Academic Employment Networks and Departmental Prestige

Debra Hevenstone

Abstract Research has found a correlation between academic departments' rank and their centrality in academic hiring networks. This correlation results from the fact that highly ranked schools train more PhDs, their graduates are more likely to find first jobs in academia, and that they have more faculty. This study is the first to consider this correlation independent of training and department size. One expects no correlation because mid-career academics move between institutions for a variety of reasons such as wages, location, and specialty areas. Nevertheless, this study finds that the correlation persists; suggesting individuals are more willing to make career switches to top departments or between them. This gives top departments a competitive advantage and positive returns to their rank, with their faculty disproportionately linked to institutions and researchers at other departments. This could be one reason for the stagnancy of academic rankings.

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1 Introduction

Academic rankings incorporate both "objective" measures of department quality (such as citation rates and funding patterns) as well as subjective measures. While we might expect that objective measures would allow departments to improve their rankings, academic rankings are relatively constant over time, with the top schools swapping the top positions (Graham and Diamond 1997). Several rankings for sociology graduate programs from 1925 to 2005 are illustrated in table 1.
Four institutions have been in the top 10 since 1925 while 8 others have since 1982. Despite their consistent results, these rankings use significantly different methodologies to come to their results. The oldest type of formula is a reputational rank, which was pioneered by Raymond M. Hughes. In his 1925 report Hughes surveyed 20 to 60 faculty members in each field, asking them to rank institutions based on “esteem at present time for graduate work in your subject.” The much critiqued US News and World Report rankings build on this formula, basing ranks on a peer assessment surveys (50% response rate) sent to academic department heads and directors of graduate study in sociology.1 The National Research Council’s (NRC) 1995 rankings are more complicated; they also use reputational measures (also with about a 50% response rate) but augments it with data for about 17 program characteristics such as: size, private vs. public, total research and development (R & D), federal R & D, library expenditures, enrollment, total faculty, % faculty FT, % faculty with research support, percent full professors, faculty awards, awarded faculty, citations per faculty, faculty characteristics, and student characteristics. The NRC found that the reputational measures were consistent with the objective measures. Critiques of the NRC rankings argued that there was too much emphasis on research-related variables and too little on doctoral training.

Table 1: Sociology Department Ranks

<table>
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<td>Northwestern</td>
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<td></td>
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</table>

*Hughes (1925)
†National Research Council (1982, 1995)

1 For an excellent critique of the US News rankings see Ehrenberg 2002

This analysis relies primarily on the NRC’s sociology rankings, when including foreign institutions in the analysis; I also use the Newsweek international rankings (not specific to sociology).2 The Newsweek score includes measures of citations, publications, international faculty, international students, faculty/student ratios, and library holdings. While the two rankings are developed using different metrics, the rankings correlate at .625 for those US schools where both ranks were available. The primary difference between the ranks is that the NRC sociology rankings exclude technical/science schools like MIT and Caltech, while these schools are near the top of the general international ranking.

Some researchers suggest the stagnant rankings indicate a closed system where departments find it difficult to move up the rankings and where well-established programs can reinforce their dominance. This organizational situation could be considered analogous to individual-level stratification in a “closed system” where intergenerational transmission of advantage trumps equal opportunity (Lipset al. 1955). Ideally stratification should function as an incentive for individuals to work harder or acquire more human capital (Davis and Moore 1945) or for organizations to innovate and improve their product. However, too much stratification might indicate that either individuals are able to earn more based on their current assets or analogously, an organization can sell more of their product not based on their current effort but on their inheritance.

There are two reasons that the rankings might remain stagnant. First, it might be that respondents to the reputational survey are rather ill informed, basing their evaluation of doctoral programs not based on their actual merit but on what they have heard. If this is the case, once a program is highly ranked, it will remain there, as professors perpetuate the reputation without objectively examining it. Second, once a program is highly ranked, it has resources to perpetuate that rank by attracting faculty. This second reason is the basis for this paper. While some lament the caste system, the simple preference for faculty to move to or between higher ranked schools can cement departments’ central position. This central position can translate into departmental prestige through many mechanisms not explored in this paper—such as research collaborations, knowing about upcoming trends in the field, or hosting small conferences leading to publications. While this paper does not explore the mechanisms linking hiring network centrality and prestige, it does confirm the existence of the correlation independent of training and department size. While departments’ central positions might aid their faculty, the pattern of the highest ranked department sitting at the centre of a hiring network

2 I tested the Shanghai rankings as well, though there was little difference.
probably gives the department an advantage as well and is a likely an example of positive feedback.

There is significant non-network research testing how the institutional prestige of PhD granting institutions influences first job placement. The literature finds that the most prestigious universities hire each other’s graduates, over-valuing the institutional prestige of applicants’ training institutions over their other characteristics that might be more predictive of success, such as the time it took to complete the PhD (Bair 2003, Baldi 1995, Burris 2004, Burke 1988, Hargens and Hagstrom 1966, McGinnis and Long 1988, Reskin 1979, Smelser and Content 1980).

In contrast, there are only four papers testing whether academic departments’ positions in academic hiring networks is linked to academic rank. Burris (2004); Wiggins et al. (2006) and Fowler et al. (2007) tie professors to their current employers and their PhD granting institutions, generating a network of institutions with weighted, directed ties indicating the number of PhDs trained at one department and currently employed in another. These studies analyze computer science, information, sociology, and political science departments and find a significant relationship between network centrality and rank for all of them. Their choice of centrality measures vary, though they all use recursive network measures (based on the adjacency matrix’s dominant eigenvector) that measure a node’s prestige based on the prestige of those nodes it is connected to. Centrality measures used include: eigenvector centrality (Bonacich 1972), PageRank (Page et al. 1999), and hub and authority centrality scores (Kleinberg 1998) (used by Burris 2004, Wiggins 2006, and Fowler 2007, respectively). Fowler et al. (2007) uses hubs and authorities, making a distinction between prestige from placing students at prestigious departments and hiring professors from prestigious departments. All three studies ignore the link between the department where an academic got their PhD and the department of their first job (the traditional question in the non-network studies) and ignore all placements between current job and training. Grannis’ (2005) approach is slightly different, looking at UCLA’s ego network of its faculty trades with other departments. These articles then use node centrality as a predictor of departmental prestige (Burris 2004, Fowler et al. 2007) and often interpret the relationship as confirming institutional stratification (Burris, 2004) or as showing that placing students in prestigious schools is more relevant to prestige than hiring professors from prestigious schools (Fowler et al. 2007).

Ultimately, it is difficult to parse the relationship out since there is a circle of causality: productive researchers increase a school’s prestige, but prestigious schools also attract researchers.

This paper expands on the current body of research in two ways. First, it considers the impact of training many more PhDs than there are openings for professors (henceforth referred to as “overtraining”), and second, it considers the spurious effect of department size – a reliable predictor of both hiring network centrality and academic rank.

![Department Size](image)

**Figure 1: Department Size**

Currently, the literature ignores that centrality and prestige are both strongly influenced by department size. As described earlier, the NRC rankings are based on both reputation and objective measures. One of these measures is department size (the number of faculty and students) (National Research Council 1982, 1995). Department size also indirectly influences the rankings insofar as there are more former employees and students from the largest schools, assuming that individuals rank prior affiliations higher. Department size also increases centrality because bigger departments have more ties. Consequently, centrality and prestige should be correlated by virtue of department size even if location in the network is unrelated to prestige. This is well illustrated in one of the four existing studies, Fowler

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3 Using PageRank as a predictor of academic Rank Wiggins finds coefficients as high as 1.12. Burris finds coefficients around 1.3 in Sociology, History, and political science, for a ln transform of eigenvector centrality. Finally, Fowler et al report correlations as high as .82 between predicted rank based on PhD exchange networks and actual rank. All three have sig. findings.
et al. (2007), who shows that ranks can change when we consider department size, particularly for boutique programs with focused research areas. Theoretically we might consider department size to play a valid, not a spurious, role since bigger departments have more depth and thus more opportunities for graduate students and researchers to expand their skills. As such, size is an indicator of program quality.

![Graph showing cumulative percentage of professors trained at top 10 and every fifth school](image)

**Figure 2: Where professors were trained**

Overtraining can also account for part of the relationship between centrality scores and academic rankings. The current research ties professors to their training departments and to their current department. If the most prestigious and largest departments train a much larger percentage of the job market than they hire, and than the less prestigious schools, they will be more central. Figure 2 shows the proportion of professors trained at the top 10 schools. The grey section shows the proportion of professors currently employed at the top ten schools who were also trained at the top ten schools. We see at the origin, that over 10 percent of faculty at top ten schools were trained by the University of Chicago and about 20% were trained at Wisconsin and Chicago combined. Bumps in the graph show that University of Michigan and particularly Harvard graduates are more likely to be at top schools. Over 70% of the professors at top ten schools were also trained in the top 10 schools. The lower line and the light grey section of the graph show where the professors at every fifth school in the rankings were trained, from the 5th to the 95th school. This line shows the same pattern as that for the top ten schools, with close to half of all professors being trained at the top ten schools.

There are 598 new PhDs every year and only 4,227 tenure and tenure track positions in the US; the entire profession could be replaced every 7 years, meaning that all universities can hire from the top schools, placing highly ranked schools at the centre of the hiring network. This analysis takes training into account, testing whether the association between hiring network centrality and rank holds independent of training.

## 2 Data and Methods

Two separate data sets were collected; each was collected by selecting sociology departments, going to their web sites, collecting the CV’s of current permanent faculty, and entering ties between the faculty and organizations they had been affiliated with in the past. The first data set collected faculty from prestigious departments (Wisconsin, University of Michigan, Harvard, Berkeley, UCLA, University of Chicago, Brown, Stanford, and University of Arizona). The second sample was collected with the intention to validate the effect of having sampled the most prestigious institutions in the first data set. This second group includes: Yale, University of Pennsylvania, Northwestern, Princeton, Johns Hopkins, and NYU. The second group was chosen to represent a still exceptional, although not top, schools with the intention of testing whether these schools became the most important when they were sampled. Surprisingly, they did not. One tie was coded for each of the faculty’s current and past institutional affiliations, modeling full career paths. Ties were then coded as PhD training institution, tenure-track jobs, and non-tenure track jobs. “Non-tenure track” jobs include lecturers, post-doctoral, non-academic, and visiting appointments. Approximately 7% of the sample did not have their CV’s posted on-line. For these cases, ties were coded to the faculty’s current institution and their PhD granting institution (which was normally listed). The samples included 193 and 241 institutions, 99 and 89 institutions that were ranked by the NRC, and a total of 886 and 882 ties for samples one and two respectively. All network measures used in this analysis were generated using the full graphs, although the secondary regression analyses use the sub-sample with academic rankings.

I analyze 12 different graphs, testing whether the relationship between centrality and prestige is robust to graph specification. The graphs analyzed differ along three dimensions: sample choice (2), ties included (3), and graph reduction (2). The graphs either: included all three types of ties, excluded non-tenure track ties, or excluded training ties. The first sample was reduced to 99 institutions when
non-tenure track ties were excluded and to 178 institutions when student ties were
excluded while the second sample was reduced to 89 and 237 institutions. Each of
the 6 graphs was then reduced to include only institutions, weighting the ties be-
tween them by the number of people had in common.

There are 4 main methodological challenges using this data. First, any sampling
method biases the graph, enhancing the sampled institutions’ centrality. One solu-
tion to this problem is to start with the seed institutions, and then sample from the
other institutions that enter the analysis (snowball), ultimately excluding the origi-
nal seed institutions from the network analysis. Instead, I include these biased ob-
servations, but use two different seeds, concluding that if the results are similar us-
ing the two seeds, the conclusions are robust to sample bias. Second, the data
includes both end-of-career and beginning of career professors. This biases the da-
ta insofar as older professors with a longer history of institutional connections are
more likely to be at more prestigious universities. Other studies have similar prob-
lems, for example, coding the tie between a department that trained a professor
and their first job the same as their emeritus job (Burris, 2004; Wiggins et al.,
2006; Fowler et al., 2007). Third, academia is not an isolated network, which can
bias network statistics like transitivity, degree distribution, and clustering (Gran-
nis, 2005) as well as mean degree (Kossinets, 2006). The final difficulty is that the
graph is bipartite with two types of nodes (professors and departments) linked by
ties (employment relations). Bipartite graphs are also called “affiliation net-
works.” Most centrality measures are designed for one-mode graphs (Borgatti and
Everett, 1997) but can easily be adjusted for use with bipartite graphs, or the orig-
inal centrality measures can be used on the reduced form of the bipartite graph.
Centrality measures (defined in the following section) differ substantially based on
the approach taken. Figure 3 shows two graphs that are different in their bipartite
forms but identical in their reduced forms. Graph 1 could be a picture of three pro-
fessors who have had very mobile careers, while graph 2 illustrates 19 professors,
each of whom is only affiliated with their training institution and their current em-
ployee. In the reduced versions of the graphs D and H are the most important
nodes, while they are more important in bipartite graph one than two. Calculating
the nodes’ centralities, D and H have similar eigenvector centralities in both graphs.
However, D & H have much higher standardized degrees and closeness centralities
in both graph 1 and the reduced graph than in graph 2. As such, I ana-
lyze the graph both as a bipartite and a reduced graph using the bipartite centrality
measures proposed by Borgatti and Everett (1997) and illustrated in Robins and
Alexander (2003) (although eigenvector centrality need not be adjusted for the bi-
partite graph (Bonacich, 1972, Faust, 1997)).

Three different centrality measures were calculated: closeness, degree, and ei-
genvector centrality. Eigenvector centrality was chosen as the recursive measure,
closeness centrality chosen as a distance measure (related to how quickly the de-
partment can access information from peers about funding, new research trends,
recruiting, etc), and degree centrality was chosen as a straw man (it should capture
department size and the experience of the department’s faculty) as it should be
the most biased for the sample seed. Surprisingly, results are similar using all three
measures.

Standardized degree, equation 1, measures the percent of possible connections
that an institution has (to institutions in the reduced graph or to professors in the
bipartite graph). In both cases, the numerator is the raw degree, and the denomina-
tor is the maximum number of possible connections in the graph, np = (the num-
ber of professors) in the bipartite graph and nd-1 = (the number of departments
less the department being considered) for the reduced graph. Degree centrality
measures a combination of department size (faculty and training depending on the
graph) and the department’s turnover rate.

Figure 3: Reducing two different bipartite graphs into one reduced graph

4 Centrality scores for D in bipartite graph 1 are: .377(eig), .667(degree), .889(closeness); in bipartite
graph 2 they are: .469(eig), .368(degree), .836(closeness); in the reduced: .490(eig), .778(degree),
.818(close)
5 Centrality measures for affiliation networks are also covered in Faust, 1997. I use several of the
methods detailed in Faust including equation 18 to calculate eigenvector centrality. Closeness
centrality is taken from Borgatti.
6 Standardized degree was calculated using the unweighted version of the reduced graph.
Closeness centrality measures the inverse of the average distance between a given node and all other nodes and is illustrated in equation 2. Here, \( i \) is the node of interest, \( n_i \) indicates the number of nodes, and \( D_{ij} \) is the distance from node \( i \) to node \( j \). The bipartite graph measure multiplies the average inverse distance by 2 to account for the fact that all connections between institutions are twice as far as in the reduced graph.\(^7\) Closeness centrality measures whether actors can contact on another through short paths (Faust, 1997).

\[
C_i^b = 2 \sum_{j=1}^{n_i} \frac{n_j - 1}{D_{ij}}, \quad C_i^u = \frac{n_j - 1}{\sum_{j=1}^{n_i} D_{ij}}
\]

Eigenvector centrality Bonacich (1972), is a recursive measure of prestige related to Page Rank (Page et al. 1999), hubs and authorities (Kleinberg 1998), and SALSA (Lempel and Moran 2000). All are based on the dominant eigenvector of the graph's adjacency matrix and all gauge the importance of a node based on the importance of its neighbors. Page Rank adds a damping factor to the adjacency matrix (reducing the ties in the adjacency matrix by some small amount and then adding uniform random ties from each node to all other nodes) and then calculates eigenvector centrality. Both SALSA and hubs and authorities use the dominant eigenvectors of the adjacency matrix times it transpose (and vice versa) with SALSA using row and column standardized versions of the adjacency matrix. For eigenvector centrality, given the adjacency matrix, \( A \) where entry \( A_{ij} \) is 1 or 0 in the bipartite graph, or the number of connections between institutions in the reduced graph, the centrality score, \( c_i \), is:

\[
c_i = \alpha \sum A_{ij} c_j
\]

where \( c \) is the eigenvector paired with \( A \)'s largest Eigen value, i.e. the principle eigenvector. For the bipartite graph, eigenvector centralities for individuals are simply dropped.\(^8\) All centrality scores were converted into ranks to be comparable.

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\(^7\) Closeness centrality was also calculated using the unweighted version of the reduced graph.

\(^8\) Page Rank and Hubs and authorities were also tested, yielding similar results.

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Figure 4: Two sample graphs
to academic rank. There were no ties because the base centrality measures are continuous.
There are three exogenous variables: the domestic and international ranks described in the first section of the paper, and department size. For domestic universities department size was taken directly from the NRC report when possible, and from departmental web sites when not. Information was drawn from departmental web sites for non-US universities.

Two of the twelve networks are depicted in figure 4 using the Kamada-Kawai spring layout algorithm. This algorithm places "springs" between each pair of connected nodes, and moves the nodes to minimize the springs' energy. Thus, nodes are connected in clusters with the nodes they share many connections with.

I present just 2 of the 12 graphs for the sake of brevity. The first graph in figure 4 is the bipartite graph from the first sample (the very prestigious sample), including all ties (tenure, non-tenure, and student). The size of the nodes indicates their degree and the shade indicates whether they are an institution (darker) or an individual (lighter). Sampled institutions, of course, have high degrees and are central while European English-speaking institutions are also central but with smaller degrees. The halo of small institutions indicates small departments like UCSF (labeled) or non-profit and public institutions. The second graph in figure 4 is sample two's reduced graph excluding non-tenure track ties. The institutions that were part of the first sample remain central, though less dominant as they were not the sample's seed, while sampled institutions like Yale take a more dominant position. In the analyses excluding non tenure track ties foreign institutions either dropped out of the graph or moved to the periphery. Self-ties (indicating that an institution had two relationships with the same individual i.e. training and then employing the same person) become apparent in the second graph because it is sparser. Removing student ties as well, the traditional central institutions remain central though not disproportionately so.

Table 2 shows the descriptive statistics for all graphs. Average degree indicates the average number of individuals the department is associated with in the bipartite graphs and the average number of institutions sharing connections to professors in the reduced graphs. Average distance measures the average number of jumps to get from one institution to another for the reduced graphs and institution-individual-institution jumps for bipartite graphs. Finally, diameter measures the longest shortest path between any two institutions, which is 4 in all graphs. The reduced graphs have higher average degrees and lower average distances, as departments are tied to most other departments. There is no marked difference between the two samples. Comparing graphs by tie inclusion, bipartite graphs' degree increases excluding non-tenure track jobs because peripheral institutions drop out. Removing student ties, average degree decreases because few nodes drop out but many ties do.

### Table 2: Sociology Department Ranks

<table>
<thead>
<tr>
<th>Sample</th>
<th>All nodes</th>
<th>Org nodes</th>
<th>edges</th>
<th>Avg degree</th>
<th>Avg distance</th>
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<td>193</td>
<td>886</td>
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<tr>
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<td>reduced no student</td>
<td>178</td>
<td>178</td>
<td>631</td>
<td>7.97</td>
</tr>
</tbody>
</table>

Diameter for all graphs was 4

### 3 Analysis

Ranks generated from centralities are strongly correlated to prestige though the relationship varies across graphs. Closeness centrality changes when the graph is reduced, eigenvector centrality changes when ties are removed, and mean degree changes both when the graph is reduced and when student or non-tenure track ties are excluded.9

Using equation 4 to calculate the sum square deviations between the predicted and actual ranks for the top universities, we assessed which graph's centrality scores best predicted academic rank. Gs is the graph's sum of squared errors, u is a university, r is u's NRC rank, and c, e, and d are the eigenvector, closeness, and degree centrality ranks respectively.

9 All the listed changes are significant at a 95% confidence level.
The bipartite graph from sample one excluding non-tenure track ties was the best predictor of academic rank while the reduced graph from sample one including all ties was the worst predictor. The first three columns of Table 3 show ranks generated from the three centrality scores for the best graph and the second shows those from the worst graph. In the last two columns, the average rank is in bold if the school was part of the sample seed. It seems that departments have higher ranks as predicted by centrality scores when they are part of the seed, but the top schools remain highly ranked even if left out of the seed. The graphs excluding student ties have significantly worse predictions of rank, with 3 of the 4 graphs excluding student ties landing in the bottom four (of 12) predictions.

Table 3: Centrality rankings for the best and worst graphs

<table>
<thead>
<tr>
<th></th>
<th>Eigen rank</th>
<th>Close rank</th>
<th>Degree rank</th>
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<th>Close rank</th>
<th>Degree rank</th>
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<th>Sample two</th>
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Best = sample 1, bipartite, non-tenure edges; worst = sample 1, reduced graph, all edges

The three centrality measures seem to all predict prestige well in Table 3 because they are closely correlated to one another as illustrated in Table 4. The first column shows the correlation between eigenvector and closeness, the second shows eigenvector and degree and the third shows closeness and degree. The main entries indicate rank correlation while the numbers in parentheses are the correlations for the raw centrality scores. While the first 12 rows illustrate the correlations within graphs, the last line is the overall correlation, ignoring graph specification. All the rank correlations are better than the ones using raw centralities. The graph with the most inconsistent centrality scores is the reduced graph from sample one with all ties. The ranks generated by the three centrality measures are similar regardless of graph specification.

Table 4: Correlations between centrality measures by graph type

<table>
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<td>.841(.944)</td>
<td>.924(.696)</td>
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Entries are rank correlations

All the centrality measures have strong correlations with domestic and foreign academic rank. For domestic ranks, the ranks generated using eigenvector centrality have a .68 rank correlation compared to .72 using closeness and .73 using degree. Correlations are slightly lower (.55, .59, and .59) for foreign international academic rank. Correlations varied substantially within the individual graphs. For example, ranks generated from eigenvector centrality had a correlation with domestic prestige ranging from .39 for sample 1's bipartite graph including all ties to .8 for sample 1's reduced graph excluding non-tenure ties. Closeness rank was somewhat more consistent with correlations ranging from .6 to .8 and from .62 to .77 for degree ranks' correlations.

In terms of biases for the seed institutions; for the first sample both eigenvector and closeness centrality under-ranked the sampled departments, though closeness centrality did less so. This is the opposite of what we expected, anticipating that
eigenvector centrality would be a more resilient estimate of academic ranking. For the second sample of less prestigious schools, using closeness centrality, seed institutions were ranked on average 10.6 positions higher than their NRC ranks and 9.28 positions too high using eigenvector centrality. (The mean rank for the sampled institutions in sample 2 was 3-7 (95% confidence) while the NRC mean rank was 13-16 (95% confidence). Because the top institutions were sampled in the first sample it was impossible to over-rank them, but in the less prestigious second sample we find the anticipated bias, with the recursive centrality measure no more resilient than closeness centrality.

Figure 5: Closeness centrality rank versus NRC rank by tie inclusion

Given the number of students the most prestigious schools train, excluding student ties should have a significant effect on their centrality. Surprisingly, this is not the case. For the top ten schools, the mean closeness and eigenvector centrality scores using all ties are statistically indistinguishable from those excluding student ties. The top schools do, however, have a statistically higher degree centrality in the graph with all ties than excluding training ties. Thus, while the top schools do train the bulk of professors, they are still at the centre of the later-career hiring net-

work. Another way to show this is illustrated in figure 5 which shows the average predicted rank using closeness centrality for graphs including and excluding student ties. Given over-training, we would expect those graphs excluding student ties to be the better predictors of rank but this is not the case. Instead, the graphs without student ties are often closer to the actual rank. Predictions are better including student ties for Chicago, UCLA, Stanford, and Northwestern while predictions are better excluding student ties for Washington, Harvard, Chapel Hill, Michigan, Berkeley, and Wisconsin. Thus highly ranked schools are central to academic hiring networks whether or not we consider their training role.

We can also test the importance of training using a k-core analysis. First, we separate the graphs into subgraphs where each node has at least degree k within the subnetwork. The subgraphs are calculated by recursively pruning those nodes with degree less than k, producing subnetworks that are interconnected at the same level. This groups together nodes based on both their clustering and their relative popularity, leaving the highest k-core to include the most prestigious departments. However, this changes when training ties are removed. Among the top ten schools 3 appear in the top k-core more often using all ties than excluding student ties. More striking, many more foreign departments enter the top k-core when we exclude training ties (European University Institute, Cambridge, the London School of Economics, and Oxford appear in the top k-cores more than 50% of the time when training ties are removed). Foreign institutions are more important when we remove training but include non-tenure ties because many academics visit the same foreign schools. Excluding non-tenure track positions, foreign institutions do not enter the top k-core at all.

Figure 6 shows the graph excluding PhD training from sample 2, an exceptional graph in the analysis, as it is the only one where the top schools were not ranked highest. In this graph the top k-core was dominated by foreign institutions (LSE, Hebrew University, McGill, University of Quebec, Montreal, and Paris, University of San Paolo, and Oxford) and also included some domestic institutions (NYU and UCSD). Inspecting the raw bipartite graph, it is clear that there are two main clusters, the foreign cluster and the traditional "top" cluster. Both have many prestigious individuals and institutions in them, but one cluster is largely foreign and slightly larger than the second group of traditionally prestigious schools. In sum, the k-core analysis shows that the top ten schools lose some of their dominance without training ties, and that the top British institutions are a central part of the American sociology labor market.

10 The same is true using top 20 schools.
I test the hypothesis of whether department size matters by first running bivariate regression between each of the centrality measure ranks and the actual academic rank. Then faculty size and the variables related to graph specification are added in, showing that faculty size accounts for very little of the relationship between hiring network centrality and academic ranks. Finally, all the centrality scores are used as predictors in the same equation followed by a Wald test of equality between the centrality measures’ coefficients. Results are illustrated in Table 5.

Each of the three centrality scores has approximately the same impact regardless of whether or not we consider faculty size. A one position increase in centrality rank predicts at least a .5 position increase in NRC or Newsweek academic rank. Running the three centrality measurements together, we see that eigenvector centrality provides no information not provided by the other two measures and in fact, controlling for the other two factors, has a negative effect. The only variable related to graph specification that predicts prestige is whether or not the graph includes PhD training ties. When the graph includes training ties, the average predicted ranks increase, because centrality scores are weighted to the academic institutions in the regression analysis and away from the non-academic institutions not included in the regression, because they have no academic rank (such as the census bureau).

Table 5: Predicting prestige with OLS regressions

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<th>international rank</th>
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<td>centrality</td>
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<td>closeness</td>
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<td>degree</td>
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**bold** text indicates bivariate regressions
*** indicates significance at the .001 level

Finally, going back to our first hypothesis, that the prestigious schools maintain their positions by overtraining, we find that running the same regression for only the top 50 schools in the sample and excluding PhD training ties increases predicted rank at least 2 points. This is the opposite of what one might expect if the top schools over-train and rely on placing fresh PhD students to increase their standing in the field. Further, running these same regressions for all observations,
still using only those graphs excluding PhD training ties, a one position increase in eigenvector rank is still correlated with a .42 increase in domestic academic rank and a one point increase in closeness centrality rank is related to a .45 increase in prestige. In sum, excluding student relationships slightly weakens the relationship between graph centrality and prestige, but overall the relationship is still strong.11

4 Conclusion

This paper began with two main hypotheses regarding the relationship between the sociology academic employment network and academic rankings. First, we suggested that the relationships might be driven by a spurious relationship with department size. Second, we posited that the relationship could entirely be driven by the dominance of a few departments training the bulk of sociologists and the over-training of sociologists.

I found support that both of these hypotheses are true. Faculty size does explain some of the relationship between centrality and academic rank, and the top institutions are somewhat less central when we consider their dominance in training new PhDs, and that the relationship between centrality and rank is somewhat weaker when we exclude PhD training ties from the analysis. That said, the positive support for these two alternative hypotheses in no way diminished the strength of the relationship between academic rank and centrality in the academic hiring network.

Other researchers finding similar patterns interpret this as an academic “caste system” or infer that training and placement consolidate departments’ prestige (Burris, 2004). While I find evidence confirming these patterns, I hesitate to consider it a “caste system” per se and perhaps would consider it a case of positive feedback. If faculty moved strictly in castes (prestigious faculty moving between prestigious institutions and other faculty moving among the other institutions) we would not see this strong relationship between hiring network centrality and academic rank. Rather, we would see two separate cores, lower ranked schools trading with each other and higher ranked school trading with each other. Instead peripheral schools trade faculty with the most prestigious schools rather than with each other. They do this first by hiring graduates of the more prestigious schools, and then by passing their successful professors on to the more prestigious schools. It is these trades that keep the most prestigious schools in the center of the graph when we exclude training ties and it is possibly a consequence of this process that highly ranked universities remain highly ranked.

Future work should use data from a wider sample of departments. With a larger sample one might also pursue block modeling, testing whether most ties occur within two distinct groups of departments, as the caste hypothesis should imply. A second possible improvement would include recoding the data as sequential cohort level data. With that sort of data we might test whether the network has become more stratified over time and we might test whether prestigious institutions consolidate their advantage by hiring more accomplished faculty later in their careers. Third, it would be interesting to develop our own measure of research quality, and control for this in predicting departments’ prestige. In addition, a study of the evolution of the network would be particularly interesting-testing whether the relationship between trading faculty and academic prestige has been constant over time. Finally, with 40% of new positions in Academic Sociology being adjunct positions, perhaps one of the most pressing questions is what role those adjunct ties play in the network (American Sociological Association, 2007).

References


11 A Wald test of equality between the centrality scores’ coefficients indicates that for both domestic and foreign rank the effects of eigenvector centrality is significantly different from both closeness and degree, though closeness and degree’s effects are statistically indistinguishable from each other.


