showed an overall convergence ratio smaller than 0.25, which indicates appropriate convergence (Ripley et al. 2019).

Regarding our theoretical expectation that accumulation dynamics diversify as neuroblastoma research ages, table B1 shows that parameters capturing the popularity of scientists according to their productivity and seniority did not consistently show statistically significant values until the second half of the 1990s. In a similar vein to our results in the main text, SAOMs indicated that productivity became a relevant factor for scientists' popularity as coauthors from 1994 onwards. It took even longer for seniority to contribute to scientists' accumulation of coauthorships (from 2004 onward). In comparison, preferential attachment was present for almost all periods.

Concerning our expectation that status homogeneity becomes stronger as a field matures, SAOMs produced results that were broadly consistent with our main analyses: as the field entered the second half of its development, the parameter capturing whether scientists with a similar publication record are more likely to collaborate gained in size and was consistently significant after 2004. In line with our conjecture that scientists with many coauthor ties tend to collaborate with others holding fewer ties because they have just entered the field as PhD

[77] Given that the networks under investigation are undirected, we followed the advice provided in Ripley et al. (2019: 52) to choose a model type informing the estimation procedure. We chose model type 3, which assumes that one actor takes the initiative in proposing a new or resolving an existing tie. While it is only possible for a new tie to form if the other actor agrees, no consent of the other actor is needed to resolve a tie.

students or postdoctoral researchers, we observed a consistently negative significant parameter for degree heterophily.[78] This corroborates the notion that while status-similar collaborations should become more prevalent as a stratified order emerges, the mentor-apprentice model of collaboration should not lose its importance for the organization of research activity.

We would like to note that the observed trends also hold for the time span from 2002 onwards. Periods in this part of the network's development show sizes between 1,155 and 1,585 actors.[79] While this is still a relevant shift in network size, previous accounts compare estimates from models that differ similarly or even more strongly in network size (An, 2015; Goodreau et al., 2009; Kronegger et al., 2012; McFarland et al., 2014; Simpson, 2019; Stark et al., 2020). Therefore, we interpret our results as at least a qualitative indication of changes in network structure. However, future research should address the problem of comparing longitudinal network models between periods with starkly differing sizes and re-evaluate our results and interpretations.

Relative importance measures

While we limit our discussion of SAOM results to a heuristic comparison of coefficients over time, we also considered the measures of relative importance (RI) proposed by Indlekofer and Brandes (2013). In principle, these measures allow a comparison of the relative importance of different network tendencies for actors' collaboration choices (for recent applications, see

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[78] This finding could also partially be due to the "friendship paradox" discovered by Feld (1991). Feld showed that the average number of friendships one's friends have is almost always higher than one's own number of friendships. In essence, the disproportionate weighting of friends with many ties in the calculation of one's friends' average number of friendships is responsible for this phenomenon. From this, it follows that scholars probably have fewer coauthorship ties than their coauthors have (on average).

[79] Please note that the number of actors for the period 2008-2012 is not comparable because this period encompasses three instead of two conferences. The reason for this decision was an issue with model degeneracy; please see the corresponding footnote in table B1.

Rambaran et al., 2020; Schaefer and Kreager, 2020; Stark et al., 2020). However, we decided not to use RIs for several reasons. First, these measures do not consider uncertainty in estimates—many coefficients were large but insignificant in early periods—making the interpretation of their RIs problematic. Second, RIs are an aggregation of individual scores and actors in our data set exhibit strong heterogeneity in terms of overall degrees and the distribution of attributes. While this is not a problem per se, it strains credulity as to how meaningful RIs are in our case. Third, the current implementation of RIs only covers undirected networks of type 2, meaning that one actor can propose or dissolve a tie without the other actor's consent. Instead, though, we chose model type 3, which assumes that one actor takes the initiative in proposing or resolving a tie, but the other actor has to agree if a tie is initiated (Ripley et al., 2019).

III. Appendix to Chapter 4

A. Derivation of analytical sample from complete dataset

The IMDb dataset which served as starting point for our analyses encompasses a time span from 1900 to 2000, entails 102,905 persons, 123,980 films, and 9,024 films that included at least one artistic reference. The following professional roles are present in the full dataset: cinematographer, composer, costume designer, director, editor, producer, production personnel, and writer. Note that actors and actresses as well as other professional roles were excluded upfront. Likewise, the following genres: news, talk-show, gameshow, reality-tv, and adult movies were omitted during the process of scraping our initial data set from IMDb. The included genres are: action, adventure, animation, biography, comedy, crime, documentary, drama, family, fantasy, film-noir, history, horror, music, musical, mystery, romance, sci-fi, short, sport, thriller, war, and western.

As our theoretical considerations are geared toward the cultural field of filmmaking, we decided to exclude all professional roles except writers and directors. The other roles contribute decisively to the creative process of filmmaking, but constitute cultural fields in their own right that often traverse the boundaries of the film industry. For instance, composers and musicians strongly influence the overall feel and aesthetic appeal of a film, yet they can only seldom decide in which films they participate, often have professional engagements outside Hollywood, and form a distinct community with their own standards of evaluation (Crossley 2019; Faulkner 1983, 2017; Lena 2012; McAndrew and Everett 2015).

Furthermore, we only included filmmakers who participated in at least two films and had a career length of at least three years. The majority of filmmakers participated in only one film before they left the industry (~62% of all writers and directors). We focus on the stable part of the sample, because we are interested in how filmmakers who manage to participate regularly in film projects form collaborations and artistic references among each other. In addition, we focused on the time from 1921 onward, because previously there are very few artistic references with less than one 1% of filmmakers referencing. Table A1 summarizes the different steps we took to arrive at our analytical sample.

Table A1. Criteria for analytical sample overview

Time frame	Roles	Career length	Minimal number of films	Total number of filmmakers	Total number of films	Total number of referenced films
1900-2000	Writer, Director	At least 1 year	At least 1 film	44,259	97,284	8,918
1900-2000	Writer, Director	At least 1 year	At least 2 films	16,699	88,432	8,583
1900-2000	Writer, Director	At least 2 years	At least 2 films	15,691	87,571	8,558
1900-2000	Writer, Director	At least 3 years	At least 2 films	14,070	85,922	8,536
1921-2000	Writer, Director	At least 3 years	At least 2 films	13,544	61,129	8,522

B. Goodness of fit (GOF)

We assessed the goodness of fit (GOF) of all models by simulating networks from estimated ERGMs and comparing their degree, edgewise-shared partner, and geodesic distance statistics with the observed statistics in the corresponding network (Hunter et al., 2008). As becomes clear from table 2 and 3, the GOF was insufficient (far below 90%) in most periods. An insufficient GOF is not unusual in large networks (similar issues are reported for SAOMs by Lewis and Kaufman, 2018: 1736, Stark et al., 2020: 458). We tried to increase the GOF by adding geometrically weighted statistics—such as the GWDEG and GWESP terms (Hunter, 2007). Yet, these statistics led to model degeneracy in several periods, which is probably due to the different estimation procedures used by models considering higher order structures.[80] Consequently, we decided to report simpler specifications that worked for all periods.

While a high GOF is desirable, we would like to point out that hypotheses 3 and 4 are concerned with the role of filmmakers' attributes for network structure (i.e., the role of artistic status for network structure). Therefore, specifications without higher order terms are sufficient for our purpose. Moreover, terms beyond dyadic configurations introduce complex interdependencies among parameters and thereby complicate interpretation (Martin, 2020; Rubineau et al., 2019).

C. Robustness checks: user preferences and probability of inclusion in the IMDb

Because IMDb is a user-generated database, we may wonder to what extent the number of a film's listed references correlates with IMDb user preferences. Otherwise, we risk ending up with a selective sample of films and references if the number of listed references per film reflects IMDb user tastes more than the actual number of a film's references. This selectivity is potentially problematic for our investigation as we study the *status order* of films in the field of filmmaking, and not the *popularity rank* of films among IMDb users. Hence, we wonder if some films score high on degree because they are truly influential among filmmakers, or because they are popular among IMDb users.

[80] While models that operate only on the dyad level use pseudo-maximum likelihood estimation, models that include terms beyond dyadic interdependence rely on Monte Carlo Markov Chains (Hunter et al., 2008). The latter simulation-based estimation procedure probably caused model instability in the networks under study.

We address this caveat in two ways. First, we measured correlations between the number of user votes for films and their average user rating scores, on the one hand, and, on the other, the indegree and outdegree in the artistic reference network among films. The number of votes for a film reflects how recognized it is among the IMDb audience, whereas the rating score tells us how valued it is. Together, both numbers indicate how popular a film is in the eyes of IMDb users. Network indegree measures the number of references a film received by other films, and network outdegree measures the number of references made to other films that a given film entails. We assess the correlation between network degree and user votes and ratings for the subset of 9,436 films that sent (n = 6,686 films) or received (n = 8,578 films) at least one reference. This may include cases where either indegree > 0, and outdegree = 0, or indegree = 0, and outdegree > 0.[81]

We find only a very moderate correlation between network degree and user scores. Certainly, IMDb users constitute a select group of film connoisseurs who are well versed in film history, and if a canon of influential films does exist, they should be able to identify such classics in the field. Hence, we expect some moderate correlation between a film's centrality in the reference network and user votes. Indeed, the number of references that a film received (network indegree) correlates modestly with the number of rating votes (r = .44), which suggests that IMDb users are able to recognize canonical films. When it comes to the valuation of films, however, the correlation between indegree and the average rating score is smaller (r = .20).

[81] We do not consider the correlations for all 52,353 films in our dataset because the vast majority of films would show a degree = 0. Substantively, these cases are not meaningful for our purpose because they played no influential role in film history, and thus are unlikely to have contributed to the emergence of an artistic status order. Including such network isolates in our robustness check would effectively amount to testing if influential films and those that left no trace in film history differed in the number of user votes and ratings they received. Instead, our purpose here is to assess to what extent any network degree > 1 is systematically related to IMDb user votes and ratings. An additional obstacle is that information on user scores is missing for about 25% of all films in the complete dataset.

Problematic for our investigation would be a strong correlation between network outdegree and user scores because it could imply that, for films they value, users see references that don't even exist. However, this is not the case as the correlations between outdegree and the number of rating votes ($r = .35$), and between outdegree and the average rating score ($r = .05$) are even weaker than for indegree.

Second, beyond these summary statistics, we further show that the status order among films (as measured by the number of references received and sent) is not strongly connected to the popularity rank of films (as measured by users' votes and ratings). In the boxplots in figure C.1, we compare three broad status groups of films (high, medium, low network degree) with respect to their average user votes and ratings.[82] For indegree, we group films that received no references into the lowest status (indegree = 0; n = 4,127 observations), films that received 1-3 references into the medium status (equal to, or above the 50th percentile in the degree distribution; n = 4,269), and films that received 4 and up to 359 references into the highest status (equal to the 90th percentile in the degree distribution; n = 1,040). For outdegree, the low status group includes films that made no references to other films (n = 2,809); the medium status group includes films that made 1-6 references (equal to, or above the 30th percentile in the degree distribution; n = 5,545); and the high-status group entails films that made 7 and up to 260 references to other films (equal to the 90th percentile; n = 1,082).[83]

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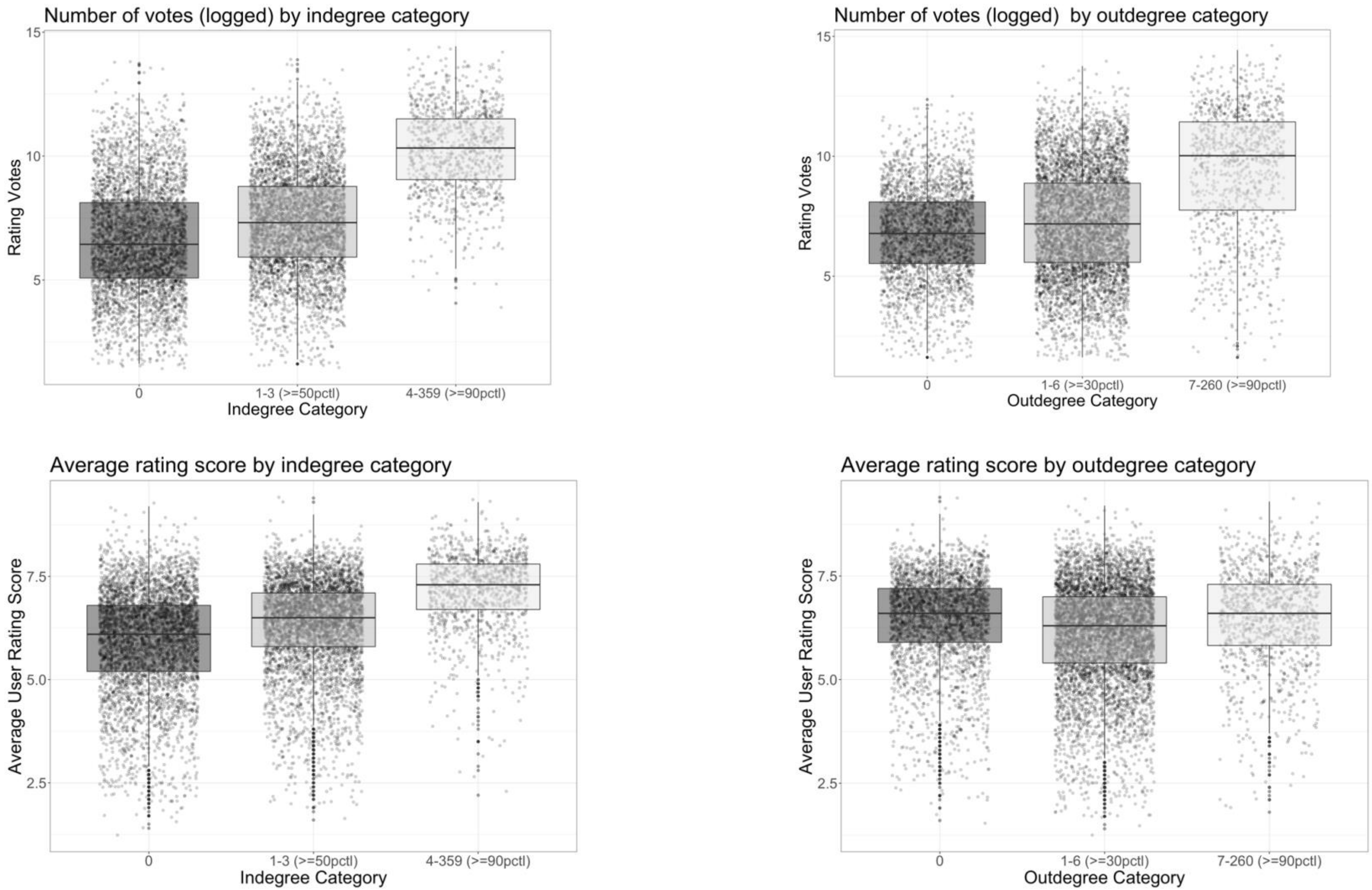
[82] We logged the number of user votes because the underlying distribution is highly skewed (mean = 19,153.05; sd = 74,819.99).

[83] Recall that the exchange of references is not necessarily reciprocal or generalized: a given film may reference others but receive no references in return, and vice versa.

Figure C1. Distribution of IMDb user votes and average rating scores across indegree and



If a film's IMDb user popularity dictates the number of sent and received references, then we should observe little, if any overlap in the distribution of user votes and ratings between the three status groups of films, and references should be concentrated on the most popular films.

Again, we may expect some moderate positive relationship because filmmakers as well as IMDb film connoisseurs may consider some films as canonical. The boxplots suggest a slight tendency towards this relationship for the number of user votes. More important, however, we find that the distributions of all three status groups overlap. In other words, films with few, middling, or large numbers of references are likely to receive low, middling, or high scores from IMDb users.[84] This finding is particularly striking for the comparison of rating scores, and hence the valuation, not only identification, of films by users. In sum, we find little evidence that supports the caveat that the recorded references among films merely reflect IMDb user preferences.

[84] We, thus, extend the sensitivity analysis by Spitz and Horvát (2014), who only focused on the top-50 cited films.

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V. Declaration on Sources

Eidesstattliche Erklärung nach § 8 Abs. 3 der Promotionsordnung vom 17.02.2015

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Ort, Datum
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