Social Networks 55 (2018) 202–212

Contents lists available at ScienceDirect

Social Networks

journal homepage: www.elsevier.com/locate/socnet

Duality of departmental specializations and PhD exchange: A Weberian analysis of status in interaction using multilevel exponential random graph models (mERGM)

Neha Gondal

Boston University, 100 Cummington Mall, Boston 02215, USA

ARTICLE INFO

Keywords:
PhD exchange networks
Academic stratification
Multilevel ERGM
Research specialties

ABSTRACT

Weber proposes that lifestyle similarities preserve status by producing interactional closure between status similar actors. I investigate this theory on academic status hierarchies by conceptualizing sub-disciplinary specializations as departmental lifestyles and PhD exchange networks as interdepartmental interactions. Multilevel exponential random graph models (mERGM) reveal that the more specializations departments share, the more likely they are to exchange personnel. On the flip side, departments that do not share specializations are less likely to exchange doctoral candidates. Moreover, shared specializations are key determinants of closure between elite departments. These results support Weber's theory and suggest that shared specializations preserve existing patterns of inequality between elite and non-elite departments.

Introduction

Status, according to Weber (1978), is an honor-based stratification order with implications for access to resources and other entitlements. It is distinctive from other social orders, such as class, because members of comparable status rank are expected to exhibit similar styles of life or *lifestyles*. Such lifestyle similarities impose strong constraints on social intercourse producing closure in the various relations interlinking members. The organizational field comprising university academic departments is an exemplary instance of a Weberian status orders (Gross, 1970). High-ranking, elite departments have privileged access to material resources such as grants, faculty lines, funding for graduate students, and institutional support (Allison and Long, 1990; Hagstrom, 1965). They also exercise greater control over the discipline's agenda as well as the norms of research (Gross, 1970; Merton, 1968). Such status differences are consequential for interdepartmental interactions, especially in reference to the exchange of PhDs (Baldi 1994; Barnett et al., 2010; Barnett and Feeley, 2011; Bothner et al., 2010; Burris, 2004; Clauset et al., 2015; Gross, 1970; Hanneman, 2001). Research emphatically demonstrates that, across time and discipline, elite departments tend to hire within ranks producing closure and are considerably more successful at placing their graduates at all other rungs of the ranking ladder, as well. Upward mobility or the employment of graduates of lower-ranked departments at higher-ranked ones is nearly nonexistent, in contrast.

Yet, we do not know how the other side of Weber's status equation - shared lifestyles - shapes personnel exchange between departments. Drawing on canonical literature in the sociology of science (e.g. Crane, 1972; Haas, 1992; Kuhn, 1970), I conceptualize departmental lifestyles as areas of sub-disciplinary *specialization*. Specializations are the self-identified areas of research expertise in which departments hire faculty, train graduate students, and conduct research. I use the case of doctoral exchange in sociology to investigate the Weberian relationship between interactional closure and lifestyle similarities. The data for this paper are sourced from the printed edition of the *American Sociological Association's* (ASA) Guide to Graduate Departments for the year 2014. This guide lists faculty members currently employed in graduate departments in the United States and where they received their doctoral degree, which forms the basis of the doctoral exchange network. The ASA guide also lists self-reported 'special programs and areas of expertise' for each department, which I employ as a measure of shared departmental lifestyles.

I use these data to construct three networks: (1) a one-mode network of interdepartmental exchange of doctoral students, (2) a two-mode network composed of departments and their disciplinary specializations, (3) a cross-level network that links departmental specializations to departmental doctoral exchange. I employ cutting edge multilevel exponential random graph models (mERGM) to analyze the three networks (Wang et al., 2013, 2016). The one- and two-mode networks reveal hierarchical core-periphery patterns of interaction –

E-mail address: gondal@bu.edu.

https://doi.org/10.1016/j.socnet.2018.07.005

Available online 08 August 2018
0378-8733/

some departments and some specializations are more popular than others. The one-mode network also reveals that departmental rankings are decisive in doctoral exchange. Yet, internal models that treat these two networks as operating independent of each other fail to explain the structure of the cross-level network that accounts for doctoral exchange and specializations simultaneously. More complex multilevel ERGM models reveal that shared departmental specializations are important to the exchange of sociology doctorates. Crucially, the more specializations departments share, the more likely they are to exchange personnel. On the flip side, departments that do not share specializations are less likely to exchange doctoral candidates. Moreover, shared specializations are key determinants of closure between elite departments.

Status and lifestyle in academia

Status is the uneven distribution of honor in a community (Weber, 1978). High status actors have claim to special privileges as well as superior access to community resources and opportunities. Moreover, while low-status actors face the burden of proving their worth, the 'social origin' of high-status actors is automatically associated with competence (Bourdieu, 1984). The distinguishing feature of status as opposed to other types of social orders, according to Weber, is that members of comparable standing are expected to exhibit similar *styles of life* (or lifestyles). "In content, status honor is normally expressed by the fact that above all else a specific *style of life* is expected from all those who wish to belong to the circle […] For the decisive role of a style of life in status honor means that status groups are the specific bearers of all conventions." (Weber, 1978: 933–936). Lifestyle similarities are significant because they help to preserve status by imposing strong constraints on social intercourse (Weber, 1978). Bourdieu (1983; 1984) similarly argues that, as possessors of legitimate culture, high-status individuals prefer to align themselves with similar others and distance themselves from those who possess culture considered to be of lower value. This produces social closure in various types of relationships such as marriage and friendship. Empirical research on homophily – the psychosocial preference for associating with those similar to oneself – captures the implications of this desire for interactional closure (Ibarra, 1992; Joyner and Kao, 2000; McPherson et al., 2001; Wimmer and Lewis, 2010). Homophilous interactions produce homogeneity in social networks or 'informal segregation' in communities and its relationship with stratifying attributes like race and socioeconomic status ensures that material and symbolic resources remain ensconced within status groups.

Academia and the business of science operate along similar statused lines. Gross (1970) conceives of academia as an organizational field recognized as such by member departments that generates a shared prestige ordering. Organizational prestige shapes access to resources, norms governing the field, inter-organizational relationships, as well as the concomitant flow of influence. Akin to hierarchies in other social spheres, the closed and centralized structure of inter-organizational relationships reflects and helps support this prestige ordering. This is evident in various forms of academic interactions including collaborations (Babchuk et al., 1999; Goyal et al., 2006; Moody, 2004), citations (Gondal, 2011; Moody and Light, 2006; Small and Griffith, 1974), organizational memberships (Barnett and Danowski, 1992; Cappell and Guterbock, 1992), as well as intellectual overlaps (Hill and Carley, 1999; Lievrouw et al., 1987; Small, 1978).

Research also emphatically demonstrates that the 'interchange of personnel' or the exchange of PhDs between departments – an important form of interaction between departments - reflects academic status hierarchies (e.g. Burris, 2004; Bothner et al., 2010; Clauset et al., 2015; Grannis, 2009). Barnett et al (2010) find that the top ten departments accounts for fifty-eight percent of the positions in communication programs. Gross finds evidence of tremendous closure in sociology departments - faculty at the highest ranked departments were almost exclusively trained within that group. Hanneman (2001) similarly finds sociology to be composed of 'bounded elites' and 'masses.' He also demonstrates that the size of the elite declined over the 1990s indicative of consolidation and worsening of inequality over time. Burris (2004) finds that ninety-one percent of all faculty employed in the top five sociology departments in 1995 received their degrees in top twenty departments. Clauset et al. (2015) demonstrate similar patterns of profound stratification in business, computer science, and history. Analyzing communication departments, Barnett and Feeley (2011) conclude that the pattern of exchange of graduate students is a 'legitimate' measure of program quality.

Despite indisputable evidence demonstrating elite closure in doctoral exchange networks, we do not know how the other side of Weber's equation – shared lifestyles - shapes those interactions. Partly, this inattention is because Weber did not elaborate very much on the concept, defining styles of life somewhat loosely as modes of conduct, speech, thought, and attitudes. Others (Horley et al., 1988; Sobel, 2013) similarly describe lifestyle as any distinctive mode of living recognizable by observable behavior. Zablocki and Kanter (1976) offer a more concrete and solidly cultural definition of lifestyles as 'practices or values that are common to sets of entities or collectivities.' While most researchers discuss lifestyles in the case of individuals, Sobel (2013) and Tumin (1970) extend Weber's definition to meaningfully apply to institutional behavior and their intergroup conduct.

If we accept Zablocki and Kanter's definition, lifestyles have two identifying features: 1) values or practices that are 2) common across entities. While many aspects of academic departmental conduct such as teaching loads and graduate student funding practices conform to this characterization, I argue that *research specializations* or *specialties* are an important domain of lifestyles in academia. Most researchers studying specializations deploy relational tools and theories to describe the concept in terms of 1) the intellectual connections between concepts and/or 2) the social connections between the scientists comprising the subfield (e.g. Chubin, 1976; Crane, 1972; Hargstrom 1970; Small and Griffith, 1974). Comparing these two methodologies, Chubin (1976) argues that a combined approach that accounts for both types of relations is necessary to describe research specialties and their structure more fully. Canonical work in this area supports this contention. In her thesis on 'invisible colleges,' Crane (1972) argues that specialties are clusters of related research areas centered on a set of specific questions or techniques of research. Specialties are composed of members with shared interests in those areas of investigation who interact intellectually and socially. Kuhn, likewise, (1970: 170–210) defines 'paradigms' as coherent traditions of research or "an entire constellation of beliefs, values, techniques, and so on shared by members of a given community." Students are trained and subsequently gain membership in the research community comprising paradigms. Fleck's (1979) 'thought collective' expresses a similar notion of a group with a common style of thinking. Haas (1992) employs a more explicitly interactionist concept – epistemic community – to refer to a network of knowledge-based experts. He, too, emphasizes shared beliefs in forms of knowledge, methods of investigation, values, and discursive practices in the consumption and production of knowledge. Empirical research investigating knowledge networks in sociology demonstrates the presence of significant topical clustering indicative of research specialties (e.g. Crane and Small, 1992; Moody and Light, 2006; Moody, 2004; Gondal, 2011; Star, 1983). Thus, scholarship confirms that research specialties fulfill the twin criteria of lifestyles – sharedness of values (e.g. forms of knowledge and methods of investigation) and practices (e.g. student training and conferences).

Although the preceding description applies the concept of lifestyles to individual researchers' participation in research specialties, the same ideas can be extended to departmental areas of expertise. Much like individual scientists, departments also self-identify with research specialties. While departments are not actors who 'directly' conduct research, their chosen areas of expertise are typically representative and supportive of the interests of the faculty members they currently employ or have employed in the recent past. Departments also collectively engage in practices such as hiring faculty, training students, organizing conferences, and inviting speakers around their chosen set of research specialties. Likewise, much like individual researchers, departments use specializations as values for purposes of self-presentation on their websites, attracting new graduate students, placing job candidates, and departmental external evaluations. Lastly, rather than being unique to particular institutions, specializations are typically common across departments. If self-identified departmental specialties can, thus, be treated as an important element of 'departmental lifestyles', comparable to scientists' social and intellectual networks, are departmental specializations associated with statused interdepartmental interactions as proposed by Weber?

Akin to the case of individual scientists, there are good reasons to expect departmental specializations, conceptualized as values and practices shared across institutions, to lead to heightened likelihood of PhD exchange between institutions. Most notably, departmental specializations manifest in faculty research clusters. Graduate students trained within these clusters are more likely to find jobs in other departments that also value the same research specializations. Second, specializations are not neutral areas of expertise. Rather, as I will demonstrate below, they are characterized by a hierarchical ordering – some fields of research are more popular than others. While the hierarchy may follow a market-driven logic so that specializations in greater demand by undergraduates garner higher prestige, it may also follow a Bourdieusian culture-driven logic whereby esoteric fields that have little 'use' value in undergraduate training or for obtaining grants are regarded more highly. Few departments may have the luxury of the administrative support necessary to specialize in such areas of investigation. Accordingly, those few elite departments are more likely to hire from one another. This feature of the market may also give rise to centralization. Institutions desirous of specializing in elite fields but lacking in administrative support may be unable to train graduate students adequately, but can nevertheless, hire students trained at prestigious schools. Lastly, shared specializations also generate clustering of faculty and graduate students at external venues such as conferences. Advisors also use these spaces to introduce their advisees on the job market to friends and colleagues. This higher density of interactions at the individual level can help produce interactional closure in the form of PhD exchange. Although others (e.g. Barnett et al., 2010; Burris, 2004; Clauset et al., 2015; Weakliem et al., 2011) have found variables such as departmental prestige, faculty size, and university status to be closely linked to inter-departmental faculty exchange, prior research has not investigated the relationship between departmental specialties and hiring hierarchies. Cappell and Guterbock (1992) and Ennis (1992) analyze overlapping memberships in research specialty sections of the American Sociological Association (ASA) in the eighties but they do so at the individual level and do not examine its relationship with departmental hiring networks. I attempt to address this gap in the literature.

While I utilize the employment outcomes of individual faculty members to construct networks of exchange between departments, it is important to note that the analysis is not about individual-level propensities for obtaining jobs. Other research uses individual-level data to investigate the effect of doctoral prestige on job prestige after accounting for individual-level productivity (e.g. Allison and Long, 1990; Allsion et al., 1982; Baldi, 1995; Bedeian et al., 2010; Crane, 1970; Cole and Cole, 1967; Hargens and Hagstrom, 1967; Headworth and Freese, 2016). Neither the data employed, nor the results in this paper are appropriate to speak explicitly to that goal. However, this does not imply that the data are inappropriate for conceptualizing and analyzing the pattern of personnel flow as an instance of Weberian statused interactions between academic departments. Lamont (1992) argues that when actors are generally in agreement that some traits and, consequently, some actors are better than others, social interaction are patterned through processes of inclusion and exclusion in association. Caplow (1964) makes a similar claim at the institutional level alleging that, as participants in the same industry, organizations generate recognizable prestige orderings, which have significant implications for interactions between its members. There is no doubt that academic departments are members of precisely such status orders. Various organizations such as the National Research Council (NRC) and U.S. News and World Report (USN) survey 'insiders' - academics and administrators - on a regular basis in an attempt to quantify this prestige ordering. Reputed departments exercise control over the formation of standards such as defining the problems that deserve to be studied as well as the norms of research pertaining to the discipline (Merton, 1968). Despite strongly criticizing the most recent NRC sociology rankings for numerous inadequacies including the omission of books, improper accounting of citations and co-authorship, and disregarding the quality of publication outlets, Evans et al. (2011:12) nevertheless acknowledge that rankings and debates surrounding their validity and meaningfulness are "unlikely to disappear" and will continue to play an important role in administrative and graduate student decision-making. Accepting that academic departments are indeed members of (albeit somewhat contested) status orders, I analyze if the structure of departmental interactions are correspondingly hierarchical. Moreover, conceptualizing it in terms of Weber's status and lifestyles, I contribute to prior research by delving into the previously unexamined relationship between PhD hiring networks and departmental shared specializations.

Specifically, I employ data on departmental hiring networks in sociology and self-reported areas of departmental expertise as reported in the American Sociological Association's Guide to Graduate Departments. I construct a multilevel network that simultaneously accounts for both hiring and specialty affiliation data and utilize a cutting edge technology for the statistical modeling of such data called Multilevel Exponential Random Graph Models or mERGM (Wang et al., 2013). I begin by modeling the complete exchange network composed of all professorial ranks to evaluate the interdependence between the specialty and hiring connections.

Data

Hiring networks

I use data on departmental hiring networks to test the interdependence between departmental hiring and specialization networks. Data for hiring in sociology are sourced from the printed edition of the *American Sociological Association's* (ASA) Guide to Graduate Departments for the year 2014. This guide lists faculty members currently employed in graduate departments in the United States, where they received their doctoral degree, and current professorial rank. I hand-coded faculty affiliation and doctoral degree and validated the information using department and faculty webpages. Ties are directed from the hiring department to the doctoral degree-granting department. Consistent with previous research employing sociology hiring networks' data (Burris, 2004; Grannis, 2010), I limit my data to the departments that were ranked by the most recent National Research Council ratings in 2010 (N = 101). This coding strategy yields a one-mode network composed of directed links between 101 graduate degree-granting departments in sociology.

Departmental specializations

The ASA guide also lists self-reported specialties under the heading of 'special programs and areas of expertise' for each department, which I employ as a measure of shared departmental lifestyles. The survey question employed to generate these areas is as follows: "Using the list below, select up to 10 special programs that your department offers by clicking on the check box next to the program. These programs should include several regularly offered courses, core faculty members, a special set of exams, or *some other indication of a concentration*. We recommend listing no more than one special program for every four faculty members in your department (with a maximum of 10)" [emphasis added]. The survey offers eighty-two options to choose from as well as write-in section for specialties not covered in the list. I construct a network from these data where edges connect departments with their chosen areas of expertise. This type of connection, recording relations between two different types of entities, forms a two-mode network (Breiger, 1974). As ties in a two-mode network capture affiliation, they are undirected edges. Restricting the data to the 101 departments used for this study yields a network composed of 101 departments and 77 areas of specialization.[1]

Departmental rankings

I draw on the 2013 rankings published by U.S. News and World Report (USN) for sociology graduate departments. USN rankings are based on peer assessment surveys. The survey asks senior faculty to rate the quality of graduate programs that had granted five or more doctorates during the preceding five-year period on a five-point scale: outstanding (5), strong (4), good (3), adequate (2) or marginal (1). USN determines the score for each department by eliminating the two highest and two lowest responses of all respondents who rated the department for the previous two surveys. As it draws on the opinions of experts rather than objective criteria, this approach is aptly described as "reputation-based" (Evans et al., 2011). Ranks are coded so that lower numbers indicate higher status.

Method: one-mode, two-mode, and multilevel exponential random graph models

Multilevel networks

Multilevel network data views nodes as belonging to two (or more) levels. Network ties can connect nodes within and across levels. In the case presented here, nodes can be departments and sub-disciplinary specialties. Departments are interconnected via the exchange of personnel or the hiring of PhDs. Connections are directed in such a way that Department A receives a tie if Department B hires someone who got their degree at Department A. This can be represented as B hires from A or B → A. Thus, a popular department receives many ties. Departments are also linked to the second set of nodes through self-reported areas of specialization forming a two-mode network. Department A's specialization in S1, S2, and S3 can be represented as A—S1, A—S2, and A—S3. Putting these two types of one-mode and two-mode networks together yields a multilevel network that accounts for both types of ties simultaneously. Fig. 1 shows a fragment of the multilevel network generated from the data used in this paper. Squares represent departments and circles represent specializations.

Whereas one-mode social network analysis seeks to explain social phenomena by finding patterns in the structures of relationships within the boundary of the one-mode network, two-mode network analysis suggests that social structure is best captured by examining the relations between actors and the groups to which they belong. Drawing on Simmel, Breiger (1974) argues that shared affiliations entail common sources of identity between actors. Joint affiliations can accordingly act as a context for the formation of interpersonal relations. Structurally, this argument is similar to Weber's claim that shared lifestyles impose constraints on interpersonal interactions. Several studies discuss such interdependence across modes in networks and analyze them descriptively (e.g. Gondal and McLean, 2013; Lazega et al., 2006, 2008; Padgett and Ansell, 1993; Padgett and McLean, 2006). However, until recently, social network researchers had rarely investigated one-mode and two-mode networks concurrently to analyze their interdependence in a statistically rigorous way (Wang et al., 2013). This inattention is largely attributable to a lack in techniques for the simultaneous analysis of one-mode and two-mode networks. Latest advances in Exponential Random Graph Modeling to multilevel networks involving one-mode and two-mode ties helps to address this gap in the literature (Wang et al., 2013, 2016).

Exponential random graph models

ERGMs are a set of simulation-based statistical techniques where the goal is to identify the set of principles conceptualized as microstructures that concatenate to produce the observed network (Lusher et al., 2013; Robins et al., 2007, 2009). Microstructures can be of two types: endogenous (like triads and reciprocated arcs) and exogenous (like socioeconomic status and gender). The former are theorized to be self-organized structural tendencies where network ties are probabilistically generated out of the existence of other ties. Structural tendencies are typically interpreted as measuring micro or macro cultural or structural tendencies. Triadic closure is an example of endogenous closure: if A spends a lot of time with B and C, B and C will likely also eventually become friends. Alternatively, such closure can arise due to demographic similarities between the three actors (see, for example, Wimmer and Lewis, 2010). Exogenous factors are typically associated with tendencies toward homophily or popularity. Based on expectations about such endogenous and exogenous factors, a model is specified with the aim of reproducing the structural properties of the network using simulations (Robins et al., 2005). This process is repeated until the model achieves a good fit (described below). The modeling framework assumes a stochastic environment in which ties serve as random variables and the number of nodes is fixed. The exponential family of distributions applied to network data is characterized by the following equation:

$$\Pr(Y=y)=\frac{1}{\kappa(\theta)}exp\sum_{Q}\{\theta_Q z_Q(y)\}$$

where y is the observed network, Q is the set of network configurations, $z_Q(y)$ is the network statistic corresponding to the network configuration of type Q, θ_Q is the vector of parameters to be estimated, and κ_θ is a normalizing constant based on the graph space of networks of size n and the model specification. Models are fit using Monte Carlo Markov Chain Maximum Likelihood Estimation (MCMCMLE).

Once a converged model is obtained, it can be used to simulate additional networks to examine how closely the structural characteristics of the simulated networks match those of the observed network. In other words, we can test if the relevant structural features of hiring networks (e.g. closure and popularity) are statistically likely under the model. If the model simulates networks that closely resemble the observed network, it is a good fit to the data.

In ERGM, model fit is assessed on the basis of the distance between the observed value of a structural characteristic and the mean of the simulated distribution of networks. This is formally measured by the t-ratio. All fits in this paper are generated by simulating 1000 networks based on model estimates. Although we can aim for all structural features to lie at the center of the simulated distributions, that is rarely the case. Instead, ERGM relies on two criteria to evaluate fit. The first, met by all models discussed in this paper, is that the distance between the

[1] The dataset contains forty-three write-ins in total. Of these, twenty were retained in the original dataset as is. The remaining twenty-three records were recoded into other categories. Seven of these were split into two categories as appropriate (e.g. two instances of 'Life Course/Family' into 'Aging/Social Gerontology' and 'Family'). Ten of the remaining sixteen were coded into options offered in the survey (e.g. 'Comparative/Global Sociology', 'Global Sociology', 'Globalizing Theory', 'Sociology of Globalization', 'Transnational Sociology', and 'Global' to 'Globalization and Transnational Sociology'), while six, which did not fit as obviously into available options were recoded into new categories (e.g. Methods into Methodology).

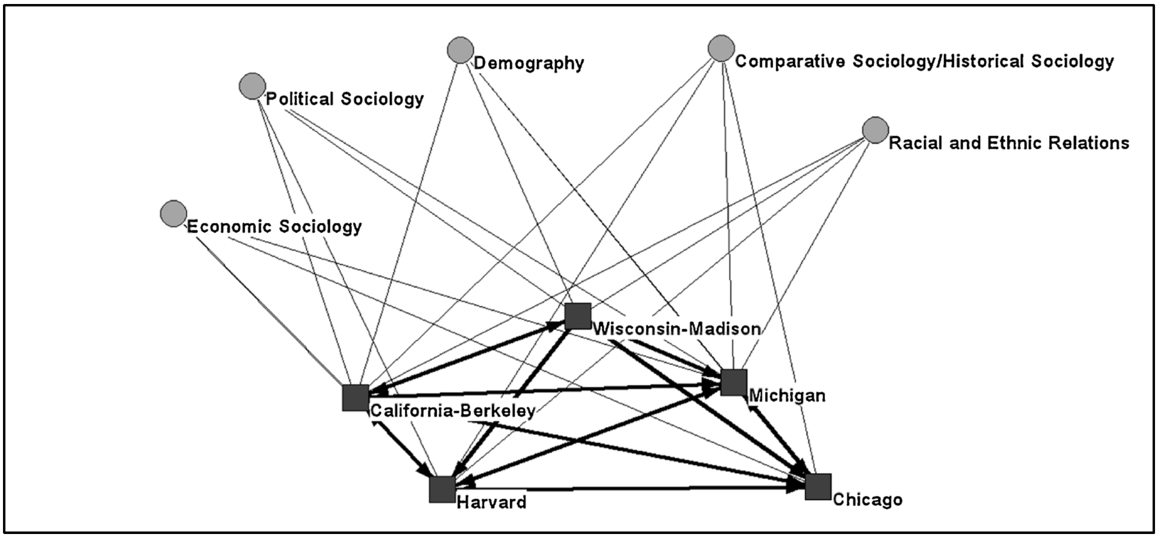

Fig. 1. Example of multilevel network. The network represents the five most popular departments in the one-mode network and specializations shared by at least three of those departments.

simulated network and the variables *included* in the model equation should be very small (the t-ratio should be approximately less than or equal to 0.1). Thus, if the model equation includes a parameter for homophilous hiring along prestige, the t-ratio for this variable in the simulations should be at or below 0.1. Yet, we also want to know how well homophily explains *other* structural features relevant to status-based hiring that are *not* included in the model equation such as triadic closure. Literature in ERGM considers t-ratios below 2 to be a good fit for such variables (Lusher et al., 2013; Robins et al., 2007, 2009). T-ratios exceeding 2 demonstrate that variables included in the model equation are unable to explain those structural features well. Adjudicating between successful and unsuccessful models depends on the number of *relevant* features that are unexplained and sizes of t-ratios. Even a good model may produce t-ratios exceeding 2 for some structural features. On the other hand, several t-ratios just under 2 may indicate the need for a better model incorporating a different set of configurations. An inadequate model will likely produce several sizeable t-ratios. The larger the t-ratios and the more numerous they are, the worse the model's ability to account for the structure of the network. Such an outcome typically implies that there are likely other determinants of the network not included in the model equation.

Although ERGMs are a relatively new technology, until very recently, models could only be fit to the individual one-mode (Robins et al., 2009) and two-mode (Wang et al., 2009a, 2009b) components of multi-level networks. While these models are useful for modeling the endogenous tendencies within each network, they assume the two networks are independent of each other. This approach is not useful for modeling the interrelationship between departmental shared specialties and PhD exchange proposed in this paper. Wang et al. (2013) proposed extensions of one-mode and two-mode ERGMS to multilevel ERGMs or mERGMs. Wang et al. (2016) extended these models to include individual- and group-level attributes. The equation relevant to the models employed in this paper is as follows:

$$\Pr(A = a, X = x) = \frac{1}{\kappa(\theta)} exp \sum_{Q} \{\theta_Q z_Q(a) + \theta_Q z_Q(x) + \theta_Q z_Q(a, x)\}$$

where $z_Q(a)$ is the set of network statistics corresponding to within-level one-mode network configurations of the PhD exchange network, $z_Q(x)$ is the set of network statistics corresponding to the two-mode network configurations of the department to specializations network, and $z_Q(a, x)$ is the set of network statistics for configurations involving ties from the PhD one-mode network and the department to specializations two-mode network simultaneously. As before, κ_θ is a normalizing constant based on the graph space of networks of size n and the model specification.

Wang et al. (2013) describe three types of multilevel networks. The first is the classic multilevel sample data where we have attribute information on micro-level actors (such as students) and macro-level collectivities (such as classrooms). Each micro-level actor is a member of one and only one collectivity. When these data are not accompanied by network data, we typically use the hierarchical linear modeling (HLM) framework to analyze the data (e.g. Hox, 2002). When we have network data on one of the levels, we can use one-mode ERGM treating membership as an attribute. The second possibility is network data on both micro- and macro-level units as well as membership data that amounts to a two-mode or affiliation network rather than each micro-level actor belonging only to a single collectivity. In this case, all three networks can be treated an endogenous and mERGM can be used to examine interdependencies between the three networks. Finally, a third possibility is network information on either the micro- or macro-level units alongside a two-mode membership network connecting the levels. Here, the analyst can investigate interdependencies between the one-mode and the two-mode data structure using mERGM.

This is the technique I employ in this paper. The one-mode network is composed of the interdepartmental hiring network and the two-mode network links departments to areas of specialization. While the data would be more complex if areas of specialization were connected independent of departmental affiliation, that is not necessary to test the Weberian hypothesis on interactional closure and shared lifestyles I pursue here. The data structure is appropriate to investigate if departments are more likely to hire from one another if they share areas of specializations or if they are less likely to exchange candidates if they do not share specializations. I first present well-fitting models for the one-mode and two-mode networks individually assuming they are independent of each other (Model 1). I examine the goodness of fit statistics generated by these models for the one-mode, two-mode, as well as the cross-level networks. I subsequently fit an overall model that accounts for the interdependence between the two networks (Model 2). I compare Models 1 and 2 in both parameter estimates and goodness of fits to examine how inclusion of cross-level network configurations affects model outcomes. This strategy can help to reveal the interdependence between shared departmental specializations and hiring outcomes. The models are fit using the MPnet software (Wang et al., 2009a, 2009b).

Table 1
Independent One-Mode and Two-Mode ERGM Models as well as joint Multilevel mERGM Model.

Configuration	Model 1				Model 2	
	One-Mode		Two-Mode		Multilevel	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
One-Mode						
Arc	−2.997[a]	0.442			−3.300[a]	0.426
Popularity						
Two-In-Star	0.032[a]	0.004			0.031[a]	0.004
Alt-In Star (α = 2)	0.604[a]	0.176			0.553*	0.171
Closure						
Reciprocity	0.161	0.143			−1.097	0.604
AT-D (α = 3)	0.124[a]	0.054			0.089	0.052
A2P-D (α = 3)	0.016	0.021			0.023	0.020
AT-T (α = 2)	0.164[a]	0.072			0.163[a]	0.066
A2P-T (α = 2)	−0.056[a]	0.010			−0.053[a]	0.010
USN Ranks						
Hire	0.002	0.003			0.003	0.003
Place	−0.020[a]	0.003			−0.021[a]	0.003
Homophily	−0.011[a]	0.003			−0.012[a]	0.003
Two-Mode						
Edge			−4.502[a]	0.299	−4.095[a]	0.291
Popularity						
Two-Star			0.148[a]	0.012	0.111[a]	0.013
Three-Star			−0.003[a]	0.000	−0.004[a]	0.000
Alt-Specialty Star			0.457[a]	0.184	0.454[a]	0.168
Closure						
Four-Cycle			−0.004	0.003	0.004	0.003
Multilevel						
ATXAX Arc (α = 2)					0.430[a]	0.083
ATXAX Reciprocity (α = 3)					0.544[a]	0.252
L3XAX					−0.002[a]	0.000

[a] Represents statistically significant estimates (standard deviation is less than half the corresponding parameter estimate).

Results

One-Mode and two-mode networks as independent

Model 1 in Table 1 shows the results of fitting ERGM models to the one-mode and two-mode networks independently ignoring any potential interdependencies between the networks. Model 2 shows the results of incorporating cross-level network configurations into the model equation. A positive significant parameter estimate in these models generally indicates that the configuration is a systematic feature of the network - i.e. more likely to occur than expected, given the other effects included in the model. Likewise, a negative one indicates that the configuration is less likely to occur after accounting for other configurations in the model equation. Parameter estimates are significantly different from zero if the reported standard deviation is less than half the corresponding parameter estimate. Note that models only symbolize statistical significance with one asterisk. Many or most of the parameter estimates shown in the tables are statistically significant at much higher levels but tradition in ERGM restricts significance to single asterisks (Lusher et al., 2013).

The one-mode model includes several endogenous parameters to account for two types of structural tendencies expected of highly statused interactions - centralization and closure. The arc parameter is akin to the intercept in a linear regression equation and is a measure of the baseline propensity for the formation of ties. Centralization is represented foremost by the popularity parameter (called alternating-in-star in ERGM terminology), which captures the variance of the indegree distribution. A significant positive estimate for this parameter demonstrates a positively skewed indegree distribution in the network. Effectively, positive estimates of this parameter are typical of networks characterized by a preferential attachment mechanism whereby nodes want to connect with others who are widely favored. The strong and significant positive estimate confirms previous findings that the sociology hiring network is characterized by a core-periphery structure where some departments are heavily in demand whereas most are unpopular. The two-in-star parameter is included to capture lower-level departmental ‘stars’ that are not adequately accounted for by the popularity parameter because of the strong skew in the indegree distribution. A positive significant estimate in this case suggests that, in addition to the core departments, some departments experience moderate demand.

Closure is modeled using five parameters. Reciprocity, modeled using the ‘reciprocity’ ERGM parameter connotes mutual hiring between two departments. The model shows that while there is a positive tendency towards mutual hiring, it is not statistically significant. The ninety-two reciprocated dyads in the sociology hiring network are explained by tendencies towards other model features. Elite closure, representing hiring between popular departments is modeled using the alternating downward triad (AT-D) and the alternating two path downward (A2P-D) parameters. Inclusion of the two-path parameter in the model equation ensures that triangulation captures closure (Lusher et al., 2013). More specifically, AT-D captures a tendency for two departments that are structurally equivalent by virtue of being popular with the same set of other departments to also exchange candidates among themselves. For example, sixteen departments have hired from both Indiana University, Bloomington and University of Michigan and the former has hired from the latter. A significant positive estimate for AT-D alongside a non-significant estimate for A2P-D suggests that, although there is a tendency for some such structural equivalences to remain open, popular departments tend to close that path by hiring amongst themselves. Transitive closure, representing a tendency for hiring two-paths (Temple University hires from University of Pennsylvania and University of Pennsylvania hires from Harvard University) to also be closed (Temple University hires from Harvard University), is likewise, modeled using two ERGM parameters simultaneously – the alternating transitive triad (AT-T) and the alternating two path transitive (A2P-T) parameters. The admixture of positive triangulation and negative two-path estimates, in this case, suggests that when two-paths are more likely to get closed than remain open.

In addition to structural parameters, the one-mode model also contains three variables to account for the effect of U.S. News departmental rankings. These parameters are selected to capture the potentially statused relationship between departmental USN ranking and a tendency to (i) hire faculty members from other departments (or rank-based expansiveness), (ii) be hired from (or rank-based popularity), and (iii) hire homophilously within closely ranked departments (or rank-based closure). Recall that, as is typical, ranks are coded so that lower numbers indicate higher status. Positive estimates for hiring and placement parameters are indicative of a direct relationship between rankings and a tendency for that action. Conversely, a negative estimate is indicative of an inverse relationship between rank and hiring or placement. With respect to homophily, a *negative* estimate shows that the rank distance between hiring and placing departments is low - indicative of *homogamy* (Lusher et al., 2013).

Thus, a positive but non-significant estimate for 'hire' suggests that lower status departments (with larger numerical rank) are more likely to hire but not significantly so. The negative significant estimate for the 'place' parameter demonstrates that higher status departments are more likely to place their students or equivalently their students are in higher demand. The negative significant homophily estimate shows that the rank-based distance between departments tends to be low - closely ranked departments are more likely to exchange candidates. In combination the two significant USN parameters suggest that, net of a greater tendency for all departments to seek out high-status candidates, elite departments tend to hire within their own status groups.

Thus, overall, the one-mode ERGM demonstrates preferential attachment towards popular departments as well as elite closure on both structural and exogenous rank-based parameters. Table 2 depicts relevant goodness of fit statistics generated from fitting the one-mode model shown in Table 1 to the empirical hiring network. As discussed in the Methods section, t-ratios for variables included in the model are all below 0.1. T-ratios for all other parameters are generally well below 2 indicating the model in Table 1 offers a very good fit for the hiring network.

It is important to acknowledge that the network under consideration (here and in other analyses using such data) is a highly detailed snapshot of trades that have occurred over a period of time. While the suppression of the temporal nature of relationship formation is characteristic of most social network data, it is worthwhile to discuss some implications of using such data in the present case. One possibility is that the effect of USN rank-based variables may be over- or under-estimated if departmental standing on ranks is unstable. For example, two departments ranked differently today could have exchanged a candidate a decade ago when they were ranked similarly. Yet, the likelihood of this is low because departmental ranks have tended to be incredibly sticky and largely unresponsive to changes in faculty scholarship since the sixties (Baldi 1994; see Burris, 2004 especially for a detailed discussion; Webster et al., 1988; Weikliem et al. 2012). Another possibility is that the structure of the network and its relationship to status considerations could vary if we distinguished between recent and dated trades. Yet, sensitivity tests on data composed only of full professors or assistant professors produced results very similar to the ones presented here for the complete network. Moreover, models for first jobs of current full professors also display comparable structural properties and a similar relationship to status as discussed in the body of the paper.

The two-mode model equation in Table 1 is comparatively simpler than the one-mode model containing five structural features. As before the edge parameter should be interpreted like the intercept in a regression equation. Akin to the one-mode case, the 'Specialty Popularity' parameter captures a preferential attachment mechanism such that departments are prone to specializing in some specialties more so than others. This feature is measured by the 'alternating-star' parameter (Alt-B-Star). The significant positive estimate for this parameter demonstrates a positively skewed degree distribution in the network as would be expected if some specialties were more popular than others (e.g. 'sex and gender' and 'racial and ethnic relations' are more popular whereas 'disabilities' and 'collective memory' are less so). The lower level two- and three-star parameters are included to capture the wide degree distribution of specializations. A positive significant estimate for the two-star parameter coupled with the negative estimate of the three-star parameter suggests that, while there is strong tendency for departments to gravitate towards popular areas of expertise, there is considerable variation beyond the popular choices. This propensity for eclecticism is confirmed by the negative and insignificant four-cycle parameter estimate, which captures the tendency for two departments to share specialization profiles. Relevant goodness of fit statistics for the model are shown in Table 2. The model does a good job of capturing the structure of the two-mode network of departmental affiliations with specializations.

One Mode and Two Mode ERGM fits for the Cross level network

The top panel of Fig. 2 shows the fits obtained from the models discussed above for selected features of the cross-level network that are relevant to hiring and shared specializations. The fit is depicted by a histogram of the simulated distribution of a specific structural feature. All fits are based on 1000 simulations. The red line dropped perpendicular to the x-axis in each figure represents the empirical value found in the cross-level hiring and specialization network. The structural parameters corresponding to these features are graphically shown in the middle panel. As before, squares represent departments and circles represent specializations. The first feature on the left (TXAXArc) represents the structural tendency for one department to hire from another if the two share a single specialization. The second feature captures a tendency for the two departments to hire mutually from each other. The third and fourth features (ATXAXArc) and (ATXAXreciprocity) are synthetic variables designed to capture the simultaneous spread of the shared specializations and one-sided and mutual hiring structural features, respectively. Much like alternating stars and triads in previous models, rather than counting the number of departments that share one, two, or three specializations etcetera and hire internally, this variable simultaneously measures all these levels at the same time (for details, see Lusher et al., 2013). The final parameter depicted (L3XAX) captures the opposing tendency for departments to hire if they do *not* share a specialization. As is evident from the histograms in the first panel, all these features are poorly fit by the one- and two-mode models. Although ATXAXreciprocity and L3XAX are somewhat less poorly fit than the other three features, none of the features are replicated well in the simulations.

Model 2 in Table 1 shows the mERGM fit for the combined cross-level network. This model adds three of the five features depicted in Fig. 2 to the one-mode and two-mode models. The first thing to note is that the addition of the cross-level parameters alters the values of the estimates in the one- and two-mode models. Reciprocity declines from being modestly positive to strongly negative, albeit both estimates are not significant. The departmental popularity and transitive triangulation estimates in the one-mode network and the two-star and specialization popularity estimates in the two-mode network decline marginally suggesting that some of the tendencies towards these endogenous structures are attributable to cross-level interactions between hiring and specializations. Most notably, the estimate for elite closure (AT-D) in the one-mode network declines substantially and loses significance in the cross-level model suggesting that hiring between popular departments is closely linked to those departments' sharing of specializations. This provides quite strong evidence in support of Weber's claim about the relationship between elite closure and shared lifestyles.

The estimates for the cross-level features in the model also support

Table 2
Relevant Goodness of Fit for One-Mode and Two-Mode Models.

One-Mode Network

Configuration	Observed	Mean	S.D.	T-Ratio
Arc	1234	1234.30	109.42	0.00
Reciprocity	92	92.69	18.76	−0.04
2-in-star	16675	16731.46	2511.56	−0.02
3-in-star	208001	200132.05	41453.95	0.19
Triad (300)	41	23.16	12.01	1.49
Triad (210)	471	331.84	137.31	1.01
Triad (120C)	949	818.65	289.40	0.45
Triad (120D)	1115	888.82	263.33	0.86
Triad (120U)	522	443.56	146.29	0.54
Transitive Triad	5528	4988.83	1154.25	0.47
Cyclical Triad	670	699.03	219.13	−0.13
Alt-In-Star	2139	2142.16	212.50	−0.01
Alt-Out-Star	2065.15	2066.39	218.16	−0.01
Alt Transitive Triad	1819.32	1832.02	259.75	−0.05
Alt Cyclical Triad	895.20	948.10	211.73	−0.25
Alt Downward Triad	1822.66	1827.81	295.24	−0.02
Alt Upward Triad	2146.47	2121.59	286.22	0.09
Alt-2-Path-Down	7195.53	7213.87	821.01	−0.02
Alt-2-Path-Transitive	3809.05	3778.02	440.79	0.07
Alt-2-Path-Up	7792.43	7982.41	500.41	−0.38
USN Hire	57048	56959.30	4879.23	0.02
USN Place	28090	27900.16	2970.29	0.06
USN Homophily	37350	37457.98	3139.17	−0.03
Clustering Out	0.36	0.32	0.02	1.62
Clustering In	0.17	0.15	0.01	1.34

Two-Mode Network

Configuration	Observed	Mean	S.D.	T-Ratio
Edge	946	948.18	45.40	−0.05
Dept-2-Star	4079	4279.38	418.65	−0.48
Specialty-2-Star	13128	13128.85	931.95	0.00
Dept-3-Star	10616	12380.08	1879.35	−0.94
Specialty-3-Star	153478	153502.83	14953.14	0.00
3-Path	226277	234483.87	26636.12	−0.31
4-Cycle	15768	15706.03	2293.27	0.03
Alt-Star-Dept	1489.87	1494.54	90.22	−0.05
Alt-Star-Specialty	1634.84	1638.25	88.02	−0.04
Alt-Cycle-Dept	7486.28	7544.96	264.84	−0.22
Alt-Cycle-Specialty	1610.57	1774.28	159.62	−1.03
Global Clustering	0.28	0.27	0.01	0.89

S.D. refers to Standard Deviation.

this theory. As in the alternating star parameters in the one- and two-mode cases, a positive estimate for the cross-level alternating triad (ATXAXarc) and alternating mutual triad (ATXAXreciprocity) captures the spread of the overlapping triad distributions. A positive estimate suggests 1) that departments that share specializations are more likely to hire from one another and 2) a positive skew in the distribution of these structures such that some departments share many specializations and hire internally while other departments share fewer specializations and hire from one another. Accordingly, the significant positive estimate for ATXAXarc shows that there is a strong tendency for one department to hire from another if the two departments share specializations. Moreover, the significant positive estimate for ATXAXreciprocity also demonstrates that departments that share specializations are more likely to hire reciprocally from one another. This finding is especially noteworthy as stand-alone reciprocity in the one-mode network is not systematic feature of the network and its estimate declines quite significantly with the addition of the cross-level parameters. The implication is that much like popularity-based elite closure (AT-D), direct reciprocal exchange in the sociology hiring network is also closely associated with shared specializations. Lastly, although the effect is smaller in size, the model also demonstrates a statistically significant negative tendency towards interdepartmental hiring when departments do *not* share specializations. The addition of these features to the one-mode and two-mode models clearly demonstrates that hiring among graduate departments in sociology is strongly positively related to shared areas of departmental expertise.

The bottom panel in Fig. 2 repeats the fits of the structural features shown in the top panel for the mERGM model. The addition of the cross-level features offers a considerable improvement in the fits of all five features. The empirical values found in the networks now lie in the center of the distributions.

Discussion

The findings in this paper demonstrate that the exchange of personnel in sociology is highly status-conscious. The one-mode model demonstrates that, structurally, the network is highly centralized and displays considerable closure – two key features expected of status-imbued interactions. ERGM models also show that, one, homophily and, two, popularity based on reputation-based departmental status rankings published by U.S. News are important to the construction of the network. As such, the results of the standalone one-mode hiring network are supportive of a Weberian model of status in interaction.

The crux of my argument, however, has been to draw attention to the role of departmental specialization in sub-disciplinary areas (conceived as lifestyles) in shaping stratified academic hiring. Recall that

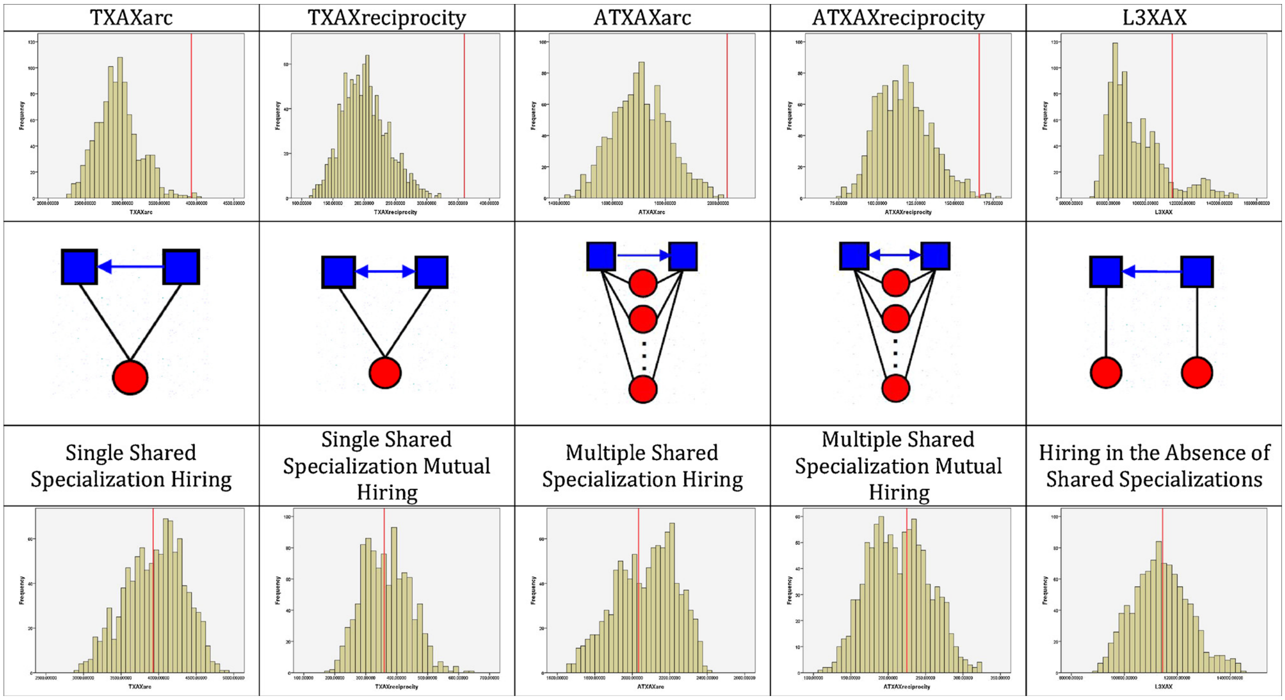

Fig. 2. Goodness of fit distributions for relevant cross-level features based on one-mode and two-mode models. Squares represent departments and circles represent areas of specialization.

Weber argues status groups to be the 'bearers of all conventions.' Although he does not explicitly propose a duality between status-based interactional closure and shared lifestyles, he does hint at such a relationship. "In whatever way it may be manifest, all stylization of life either originates in status groups or is at least conserved by them. Even if the principles of status conventions differ greatly, they reveal certain typical traits, especially among the most privileged strata" (Weber, 1978: 936). Thus, lifestyles help produce and maintain status through closure but status groups then become possessors of certain styles and contribute to their conservation. By implication, an examination of those shared conventions ought to reveal status-based clustering, particularly among the privileged.

Yet, this dual relationship is not immediately evident from an analysis of the two-mode network for specialty affiliations by itself. While the bipartite model demonstrates popularity-based hierarchy in areas of expertise, the parameter estimate for four-cycles representing sharedness of specializations between departments is negative and statistically insignificant. Moreover, models including parameters for sameness of specialization choice by closeness of departmental USN rank (not shown) do not produce significant estimates or improve model fit in any discernible way demonstrating that areas of expertise are not neatly clustered by departmental status. Thus, while there are some overlaps between departmental choices of specialties, these commonalities do not occur in a manner systematic enough to parse specialization choices into 'islands of meaning' (Zerubavel, 1991) either among the elite or the non-elite, as hinted by Weber.

The cross-level analysis, on the other hand, is strongly indicative of such a co-constitutive relationship between hiring and specializations. mERGM demonstrates that departments are not only more likely to hire from other departments if they share specializations, they are also more likely to do so reciprocally. Moreover, departments that do not share any specializations are less likely to exchange personnel than those who do. These findings seem intuitive – departments that have similar research profiles and agendas ought to be more interested in hiring from one another. The intriguing question is whether these tendencies contribute to preserving or breaching the status-based hiring inequalities evident in the one-mode network. We know that elite departments are successful in placing their candidates in non-elite departments, which produces a core-periphery structure in hiring networks. Yet, elite departments typically hire from within their own status circles generating the closure we observe in the one-mode network. Thus, specializations would help to erode existing inequalities only if non-elite departments could expand their areas of expertise in order to make their own candidates more attractive to elite departments.

However, expanding specializations is neither an easy nor a straightforward task. The ability to create and nurture specialty clusters within departments is contingent upon considerable resources aimed towards hiring and retaining clusters of faculty, competing for graduate students, and obtaining scarce internal and external sources of funding. Consequently, areas of specialization within departments are likely to remain sticky over time. The implication is that the relationship between specializations and hiring is likely to exacerbate inter-departmental stratification. Findings from the cross-level model confirm this theory. Stratified hiring patterns in the one-mode network manifest in both centralized core-periphery structures as well as elite closure. But, crucially, while inclusion of cross-level parameters does not have much effect on centralization, it explains away the tendency towards elite closure. The cross-level model also improves the fits of other triadic structures in the hiring network including the most closed interactional form between three nodes – the complete triad made up of all reciprocated dyads. This and other types of similar triads are prevalent in the network among the most elite departments. Thus, although the specialization space is not marked by strong boundaries characteristic of status-based fracturing, these findings clearly demonstrate that shared research expertise contributes to consolidating existing status-based inequalities between departments. More generally, the results emphatically support Weber's claim that shared lifestyles coincide with interactional closure, especially among the elite.

Conclusion

The analysis and findings in this paper are significant for several reasons. Methodologically speaking, I demonstrate the use of a relatively new technology - multilevel ERGMs – to analyze empirical data to produce sociologically relevant findings. Examining either one of the hiring or specialization affiliation networks alone is not as effective in demonstrating the joint relationship as a simultaneous analysis. The model of the two-mode network by itself, in fact, suggests that having accounted for a tendency towards popularity of some specializations, departments did not display an especially systematic tendency towards sharing specializations. The one-mode ERGM for the hiring network, likewise, demonstrates a good fit based on tendencies towards rank-based hiring and endogenous preferential attachment and elite closure. The joint model confirms that one-sided and mutual exchange between departments is more likely if they also share specializations and less likely if they do not.

Substantively, I expand upon previous research on academic exchange networks to show that shared specializations, conceptualized as departmental lifestyles, have important consequences for the network of personnel exchange between sociology departments. Not only are they strongly correlated with hiring, shared areas of expertise also contribute to preserving the existing pattern of inequalities between elite and non-elite departments. Thus, in addition to prestige rankings, doctoral exchange between academic departments is also predicated on shared disciplinary specializations.

Theoretically, I contribute to the literature on social networks, stratification, and culture by testing Weber's theory linking interactional closure and shared lifestyles. To the extent shared specializations are a measure of academic habitus, these results support Weber's theory that lifestyle similarities preserve status by imposing strong constraints on social intercourse. In his seminal paper, Breiger (1974) elaborates on Simmel's 'intersection of social circles' to propose two-mode network analytic techniques appropriate for the analysis of duality between actors and their affiliations. Breiger argues that affiliations are important to analyze because they reflect 'shared interests, personal affinities, or ascribed status' of the actors involved in them. Accordingly, shared affiliations can be viewed as contexts for the formation of interpersonal relationships and an examination of affiliations can tell us much about the structure of interpersonal relations. Dually, the 'identity' of a group is related to the intersection of the actors affiliated with the group. Wasserman and Faust (1994) similarly argue that affiliations are important because affiliates are more likely to form interpersonal relations. The results from this paper are highly suggestive of such a co-constitutive relationship between shared affiliations and interactions.

References

Allison, P., Long, J.S., 1990. Departmental effects on scientific productivity. Am. Sociol. Rev. 55 (4), 469–478.
Allsion, P., Long, J., Krauze, T., 1982. Cumulative advantage and inequality in science. Am. Sociol. Rev. 47 (5), 615–625.
Babchuk, N., Keith, B., Peters, G., 1999. Collaboration in sociology and other scientific disciplines: a comparative trend analysis of scholarship in the social, physical, and mathematical sciences. Am. Sociol. 30 (3), 5–21.
Baldi, S., 1995. Prestige determinants of first academic job for New sociology Ph.D.s 1985–1992. Sociol. Q. 36 (4), 777–789.
Barnett, G., Danowski, J., 1992. The structure of communication. Hum. Commun. Res. 19 (2), 264–285.
Barnett, G., Feeley, T., 2011. Comparing the NRC and the faculty hiring network methods of ranking doctoral programs in communication. Commun. Educ. 60 (3), 362–370.
Barnett, G., Danowski, J., Feeley, T., Stalker, J., 2010. Measuring quality in communication doctoral education using network analysis of faculty-hiring patterns. J. Commun. 60 (2), 388–411.
Bedeian, A., Cavazos, D., Hunt, J., Jauch, L., 2010. Doctoral degree prestige and the academic marketplace: a study of career mobility within the management discipline. Acad. Manag. Learn. Educ. 9 (1), 11–25.
Bothner, M., Smith, E., White, H., 2010. A model of robust positions in social networks. Am. J. Sociol. 116 (3), 943–992.
Bourdieu, P., 1983. The Field of cultural production, or: the economic world reversed. Poetics 12 (4-5), 311–356.
Bourdieu, P., 1984. Distinction: A Social Critique of the Judgment of Taste. Harvard University Press, Cambridge, MA.
Breiger, R.L., 1974. The duality of persons and groups. Soc. Forces 53 (2), 181–190.
Burris, V., 2004. The academic caste system: prestige hierarchies in PhD Exchange networks. Am. Sociol. Rev. 69 (2), 239–264.
Caplow, T., 1964. Principles of Organization. Basic Books, New York.
Cappell, C., Guterbock, T., 1992. Visible colleges: the social and conceptual structure of sociology specialties. Am. Sociol. Rev. 57 (2), 266–273.
Chubin, D., 1976. The conceptualization of scientific specialties. Sociol. Q. 17 (4), 448–476.
Clauset, A., Arbesman, S., Larremore, D., 2015. Systematic inequality and hierarchy in faculty hiring networks. Sci. Adv. 1 (1), 1–6.
Cole, S., Cole, J., 1967. Scientific output and recognition: a study in the operation of the reward system in science. Am. Sociol. Rev. 32 (3), 377–390.
Crane, D., 1970. The academic marketplace revisited: a study of faculty mobility using the cartter ratings. Am. J. Sociol. 75 (6), 953–964.
Crane, D., 1972. Invisible Colleges; Diffusion of Knowledge in Scientific Communities. University of Chicago Press, Chicago.
Crane, D., Small, H., 1992. American sociology since the seventies: the emerging identity crisis. Sociology and Its Publics: The Forms and Fates of Disciplinary Organization. pp. 197–234.
Ennis, J.G., 1992. The social organization of sociological knowledge: modeling the intersection of specialties. Am. Sociol. Rev. 57 (2), 259–265.
Evans, J., Hillsman, S., Perrin, A., Small, M., Smith, S., 2011. Report to the American Sociological Association Council Regarding the 2010 National Research Council Assessment of Doctorate Programs. American Sociological Association.
Fleck, L., 1979. Genesis and Development of a Scientific Fact. University of Chicago Press, Chicago.
Gondal, N., 2011. The local and global structure of knowledge production in an emergent research Field: an exponential random graph analysis. Soc. Netw. 33 (1), 20–30.
Gondal, N., McLean, P.D., 2013. What makes a network go round? Exploring the structure of a strong component with exponential random graph models. Soc. Netw. 35 (4), 499–513.
Goyal, S., Van Der Leij, M., Moraga-González, J., 2006. Economics: an emerging small world. J. Polit. Econ. 114 (2), 403–412.
Grannis, R., 2009. Paths and semipaths: reconceptualizing structural cohesion in terms of directed relations. Sociol. Methodol. 39 (1), 117–150.
Grannis, R., 2010. Six degrees of "who cares?". Am. J. Sociol. 115 (4), 991–1017.
Gross, G., 1970. The organization set: a study of sociology departments. Am. Sociol. 5 (1), 25–29.
Haas, P.M., 1992. Introduction: epistemic communities and international policy coordination. Int. Organ. 46 (1), 1–35.
Hagstrom, W., 1965. The Scientific Community. Basic Books, New York.
Hanneman, R., 2001. The prestige of Ph.D. Granting departments of sociology: a simple network approach. Connections 24 (1), 68–77.
Hargens, L., Hagstrom, W., 1967. Sponsored and contest mobility of American academic scientists. Sociol. Educ. 40 (1), 24–38.
Headworth, S., Freese, J., 2016. Credential privilege or cumulative advantage? Prestige, productivity, and placement in the academic sociology job market. Soc. Forces 94 (3), 1257–1282.
Hill, V., Carley, K., 1999. An approach to identifying consensus in a subfield: the case of organizational culture. Poetics 27 (1), 1–30.
Horley, J., Carroll, B., Little, B., 1988. A typology of lifestyles. Soc. Indic. Res. 20 (4), 383–398.
Hox, Joop., 2002. Multilevel Analysis: Techniques and Applications. Lawrence Earbaum, London.
Ibarra, H., 1992. Homophily and differential returns: sex differences in network structure and access in an advertising firm. Admin. Sci. Q. 37 (3), 422–447.
Joyner, K., Kao, G., 2000. School racial composition and adolescent racial homophily. Soc. Sci. Q. 81 (3), 810–825.
Kuhn, T., 1970. The Structure of Scientific Revolutions. University of Chicago Press, Chicago.
Lamont, M., 1992. Money, Morals, and Manners: The Culture of the French and the American Upper-Middle Class. University of Chicago Press, Chicago, IL.
Lazega, E., Mounier, L., Jourda, M.T.S., Stofer, R., 2006. Organizational vs. Personal social capital in scientists' performance: a multi-level network study of elite French cancer researchers (1996-1998). Scientometrics 67 (1), 27–44.
Lazega, E., Jourda, M.T., Mounier, L., Stofer, R., 2008. Catching up with big fish in the big pond? Multi-level network analysis through linked design. Soc. Netw. 30 (2), 159–176.
Lievrouw, L., Rogers, E., Lowe, C., Nadel, E., 1987. Triangulation as a research strategy for identifying invisible colleges among biomedical scientists. Soc. Netw. 9 (3), 217–248.
Lusher, D., Koskinen, J., Robins, G., 2013. Exponential Random Graph Models for Social Networks: Theory, Methods, and Applications. Cambridge University Press, New York, NY.
McPherson, M., Smith-Lovin, L., Cook, J., 2001. Birds of a feather: homophily in social networks. Annu. Rev. Sociol. 27 (1), 415–444.
Merton, R., 1968. The Matthew effect in science. Science 159 (3810), 56–63.
Moody, J., 2004. The structure of a social science collaboration network: disciplinary cohesion from 1963 to 1999. Am. Sociol. Rev. 69 (2), 213–238.
Moody, J., Light, R., 2006. A View from Above: the evolving sociological landscape. Am. Sociol. 37 (2), 67–86.
Padgett, J., Ansell, C., 1993. Robust action and the rise of the medici, 1400-1434. Am. J. Sociol. 98 (6), 1259–1319.
Padgett, J., McLean, P., 2006. Organizational invention and elite transformation: the birth of partnership systems in Renaissance Florence. Am. J. Sociol. 111 (5), 1463–1568.
Robins, G., Pattison, P., Woolcock, J., 2005. Small and other worlds: global network structures from local processes. Am. J. Sociol. 110 (4), 894–936.
Robins, G., Snijders, T., Wang, P., Handcock, M., Pattison, P., 2007. Recent developments in exponential random graph (p*) models for social networks. Soc. Netw. 29 (2),

192–215.
Robins, G., Pattison, P., Wang, P., 2009. Closure, connectivity and degrees: New specifications for exponential random graph (p*) models for directed social networks. Soc. Netw. 31 (2), 105–117.
Small, H., 1978. Cited documents as concept symbols. Soc. Stud. Sci. 8 (3), 327–340.
Small, H., Griffith, B., 1974. The structure of scientific literatures I: identifying and graphing specialties. Sci. Stud. 4 (1), 17–40.
Sobel, M.E., 2013. Lifestyle and Social Structure: Concepts, Definitions, Analyses. Academic Press, New York.
Star, J.M., 1983. Specialization and the development of sociology: differentiation of fragmentation? Qual. Sociol. 6 (1), 66–86.
Tumin, M.M., 1970. Readings on Social Stratification. Prentice Hall, Englewood Cliffs.
Wang, P., Robins, G., Pattison, P., 2009a. PNet: Program for the Simulation and Estimation of Exponential Random Graph Models. Melbourne School of Psychological Sciences, The University of Melbourne.
Wang, P., Sharpe, K., Robins, G., Pattison, P., 2009b. Exponential random graph (p*) models for affiliation networks. Soc. Netw. 31 (1), 12–25.
Wang, P., Robins, G., Pattison, P., Lazega, E., 2013. Exponential random graph models for multilevel networks. Soc. Netw. 35 (1), 96–115.
Wang, P., Robins, G., Matous, P., 2016. . Multilevel network analysis using ERGM and its extension. Multilevel Network Analysis for the Social Sciences. Springer International Publishing, pp. 125–143.
Wasserman, S., Faust, K., 1994. Social Network Analysis: Methods And Applications. Cambridge University Press, Cambridge.
Weakliem, D.L., Gauchat, G., Wright, B.R., 2011. Sociological stratification: change and continuity in the distribution of departmental prestige, 1965–2007. Am. Sociol. 43, 310–327.
Weber, M., 1978. In: In: Roth, Guenther, Wittich, Claus (Eds.), Economy and Society, 2 volumes University of California Press, Berkeley, CA.
Webster, D.S., Conrad, C.F., Jensen, E.L., 1988. Objective and reputational rankings of Ph. D.-Granting departments of sociology, 1965–1982. Sociol. Focus 21 (2), 177–198.
Wimmer, A., Lewis, K., 2010. Beyond and below racial homophily: ERG models of a Friendship network documented on facebook. Am. J. Sociol. 116 (2), 583–642.
Zablocki, B., Kanter, R., 1976. The differentiation of life-styles. Annu. Rev. Sociol. 2, 269–298.
Zerubavel, E., 1991. The Fine Line: Making Distinctions in Everyday Life. University of Chicago Press, Chicago.