Academic Employment Networks & Departmental Prestige

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This study is the first to consider the relationship between university departments' prestige rank and their centrality in the academic hiring network independent of department size and training. These new controls are important as the correlation between prestige rank and employment network centrality may result from the fact that highly ranked schools train more PhDs, their graduates are more likely to continue in academia, and that highly ranked schools have more faculty. Past research has characterized the correlation between academic departments' prestige rank and their centrality in academic hiring networks as indicative of a "caste" system. However, if academics move between institutions for assorted reasons like wages, location, and specialty areas, there should be no correlation between hiring network centrality and rank. This suggests that academics might prefer to make career switches to top ranked departments, creating the correlation between prestige and centrality, and giving top departments a competitive advantage. This would be one possible explanation why academic rankings are static. In addition, this paper tests this relationship under a variety of several methodological variations in sample selection, bipartite graph reduction, and the choice of centrality measures. Results are robust to all specifications.

keywords: academic prestige, network analysis, centrality measures, intermediaries

1 Introduction

Sociology departments'academic rankings incorporate both "'objective" measures of department quality (such as citation rates and funding patterns) and "subjective" measures (such as faculty perceptions of graduate school quality). While we might expect that departments could improve their rankings when objective measures are used while they might be unable to improve their positions when reputational measures are used. Yet, regardless of the measure used, 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. These rankings find remarkably consistent results despite their significantly different methodologies. 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 augment it with data for about 17 program characteristics such as: size, private vs public university, total research and development (R&D) expenditures , federal R&D, library expenditures, enrollment, total faculty, percent full time faculty, percent faculty with research support, percent full professors, faculty awards, citations per faculty, faculty characteristics, and student characteristics. The NRC found that the reputational measures are consistent with the objective measures. Critics of the NRC rankings argued there was too much emphasis on research-related variables and too little on doctoral training, though the next version of the ratings will incorporate more training-related variables.

The analysis here is done twice, once using the NRC's sociology rankings. Unfortunately this rank does not include foreign institutions. Thus the analysis was done again using the US News and World Report international rankings, which are 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 were developed using different metrics and only one focused on sociology, 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

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

[2]I tested the Shanghai rankings as well, but because there was little difference those results are not presented here.

1925*	1982+	1995**	1995+	2005**
Chicago	Chicago	Chicago	Chicago	Wisconsin
Columbia	Wisconsin	Wisconsin(2/3)	Wisconsin	Berkeley
Wisconsin	Berkeley	Berkeley(2/3)	Berkeley	Michigan (3/4)
Minnesota	Michigan	Michigan(4/5)	Michigan	Chicago (3/4)
Michigan	Harvard	Chapel Hill(4/5)	UCLA	Chapel Hill
Harvard	Chapel Hill	Harvard(6/7)	Chapel Hill	Princeton (6/7)
Missouri	Stanford	UCLA(6/7)	Harvard	Stanford (6/7)
	Columbia	Stanford	Stanford	Harvard (8/9)
	UCLA	Northwestern(9/10)	Northwestern	UCLA (8/9)
	Arizona	Princeton(9/10)	Washington	UPenn

∗ Hughes (1925)

+ National Research Council (1982, 1995)

∗∗ US News and World Report (1995,2005)

Table 1: Sociology department ranks

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 et al., 1955). Ideally, stratification should function as an incentive for individuals to work harder or to 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 can propagate their advantage through their current assets or analogously, an organization can sell more of their product not based on their current effort, but on their brand name or reputational inheritance.

There are two ways sociology departments may maintain their advantages in the rankings. First, it might be that respondents to the reputational survey are rather ill informed, basing their evaluation of doctoral programs not on the programs' actual merit but on what respondents have heard about departments (although the correlation between NRC's objective and subjective measures speaks against this). If this is the case, once a program is highly ranked, it will remain there, as professors perpetuate the reputation without objectively examining it. More likely, once a program is highly ranked, it has the ability to perpetuate its rank by attracting faculty and resources. The simple preference for faculty to move to or between higher ranked schools can cement departments' rank. Departments' consequent central positions in the academic hiring network can further enhance departmental prestige through many mechanisms such as research collaborations or knowing about upcoming trends in the field. While this paper does not explore the specific mechanisms linking hiring network centrality and prestige, it does confirm the existence of the correlation between centrality and prestige, independent of training and department size–possible spurious causes not previously considered.

There is significant non-network research testing how the institutional prestige of PhD granting institutions influences first job placement. This literature finds that the most prestigious universities hire each other's graduates, over-valuing the institutional prestige of applicants' training institution over other characteristics that might be more predictive of long-term 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 are linked to academic rank. Burris (2004); Wiggins et al. (2006) and Fowler et al. (2007) create networks linking professors to their current employers and their PhD granting institutions, generating a network of institutions with weighted, directed edges indicating the number of PhDs trained at one department and currently employed in another. These studies analyze computer science, information schools (formerly called schools of library science), sociology, and political science departments and find a significant relationship between network centrality and rank. 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 et al. (2006), and Fowler et al. (2007) respectively. Fowler et al. (2007) uses hubs and authorities, making a distinction between prestige from placing students in 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 non-network studies) and all ignore placements taking place between the professor's current job and his or her training. The Grannis (2005) approach is slightly different, looking at UCLA's ego network of its faculty trades with other departments. These articles then use centrality scores as a predictor of departmental prestige (Burris, 2004; Fowler et al., 2007) and interpret the relationship as confirming institutional stratification (Burris, 2004) or in the hubs and authorities case showing that placing students in prestigious schools is more relevant to prestige than hiring professors from prestigious schools (Fowler et al., 2007).[3] Ultimately, it is difficult to parse out the relationship

[3]Using the natural log of eigenvector centrality as a predictor of academic rank in regressions,Burris finds coefficients around 1.3 in sociology, history, and political science. Using PageRank, Wiggins

since there is a circle of causality—productive researchers increase a school's prestige, but prestigious schools also attract productive researchers.

This paper expands on the current body of research in two ways. First, it considers the impact of prestigious schools training many more PhDs than there are openings in the entire field (henceforth referred to as "overtraining"), and second, it considers that the relationship between between hiring network centrality and academic rank might be spurious, driven by department size which is a reliable predictor of both. In addition, this paper uses a more robust methodological procedure considering the effect of sample bias, bipartite graph reduction, and the choice of network centrality measures.

Currently, most of the literature ignores that centrality and prestige are both strongly influenced by department size (National Research Council, 1982, 1995). Department size *indirectly* influences the rankings insofar as there are more former employees and students from the largest schools and insofar as those individuals rank their previous affiliations higher than those departments they were never affiliated with. Department size also increases centrality *directly* because bigger departments have more edges. 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 et al. (2007) shows that ranks can change when we control for department size, particularly for boutique programs with focused research areas. It should be noted that, theoretically, department size might play a valid role in determining prestige since bigger departments have more depth and thus more opportunities for graduate students and researchers to expand their skills. The size distribution of sociology departments included in this study are shown in figure 1. The bars indicate actual department size while the line is just a smoothed estimate. The distribution is more concentrated around faculties of about 20, rapidly petering out. Wisconsin has an extreme number of faculty, presumably because the NRC numbers include cross listed faculty.

Overtraining can also account for part of the relationship between centrality scores and academic rankings. The current research creates edges between professors and their training departments and their current employers. If the most prestigious and largest departments train a much larger percentage of the job market than they hire, and train more than the less prestigious schools, they will be more central. Figure 2 shows two lines illustrating first where professors at the top ten schools were trained and second where professors at the average school were trained. The dark grey section shows the proportion of professors currently employed at the top ten schools who were also trained at the top ten schools slowly incrementing from those trained at the top school to those trained at the 10th school. We see at the

finds a correlation between centrality and rank of .81. while Fowler et. al. find correlations as high as .82 between network centrality and prestige rank.

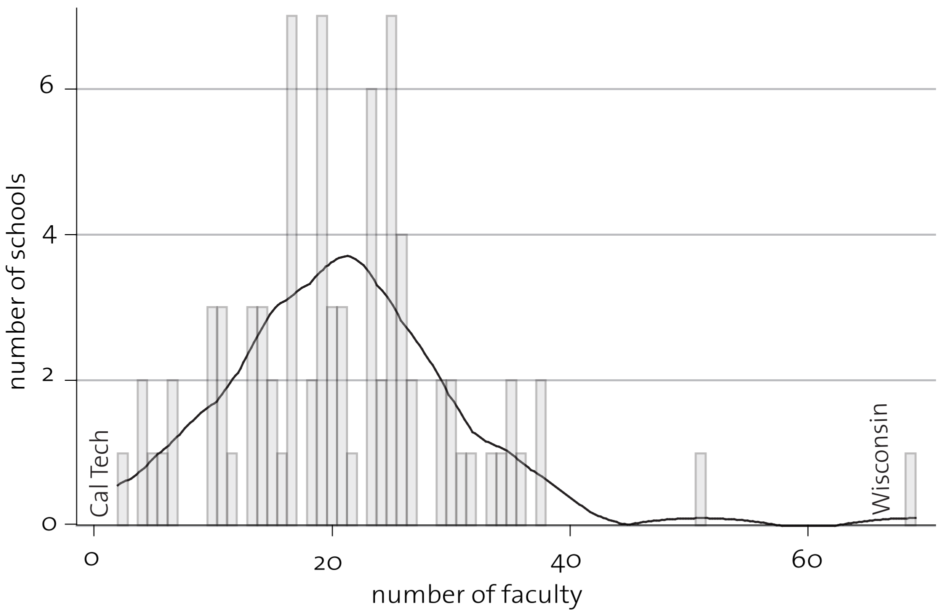

Figure 1: Department size

origin, that over 10 percent of the 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 trained more of the faculty at top schools. By the end of the chart, we see that over 70% of the professors at top ten schools were also trained in the top 10 schools. The lower line and light grey section of the graph shows where the professors at the average school were trained (including professors from every fifth school in the rankings from 5 to 95). The training school of all faculty at every fifth school was collected as a sample indicative of the training of the average school. The percentage measures the percent of total faculty, not the average percent at each school. This is an important difference because it weights the bigger (and usually better) schools more and is ultimately representative of the mean in the labor market, not the mean 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. The American Sociological Association (ASA) reports there are 598 new PhDs every year and a stock of only 4,227 tenure and tenure track positions in the US. This means that enough students graduate to replace the entire profession every 7 years. At this level of production, all universities can hire from the top schools, while the graduates from the other schools must simply leave the market. This places highly ranked schools at the center of the hiring network. This analysis tests whether the association between hiring network centrality and rank holds independent of this over-training.

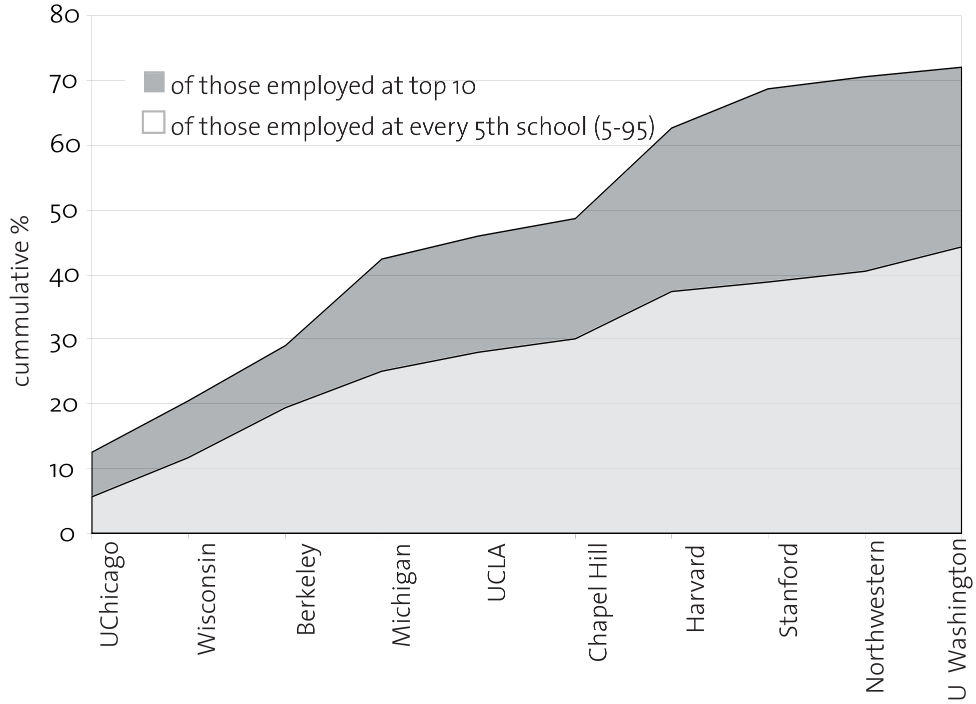

Figure 2: Where professors were trained

2 Data and methods

Two separate data sets were collected by choosing sociology departments and using current permanent faculty's CV's to code edges between faculty and the departments and organizations they had been affiliated with. The first data set collected faculty from prestigious (according to the NRC rankings) 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 test 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 still represents exceptional schools; the comparison between these two networks allows us to test whether sampled schools automatically become the most central schools. Edges between individuals and institutions were coded as "PhD training", "tenure-track," and "non-tenure track." Non-tenure track jobs include lectureships, post-doctoral positions, non-academic, and visiting appointments. Approximately 7% of the sample did not have their CV's posted on-line. For these cases, edges were coded to the faculty's current institution and their PhD granting institution (which were normally listed). Including these CV's will place the departments that train more students at the center of the network. The edges will drop out for those graphs were training edges were excluded. Thus, including this 7 % should sharpen the difference between the findings using graphs with and without training edges. The two samples included 193 and 241 institutions, 99 and 89 institutions that were ranked by the NRC, and a total of 886 and 882 links for samples one and two, respectively. All network measures used in this analysis were generated using the full graphs including non-academic institutions although the secondary regression analyses use the sub-sample of academic departments with prestige rankings.

Twelve different graphs (differing by sample choice (2), edges included (3), and graph reduction (2)) were used to test whether the relationship between centrality and prestige is robust to graph specification. The graphs either included all three types of edges, excluded non-tenure track edges, or excluded training edges. The first sample was reduced to 99 institutions when non-tenure track edges were excluded and to 178 institutions when student edges were excluded, while the second sample was reduced to 89 and 237 institutions. Each of the 6 graphs was first analyzed as a full bipartite graph with both individuals and institutions and then then analyzed as a reduced graph including only institutions, weighting the edges between institutions by the number of faculty they 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 solution to this problem is to start with seed institutions, and then to sample from the other institutions that enter the analysis, ultimately excluding the original seed institutions from the network analysis. Instead, I include these biased observations, but use two different seeds, concluding that if the results are similar using 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 data insofar as older professors with a longer history of institutional connections are more likely to be at more prestigious universities. Other studies have similar problems, for example, coding the edges 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 (Grannis, 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 edges (employment relations). Bipartite graphs are also called "affiliation networks." 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 original centrality measures can be used on the reduced form of the bipartite graph. Centrality measures (defined in the following section) differ based on the approach taken. Figure 3 shows two graphs that are different in their bipartite forms but identical in their reduced forms. In the figure, node size indicates degree. Graph 1 could illustrate three professors who have had very mobile careers, while graph 2 could illustrate 19 professors, each of whom is only affiliated with their training institution and their current employer. 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 in bipartite graph two. Calculating the nodes' centralities, D and H have similar eigenvector centralities in all three graphs. However, D and H have much higher standardized degrees and closeness centralities in graph 1 and the reduced graphs than in the bipartite graph two.[4] Because of these differences, I analyze the graphs both as bipartite and reduced, using the bipartite centrality measures proposed by Borgatti and Everett (1997) and illustrated in Robins and Alexander (2003) (although eigenvector centrality does not need to be adjusted for the bipartite graph (Bonacich, 1972)).

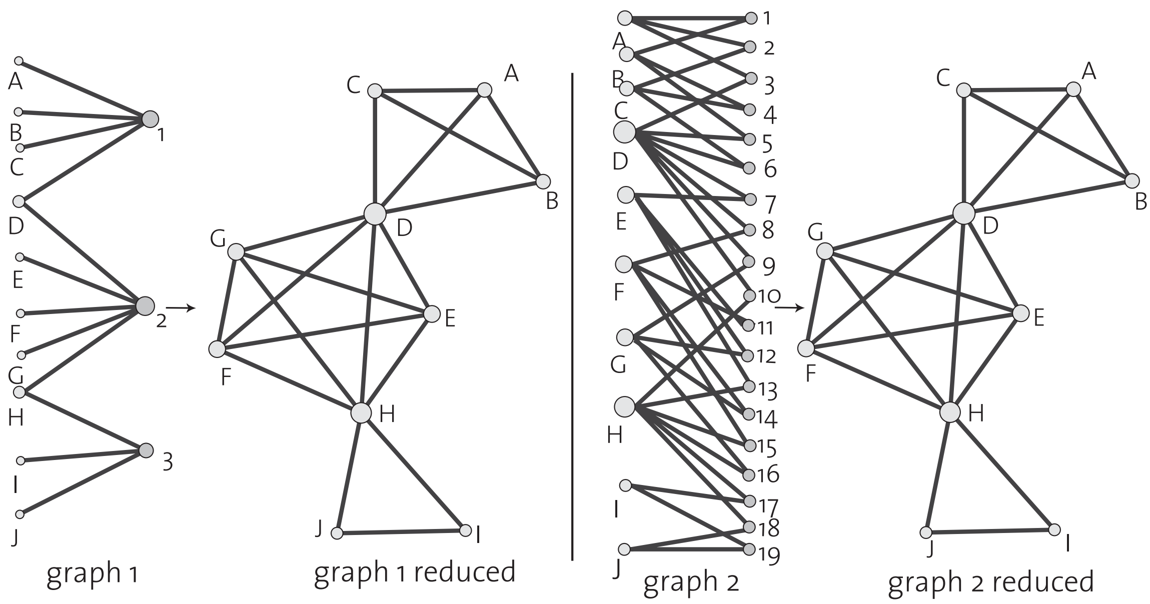

Figure 3: Reducing two different bipartite graphs into one reduced graph

Three different centrality measures were calculated: closeness centrality, standardized degree, and eigenvector centrality. Eigenvector centrality was chosen as the recursive measure, closeness centrality chosen as a distance

[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)

measure (related to how quickly the department 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) and should be the most biased by the sample seed. Most studies focus on using one of the recursive measures of centrality since these measures indicate how important a node is based on the nodes it is connected to. This should be more robust to the sampling limitations. A good example of this would be a prestigious foreign university like Cambridge. While perhaps not many professors in the US system have worked at Cambridge, those that did should be the ones also connected to top US universities. A recursive measure would, as such, give Cambridge a high score, while the standardized degree would not. Surprisingly, as we will see in section 5.3, results are similar using all three measures.

Equation 1 illustrates the calculation for standardized degree for node i. Standardized degree measures the percent of all possible connections that an institution has to institutions in the reduced graph (D_i^r) or to professors in the bipartite graph(D_i^b). In both cases, the numerator is the degree of department (the number of edges it has) d_i, and the denominator is the total possible connections in the graph, n_p, the number of professors in the bipartite graph, and $n_d - 1$, the number of departments less the department whose standardized degree is being calculated in the reduced graph. As such, standardized degree measures a combination of department size (faculty and training depending on the graph) and the department's turnover rate.

$$D_i^r = \frac{d_i}{n_d - 1} \qquad\qquad D_i^b = \frac{d_i}{n_p} \tag{1}$$

Closeness centrality measures the inverse of the average distance between a given node (i) and all other nodes (j) and is illustrated as C_i^r for the reduced graph and C_i^b for the bipartite graph in equation 2. Here, n indicates the number of departments, and and D_{ij} is the distance from node i to node j. The version of the measure used for the bipartite graph (C_i^b) 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. Thus, closeness centrality measures whether actors can contact one another through short paths (Faust, 1997).

$$C_i^r = \frac{n-1}{\sum_{j=1}^{j=n} D_{ij}} \qquad\qquad C_i^b = 2 * \frac{n-1}{\sum_{j=1}^{j=n} D_{ij}} \tag{2}$$

Eigenvector centrality (Bonacich, 1972), is a recursive measure of prestige related to PageRank (Page et al., 1999), hubs and authorities (Kleinberg, 1998), and SALSA (Lempel and Moran, 2000). All four 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 edges in the adjacency matrix by some small amount and adding uniform random edges from each node to all other nodes) and then calculates eigenvector centrality. The PageRank adjustment is necessary when a graph has directed edges leading into a node, but no edges leading out. Both SALSA and hubs and authorities use the dominant eigenvectors of the adjacency matrix times its 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, and where e is the eigenvector pared with A's largest eigenvalue, λ, the i^{th} entry of vector e is the eigenvector centrality for the i^{th} node.

$$Ae = \lambda e \tag{3}$$

In other words, the centrality scores are the principle eigenvector of the adjacency matrix. For the bipartite graph, eigenvector centralities for individuals are simply dropped.[5]

It is expected that the degree centrality score will be the most influenced by department size and sampling bias while the recursive measure should be more robust. All the centrality scores are continuous and can be converted into a rank comparable to prestige rank. Analyses were conducted using both the continuous measures and the rank.

There are three variables exogenous to the networks: 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 (Kamada and Kawai, 1989). This algorithm places "springs" between each pair of connected nodes, where the strength of the string is proportional to the strength of the edge, and places 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 sample one (the prestige sample), including all edges (tenure, non-tenure, and student). The size of the nodes indicates their degree and the shade

[5] PageRank and hubs and authorities were also tested, yielding similar results.

indicates whether they are institutions (grey) or individuals (white). 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 like the Census Bureau. The second graph in figure 4 is sample two's (the less prestigious sample) reduced graph excluding non-tenure track edges. 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 those analyses excluding non-tenure track edges, foreign institutions either dropped out of the graph or moved to the periphery. Self-edges (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 edges as well, the prestigious central institutions lose a little centrality.

Table 2 shows the descriptive statistics for all graphs. Average degree indicates the average number of individuals the organization is associated with in the bipartite graphs and the average number of organizations sharing connections to professors in the reduced graphs, weighted by the number of professors they had in common. Note that the average degree is smaller than the average academic department size because the graphs (particularly those including non-tenure track edges) include peripheral non-academic institutions that only one or two individuals have worked for. 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 shortest path between the institutions that are the most distant. Comparing the two samples in table 2, the two samples seem similar in at least their descriptive statistics. The reduced graphs have higher average degrees than the bipartite because departments are linked to most other departments. The reduced all edges graph from sample 2 (the less prestigious sample) is more dense than the same graph from sample 1. This is also visible when we plot the two graphs. The version from sample one looks like a few main departments have ties to each other, while in the second sample the same graph looks like there are more small connections throughout the graph. We will see whether this is the case in a more rigorous test later in the paper. In all networks the diameter is small (equal to 4 in all cases) because the networks are star shaped with a few central institutions keeping all organizations closely linked. Removing student edges, average degree decreases because few nodes drop out but many edges do. Those nodes dropping out in the no student edges graph would be schools that only one person in the data is affiliated with–this could be, for example, due to a foreign professor trained abroad but working in the US.

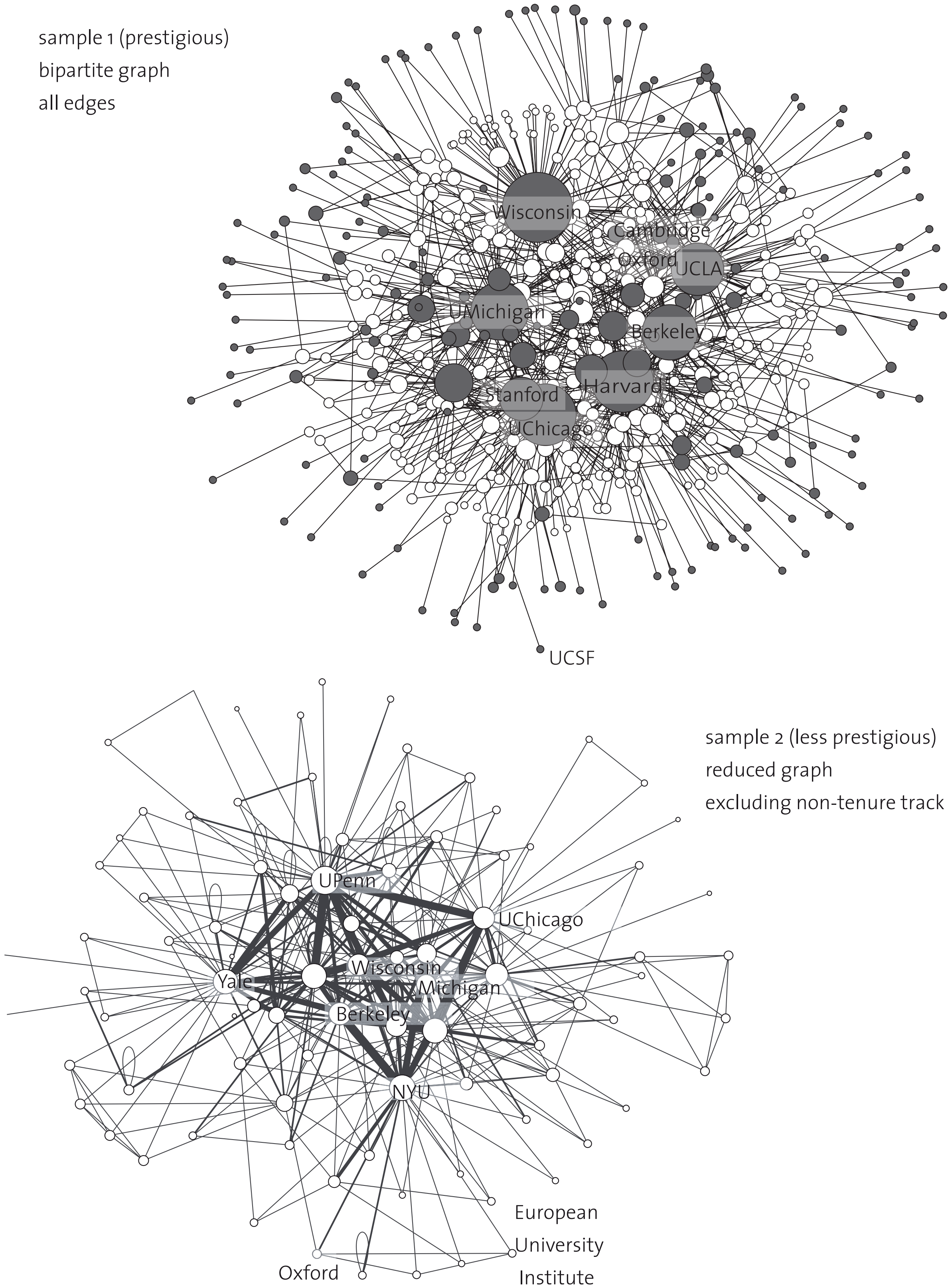

Figure 4: Two sample graphs

	all nodes	org nodes	avg degree	avg distance	diameter
sample 1					
bipartite all edges	479	193	4.59	1.92	4
reduced all edges	193	193	9.87	2.30	4
bipartite no non-tenure	386	99	6.57	1.73	4
reduced no non-tenure	99	99	6.55	2.35	4
bipartite no student	457	178	3.56	2.08	4
reduced no student	178	178	8.10	2.45	4
sample 2					
bipartite all edges	425	241	3.66	1.98	4
reduced all edges	241	241	21.84	2.28	4
bipartite no non-tenure	273	89	5.79	3.83	4
reduced no non-tenure	89	89	7.44	2.37	4
bipartite no student	421	237	2.95	2.07	4
reduced no student	237	237	12.90	2.35	4

Table 2: Descriptive statistics for the 12 graphs

3 Analysis

Generally, the analysis finds that ranks generated from centrality measures are strongly correlated to prestige, though the strength of the relationship varies by graph. Closeness centrality changes when the graph is reduced, eigenvector centrality changes when student edges are removed, and mean degree changes both when the graph is reduced and when student or non-tenure track edges are removed.[6]

Using equation 4 to calculate the sum square deviations between the predicted and actual ranks for the top universities, I assessed which graph's centrality scores best predicted academic rank. G_s is the graph's sum of squared errors, u is a university, r is u's NRC rank, and e, c, and d are the eigenvector, closeness, and degree centrality ranks, respectively. In this way, the graphs were assessed by their ability to generate centrality measures predictive of prestige for all three types of centrality scores. One could use the original data in the appendix to do the same calculation for each centrality score independently. However, given the high correlation across the three centrality scores illustrated in figure 4, it was both reasonable and parsimonious to asses the graphs' predictive quality jointly for the three centrality scores.

$$G_s = \sum_{u=1}^{u=10} [(e-r)^2 + (c-r)^2 + (d-r)^2] \quad (4)$$

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

[6] All the listed changes are significant at a 95% confidence level.

graph. The bipartite graph from sample 1 (the more prestigious sample) excluding non-tenure track edges was the best predictor of academic rank, while the reduced graph from sample 1 including all edges was the worst predictor. It is notable that the best and worst graphs have similar predictions. The primary difference in their predictive values stems from their inconsistent ranking of UNC Chapel Hill. The graph that is reduced using all edges from sample one grossly under-estimates UNC's prestige rank compared to graphs omitting non-tenure track edges (not shown here, see appendix). This would make sense if UNC hired fewer post docs and visiting professors. The last two columns of table 3 show the average predicted rank for each school when we average the eigenvector, closeness, and degree centrality ranks across all 6 graphs in each of the two samples (the average of 18 predictions). In the table, the average rank is in bold if the school was part of the sample seed. These two columns highlight the fact that departments have higher rank by all three centrality scores when they are part of the seed. Nevertheless, the top schools remain relatively highly ranked even when left out of the seed. This emphasizes the fact that the sampling bias does influence the analysis somewhat, though the non-sampled schools are still appropriately ranked. While not listed in table 3, it is important to note that all the graphs excluding student edges (both sample 1 and 2) were significantly *worse* predictors of rank. In fact, three of the four graphs excluding student edges landing are in the bottom four (of 12) predictions. This lends support to the hypothesis that over-training accounts for a large portion of the centrality-prestige correlation.

		best graph*			worst graph**			across graphs	
	NRC rank	eigen rank	closeness rank	degree rank	eigen rank	closeness rank	degree rank	sample 1	sample 2
UChicago	1	2	2	2	2	3	3	**2**	12
Wisconsin	2	1	1	1	2	1	1	**1**	8
Berkeley	3	5	4	5	4	6	5	**5**	5
UMichigan	4	4	5	4	1	4	2	**3**	13
UCLA	5	6	6	6	5	2	6	**4**	14
Chapel Hill	6	15	15	13	55	21	16	15	15
Harvard	7	3	3	3	57	5	4	**6**	7
Stanford	8	7	7	7	6	7	7	**7**	9
Northwestern	9	11	10	12	10	12	12	11	**4**
U of Washington	10	37	28	29	81	35	45	41	23

$*$ best = sample 1, bipartite, no non-tenure edges
$**$ worst = sample 1, reduced graph, all edges

Table 3: Centrality rankings for the best and worst graphs

The three centrality measures are highly correlated with one another, as illustrated in table 4. The first column shows the correlation between eigenvector and closeness centrality, the second shows the correlation between eigenvector and degree centrality, and the third column shows the correlation between closeness and degree. The main entries of table 4 indicate rank correlation between the centrality score ranks and prestige ranks, while the numbers in parentheses are the correlations between the continuous centrality scores (see equations 1, 2, and 3). While the first 12 rows illustrate the correlations within graphs, the last row is the overall correlation, averaging over all graph specifications. All the correlations using rank generated from centrality measures are better than those directly using the continuous centrality measures. The three centrality measures are inconsistent in the reduced graph from sample one with all edges, the same graph that was the worst predictor of prestige. This is somewhat surprising since visually inspecting that graph, more than any other graph in the analysis, this one is heavily centered around the top schools, and shows strong edges between them. It could be that while this graph is good at predicting the top schools, it fails to predict the others. The key finding in table 4 is that the ranks generated by the three centrality measures are similar. Researchers generally use the recursive measures because of the aforementioned reasons, such as being robust to sampling bias. However, all three centrality measures generate the same outcomes, suggesting that even the simplest measures, like standardized degree, are robust.

All the centrality measures are strongly correlated with academic rank as calculated by the NRC (domestic) and US News and World Report (international). For domestic rank, the ranks generated using eigenvector centrality have a .68 rank correlation compared to .72 using closeness and .73 using degree (calculated across all observations where an observation is an academic department in one of the 12 graphs). Correlations are slightly lower (.55, .59, and .59) for foreign international academic rank, because this ranking is not specific to sociology. Correlations between centrality and prestige varied substantially across the individual graphs when they are calculated separately. For example, ranks generated from eigenvector centrality had a correlation with domestic prestige ranging from .39 for sample one's bipartite graph including all edges to .8 for sample one's reduced graph excluding non-tenure edges. The best predictions tend to come from excluding non-tenure track edges. This makes sense because non-tenure track edges tend to not follow the general hierarchical order in academia. Some individuals work in non-academic jobs at other institutions, drawing power away from the central academic institutions. Early in their careers, many individuals who later end up at lower ranked schools spend some time as post-docs at higher ranked schools. Finally, later in their careers many of those employed at high ranked schools will visit other schools based on characteristics besides prestige, like location, perhaps visiting the European University Institute in Florence over Wisconsin. These non-tenure track relationships create links between low and high ranked schools that do not exist in the regular academic labor market. Of the three types of centrality scores, closeness rank has the most consistent correlations with domestic prestige, ranging from .6 to .8 compared to degree rank, which correlates with domestic prestige from .62 to .77. Thus, we might say that the closeness centrality from graphs excluding non-tenure track relationships are the best predictors of prestige.

graph type			eig-close	eig-degree	close-degree
samp	reduce	edges			
1	yes	all	.614 (.733)	.589 (.888)	.889 (.840)
1	yes	PhD & ten	.915 (.866)	.948 (.989)	.922 (.878)
1	yes	no PhD	.929 (.891)	.935 (.977)	.927 (.870)
1	no	all	.979 (.759)	.865 (.990)	.836 (.792)
1	no	PhD & ten	.983 (.681)	.935 (.981)	.930 (.732)
1	no	no PhD	.949 (.648)	.787 (.873)	.827 (.810)
2	yes	all	.959 (.828)	.931 (.987)	.958 (.863)
2	yes	PhD & ten	.977 (.897)	.955 (.944)	.969 (.951)
2	yes	no PhD	.975 (.854)	.940 (.924)	.955 (.928)
2	no	all	.985 (.811)	.903 (.988)	.905 (.817)
2	no	PhD & ten	.961 (.721)	.936 (.974)	.952 (.764)
2	no	no PhD	.908 (.767)	.841 (.944)	.924 (.696)
overall			.877 (.650)	.913 (.523)	.911 (.795)

entries are rank correlations
(...) are continuous correlations

Table 4: Correlations across centrality measures

In terms of biases introduced by using prestigious schools as sample seeds, in sample one (the more prestigious sample) both eigenvector and closeness centrality *under-ranked* the sampled departments, though closeness centrality did less so. This is the opposite of what was expected; as explained before, it was anticipated that eigenvector centrality (as a recursive measure) would be a more resilient estimate of academic prestige. For sample two, using closeness centrality, seed institutions were ranked on average between 10 and 11 positions *higher* than their NRC ranks and slightly more than 9 positions too high using eigenvector centrality. In fact, the mean rank for the sampled institutions in sample 2 was 3-7 while the NRC mean rank was 13-16 (both 95% confidence intervals). These confidence intervals do not even overlap, suggesting sample bias. The reason that sample one actually under-ranked the sampled institutions is that the sampled institutions were the top ranked ones. As such, it was impossible to over-rank them. However, in the less prestigious second sample there is the anticipated sample bias, with the recursive centrality measure surprisingly *no* more resilient than closeness centrality.

Given the number of students the most prestigious schools train, excluding student edges should have a significant effect on prestigious schools' centralities. Surprisingly, this is not the case for eigenvector and closeness centrality. The mean closeness and eigenvector centralities for the top ten schools (averaged across all those graphs including all edges) are statistically indistinguishable from the averages across those graphs excluding student edges. The top ten schools do, however, have a statistically higher *degree centrality* in those including training edges. The effect of including training edges on degree centrality is inevitable since training more students directly increases departments' degrees. However, the findings from the closeness and eigenvector centrality scores suggest that the top schools are central in a hiring network even ignoring their important role in training.[7]

Another way to show that the relationship between centrality and prestige holds after accounting for over-training is illustrated in figure 5. To show this, I re-ranked universities using the average of their closeness centrality ranks from those graphs that either included all edges or excluded student edges. The newly generated rank excluding student edges is shown on the x-axis while the new rank from all graphs including all edges is on the y-axis. The correlation (for all observed departments) between the two new rankings is .878, showing that ranks with and without training edges are similar. The graphic focuses on the origin of the graph where the more prestigious schools are located. If training future academics is a key component of prestige, we would expect the most prestigious schools to lie below the 45 degree line, with higher ranks when we include training edges. However, this is not the case as most schools lie just along the 45 degree line- only the University of Chicago follows this pattern. The top schools' NRC ranks are also shown in parentheses though there is no particular pattern for these top schools. In conclusion, highly ranked schools are central to academic hiring networks whether or not we consider their training role.

Up to this point, it has been shown that the effects of reducing the bipartite graph, excluding training or non-tenure track edges, sampling prestigious school, and the choice of centrality measures all have an effect on the relationship between centrality and prestige. On the other hand, the most important aspect of the analysis to this point (and this will become even clearer in the regression analysis) is how surprisingly robust the results are to these choices. While the strength of the relationship between prestige and centrality can change a little in response to these methodological choices, overall there is a strong and significant relationship between centrality and prestige that persists regardless of the approach taken.

We can also test the importance of training using a k-core analysis. A k-core groups together nodes based on both their clustering and their relative popularity, leaving the highest k-core to include the most prestigious departments. First, the graphs are separated 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. The groupings change when training edges are removed. Among the top ten schools, three schools are in

[7]The same is true in an analysis using top 20 schools.

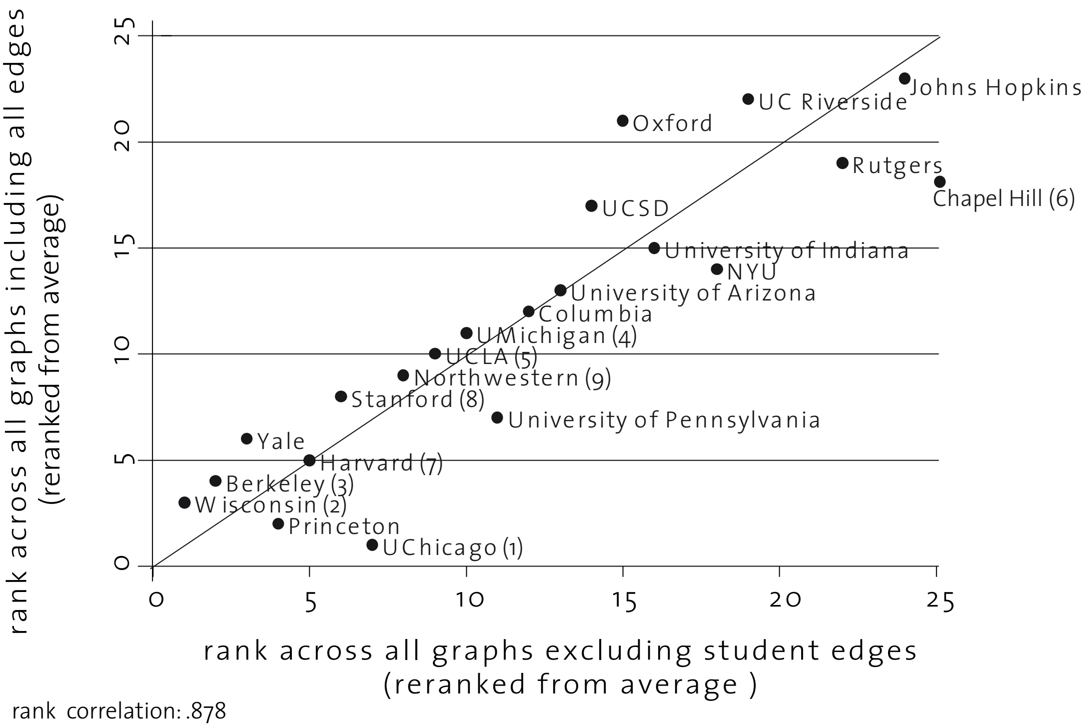

Figure 5: Closeness centrality rank versus NRC rank by edge inclusion

the top k-core more frequently among those graphs including all edges than among those excluding student edges. More striking, many more foreign departments enter the top k-core when training edges are excluded (European University Institute, Cambridge, the London School of Economics, and Oxford appear in the top k-cores more when training edges are removed). Foreign institutions are more important when we remove training but include non-tenure edges because academics tend to visit the same foreign universities and since each of these visits are short, many professors can visit bringing prestigious foreign institutions into the center of the graph. Excluding non-tenure track positions, foreign institutions do not enter the top k-core at all.

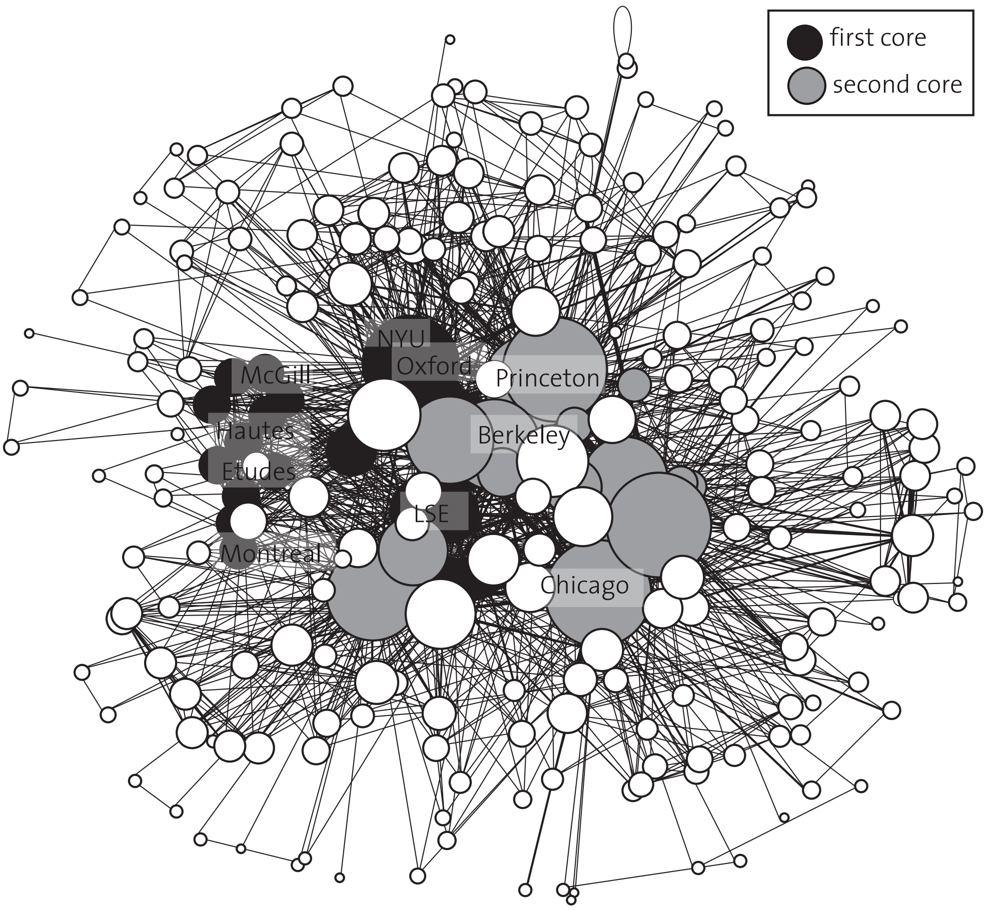

Figure 6: K-core for the reduced sample 2 graph excluding PhD training edges

Figure 6 shows the k-cores for the graph excluding PhD training edges from sample 2, an exceptional graph in the k-core analysis because it is the only one where the top schools were not in the top k-core. In this graph, the top k-core (black) was dominated by foreign institutions (LSE, Hebrew University, McGill, Universite of Quebec, Montreal, and Paris, University of San Paolo, and Oxford) and also included some domestic institutions (NYU and UCSD). The second highest ranked k-core (grey) includes the traditionally high-ranked schools. Inspecting the raw bipartite graph (not illustrated here), it is clear that there are two main clusters. Both clusters 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 edges, and that the top British institutions are a central part of the American sociology labor market.

I test the hypothesis of whether department size drives the correlation between academic departments' prestige and labor market centrality 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, 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.

The three centrality scores have approximately the same predictive value for prestige regardless of whether or not we control for faculty size. A one-position increase in centrality rank predicts at least a .5 position increase in NRC or Newsweek academic rank, as shown by the coefficients in the first three columns for domestic and international rank in table 5. In the first three columns of each entry we see a coefficient in bold. This is the coefficient for the centrality measure in a bivariate regression without any controls. The network data used to calculate these regressions is shown in the appendix. The non-bold entry directly above the bold bivariate coefficient shows the coefficient when controlling for faculty size and graph specification. For closeness centrality, we see that in a bivariate regression a one-position improvement in centrality-generate rank is associated with a .584 position increase in prestige rank. After controlling for department size, this drops to .525. Most interesting, there is a negative coefficient on department size, suggesting that the labor market position is so important that for two equally sized programs in the same position in the labor market graph, the smaller department would actually be more prestigious. The last column of 5 shows the results of regressing all three centrality measurements together. (One should note that this introduces the problem of multicollinearity which increases the standard errors of coefficients.) In this joint model, eigenvector centrality seems to provide no information not provided by the other two measures. While we expect that including training edges would increase predicted prestige for the top schools, it is surprising that in fact it increases predicted prestige by about .2 positions in rank in the regression including

	domestic rank				international rank			
eigenvector	.481***			-.037	.588***			-.196*
	.542******				**.608********			
closeness		.525***		.339***		.663***		.437**
		.584******				**.669********		
degree			.516***	.241***			.670***	.436***
			.577******				**.686********	
faculty size	-.492***	-.460***	-.499***	-.466***	-.121	-.077	-.067	-.063
all edges	.260	.477	.228	.395	.006	.307	.265	.373
no stud edges	.233*	2.47*	1.86	2.29*	-.891	-.629	-.130	-.202
bipartite	.120	.089	.464	.265	.006	.248	.097	.225
sample one	.461	.461	.954	.650	-1.27	-1.51	-1.85	-1.73
R^2	.514	.571	.560	.583	.253	.312	.319	.330
	.426	**.493**	**.469**		**.239**	**.293**	**.314**	
coefficient tests	$\beta_{eig} = \beta_{degree}$		P:.0013		$\beta_{eig} = \beta_{degree}$		P: .0001	
	$\beta_{eig} = \beta_{closeness}$		P: .0004		$\beta_{eig} = \beta_{closeness}$		P: .0036	
	$\beta_{closeness} = \beta_{degree}$		P: .0004		$\beta_{closeness} = \beta_{degree}$		P: .9789	

bold text indicates bivariate regressions

$***$ indicates significance at the .001 level

Table 5: OLS regression predicting academic prestige

all schools.

Going back to the 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, excluding PhD training edges increases predicted rank at least 2 positions. This is the opposite of what one might expect if the top schools overtrain and rely on placing fresh PhD students to increase their standing in the field. Finally, running these same regressions for all departments, using only those graphs excluding PhD training edges, 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 (about 20%), but overall the relationship is still strong.[8]

In sum, the regression analyses allow us to definitively reject the idea that the relationship between employment network centrality and departmental prestige are driven by department size and prestigious schools' dominance in training new PhDs.

[8] 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 degrees' effects are statistically indistinguishable from each other.

4 Conclusion

This paper began with two main hypotheses regarding the relationship between the sociology academic employment network and academic rankings. First, I suggested that the relationship might be driven by department size and by the dominance of a few departments training the bulk of sociologists combined with the general over-training of sociologists. Second, I posited that the relationship could be driven by researchers' methodological choices of how to sample academic sociology networks, what sorts of employment relationships to include, and which centrality measures to use. I found support for the fact that training does play a definitive role in academic prestige. The initial analyses showed that the top institutions are somewhat less central using a network excluding training edges, and the regression suggested that network centrality has slightly less predictive power when it is defined exclusive of training edges. There was no support for the hypothesis that department size drives results. With respect to methodology, sample seeds certainly biased predictions (particularly degree centrality), although the results were still more or less accurate. Finally, the decision to analyze the reduced or bipartite graph seems to have no effect.

The major finding of this paper was that the relationship between academic rank and centrality in the academic hiring network is very robust. Independent of graph specification (the centrality measure used, the sample seed, or whether the bipartite or reduced graph is used) and independent of prestigious departments' size, or the fact that prestigious schools train most PhD's, the prestigious schools are *still* at the center of the academic labor market.

Other researchers finding a correlation between academic prestige and labor market position 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 the other faculty moving among other institutions) there would not be this strong relationship between the hiring network centrality and academic rank. Rather, there would be two separate cores: lower ranked schools trading faculty with each other and higher ranked schools trading faculty 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 from the more prestigious schools, and then by passing their successful professors on to the more prestigious schools. It it is these trades, or academics' preferred career paths, that keep the most prestigious schools in the center of the employment graph (even when training edges are excluded). This pattern of career moves is advantageous for the institutions that are already prestigious. As such, the pattern of the academic employment network could reinforce current prestige rankings.

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5 Appendix

Table 6: Data from 12 employment networks

institution	sample	edge inclusion	bi-partite	domestic prestige	foreign prestige	eigen rank	closeness rank	degree rank
UChicago	1	all edges	false	1	20	2	3	3
Wisconsin	1	all edges	false	2	28	3	1	1
Berkeley	1	all edges	false	3	5	4	6	5
UMichigan	1	all edges	false	4	11	1	4	2
UCLA	1	all edges	false	5	12	5	2	6
UNC Chapel Hill	1	all edges	false	6	41	55	21	16
Harvard	1	all edges	false	7	1	57	5	4
Stanford	1	all edges	false	8	2	6	7	7
Northwestern	1	all edges	false	9	35	10	12	12
U of Washington	1	all edges	false	10	22	81	35	45
U of Pennsylvania	1	all edges	false	11	13	74	15	17
U Indiana Bloomington	1	all edges	false	12		40	19	22
Princeton	1	all edges	false	13	15	8	10	10
U of Arizona	1	all edges	false	14		9	9	8
Columbia	1	all edges	false	15	10	69	13	13
UT Austin	1	all edges	false	16	27	53	20	27
Johns Hopkins	1	all edges	false	17	24	21	33	34
Penn State	1	all edges	false	18	40	32	45	43
Yale	1	all edges	false	19	3	12	11	11
Duke	1	all edges	false	20	14	52	30	33
NYU	1	all edges	false	21	39	23	28	29
UCSD	1	all edges	false	22	23	11	23	15
UC Santa Barbara	1	all edges	false	23	59	19	25	21
U of Minnesota	1	all edges	false	24	30	59	36	40
SUNY Stoneybrook	1	all edges	false	25.5		22	31	26
Ohio State U	1	all edges	false	25.5		42	37	38
Vanderbilt	1	all edges	false	27.5	66	82	82	80
U Illinois Urbana	1	all edges	false	29	48	36	34	62
U of Albany	1	all edges	false	30		51	49	57
Rutgers	1	all edges	false	31		15	22	25
Washington State U	1	all edges	false	32	33	43	40	61
U of Maryland	1	all edges	false	33	45	56	77	66
SUNY Binghamton	1	all edges	false	34		49	44	36
Cornell	1	all edges	false	35	19	62	16	19
CUNY	1	all edges	false	37		66	59	79
Brown	1	all edges	false	38	56	7	8	9
UMass Amherst	1	all edges	false	39	99	30	67	74
U of Iowa	1	all edges	false	40.5		73	48	30
USC	1	all edges	false	40.5	54	63	72	58
Michigan State U	1	all edges	false	42	62	14	18	23
U of Florida	1	all edges	false	43		79	70	70
Boston U	1	all edges	false	44	65	27	38	55
U Illinois Chicago	1	all edges	false	45		48	75	46
Notre Dame	1	all edges	false	46		46	74	65
U of Virginia	1	all edges	false	47.5	80	35	66	78
U of Georgia	1	all edges	false	47.5		34	51	28
UConn	1	all edges	false	49		31	47	39
U of San Francisco	1	all edges	false	50.5	9	64	39	64
UC Santa Cruz	1	all edges	false	53		47	73	52
Boston College	1	all edges	false	55		54	53	49
U of Oregon	1	all edges	false	56.5		33	43	60
Syracuse	1	all edges	false	58		60	52	72
Brandeis	1	all edges	false	60		24	26	20
Iowa State U	1	all edges	false	61.5		68	63	54
U Missouri Columbia	1	all edges	false	63		76	68	67
Louisiana State U	1	all edges	false	65		44	42	41
Loyola	1	all edges	false	68		29	56	35
Tulane	1	all edges	false	72		80	76	68
U of Tokyo	1	all edges	false		16	78	65	44
U of Amsterdam	1	all edges	false		89	50	50	56
U of Bristol	1	all edges	false		49	71	69	69
Caltech	1	all edges	false		4	38	46	63
Oxford	1	all edges	false		8	16	14	14
McGill	1	all edges	false		42	77	80	81
U of Vienna	1	all edges	false		72	61	81	82
U of Edinburgh	1	all edges	false		47	18	32	37
U of Zurich	1	all edges	false		46	58	60	76
Uppsala	1	all edges	false		88	45	54	47
U of Lund	1	all edges	false		76	72	61	42
U of Munich	1	all edges	false		63	25	79	77
U of Newcastle	1	all edges	false		97	13	64	51
Hong Kong U	1	all edges	false		60	26	58	71
Cambridge	1	all edges	false		6	20	17	18
Emory	1	all edges	false		93	70	57	48
Hebrew U Jerusalem	1	all edges	false		82	41	41	59

institution	sample	edge inclusion	bi-partite	domestic prestige	foreign prestige	eigen rank	closeness rank	degree rank
Chinese U Hong Kong	1	all edges	false		96	65	55	73
Australian National U	1	all edges	false		38	39	29	32
LSE	1	all edges	false		34	28	24	24
U College London	1	all edges	false		25	67	62	50
U of Queensland	1	all edges	false		91	37	71	53
MIT	1	all edges	false		7	17	27	31
U of Heidelberg	1	all edges	false		90	75	78	75
UChicago	1	all edges	true	1	20	3	2	2
Wisconsin	1	all edges	true	2	28	1	1	1
Berkeley	1	all edges	true	3	5	5	6	5
UMichigan	1	all edges	true	4	11	4	4	4
UCLA	1	all edges	true	5	12	6	5	6
UNC Chapel Hill	1	all edges	true	6	41	13	16	11
Harvard	1	all edges	true	7	1	2	3	3
Stanford	1	all edges	true	8	2	7	7	7
Northwestern	1	all edges	true	9	35	11	11	13
U of Washington	1	all edges	true	10	22	36	38	27
U of Pennsylvania	1	all edges	true	11	13	15	14	14
U Indiana Bloomington	1	all edges	true	12		24	17	19
Princeton	1	all edges	true	13	15	8	9	10
U of Arizona	1	all edges	true	14		9	10	8
Columbia	1	all edges	true	15	10	12	13	12
UT Austin	1	all edges	true	16	27	21	19	21
Johns Hopkins	1	all edges	true	17	24	28	33	28
Penn State	1	all edges	true	18	40	39	41	29
Yale	1	all edges	true	19	3	14	12	16
Duke	1	all edges	true	20	14	26	30	34
NYU	1	all edges	true	21	39	27	27	24
UCSD	1	all edges	true	22	23	16	23	17
UC Santa Barbara	1	all edges	true	23	59	18	24	20
U of Minnesota	1	all edges	true	24	30	38	34	43
Ohio State U	1	all edges	true	25.5		45	40	45
SUNY Stoneybrook	1	all edges	true	25.5		34	31	31
Vanderbilt	1	all edges	true	27.5	66	82	82	66
U Illinois Urbana	1	all edges	true	29	48	40	35	32
U of Albany	1	all edges	true	30		54	49	61
Rutgers	1	all edges	true	31		17	21	25
Washington State U	1	all edges	true	32	33	43	36	47
U of Maryland	1	all edges	true	33	45	75	80	79
SUNY Binghamton	1	all edges	true	34		46	48	36
Cornell	1	all edges	true	35	19	22	15	15
CUNY	1	all edges	true	37		64	59	75
Brown	1	all edges	true	38	56	10	8	9
UMass Amherst	1	all edges	true	39	99	60	61	63
USC	1	all edges	true	40.5	54	72	72	80
U of Iowa	1	all edges	true	40.5		57	55	33
Michigan State U	1	all edges	true	42	62	19	18	22
U of Florida	1	all edges	true	43		71	70	52
Boston U	1	all edges	true	44	65	35	37	42
U Illinois Chicago	1	all edges	true	45		74	73	38
Notre Dame	1	all edges	true	46		73	74	56
U of Virginia	1	all edges	true	47.5	80	62	63	53
U of Georgia	1	all edges	true	47.5		32	51	26
UConn	1	all edges	true	49		33	47	41
U of San Francisco	1	all edges	true	50.5	9	44	39	67
UC Santa Cruz	1	all edges	true	53		59	71	44
Boston College	1	all edges	true	55		50	54	77
U of Oregon	1	all edges	true	56.5		53	42	81
Syracuse	1	all edges	true	58		51	53	82
Brandeis	1	all edges	true	60		25	25	18
Iowa State U	1	all edges	true	61.5		68	66	62
U Missouri Columbia	1	all edges	true	63		69	68	57
Louisiana State U	1	all edges	true	65		48	44	39
Loyola	1	all edges	true	68		42	56	46
Tulane	1	all edges	true	72		81	81	55
Uppsala	1	all edges	true		88	49	46	74
Chinese U Hong Kong	1	all edges	true		96	47	52	54
U of Munich	1	all edges	true		63	76	76	73
U of Tokyo	1	all edges	true		16	65	67	70
Oxford	1	all edges	true		8	23	20	23
U of Zurich	1	all edges	true		46	63	60	78
U College London	1	all edges	true		25	66	64	64
U of Lund	1	all edges	true		76	58	62	50
Cambridge	1	all edges	true		6	20	22	35
Hong Kong U	1	all edges	true		60	56	57	71
Caltech	1	all edges	true		4	41	43	51
U of Heidelberg	1	all edges	true		90	79	77	60
U of Vienna	1	all edges	true		72	77	79	68
U of Amsterdam	1	all edges	true		89	52	50	65
U of Queensland	1	all edges	true		91	80	75	69
McGill	1	all edges	true		42	78	78	58
Hebrew U Jerusalem	1	all edges	true		82	55	45	76
Australian National U	1	all edges	true		38	37	29	49
U of Bristol	1	all edges	true		49	70	69	59
Emory	1	all edges	true		93	61	58	40
U of Newcastle	1	all edges	true		97	67	65	72
U of Edinburgh	1	all edges	true		47	29	32	48
MIT	1	all edges	true		7	30	26	37

institution	sample	edge inclusion	bi-partite	domestic prestige	foreign prestige	eigen rank	closeness rank	degree rank
LSE	1	all edges	true		34	31	28	30
UChicago	1	no non-tenure	false	1	20	2	3	3
Wisconsin	1	no non-tenure	false	2	28	4	1	1
Berkeley	1	no non-tenure	false	3	5	5	4	5
UMichigan	1	no non-tenure	false	4	11	3	6	4
UCLA	1	no non-tenure	false	5	12	6	5	6
UNC Chapel Hill	1	no non-tenure	false	6	41	17	17	15
Harvard	1	no non-tenure	false	7	1	1	2	2
Stanford	1	no non-tenure	false	8	2	7	7	7
Northwestern	1	no non-tenure	false	9	35	10	9	10
U of Washington	1	no non-tenure	false	10	22	48	27	43
U of Pennsylvania	1	no non-tenure	false	11	13	13	14	16
U Indiana Bloomington	1	no non-tenure	false	12		20	15	18
Princeton	1	no non-tenure	false	13	15	11	10	11
U of Arizona	1	no non-tenure	false	14		8	8	8
Columbia	1	no non-tenure	false	15	10	12	12	12
UT Austin	1	no non-tenure	false	16	27	19	18	20
Johns Hopkins	1	no non-tenure	false	17	24	70	45	33
Penn State	1	no non-tenure	false	18	40	23	32	25
Yale	1	no non-tenure	false	19	3	18	22	17
Duke	1	no non-tenure	false	20	14	26	41	37
NYU	1	no non-tenure	false	21	39	31	26	36
UCSD	1	no non-tenure	false	22	23	14	20	13
UC Santa Barbara	1	no non-tenure	false	23	59	22	19	26
U of Minnesota	1	no non-tenure	false	24	30	35	28	35
Ohio State U	1	no non-tenure	false	25.5		63	63	59
SUNY Stoneybrook	1	no non-tenure	false	25.5		21	38	21
Vanderbilt	1	no non-tenure	false	27.5	66	61	64	63
U Illinois Urbana	1	no non-tenure	false	29	48	25	25	30
U of Albany	1	no non-tenure	false	30		38	35	40
Rutgers	1	no non-tenure	false	31		27	21	29
Washington State U	1	no non-tenure	false	32	33	29	24	31
U of Maryland	1	no non-tenure	false	33	45	58	61	62
SUNY Binghamton	1	no non-tenure	false	34		47	36	42
Cornell	1	no non-tenure	false	35	19	15	13	14
CUNY	1	no non-tenure	false	37		64	74	81
Brown	1	no non-tenure	false	38	56	9	11	9
UMass Amherst	1	no non-tenure	false	39	99	39	43	45
U of Iowa	1	no non-tenure	false	40.5		36	52	24
USC	1	no non-tenure	false	40.5	54	49	57	39
Michigan State U	1	no non-tenure	false	42	62	16	16	23
U of Florida	1	no non-tenure	false	43		54	48	50
Boston U	1	no non-tenure	false	44	65	40	79	48
U Illinois Chicago	1	no non-tenure	false	45		60	58	44
Notre Dame	1	no non-tenure	false	46		56	69	72
U of Virginia	1	no non-tenure	false	47.5	80	68	70	69
U of Georgia	1	no non-tenure	false	47.5		24	34	19
UConn	1	no non-tenure	false	49		30	33	38
U of San Francisco	1	no non-tenure	false	50.5	9	67	76	78
UC Santa Cruz	1	no non-tenure	false	53		59	59	57
Boston College	1	no non-tenure	false	55		79	37	71
U of Oregon	1	no non-tenure	false	56.5		37	30	46
Syracuse	1	no non-tenure	false	58		50	46	53
Brandeis	1	no non-tenure	false	60		28	23	22
Iowa State U	1	no non-tenure	false	61.5		51	47	54
U Missouri Columbia	1	no non-tenure	false	63		42	49	51
Louisiana State U	1	no non-tenure	false	65		32	39	34
Loyola	1	no non-tenure	false	68		62	62	58
Tulane	1	no non-tenure	false	72		71	80	66
U of Tokyo	1	no non-tenure	false		16	80	75	79
Australian National U	1	no non-tenure	false		38	77	67	77
U of Amsterdam	1	no non-tenure	false		89	65	68	75
Caltech	1	no non-tenure	false		4	44	51	49
LSE	1	no non-tenure	false		34	33	31	32
Hong Kong U	1	no non-tenure	false		60	41	42	41
U of Edinburgh	1	no non-tenure	false		47	75	66	82
Hebrew U Jerusalem	1	no non-tenure	false		82	72	71	73
U of Lund	1	no non-tenure	false		76	82	65	74
Oxford	1	no non-tenure	false		8	76	60	61
U of Newcastle	1	no non-tenure	false		97	81	72	80
U of Queensland	1	no non-tenure	false		91	69	77	68
Chinese U Hong Kong	1	no non-tenure	false		96	45	50	55
U College London	1	no non-tenure	false		25	74	81	65
U of Heidelberg	1	no non-tenure	false		90	52	53	56
U of Zurich	1	no non-tenure	false		46	46	44	52
MIT	1	no non-tenure	false		7	34	29	27
McGill	1	no non-tenure	false		42	57	55	60
Cambridge	1	no non-tenure	false		6	78	73	70
Emory	1	no non-tenure	false		93	43	40	28
U of Bristol	1	no non-tenure	false		49	66	78	76
U of Munich	1	no non-tenure	false		63	53	54	47
Uppsala	1	no non-tenure	false		88	73	82	67
U of Vienna	1	no non-tenure	false		72	55	56	64
UChicago	1	no non-tenure	true	1	20	2	2	2
Wisconsin	1	no non-tenure	true	2	28	1	1	1
Berkeley	1	no non-tenure	true	3	5	5	4	5
UMichigan	1	no non-tenure	true	4	11	4	5	4
UCLA	1	no non-tenure	true	5	12	6	6	6

institution	sample	edge inclusion	bi-partite	domestic prestige	foreign prestige	eigen rank	closeness rank	degree rank
UNC Chapel Hill	1	no non-tenure	true	6	41	15	15	13
Harvard	1	no non-tenure	true	7	1	3	3	3
Stanford	1	no non-tenure	true	8	2	7	7	7
Northwestern	1	no non-tenure	true	9	35	11	10	12
U of Washington	1	no non-tenure	true	10	22	37	28	29
U of Pennsylvania	1	no non-tenure	true	11	13	13	14	14
U Indiana Bloomington	1	no non-tenure	true	12		19	16	20
Princeton	1	no non-tenure	true	13	15	10	8	10
U of Arizona	1	no non-tenure	true	14		8	9	8
Columbia	1	no non-tenure	true	15	10	12	11	11
UT Austin	1	no non-tenure	true	16	27	16	18	17
Johns Hopkins	1	no non-tenure	true	17	24	48	44	32
Penn State	1	no non-tenure	true	18	40	27	29	21
Yale	1	no non-tenure	true	19	3	23	22	18
Duke	1	no non-tenure	true	20	14	29	35	36
NYU	1	no non-tenure	true	21	39	34	26	25
UCSD	1	no non-tenure	true	22	23	14	21	19
UC Santa Barbara	1	no non-tenure	true	23	59	22	19	22
U of Minnesota	1	no non-tenure	true	24	30	30	27	39
Ohio State U	1	no non-tenure	true	25.5		63	61	63
SUNY Stoneybrook	1	no non-tenure	true	25.5		42	42	28
Vanderbilt	1	no non-tenure	true	27.5	66	64	62	43
U Illinois Urbana	1	no non-tenure	true	29	48	28	25	27
U of Albany	1	no non-tenure	true	30		35	36	57
Rutgers	1	no non-tenure	true	31		20	20	26
Washington State U	1	no non-tenure	true	32	33	26	24	37
U of Maryland	1	no non-tenure	true	33	45	58	59	54
SUNY Binghamton	1	no non-tenure	true	34		39	38	40
Cornell	1	no non-tenure	true	35	19	17	13	15
CUNY	1	no non-tenure	true	37		82	78	82
Brown	1	no non-tenure	true	38	56	9	12	9
UMass Amherst	1	no non-tenure	true	39	99	43	43	64
USC	1	no non-tenure	true	40.5	54	57	57	42
U of Iowa	1	no non-tenure	true	40.5		52	52	30
Michigan State U	1	no non-tenure	true	42	62	18	17	24
U of Florida	1	no non-tenure	true	43		49	50	44
Boston U	1	no non-tenure	true	44	65	36	37	56
U Illinois Chicago	1	no non-tenure	true	45		61	64	47
Notre Dame	1	no non-tenure	true	46		78	79	70
U of Virginia	1	no non-tenure	true	47.5	80	65	69	76
U of Georgia	1	no non-tenure	true	47.5		21	39	23
UConn	1	no non-tenure	true	49		24	34	38
U of San Francisco	1	no non-tenure	true	50.5	9	73	70	67
UC Santa Cruz	1	no non-tenure	true	53		59	58	55
Boston College	1	no non-tenure	true	55		68	68	69
U of Oregon	1	no non-tenure	true	56.5		33	30	49
Syracuse	1	no non-tenure	true	58		45	48	52
Brandeis	1	no non-tenure	true	60		25	23	16
Iowa State U	1	no non-tenure	true	61.5		50	49	51
U Missouri Columbia	1	no non-tenure	true	63		46	51	59
Louisiana State U	1	no non-tenure	true	65		38	33	34
Loyola	1	no non-tenure	true	68		62	63	60
Tulane	1	no non-tenure	true	72		76	73	71
Uppsala	1	no non-tenure	true		88	77	80	80
U of Newcastle	1	no non-tenure	true		97	80	76	75
Hebrew U Jerusalem	1	no non-tenure	true		82	66	75	66
LSE	1	no non-tenure	true		34	31	31	33
Hong Kong U	1	no non-tenure	true		60	41	40	61
Oxford	1	no non-tenure	true		8	60	60	41
U College London	1	no non-tenure	true		25	71	81	68
U of Heidelberg	1	no non-tenure	true		90	54	54	62
Emory	1	no non-tenure	true		93	40	41	31
U of Bristol	1	no non-tenure	true		49	74	71	81
U of Vienna	1	no non-tenure	true		72	56	55	58
Australian National U	1	no non-tenure	true		38	70	65	73
U of Zurich	1	no non-tenure	true		46	51	45	53
U of Amsterdam	1	no non-tenure	true		89	75	82	77
McGill	1	no non-tenure	true		42	55	56	46
MIT	1	no non-tenure	true		7	32	32	35
Cambridge	1	no non-tenure	true		6	67	67	65
U of Munich	1	no non-tenure	true		63	53	53	45
U of Tokyo	1	no non-tenure	true		16	72	77	74
Chinese U Hong Kong	1	no non-tenure	true		96	47	47	48
U of Lund	1	no non-tenure	true		76	81	66	79
U of Queensland	1	no non-tenure	true		91	79	72	78
Caltech	1	no non-tenure	true		4	44	46	50
U of Edinburgh	1	no non-tenure	true		47	69	74	72
UChicago	1	no student edges	false	1	20	5	5	5
Wisconsin	1	no student edges	false	2	28	2	1	1
Berkeley	1	no student edges	false	3	5	6	6	6
UMichigan	1	no student edges	false	4	11	4	4	4
UCLA	1	no student edges	false	5	12	3	2	2
UNC Chapel Hill	1	no student edges	false	6	41	23	28	28
Harvard	1	no student edges	false	7	1	1	3	3
Stanford	1	no student edges	false	8	2	8	8	10
Northwestern	1	no student edges	false	9	35	11	13	12
U of Washington	1	no student edges	false	10	22	66	56	68
U of Pennsylvania	1	no student edges	false	11	13	29	21	19

institution	sample	edge inclusion	bi-partite	domestic prestige	foreign prestige	eigen rank	closeness rank	degree rank
U Indiana Bloomington	1	no student edges	false	12		19	17	22
Princeton	1	no student edges	false	13	15	9	10	11
U of Arizona	1	no student edges	false	14		12	14	8
Columbia	1	no student edges	false	15	10	14	11	13
UT Austin	1	no student edges	false	16	27	21	16	32
Johns Hopkins	1	no student edges	false	17	24	24	40	33
Penn State	1	no student edges	false	18	40	60	66	62
Yale	1	no student edges	false	19	3	10	7	9
Duke	1	no student edges	false	20	14	28	22	30
NYU	1	no student edges	false	21	39	31	41	31
UCSD	1	no student edges	false	22	23	13	20	16
UC Santa Barbara	1	no student edges	false	23	59	20	18	17
U of Minnesota	1	no student edges	false	24	30	43	54	46
SUNY Stoneybrook	1	no student edges	false	25.5		33	29	34
Ohio State U	1	no student edges	false	25.5		44	47	36
Vanderbilt	1	no student edges	false	27.5	66	79	82	78
U Illinois Urbana	1	no student edges	false	29	48	41	49	61
U of Albany	1	no student edges	false	30		56	44	56
Rutgers	1	no student edges	false	31		17	19	20
Washington State U	1	no student edges	false	32	33	77	76	79
U of Maryland	1	no student edges	false	33	45	72	72	60
SUNY Binghamton	1	no student edges	false	34		47	32	35
Cornell	1	no student edges	false	35	19	25	23	21
CUNY	1	no student edges	false	37		68	64	71
Brown	1	no student edges	false	38	56	7	9	7
UMass Amherst	1	no student edges	false	39	99	51	62	66
U of Iowa	1	no student edges	false	40.5		38	55	24
USC	1	no student edges	false	40.5	54	62	67	53
Michigan State U	1	no student edges	false	42	62	18	25	18
U of Florida	1	no student edges	false	43		73	75	73
Boston U	1	no student edges	false	44	65	36	59	55
U Illinois Chicago	1	no student edges	false	45		48	58	43
Notre Dame	1	no student edges	false	46		59	61	58
U of Georgia	1	no student edges	false	47.5		32	35	25
U of Virginia	1	no student edges	false	47.5	80	69	70	70
UConn	1	no student edges	false	49		35	33	39
U of San Francisco	1	no student edges	false	50.5	9	40	30	57
UC Santa Cruz	1	no student edges	false	53		61	68	59
Boston College	1	no student edges	false	55		64	51	49
U of Oregon	1	no student edges	false	56.5		63	39	52
Syracuse	1	no student edges	false	58		76	81	75
Brandeis	1	no student edges	false	60		70	65	72
Iowa State U	1	no student edges	false	61.5		54	38	42
U Missouri Columbia	1	no student edges	false	63		75	78	76
Louisiana State U	1	no student edges	false	65		46	42	45
Loyola	1	no student edges	false	68		30	50	26
Tulane	1	no student edges	false	72		67	63	65
Chinese U Hong Kong	1	no student edges	false		96	50	60	64
U of Bristol	1	no student edges	false		49	65	53	69
U of Amsterdam	1	no student edges	false		89	57	43	54
U of Newcastle	1	no student edges	false		97	53	36	44
U of Lund	1	no student edges	false		76	37	45	50
Cambridge	1	no student edges	false		6	15	15	15
McGill	1	no student edges	false		42	82	74	74
Caltech	1	no student edges	false		4	42	52	63
U of Munich	1	no student edges	false		63	81	73	80
Hebrew U Jerusalem	1	no student edges	false		82	39	31	51
U of Edinburgh	1	no student edges	false		47	22	26	29
U of Heidelberg	1	no student edges	false		90	78	79	82
Hong Kong U	1	no student edges	false		60	49	69	67
U of Zurich	1	no student edges	false		46	74	80	81
U of Tokyo	1	no student edges	false		16	55	48	37
Australian National U	1	no student edges	false		38	34	24	27
U of Vienna	1	no student edges	false		72	80	77	77
LSE	1	no student edges	false		34	26	27	23
Uppsala	1	no student edges	false		88	45	34	38
MIT	1	no student edges	false		7	27	46	40
Oxford	1	no student edges	false		8	16	12	14
U of Queensland	1	no student edges	false		91	58	57	48
Emory	1	no student edges	false		93	71	71	47
U College London	1	no student edges	false		25	52	37	41
UChicago	1	no student edges	true	1	20	5	6	4
Wisconsin	1	no student edges	true	2	28	1	1	1
Berkeley	1	no student edges	true	3	5	6	5	6
UMichigan	1	no student edges	true	4	11	3	4	3
UCLA	1	no student edges	true	5	12	2	2	2
UNC Chapel Hill	1	no student edges	true	6	41	17	28	16
Harvard	1	no student edges	true	7	1	4	3	5
Stanford	1	no student edges	true	8	2	10	8	8
Northwestern	1	no student edges	true	9	35	11	12	12
U of Washington	1	no student edges	true	10	22	44	54	58
U of Pennsylvania	1	no student edges	true	11	13	27	20	27
U Indiana Bloomington	1	no student edges	true	12		24	21	18
Princeton	1	no student edges	true	13	15	7	10	10
U of Arizona	1	no student edges	true	14		12	13	7
Columbia	1	no student edges	true	15	10	15	11	13
UT Austin	1	no student edges	true	16	27	22	15	21
Johns Hopkins	1	no student edges	true	17	24	45	35	28

institution	sample	edge inclusion	bi-partite	domestic prestige	foreign prestige	eigen rank	closeness rank	degree rank
Penn State	1	no student edges	true	18	40	64	63	30
Yale	1	no student edges	true	19	3	9	9	11
Duke	1	no student edges	true	20	14	25	22	41
NYU	1	no student edges	true	21	39	47	39	25
UCSD	1	no student edges	true	22	23	21	18	14
UC Santa Barbara	1	no student edges	true	23	59	18	19	23
U of Minnesota	1	no student edges	true	24	30	55	47	65
SUNY Stoneybrook	1	no student edges	true	25.5		72	27	40
Ohio State U	1	no student edges	true	25.5		53	53	48
Vanderbilt	1	no student edges	true	27.5	66	77	77	75
U Illinois Urbana	1	no student edges	true	29	48	52	42	33
U of Albany	1	no student edges	true	30		39	40	62
Rutgers	1	no student edges	true	31		14	17	20
Washington State U	1	no student edges	true	32	33	75	73	81
U of Maryland	1	no student edges	true	33	45	71	72	56
SUNY Binghamton	1	no student edges	true	34		31	32	36
Cornell	1	no student edges	true	35	19	26	23	15
CUNY	1	no student edges	true	37		63	67	54
Brown	1	no student edges	true	38	56	8	7	9
UMass Amherst	1	no student edges	true	39	99	59	61	52
USC	1	no student edges	true	40.5	54	66	65	45
U of Iowa	1	no student edges	true	40.5		58	59	24
Michigan State U	1	no student edges	true	42	62	33	24	29
U of Florida	1	no student edges	true	43		81	74	79
Boston U	1	no student edges	true	44	65	51	57	43
U Illinois Chicago	1	no student edges	true	45		60	55	31
Notre Dame	1	no student edges	true	46		65	62	46
U of Virginia	1	no student edges	true	47.5	80	68	70	67
U of Georgia	1	no student edges	true	47.5		16	37	17
UConn	1	no student edges	true	49		19	33	35
U of San Francisco	1	no student edges	true	50.5	9	32	30	59
UC Santa Cruz	1	no student edges	true	53		67	64	47
Boston College	1	no student edges	true	55		41	52	49
U of Oregon	1	no student edges	true	56.5		42	36	66
Syracuse	1	no student edges	true	58		79	81	73
Brandeis	1	no student edges	true	60		62	68	61
Iowa State U	1	no student edges	true	61.5		37	44	53
U Missouri Columbia	1	no student edges	true	63		73	75	78
Louisiana State U	1	no student edges	true	65		54	50	32
Loyola	1	no student edges	true	68		49	46	38
Tulane	1	no student edges	true	72		61	66	60
U of Tokyo	1	no student edges	true		16	35	49	70
U of Bristol	1	no student edges	true		49	43	51	63
Oxford	1	no student edges	true		8	20	14	19
Australian National U	1	no student edges	true		38	29	26	42
U College London	1	no student edges	true		25	36	45	68
U of Heidelberg	1	no student edges	true		90	78	76	77
McGill	1	no student edges	true		42	76	78	80
Uppsala	1	no student edges	true		88	34	34	72
U of Zurich	1	no student edges	true		46	80	82	74
U of Vienna	1	no student edges	true		72	82	79	82
Caltech	1	no student edges	true		4	48	56	44
U of Newcastle	1	no student edges	true		97	38	43	71
Emory	1	no student edges	true		93	70	71	39
Chinese U Hong Kong	1	no student edges	true		96	57	58	55
Hebrew U Jerusalem	1	no student edges	true		82	30	31	50
Cambridge	1	no student edges	true		6	13	16	26
Hong Kong U	1	no student edges	true		60	69	69	69
U of Amsterdam	1	no student edges	true		89	40	41	64
U of Queensland	1	no student edges	true		91	56	60	57
U of Lund	1	no student edges	true		76	46	48	37
LSE	1	no student edges	true		34	23	29	22
U of Munich	1	no student edges	true		63	74	80	76
MIT	1	no student edges	true		7	50	38	51
U of Edinburgh	1	no student edges	true		47	28	25	34
UChicago	2	all edges	false	1	20	6	7	8
Wisconsin	2	all edges	false	2	28	10	11	9
Berkeley	2	all edges	false	3	5	1	5	1
UMichigan	2	all edges	false	4	11	13	17	15
UCLA	2	all edges	false	5	12	12	15	13
UNC Chapel Hill	2	all edges	false	6	41	23	18	18
Harvard	2	all edges	false	7	1	5	8	6
Stanford	2	all edges	false	8	2	7	9	10
Northwestern	2	all edges	false	9	35	8	6	5
U of Washington	2	all edges	false	10	22	22	24	28
U of Pennsylvania	2	all edges	false	11	13	3	3	3
Princeton	2	all edges	false	13	15	2	1	2
U of Arizona	2	all edges	false	14		38	22	25
Columbia	2	all edges	false	15	10	11	14	11
UT Austin	2	all edges	false	16	27	27	37	32
Johns Hopkins	2	all edges	false	17	24	14	10	12
Penn State	2	all edges	false	18	40	63	61	70
Yale	2	all edges	false	19	3	4	2	4
Duke	2	all edges	false	20	14	20	27	21
NYU	2	all edges	false	21	39	9	4	7
UCSD	2	all edges	false	22	23	17	12	16
UC Santa Barbara	2	all edges	false	23	59	28	34	34
U of Minnesota	2	all edges	false	24	30	39	36	33

institution	sample	edge inclusion	bi-partite	domestic prestige	foreign prestige	eigen rank	closeness rank	degree rank
SUNY Stoneybrook	2	all edges	false	25.5		45	51	50
Ohio State U	2	all edges	false	25.5		55	68	58
Vanderbilt U	2	all edges	false	27.5	66	53	58	64
UC Riverside	2	all edges	false	27.5		15	21	20
U Illinois Urbana	2	all edges	false	29	48	44	55	47
Rutgers	2	all edges	false	31		16	19	22
U of Maryland	2	all edges	false	33	45	50	57	56
SUNY Binghamton	2	all edges	false	34		57	52	42
Cornell	2	all edges	false	35	19	26	26	24
Florida State U	2	all edges	false	36		35	44	38
CUNY	2	all edges	false	37		31	28	36
Brown	2	all edges	false	38	56	40	53	52
UMass Amherst	2	all edges	false	39	99	54	60	60
USC	2	all edges	false	40.5	54	29	25	37
U of Iowa	2	all edges	false	40.5		47	47	48
U of Florida	2	all edges	false	43		66	65	66
Boston U	2	all edges	false	44	65	64	64	61
U Illinois Chicago	2	all edges	false	45		67	66	67
Notre Dame	2	all edges	false	46		70	63	71
U of Virginia	2	all edges	false	47.5	80	32	31	41
U of Georgia	2	all edges	false	47.5		51	50	46
U of San Francisco	2	all edges	false	50.5	9	62	62	68
UC Santa Cruz	2	all edges	false	53		58	43	49
U of Kentucky	2	all edges	false	54		65	67	57
Boston College	2	all edges	false	55		52	49	45
Syracuse	2	all edges	false	58		60	59	62
Brandeis	2	all edges	false	60		34	35	31
Temple U	2	all edges	false	61.5		36	33	27
U of New Hampshire	2	all edges	false	70		69	71	65
LSE	2	all edges	false		34	18	16	19
Emory	2	all edges	false		93	46	45	59
U of Toronto	2	all edges	false		18	42	39	43
Oxford	2	all edges	false		8	25	23	14
Ecole Polytechnique	2	all edges	false		43	59	56	54
cole Normale Suprieure	2	all edges	false		79	48	46	51
U Indiana Bloomington	2	all edges	false		12	30	29	26
McGill	2	all edges	false		42	61	48	35
U of Alberta	2	all edges	false		55	56	41	29
U of Lund	2	all edges	false		76	49	40	53
MIT	2	all edges	false		7	68	69	55
Cambridge	2	all edges	false		6	33	32	40
U of Edinburgh	2	all edges	false		47	24	30	30
U of Rochester	2	all edges	false		67	71	70	69
Hebrew U Jerusalem	2	all edges	false		82	19	13	17
U of Louvain	2	all edges	false		92	43	54	63
Hong Kong U of S&T	2	all edges	false		60	41	38	39
Australian National U	2	all edges	false		38	21	20	23
Chinese U Hong Kong	2	all edges	false		96	37	42	44
UChicago	2	all edges	true	1	20	6	7	7
Wisconsin	2	all edges	true	2	28	10	9	9
Berkeley	2	all edges	true	3	5	3	6	5
UMichigan	2	all edges	true	4	11	12	15	13
UCLA	2	all edges	true	5	12	13	13	14
UNC Chapel Hill	2	all edges	true	6	41	24	19	16
Harvard	2	all edges	true	7	1	8	8	8
Stanford	2	all edges	true	8	2	9	10	11
Northwestern	2	all edges	true	9	35	5	4	4
U of Washington	2	all edges	true	10	22	25	23	25
U of Pennsylvania	2	all edges	true	11	13	1	1	1
Princeton	2	all edges	true	13	15	2	2	2
U of Arizona	2	all edges	true	14		19	22	30
Columbia	2	all edges	true	15	10	11	12	10
UT Austin	2	all edges	true	16	27	26	36	27
Johns Hopkins	2	all edges	true	17	24	14	11	12
Penn State	2	all edges	true	18	40	61	62	54
Yale	2	all edges	true	19	3	4	3	3
Duke	2	all edges	true	20	14	22	28	15
NYU	2	all edges	true	21	39	7	5	6
UCSD	2	all edges	true	22	23	18	14	22
UC Santa Barbara	2	all edges	true	23	59	31	31	31
U of Minnesota	2	all edges	true	24	30	38	35	38
Ohio State U	2	all edges	true	25.5		66	67	61
SUNY Stoneybrook	2	all edges	true	25.5		48	46	35
UC Riverside	2	all edges	true	27.5		21	21	32
Vanderbilt U	2	all edges	true	27.5	66	56	58	50
U Illinois Urbana	2	all edges	true	29	48	55	56	65
Rutgers	2	all edges	true	31		15	17	17
U of Maryland	2	all edges	true	33	45	52	55	70
SUNY Binghamton	2	all edges	true	34		57	53	28
Cornell	2	all edges	true	35	19	23	24	19
Florida State U	2	all edges	true	36		41	44	40
CUNY	2	all edges	true	37		30	26	33
Brown	2	all edges	true	38	56	42	52	39
UMass Amherst	2	all edges	true	39	99	59	60	47
U of Iowa	2	all edges	true	40.5		51	45	44
USC	2	all edges	true	40.5	54	32	25	43
U of Florida	2	all edges	true	43		62	64	67

institution	sample	edge inclusion	bi-partite	domestic prestige	foreign prestige	eigen rank	closeness rank	degree rank
Boston U	2	all edges	true	44	65	64	66	63
U Illinois Chicago	2	all edges	true	45		63	65	51
Notre Dame	2	all edges	true	46		71	63	60
U of Virginia	2	all edges	true	47.5	80	35	33	62
U of Georgia	2	all edges	true	47.5		49	51	68
U of San Francisco	2	all edges	true	50.5	9	60	61	53
UC Santa Cruz	2	all edges	true	53		53	43	46
U of Kentucky	2	all edges	true	54		70	68	71
Boston College	2	all edges	true	55		50	50	59
Syracuse	2	all edges	true	58		58	59	58
Brandeis	2	all edges	true	60		33	37	29
Temple U	2	all edges	true	61.5		37	34	34
U of New Hampshire	2	all edges	true	70		68	71	69
Ecole Polytechnique	2	all edges	true		43	54	54	66
Chinese U Hong Kong	2	all edges	true		96	36	40	41
MIT	2	all edges	true		7	67	69	57
U of Alberta	2	all edges	true		55	43	42	36
U of Toronto	2	all edges	true		18	39	39	42
McGill	2	all edges	true		42	65	57	48
U of Edinburgh	2	all edges	true		47	28	29	26
Emory	2	all edges	true		93	44	48	56
cole Normale Suprieure	2	all edges	true		79	47	47	55
Australian National U	2	all edges	true		38	20	18	23
Oxford	2	all edges	true		8	29	27	20
Hong Kong U of S&T	2	all edges	true		60	40	38	45
U of Louvain	2	all edges	true		92	45	49	64
LSE	2	all edges	true		34	16	20	18
Cambridge	2	all edges	true		6	34	32	49
U Indiana Bloomington	2	all edges	true		12	27	30	24
U of Lund	2	all edges	true		76	46	41	37
Hebrew U Jerusalem	2	all edges	true		82	17	16	21
U of Rochester	2	all edges	true		67	69	70	52
UChicago	2	no non-tenure	false	1	20	5	10	8
Wisconsin	2	no non-tenure	false	2	28	9	6	9
Berkeley	2	no non-tenure	false	3	5	4	5	7
UMichigan	2	no non-tenure	false	4	11	11	8	12
UCLA	2	no non-tenure	false	5	12	14	14	13
UNC Chapel Hill	2	no non-tenure	false	6	41	24	16	14
Harvard	2	no non-tenure	false	7	1	6	11	10
Stanford	2	no non-tenure	false	8	2	12	15	16
Northwestern	2	no non-tenure	false	9	35	3	3	4
U of Washington	2	no non-tenure	false	10	22	23	24	24
U of Pennsylvania	2	no non-tenure	false	11	13	1	2	1
Princeton	2	no non-tenure	false	13	15	2	1	3
U of Arizona	2	no non-tenure	false	14		20	23	33
Columbia	2	no non-tenure	false	15	10	10	12	11
UT Austin	2	no non-tenure	false	16	27	19	21	27
Johns Hopkins	2	no non-tenure	false	17	24	13	9	6
Penn State	2	no non-tenure	false	18	40	39	43	48
Yale	2	no non-tenure	false	19	3	8	7	5
Duke	2	no non-tenure	false	20	14	22	19	21
NYU	2	no non-tenure	false	21	39	7	4	2
UCSD	2	no non-tenure	false	22	23	32	26	25
UC Santa Barbara	2	no non-tenure	false	23	59	21	20	19
U of Minnesota	2	no non-tenure	false	24	30	27	25	20
SUNY Stoneybrook	2	no non-tenure	false	25.5		48	47	49
Ohio State U	2	no non-tenure	false	25.5		49	44	51
UC Riverside	2	no non-tenure	false	27.5		18	18	18
Vanderbilt U	2	no non-tenure	false	27.5	66	35	35	39
U Illinois Urbana	2	no non-tenure	false	29	48	36	36	30
Rutgers	2	no non-tenure	false	31		16	22	22
U of Maryland	2	no non-tenure	false	33	45	42	37	43
SUNY Binghamton	2	no non-tenure	false	34		46	38	29
Cornell	2	no non-tenure	false	35	19	15	17	17
Florida State U	2	no non-tenure	false	36		33	41	45
CUNY	2	no non-tenure	false	37		17	13	15
Brown	2	no non-tenure	false	38	56	26	33	36
UMass Amherst	2	no non-tenure	false	39	99	38	45	52
U of Iowa	2	no non-tenure	false	40.5		29	28	23
USC	2	no non-tenure	false	40.5	54	52	49	38
U of Florida	2	no non-tenure	false	43		41	40	50
Boston U	2	no non-tenure	false	44	65	54	54	54
U Illinois Chicago	2	no non-tenure	false	45		53	55	46
Notre Dame	2	no non-tenure	false	46		70	58	62
U of Virginia	2	no non-tenure	false	47.5	80	37	34	34
U of Georgia	2	no non-tenure	false	47.5		40	42	42
U of San Francisco	2	no non-tenure	false	50.5	9	68	68	63
UC Santa Cruz	2	no non-tenure	false	53		64	59	69
U of Kentucky	2	no non-tenure	false	54		56	56	47
Boston College	2	no non-tenure	false	55		60	70	66
Syracuse	2	no non-tenure	false	58		43	39	40
Brandeis	2	no non-tenure	false	60		25	32	26
Temple U	2	no non-tenure	false	61.5		57	57	65
U of New Hampshire	2	no non-tenure	false	70		51	51	56
U of Louvain	2	no non-tenure	false		92	50	50	53
Hebrew U Jerusalem	2	no non-tenure	false		82	28	31	31
U of Rochester	2	no non-tenure	false		67	61	69	60
McGill	2	no non-tenure	false		42	66	71	70

institution	sample	edge inclusion	bi-partite	domestic prestige	foreign prestige	eigen rank	closeness rank	degree rank
Australian National U	2	no non-tenure	false		38	69	64	59
Oxford	2	no non-tenure	false		8	44	48	35
U of Alberta	2	no non-tenure	false		55	34	30	32
U of Lund	2	no non-tenure	false		76	55	53	55
Emory	2	no non-tenure	false		93	59	67	67
cole Normale Suprieure	2	no non-tenure	false		79	71	61	64
Chinese U Hong Kong	2	no non-tenure	false		96	63	60	58
U Indiana Bloomington	2	no non-tenure	false		12	30	29	37
LSE	2	no non-tenure	false		34	45	46	44
U of Toronto	2	no non-tenure	false		18	31	27	28
Cambridge	2	no non-tenure	false		6	62	62	61
Ecole Polytechnique	2	no non-tenure	false		43	58	65	57
Hong Kong U of S&T	2	no non-tenure	false		60	65	66	68
MIT	2	no non-tenure	false		7	67	63	71
U of Edinburgh	2	no non-tenure	false		47	47	52	41
UChicago	2	no non-tenure	true	1	20	4	8	6
Wisconsin	2	no non-tenure	true	2	28	9	7	9
Berkeley	2	no non-tenure	true	3	5	5	4	7
UMichigan	2	no non-tenure	true	4	11	11	9	12
UCLA	2	no non-tenure	true	5	12	29	14	13
UNC Chapel Hill	2	no non-tenure	true	6	41	22	16	16
Harvard	2	no non-tenure	true	7	1	8	10	8
Stanford	2	no non-tenure	true	8	2	13	13	14
Northwestern	2	no non-tenure	true	9	35	2	2	2
U of Washington	2	no non-tenure	true	10	22	25	22	25
U of Pennsylvania	2	no non-tenure	true	11	13	1	1	1
Princeton	2	no non-tenure	true	13	15	3	3	4
U of Arizona	2	no non-tenure	true	14		20	24	24
Columbia	2	no non-tenure	true	15	10	10	12	11
UT Austin	2	no non-tenure	true	16	27	17	23	20
Johns Hopkins	2	no non-tenure	true	17	24	12	11	10
Penn State	2	no non-tenure	true	18	40	38	42	49
Yale	2	no non-tenure	true	19	3	7	6	5
Duke	2	no non-tenure	true	20	14	19	20	18
NYU	2	no non-tenure	true	21	39	6	5	3
UCSD	2	no non-tenure	true	22	23	57	27	30
UC Santa Barbara	2	no non-tenure	true	23	59	21	19	21
U of Minnesota	2	no non-tenure	true	24	30	30	25	28
Ohio State U	2	no non-tenure	true	25.5		41	45	52
SUNY Stoneybrook	2	no non-tenure	true	25.5		49	47	57
Vanderbilt U	2	no non-tenure	true	27.5	66	33	35	38
UC Riverside	2	no non-tenure	true	27.5		16	17	23
U Illinois Urbana	2	no non-tenure	true	29	48	39	37	45
Rutgers	2	no non-tenure	true	31		15	21	17
U of Maryland	2	no non-tenure	true	33	45	35	36	37
SUNY Binghamton	2	no non-tenure	true	34		47	40	27
Cornell	2	no non-tenure	true	35	19	14	18	15
Florida State U	2	no non-tenure	true	36		40	41	51
CUNY	2	no non-tenure	true	37		18	15	19
Brown	2	no non-tenure	true	38	56	27	32	31
UMass Amherst	2	no non-tenure	true	39	99	37	43	40
U of Iowa	2	no non-tenure	true	40.5		31	29	36
USC	2	no non-tenure	true	40.5	54	51	50	39
U of Florida	2	no non-tenure	true	43		36	39	47
Boston U	2	no non-tenure	true	44	65	53	53	56
U Illinois Chicago	2	no non-tenure	true	45		50	55	44
Notre Dame	2	no non-tenure	true	46		66	71	60
U of Georgia	2	no non-tenure	true	47.5		42	44	54
U of Virginia	2	no non-tenure	true	47.5	80	32	33	42
U of San Francisco	2	no non-tenure	true	50.5	9	65	66	58
UC Santa Cruz	2	no non-tenure	true	53		58	64	68
U of Kentucky	2	no non-tenure	true	54		55	56	48
Boston College	2	no non-tenure	true	55		67	61	65
Syracuse	2	no non-tenure	true	58		44	38	43
Brandeis	2	no non-tenure	true	60		23	34	22
Temple U	2	no non-tenure	true	61.5		56	57	53
U of New Hampshire	2	no non-tenure	true	70		45	48	50
Australian National U	2	no non-tenure	true		38	71	70	69
Hong Kong U of S&T	2	no non-tenure	true		60	61	59	63
U of Edinburgh	2	no non-tenure	true		47	52	52	34
Oxford	2	no non-tenure	true		8	43	51	32
U of Toronto	2	no non-tenure	true		18	28	26	33
cole Normale Suprieure	2	no non-tenure	true		79	62	62	62
Chinese U Hong Kong	2	no non-tenure	true		96	63	63	67
U of Lund	2	no non-tenure	true		76	54	54	46
U of Rochester	2	no non-tenure	true		67	59	68	64
Cambridge	2	no non-tenure	true		6	64	60	59
Hebrew U Jerusalem	2	no non-tenure	true		82	24	31	35
MIT	2	no non-tenure	true		7	60	69	61
Emory	2	no non-tenure	true		93	70	58	70
LSE	2	no non-tenure	true		34	48	46	41
U Indiana Bloomington	2	no non-tenure	true		12	26	28	26
U of Louvain	2	no non-tenure	true		92	46	49	55
U of Alberta	2	no non-tenure	true		55	34	30	29
McGill	2	no non-tenure	true		42	68	67	71
Ecole Polytechnique	2	no non-tenure	true		43	69	65	66
UChicago	2	no student edges	false	1	20	11	12	15
Wisconsin	2	no student edges	false	2	28	7	8	9

institution	sample	edge inclusion	bi-partite	domestic prestige	foreign prestige	eigen rank	closeness rank	degree rank
Berkeley	2	no student edges	false	3	5	4	4	5
UMichigan	2	no student edges	false	4	11	16	17	22
UCLA	2	no student edges	false	5	12	12	15	14
UNC Chapel Hill	2	no student edges	false	6	41	19	19	18
Harvard	2	no student edges	false	7	1	6	11	11
Stanford	2	no student edges	false	8	2	5	7	7
Northwestern	2	no student edges	false	9	35	9	6	6
U of Washington	2	no student edges	false	10	22	24	23	30
U of Pennsylvania	2	no student edges	false	11	13	3	2	1
Princeton	2	no student edges	false	13	15	1	3	4
U of Arizona	2	no student edges	false	14		20	18	23
Columbia	2	no student edges	false	15	10	10	14	13
UT Austin	2	no student edges	false	16	27	41	46	40
Johns Hopkins	2	no student edges	false	17	24	14	10	8
Penn State	2	no student edges	false	18	40	66	67	67
Yale	2	no student edges	false	19	3	2	5	3
Duke	2	no student edges	false	20	14	22	28	24
NYU	2	no student edges	false	21	39	8	1	2
UCSD	2	no student edges	false	22	23	15	13	12
UC Santa Barbara	2	no student edges	false	23	59	37	39	55
U of Minnesota	2	no student edges	false	24	30	38	34	27
SUNY Stoneybrook	2	no student edges	false	25.5		56	49	58
Ohio State U	2	no student edges	false	25.5		46	58	60
Vanderbilt U	2	no student edges	false	27.5	66	51	56	61
UC Riverside	2	no student edges	false	27.5		13	22	19
U Illinois Urbana	2	no student edges	false	29	48	40	45	41
Rutgers	2	no student edges	false	31		25	29	29
U of Maryland	2	no student edges	false	33	45	47	50	54
SUNY Binghamton	2	no student edges	false	34		61	60	47
Cornell	2	no student edges	false	35	19	28	33	28
Florida State U	2	no student edges	false	36		54	57	52
CUNY	2	no student edges	false	37		29	25	32
Brown	2	no student edges	false	38	56	44	43	50
UMass Amherst	2	no student edges	false	39	99	58	51	56
USC	2	no student edges	false	40.5	54	27	24	33
U of Iowa	2	no student edges	false	40.5		48	42	46
U of Florida	2	no student edges	false	43		67	66	63
Boston U	2	no student edges	false	44	65	71	71	69
U Illinois Chicago	2	no student edges	false	45		62	62	62
Notre Dame	2	no student edges	false	46		68	68	68
U of Virginia	2	no student edges	false	47.5	80	31	30	34
U of Georgia	2	no student edges	false	47.5		53	52	37
U of San Francisco	2	no student edges	false	50.5	9	65	63	66
UC Santa Cruz	2	no student edges	false	53		55	37	45
U of Kentucky	2	no student edges	false	54		59	59	57
Boston College	2	no student edges	false	55		52	53	38
Syracuse	2	no student edges	false	58		60	65	65
Brandeis	2	no student edges	false	60		39	38	44
Temple U	2	no student edges	false	61.5		34	27	20
U of New Hampshire	2	no student edges	false	70		70	70	71
Ecole Polytechnique	2	no student edges	false		43	50	48	48
Oxford	2	no student edges	false		8	23	21	17
MIT	2	no student edges	false		7	64	61	53
McGill	2	no student edges	false		42	45	40	26
U Indiana Bloomington	2	no student edges	false		12	33	32	25
U of Louvain	2	no student edges	false		92	69	69	70
LSE	2	no student edges	false		34	17	16	16
U of Rochester	2	no student edges	false		67	63	64	64
Cambridge	2	no student edges	false		6	30	31	36
Emory	2	no student edges	false		93	43	44	59
U of Edinburgh	2	no student edges	false		47	26	26	39
U of Alberta	2	no student edges	false		55	49	54	43
Hebrew U Jerusalem	2	no student edges	false		82	18	9	10
Chinese U Hong Kong	2	no student edges	false		96	32	47	42
Hong Kong U of S&T	2	no student edges	false		60	36	36	31
U of Lund	2	no student edges	false		76	57	55	51
Australian National U	2	no student edges	false		38	21	20	21
U of Toronto	2	no student edges	false		18	35	35	35
cole Normale Suprieure	2	no student edges	false		79	42	41	49
UChicago	2	no student edges	true	1	20	67	9	12
Wisconsin	2	no student edges	true	2	28	9	8	10
Berkeley	2	no student edges	true	3	5	4	6	8
UMichigan	2	no student edges	true	4	11	13	14	13
UCLA	2	no student edges	true	5	12	12	16	14
UNC Chapel Hill	2	no student edges	true	6	41	21	21	17
Harvard	2	no student edges	true	7	1	8	11	7
Stanford	2	no student edges	true	8	2	7	7	6
Northwestern	2	no student edges	true	9	35	5	3	3
U of Washington	2	no student edges	true	10	22	22	20	21
U of Pennsylvania	2	no student edges	true	11	13	1	1	1
Princeton	2	no student edges	true	13	15	3	4	5
U of Arizona	2	no student edges	true	14		20	17	27
Columbia	2	no student edges	true	15	10	10	13	11
UT Austin	2	no student edges	true	16	27	47	49	55
Johns Hopkins	2	no student edges	true	17	24	14	10	9
Penn State	2	no student edges	true	18	40	66	66	68
Yale	2	no student edges	true	19	3	2	5	2
Duke	2	no student edges	true	20	14	24	29	22

institution	sample	edge inclusion	bi-partite	domestic prestige	foreign prestige	eigen rank	closeness rank	degree rank
NYU	2	no student edges	true	21	39	6	2	4
UCSD	2	no student edges	true	22	23	15	15	16
UC Santa Barbara	2	no student edges	true	23	59	53	37	42
U of Minnesota	2	no student edges	true	24	30	38	34	36
Ohio State U	2	no student edges	true	25.5		55	57	66
SUNY Stoneybrook	2	no student edges	true	25.5		42	42	31
UC Riverside	2	no student edges	true	27.5		36	22	25
Vanderbilt U	2	no student edges	true	27.5	66	44	55	43
U Illinois Urbana	2	no student edges	true	29	48	46	50	57
Rutgers	2	no student edges	true	31		19	27	20
U of Maryland	2	no student edges	true	33	45	39	47	47
SUNY Binghamton	2	no student edges	true	34		63	64	33
Cornell	2	no student edges	true	35	19	23	30	24
Florida State U	2	no student edges	true	36		50	58	54
CUNY	2	no student edges	true	37		27	24	23
Brown	2	no student edges	true	38	56	43	43	37
UMass Amherst	2	no student edges	true	39	99	57	54	67
USC	2	no student edges	true	40.5	54	28	25	35
U of Iowa	2	no student edges	true	40.5		49	44	32
U of Florida	2	no student edges	true	43		65	65	60
Boston U	2	no student edges	true	44	65	69	70	70
U Illinois Chicago	2	no student edges	true	45		60	61	64
Notre Dame	2	no student edges	true	46		68	68	44
U of Georgia	2	no student edges	true	47.5		51	53	50
U of Virginia	2	no student edges	true	47.5	80	30	32	48
U of San Francisco	2	no student edges	true	50.5	9	62	62	46
UC Santa Cruz	2	no student edges	true	53		11	38	39
U of Kentucky	2	no student edges	true	54		59	59	65
Boston College	2	no student edges	true	55		52	52	62
Syracuse	2	no student edges	true	58		61	67	61
Brandeis	2	no student edges	true	60		37	39	34
Temple U	2	no student edges	true	61.5		34	28	38
U of New Hampshire	2	no student edges	true	70		70	69	71
Chinese U Hong Kong	2	no student edges	true		96	31	40	40
cole Normale Suprieure	2	no student edges	true		79	41	41	51
McGill	2	no student edges	true		42	54	46	45
U of Toronto	2	no student edges	true		18	33	35	30
Australian National U	2	no student edges	true		38	18	19	19
MIT	2	no student edges	true		7	64	63	53
U Indiana Bloomington	2	no student edges	true		12	32	33	29
U of Edinburgh	2	no student edges	true		47	26	26	28
Oxford	2	no student edges	true		8	25	23	26
LSE	2	no student edges	true		34	16	18	15
U of Rochester	2	no student edges	true		67	56	60	49
U of Alberta	2	no student edges	true		55	48	51	58
U of Louvain	2	no student edges	true		92	71	71	69
Emory	2	no student edges	true		93	45	48	56
U of Lund	2	no student edges	true		76	58	56	59
Hong Kong U of S&T	2	no student edges	true		60	35	36	41
Cambridge	2	no student edges	true		6	29	31	63
Ecole Polytechnique	2	no student edges	true		43	40	45	52
Hebrew U Jerusalem	2	no student edges	true		82	17	12	18