Social Networks in Political Science: Hiring and Placement of Ph.D.s, 1960–2002

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Social scientists have long been interested in how academic disciplines are organized (Ben-David and Collins 1966; Kuhn 1970; Lipset 1994; Rojas 2003; Somit and Tanenhaus 1964; 1967). One important element of this organization is the network of Ph.D. placements among Ph.D.-granting institutions. Various authors have linked the structure of placements to prestige rankings of departments (for sociology departments see e.g., Hanneman 2001; and Burris 2004; for political science departments see Masuoka, Grofman, and Feld 2007c), or have used various features of the structure of academic exchange networks to examine the shaping of disciplinary careers and practices (Feld, Bisciglia, and Ynalvez 2003; Masuoka, Grofman, and Feld 2007b). There is also a more general literature on status and market exchange (see e.g., Podolny 2005).

Using data on the structure of placements in Ph.D.-granting political science departments in the U.S. over the period 1960–2000 taken from Masuoka, Grofman, and Feld (2007a; 2007b; 2007c), and recent statistical (Kleinberg 1999) and graphical (Kamada and Kawai 1989) innovations in the study of social networks, we show how social network analysis can be used to illuminate the structure of the political science academic network. Our graphical representations clearly show the structure of the discipline in terms of what might be conceived of as a *core-periphery network* (Borgatti and Everett 1999; Feld, Bisciglia, and Ynalvez 2003).[1]

The structure of this research note is to first discuss the methodology we use to combine information about (1) which departments are able to place their students in core departments and (2) which departments successfully hire and retain Ph.D.s from core departments. Next, we show graphical representations of the Ph.D.-placement network in the discipline. Then we consider how well various social network measures conform to reputation rankings of departments provided by *U.S. News and World Report*. Finally, we explore additional complications, such as how the structure of the discipline has changed over time, and what happens to placement rankings when we utilize information about the proportion of a department's Ph.D.s that were *not* placed in a Ph.D.-granting institution.

Introduction: Features of Directed Networks

In any directed network—such as one involving the placement of Ph.D. candidates—social *ties* (placements) indicate a one-way relationship from one *node* (department) to another. In our case, each direction is of interest because each contains different kinds of information. Outward ties reflect the capacity of the sending department to place its own students, while inward ties reflect the capacity of the receiving department to hire and retain faculty. One way to measure these capacities is simply to aggregate the number of outward ties (number of placements) or the number of inward ties (faculty size). Social network theorists call these measures of *degree centrality* (Proctor and Loomis 1951; Freeman 1979).

A department's degree centrality can be connected to its level of prestige within the academic profession a number of ways. Those departments with high *outward degree centrality* influence the basic structure of the profession by populating other Ph.D.-granting departments, thereby increasing the successful program's reputation (Grofman, Feld, and Masuoka 2005; Somit and Tanenhaus 1964; 1967).[2] Further, given their placement success, these departments can attract high quality graduate students which, in turn, increases the ability of these departments to place its Ph.D.s in other highly ranked departments. Departments with more *inward degree centrality* have larger faculties, which suggests that they will generally be able to produce more research, as well as be able to produce more graduate students who will get jobs at other institutions. But, of course, not all large departments, or departments that produce many Ph.D.s, will be able to place their students in prestigious departments. In fact, given the limited number of faculty positions available in political science at any given time, we can expect that no department, regardless of its reputation or prestige, will be able to place all of its Ph.D.s in a prestigious department.

Therefore, rather than looking simply at raw in-degree and out-degree numbers, we want to make better use of the information in the Ph.D.-placement network so as not to treat all placements in exactly the same way. In particular, we

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should be able to use information about which institutions take Ph.D. students from which other institutions to improve our estimate of each department's capacity to place its graduate students. The limited number of faculty openings in Ph.D.-granting institutions means that there is a significant level of competition to place students. For example, suppose department i places most of its students in departments that place many of their own students, and department j places its students largely in departments that place few of their own students. This suggests that department i may be more prestigious than department j.[3]

Methodology

In order to estimate simultaneously the prestige of all departments in a network, some scholars (e.g., Burris 2004) use a measure called *eigenvector centrality* (Bonacich 1972). Suppose A is an $n \times n$ adjacency matrix representing all the departments in a network such that a_{ij} indicates the number of candidates that the ith department places in the jth department.[4] Let x be a vector of centrality scores so that each department's prestige x_i is the sum of the prestige of the departments where it places candidates: $x_i = a_{1i}x_1 + a_{2i}x_2 + \cdots + a_{ni}x_n$. This yields n equations that we can represent in matrix format as $x = A^T x$. It is unlikely that these equations have a nonzero solution, so Bonacich (1972) suggests an important modification. Suppose the prestige of a department is proportional to instead of equal to the prestige of the departments where it places students. Then $\lambda x_i = a_{1i}x_1 + a_{2i}x_2 + \cdots + a_{ni}x_n$ which can be represented as $\lambda x = A^T x$. The vector of centrality scores x can now be computed since it is an eigenvector of the eigenvalue λ.[5]

However, there are technical and substantive reasons why we might not want to use eigenvector centrality to estimate the prestige of political science departments. First, there is a technical problem with the Ph.D.-placement network data because many departments have not placed any of their students in other departments. This means their centrality scores are 0 and the eigenvector method assumes they add nothing at all to the reputation of the departments that place candidates there. Second, the eigenvector centrality approach to identifying prestigious departments assumes that only placements contain information about prestige.

While placements may be a primary indicator of network structure, the acquisition of faculty can also be informative. Hiring patterns may demonstrate the capacity of a department to attract and retain the faculty it wishes. Most departments, in principle, probably prefer to hire faculty from prestigious departments, although of course there will be exceptions (even many exceptions) based on the caliber and special skills of particular candidates. But, in any case, not all departments can always hire only from top departments, since there is only a limited pool of candidates from such departments, and there is strong competition for them. Thus, we can also use hiring results to provide additional information relevant to estimating prestige among departments. For example, suppose department i gets all of its faculty from departments that place well, while department j gets few of its faculty from such departments. This suggests that department i may itself be more prestigious than department j.

A recent advance in social network theory (Kleinberg 1999) allows us to draw on both placements and hires for assessing prestige.[6] This procedure relies conceptually on two different kinds of nodes in the network, which Kleinberg call hubs and authorities. Hubs are nodes that have many high quality outward connections, while authorities are nodes that have many high quality inward connections. In particular, a good hub points to many good authorities, and a good authority is pointed to by many good hubs. In the Ph.D.-placement network, a hub is a department that places its students in the most prestigious departments, while an authority is a department that hires prestigious faculty. Since Kleinberg's terminology, hub and authority, is not intuitive and has some unnecessarily strong normative overtones in the current analysis, we will instead refer to these aspects of network structure simply as "placement capacity" and "hiring capacity."

The extent to which each department fulfills these two roles can be determined using a method closely related to eigenvector centrality. Suppose x is a vector of hiring capacity (authority) scores, y is a vector of placement capacity (hub) scores, and that these vectors are normalized so their squares sum to 1. Let each department's hiring capacity be equal to the sum of the placement capacity scores of the departments from which they hire candidates: $x_i = a_{1i}y_1 + a_{2i}y_2 + \cdots + a_{ni}y_n$ and let each department's placement capacity score be the sum of the hiring capacity scores for the departments where they place candidates: $y_i = a_{i1}x_1 + a_{i2}x_2 + \cdots + a_{in}x_n$. This yields $2n$ equations that we can represent in matrix format as $x = A^T y$ and $y = Ax$. Kleinberg (1999) shows that the solution to these equations converges to $\lambda x^* = A^T A x^*$ and $\lambda y^* = AA^T y^*$, where λ is the principal eigenvalue and x^* and y^* are the principal eigenvectors of the symmetric positive definite matrices $A^T A$ and AA^T, respectively. The resulting placement and hiring capacity scores allow us to identify the most prestigious departments in the network—those that hire faculty from other prestigious departments and those that do well placing their own students.

Data

We use data compiled by Masuoka, Grofman, and Feld (2007b; see also 2007a; 2007c) that shows all placements of U.S. Ph.D.s within U.S. Ph.D.-granting political science departments for the period 1960–2000. The data combine information provided in the APSA 2000 *Graduate Faculty and Programs in Political Science* with supplementary information on faculty taken as needed from the APSA 2002–2004 *Directory of Political Science Faculty*. With a relatively limited number of exceptions, the data contain not just the information on which U.S. Ph.D.-granting institution a faculty member is currently teaching at (circa 2002), but also information about the institution from which that faculty member received his or her Ph.D. and the date of Ph.D completion.[7] This allows us to create a 132×132 matrix for Ph.D. placements using the department as our unit of analysis.[8] We present in the Appendix (Table A1) data on faculty size and total placements for all 132 departments.

Results

Table 1 shows placement and hiring capacity scores for the whole network. As noted above, placement scores indicate the capacity of the sender institution to prepare scholars to get jobs at Ph.D.-granting departments that hire well. Hiring capacity scores indicate the ability of the receiving institution to add scholars to its ranks from institutions that place well.[9] Notice, for example, that Berkeley's department does well in both placement and hiring, while Chicago's places better than it hires and UCLA's hires better than it places.

Figure 1 shows a picture of the Ph.D.-placement network. The sizes of the nodes in Figure 1 are proportional to placement scores and the darkness of each arc is proportional to the number of Ph.D.s that have gone from the sending institution to the receiving institution.[10]

Table 1
Placement and Hiring Capacity Scores, Full Network

	Placement		Hiring			Placement		Hiring	
Department	Rank	Score	Rank	Score	Department	Rank	Score	Rank	Score
Harvard	1	0.5200	23	0.1208	Arizona	67	0.0081	40	0.0932
Chicago	2	0.3610	13	0.1398	Hawaii	68	0.0080	77	0.0444
Berkeley	3	0.3529	2	0.2396	New School	69	0.0079	82	0.0409
Yale	4	0.3300	4	0.1881	Connecticut	70	0.0077	42	0.0870
Michigan	5	0.2659	9	0.1647	Purdue	71	0.0075	59	0.0662
Columbia	6	0.2592	11	0.1577	Delaware	72	0.0074	94	0.0292
Princeton	7	0.2333	5	0.1880	GWU	73	0.0074	34	0.1058
Stanford	8	0.1754	22	0.1252	Brown	74	0.0070	67	0.0538
MIT	9	0.1446	16	0.1343	South Carolina	75	0.0068	57	0.0668
Wisconsin	10	0.1205	3	0.1958	UC Davis	76	0.0062	33	0.1062
UCLA	11	0.1199	1	0.2487	SUNY Albany	77	0.0056	46	0.0802
Cornell	12	0.1114	31	0.1107	Cincinnati	78	0.0047	68	0.0527
Minnesota	13	0.1080	37	0.0978	Texas A&M	79	0.0044	75	0.0449
Northwestern	14	0.0998	27	0.1125	Tulane	80	0.0041	76	0.0447
UNC	15	0.0841	14	0.1395	Kansas	81	0.0039	61	0.0658
Indiana	16	0.0831	12	0.1470	Miami U	82	0.0037	88	0.0370
Johns Hopkins	17	0.0728	28	0.1121	Alabama	83	0.0035	123	0.0132
Rochester	18	0.0692	56	0.0670	North Texas	84	0.0033	119	0.0140
Syracuse	19	0.0637	51	0.0744	Nebraska	85	0.0032	92	0.0311
Duke	20	0.0623	17	0.1337	UC Riverside	86	0.0032	90	0.0325
Ohio St	21	0.0585	8	0.1686	Washington St	87	0.0031	91	0.0312
Wash U St Louis	22	0.0490	52	0.0739	Arizona St	88	0.0030	58	0.0666
Iowa	23	0.0446	69	0.0525	Northern Illinois	89	0.0027	60	0.0661
UCSD	24	0.0418	15	0.1385	Boston Coll	90	0.0027	43	0.0841
Illinois-Urbana	25	0.0402	20	0.1266	West Virginia	91	0.0026	116	0.0161
Texas	26	0.0390	35	0.1055	New Orleans	92	0.0025	112	0.0179
Penn	27	0.0368	38	0.0955	St Louis U	93	0.0024	131	0.0026
Virginia	28	0.0312	7	0.1690	Louisiana St	93	0.0024	86	0.0375
Pittsburgh	29	0.0281	50	0.0756	Missouri	95	0.0022	66	0.0565
NYU	30	0.0274	45	0.0806	George Mason	96	0.0022	30	0.1114
Cal Tech	31	0.0274	118	0.0140	New Mexico	97	0.0021	107	0.0215
U Washington	32	0.0264	19	0.1306	Texas-Arlington	98	0.0016	121	0.0135
SUNY Stony Brook	33	0.0246	73	0.0466	Georgia St	99	0.0015	108	0.0214
Rutgers	34	0.0245	25	0.1190	Tennessee	100	0.0014	127	0.0080
American	35	0.0244	6	0.1700	Kent St	101	0.0014	113	0.0179
Florida St	36	0.0232	81	0.0417	Case Western	102	0.0011	115	0.0163
Michigan St	37	0.0229	29	0.1121	Virginia Tech	103	0.0011	104	0.0232
Maryland	38	0.0220	10	0.1590	Southern Illinois	104	0.0010	87	0.0374
Georgetown	39	0.0217	21	0.1255	Temple	105	0.0010	74	0.0465
Denver	40	0.0165	97	0.0281	Wayne St	106	0.0007	65	0.0618
Claremont Grad	41	0.0163	109	0.0213	Fordham	106	0.0007	39	0.0948
Massachusetts	42	0.0159	47	0.0787	Northern Arizona	108	0.0006	105	0.0227
USC	43	0.0153	24	0.1194	Idaho	109	0.0006	132	0.0014
Kentucky	44	0.0152	95	0.0290	Utah	110	0.0005	80	0.0425
Penn St	45	0.0151	72	0.0474	Colorado St	111	0.0004	102	0.0250
Brandeis	46	0.0145	49	0.0758	Mississippi	112	0.0003	101	0.0261
Emory	47	0.0142	62	0.0636	Virginia Commonwealth	113	0.0003	124	0.0103
Oregon	48	0.0139	55	0.0671	Clark Atlanta	114	0.0002	129	0.0047
Illinois-Chicago	48	0.0139	64	0.0619	Auburn	115	0.0001	120	0.0135
SUNY Buffalo	50	0.0137	106	0.0220	U Miami	116	0.0000	111	0.0207
Rice	51	0.0135	54	0.0692	Southern	116	0.0000	128	0.0073
Colorado	52	0.0132	32	0.1083	Dallas	116	0.0000	110	0.0209
UC Santa Barbara	53	0.0128	26	0.1168	Missouri-Kansas City	116	0.0000	125	0.0103
Florida	53	0.0128	53	0.0711	Mississippi St	116	0.0000	130	0.0044
Vanderbilt	55	0.0121	70	0.0510	Old Dominion	116	0.0000	117	0.0147
Carnegie Mellon	56	0.0118	41	0.0876	Nebraska-Omaha	116	0.0000	122	0.0134
CUNY	57	0.0117	71	0.0494	Nevada	116	0.0000	100	0.0265
Georgia	58	0.0096	48	0.0767	Texas Tech	116	0.0000	126	0.0096
Notre Dame	59	0.0093	18	0.1327	Catholic	116	0.0000	98	0.0280
Houston	60	0.0089	63	0.0621	Florida Intl	116	0.0000	114	0.0167
Howard	61	0.0088	89	0.0369	Texas-Dallas	116	0.0000	103	0.0236
SUNY Binghamton	62	0.0087	79	0.0436	Rutgers-Newark	116	0.0000	93	0.0306
Wisconsin-Milwaukee	63	0.0086	84	0.0377	Loyola	116	0.0000	85	0.0376
Boston U	64	0.0086	44	0.0821	Northeastern	116	0.0000	77	0.0444
UC Irvine	65	0.0085	36	0.1023	Missouri-St Louis	116	0.0000	96	0.0290
Oklahoma	66	0.0085	99	0.0280	Western Michigan	116	0.0000	83	0.0396

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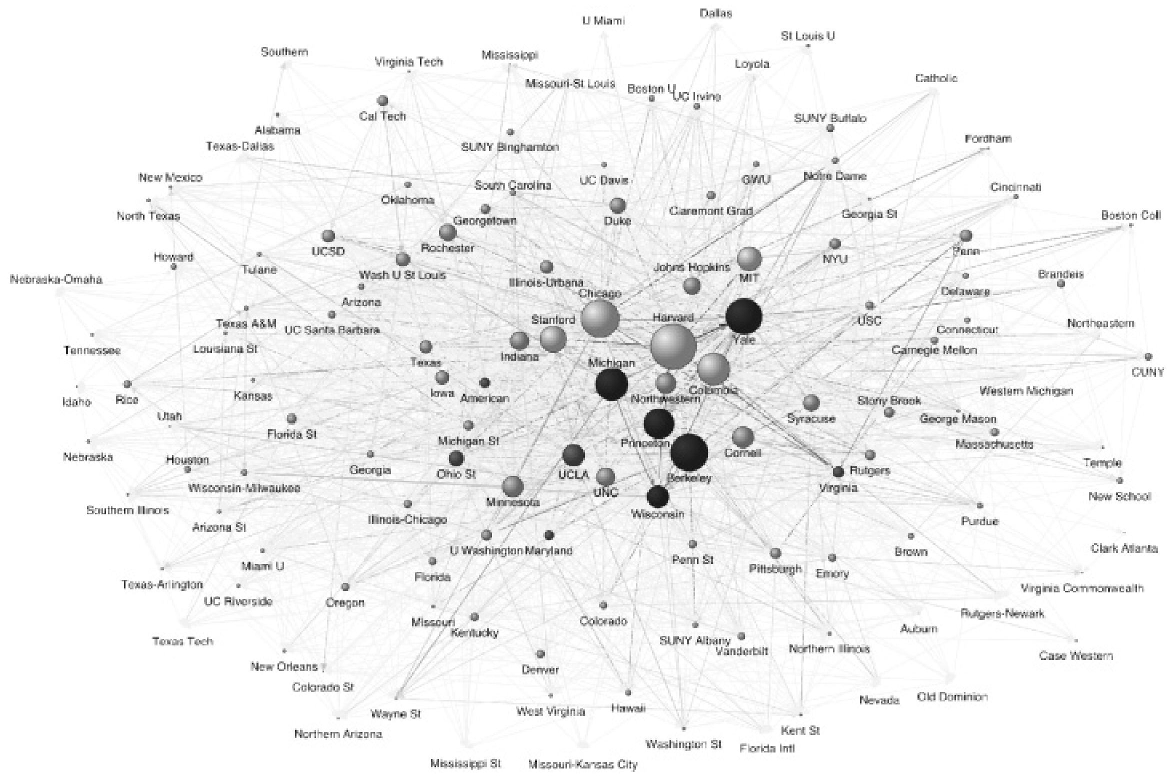
Figure 1
Full Network of Ph.D.s



Notes: Each arrow indicates at least one placement was made by the originating department at the destination department. Number of placements is proportional to the shade of the arrow. Node size is proportional to placement score. Black nodes indicate top departments for both placement and hiring capacity.

The black nodes indicate the top departments for both placement and hiring.

Figure 1 reveals the extent to which there is an apparent core-periphery structure, with a density of ties in the center of the graph around the political science departments at Harvard, Chicago, and Columbia, with further strong ties to departments such as Yale, Berkeley, and Michigan, and then to departments such as Stanford, Princeton, Wisconsin, Northwestern, UCLA, Cornell, and Indiana.

Using Network Connectivity Measures to Predict Departmental Prestige

There are numerous way to rank departments, from citation counts or publication rates of faculty, to dollar value of grants received, to faculty memberships in organizations such as the American Academy of Arts and Sciences, and there may be multiple dimensions of success, e.g., some schools may simply be especially good at turning out scholars who get jobs at highly ranked departments and have distinguished careers in the discipline (see, for example, Masuoka, Grofman, and Feld 2007a; Miller, Tien, and Peebler 1996; Rice, McCormick, and Bergmann 2002). Often measures are based simply on reputation or on perceptions about the quality of the department in the minds of those doing the ranking (Somit and Tanenhaus 1964). For example, *U.S. News and World Report*, which compiles a list of the best departments based on surveys of department chairs, is an example of a reputation ranking. Research has shown that objective rankings that are based on measures such as publication rates or citation counts do not perfectly correlate with reputation rankings, telling us that each type of ranking depicts a different way of measuring prestige (Garand and Grady 1999; Jackman and Silver 1996; Masuoka, Grofman, and Feld 2007c).

The exchange of Ph.D. students among departments tells us at least some information about prestige, on the one hand, and quality, vis-à-vis the training of graduate students, on the other. The Ph.D.-placement network provides valuable aggregate information about the structure of the profession in ways that can be used to rank departments.

Figure 2 shows a strong relationship between the *U.S. News and World Report* rankings in 2005 and rankings derived from our placement scores based on the Ph.D.-placement network from 1993–2002. For all years, the Spearman rank correlation (henceforth r) between them is 0.84. The corresponding r for our hiring capacity scores is only 0.59, suggesting that scholars may be more strongly influenced in their perception of a department's quality by its ability to place students in good departments than the types of scholars hired as faculty. These results are verified in OLS regressions presented in the Appendix (Table A2). These regressions also show that the placement rank variable fits reputation rankings better than simple counts of inward or outward placements. In other words, the placement and hiring capacity scores generated by our method contain important information about department reputation that is not revealed in a simple count of placements to other departments.

The Dynamics of Placement

The data used in Table 1 and Figure 1 aggregate all available information for

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Figure 2
Placement Score Ranks and *U.S. News and World Report* Rankings

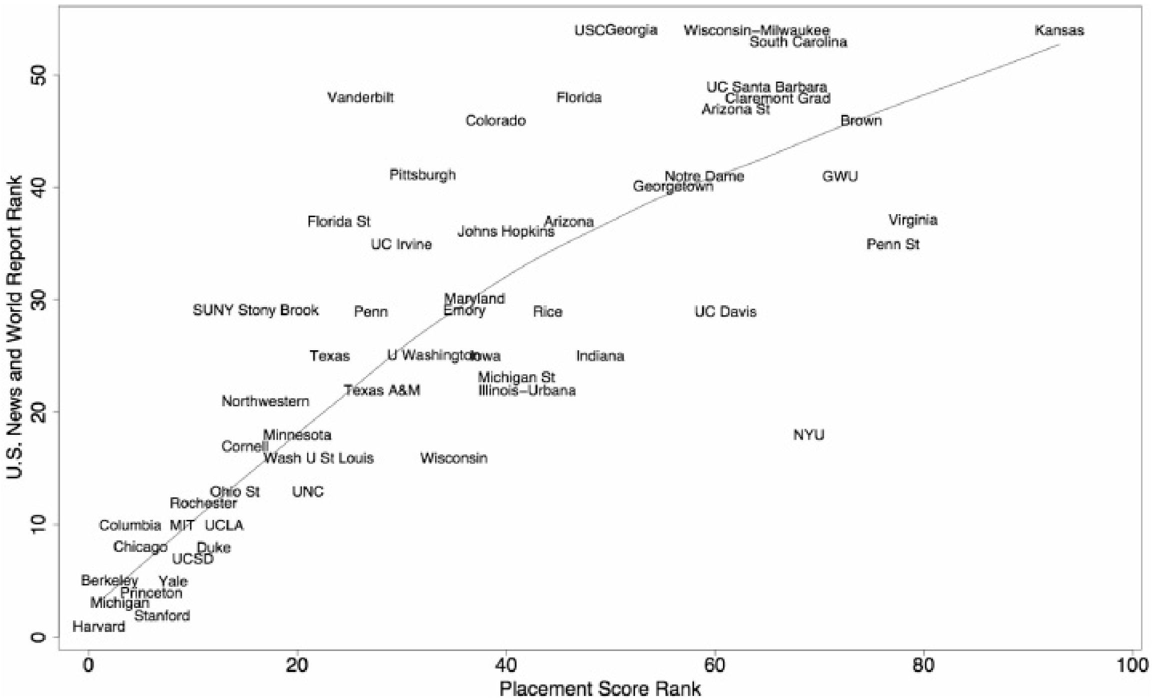
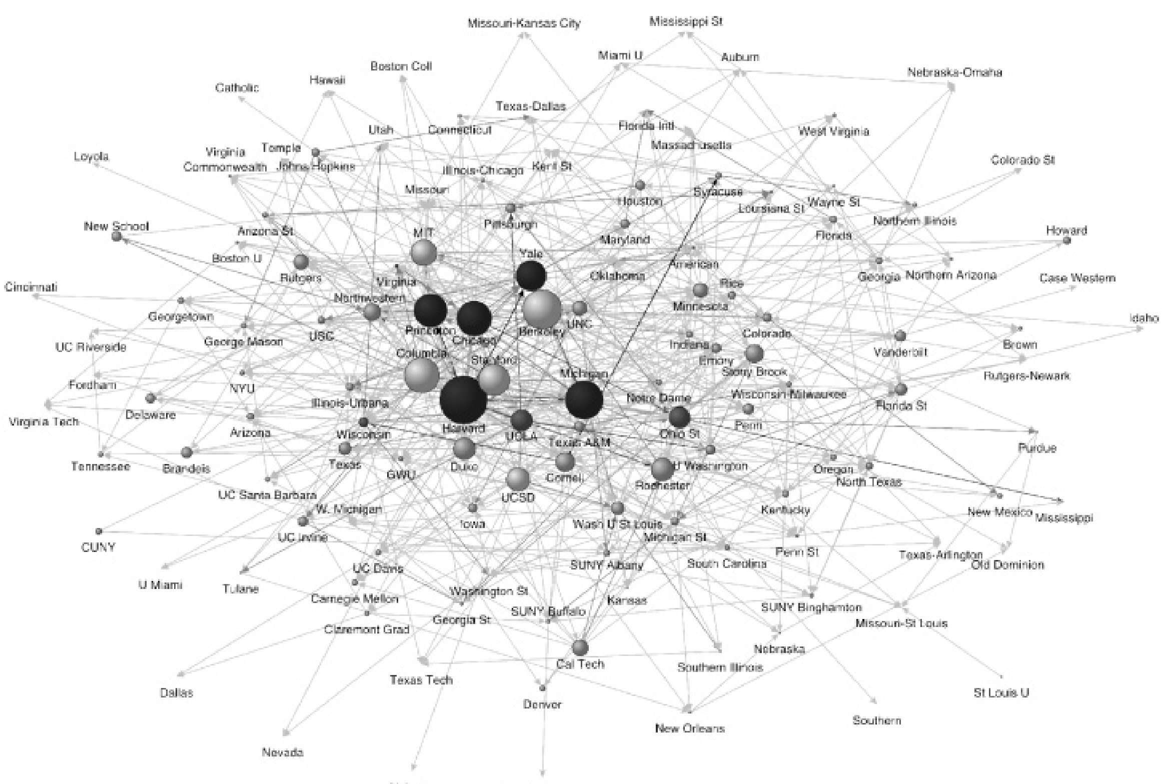


Figure 3
Network of Ph.D.s, 1993–2002



Notes: Each arrow indicates at least one placement was made by the originating department at the destination department. Number of placements is proportional to the shade of the arrow. Node size is proportional to placement score. Black nodes indicate top departments for both placement and hiring capacity.

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1960–2002. As a result, these graphs do not indicate how the performance of some departments may have changed over time. Table 2 shows placement scores for four time periods (based roughly on equalizing total placements from each longitudinal cohort). These rankings show much the same pattern as the overall rankings, but dynamic phenomena are visible, such as dramatic improvements in the overall placements of departments like Rochester's and UCSD's as compared to their placement rate in the pre-1970 period, and the rise of Cal Tech's social science department to prominence.

For comparative purposes, Figure 3 shows the graph of the network structure created from placement and hiring capacity scores for the sub network containing only scholars who received their Ph.D.s in the most recent of these periods, from 1993–2002. This is a sparser graph than the one shown in Figure 1, reflecting fewer placements in this smaller period. Departments like Harvard's continue to dominate the political science network, but we see some improving departments like those at Stanford and UCSD drawn closer into the core. However, other improving departments like Cal Tech's and Rochester's remain relatively peripheral in spite of their placement capacity. This is because their relatively small faculty size keeps them from receiving many ties from other institutions.

If we restrict observations to recent Ph.D.s., as in Figure 3, we have the problem of a smaller sample and more random error variation in the "match" between the placements and hires (754 placements vs. 3,261 in the full network). Still, the findings are nearly identical: again placement scores conform much more closely to *US News and World Report* rankings ($r = 0.82$) than do hiring capacity scores ($r = 0.56$). Moreover, the low difference in correlation between the full network and the sub network suggests there is very little additional information about the current prestige of departments contained in the 2,537 placements of scholars with Ph.D.s granted in 1992 or earlier.

Table 2
Change in Placement Ranks over Time

	Pre-1970		1970–1979		1980–1992		1993–2002	
Department	Rank	Score	Rank	Score	Rank	Score	Rank	Score
Harvard	1	0.6228	1	0.5505	2	0.3251	1	0.5289
Berkeley	6	0.2265	5	0.2343	1	0.5482	2	0.3673
Michigan	7	0.1320	3	0.3490	4	0.3090	3	0.3360
Columbia	3	0.3706	7	0.1652	11	0.1386	4	0.2906
Chicago	2	0.4032	2	0.3814	3	0.3199	5	0.2843
Princeton	5	0.2370	12	0.1334	6	0.2302	6	0.2588
Stanford	9	0.0927	14	0.1119	8	0.2001	7	0.2330
Yale	4	0.3316	4	0.3165	5	0.2924	8	0.2177
MIT	19	0.0430	8	0.1492	7	0.2241	9	0.1611
UCSD	73	0.0000	87	0.0000	26	0.0413	10	0.1295
Rochester	73	0.0000	23	0.0438	14	0.0955	11	0.1230
Duke	18	0.0456	25	0.0429	34	0.0318	12	0.1164
UCLA	11	0.0819	15	0.1053	16	0.0890	13	0.1062
Ohio St	33	0.0166	20	0.0657	21	0.0557	14	0.1040
Cornell	12	0.0806	17	0.0816	10	0.1391	15	0.0883
SUNY Stony Brook	73	0.0000	87	0.0000	42	0.0205	16	0.0802
Northwestern	8	0.1204	16	0.0991	20	0.0591	17	0.0690
Cal Tech			66	0.0078	32	0.0344	18	0.0604
Rutgers	46	0.0081	72	0.0062	27	0.0395	19	0.0529
Minnesota	14	0.0715	10	0.1361	12	0.1247	20	0.0514
UNC	21	0.0384	13	0.1280	19	0.0678	21	0.0496
Wash U St Louis	40	0.0109	35	0.0260	13	0.1117	22	0.0412
Texas	38	0.0117	31	0.0311	18	0.0740	23	0.0359
Florida St	39	0.0110	38	0.0226	50	0.0155	24	0.0323
Brandeis	73	0.0000	43	0.0193	52	0.0137	25	0.0283
Vanderbilt	45	0.0087	46	0.0158	92	0.0000	26	0.0270
Penn	17	0.0473	51	0.0121	23	0.0501	27	0.0256
Texas A&M	73	0.0000	87	0.0000	92	0.0000	28	0.0243
New School	63	0.0017	78	0.0030	82	0.0025	29	0.0237
UC Irvine	73	0.0000	87	0.0000	65	0.0062	30	0.0229
Delaware	54	0.0033	87	0.0000	92	0.0000	31	0.0220
Pittsburgh	24	0.0278	64	0.0079	24	0.0422	32	0.0216
U Washington	31	0.0175	28	0.0368	35	0.0286	33	0.0216
Houston	73	0.0000	73	0.0059	76	0.0040	34	0.0212
Wisconsin	13	0.0733	6	0.2197	9	0.1490	35	0.0210
Emory	72	0.0001	68	0.0076	49	0.0169	36	0.0200
Maryland	43	0.0092	69	0.0075	31	0.0367	37	0.0200
Iowa	28	0.0198	21	0.0616	22	0.0505	38	0.0189
Colorado	68	0.0009	77	0.0034	45	0.0192	39	0.0186
Johns Hopkins	15	0.0533	18	0.0756	15	0.0932	40	0.0149
Michigan St	26	0.0263	36	0.0249	37	0.0250	41	0.0144
Illinois-Urbana	20	0.0421	19	0.0712	33	0.0336	42	0.0138
Howard	48	0.0063	76	0.0041	92	0.0000	43	0.0136
Rice	73	0.0000	47	0.0150	46	0.0191	44	0.0130
North Texas	73	0.0000	87	0.0000	81	0.0032	45	0.0117
Arizona	59	0.0022	56	0.0092	80	0.0033	46	0.0113
Florida	34	0.0152	34	0.0276	83	0.0024	47	0.0112
USC	30	0.0178	55	0.0097	41	0.0227	48	0.0111
Indiana	10	0.0884	9	0.1446	17	0.0741	49	0.0100
Kentucky	49	0.0058	29	0.0352	51	0.0154	50	0.0099
SUNY Albany	69	0.0005	75	0.0051	71	0.0051	51	0.0093
Georgia	73	0.0000	79	0.0023	36	0.0278	52	0.0093
CUNY	73	0.0000	49	0.0129	44	0.0202	53	0.0092
Syracuse	16	0.0476	11	0.1349	28	0.0389	54	0.0089
Carnegie Mellon	54	0.0033	57	0.0089	38	0.0243	55	0.0084
Georgetown	23	0.0293	42	0.0196	57	0.0099	56	0.0082
Oregon	27	0.0229	30	0.0325	85	0.0019	57	0.0081
Denver	42	0.0099	61	0.0084	30	0.0378	58	0.0078
Notre Dame	60	0.0020	74	0.0053	39	0.0238	59	0.0078
George Mason	73	0.0000	87	0.0000	92	0.0000	60	0.0073
UC Davis	73	0.0000	65	0.0079	64	0.0068	61	0.0072
Arizona St	73	0.0000	87	0.0000	63	0.0073	62	0.0065
New Mexico	73	0.0000	87	0.0000	92	0.0000	63	0.0059
Wisconsin-Milwaukee	73	0.0000	45	0.0162	67	0.0059	64	0.0056
UC Santa Barbara	73	0.0000	37	0.0241	61	0.0079	65	0.0055
Claremont Grad	44	0.0090	22	0.0470	58	0.0087	66	0.0055
Tennessee	73	0.0000	87	0.0000	92	0.0000	67	0.0055
South Carolina	73	0.0000	87	0.0000	47	0.0187	68	0.0050

(continued)

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Table 2 (Continued)

Department	Pre-1970 Rank	Pre-1970 Score	1970–1979 Rank	1970–1979 Score	1980–1992 Rank	1980–1992 Score	1993–2002 Rank	1993–2002 Score
NYU	22	0.0300	27	0.0393	66	0.0060	69	0.0046
Northern Illinois	73	0.0000	85	0.0010	59	0.0085	70	0.0044
SUNY Binghamton	73	0.0000	40	0.0215	48	0.0176	71	0.0042
GWU	56	0.0032	57	0.0089	55	0.0126	72	0.0040
SUNY Buffalo	73	0.0000	24	0.0434	75	0.0045	73	0.0039
Brown	36	0.0119	67	0.0077	70	0.0054	74	0.0037
West Virginia	73	0.0000	87	0.0000	92	0.0000	75	0.0035
Illinois-Chicago	29	0.0198	39	0.0221	91	0.0007	76	0.0035
Penn St	32	0.0174	32	0.0305	60	0.0079	77	0.0033
Connecticut	37	0.0117	53	0.0107	79	0.0033	78	0.0028
Virginia	25	0.0274	33	0.0277	25	0.0422	79	0.0027
Louisiana St	73	0.0000	84	0.0017	87	0.0013	80	0.0026
Georgia St	73	0.0000	87	0.0000	92	0.0000	81	0.0022
American	35	0.0147	26	0.0393	29	0.0385	82	0.0018
Northern Arizona			87	0.0000	92	0.0000	83	0.0015
Wayne St	73	0.0000	87	0.0000	90	0.0008	84	0.0014
Virginia Commonwealth	73	0.0000	87	0.0000	92	0.0000	84	0.0014
Boston U	41	0.0107	44	0.0183	68	0.0054	86	0.0014
New Orleans	73	0.0000	87	0.0000	69	0.0054	87	0.0013
Purdue	73	0.0000	41	0.0203	43	0.0202	88	0.0009
Nebraska	67	0.0010	87	0.0000	74	0.0046	89	0.0008
St Louis U			59	0.0089	92	0.0000	90	0.0007
Southern Illinois	62	0.0018	82	0.0019	92	0.0000	90	0.0007
Tulane	51	0.0047	81	0.0021	86	0.0018	92	0.0006
Kansas	50	0.0056	54	0.0106	92	0.0000	93	0.0005
Miami U	73	0.0000	52	0.0109	71	0.0051	94	0.0001
Missouri	70	0.0005	60	0.0086	92	0.0000	95	0.0001
Auburn	73	0.0000	87	0.0000	92	0.0000	96	0.0000
Washington St			70	0.0067	56	0.0105	97	0.0000
Massachusetts	66	0.0015	50	0.0128	40	0.0234	98	0.0000
Oklahoma	65	0.0016	48	0.0130	62	0.0077	98	0.0000
Hawaii	53	0.0034	70	0.0067	54	0.0129	98	0.0000
Cincinnati	61	0.0018	63	0.0080	92	0.0000	98	0.0000
Alabama	47	0.0080	86	0.0005	92	0.0000	98	0.0000
UC Riverside	52	0.0036	62	0.0081	92	0.0000	98	0.0000
Boston Coll	73	0.0000	87	0.0000	53	0.0135	98	0.0000
Texas-Arlington	73	0.0000	87	0.0000	73	0.0048	98	0.0000
Kent St	57	0.0030	87	0.0000	92	0.0000	98	0.0000
Case Western			58	0.0028	92	0.0000	98	0.0000
Virginia Tech	73	0.0000	87	0.0000	77	0.0039	98	0.0000
Temple	73	0.0000	87	0.0000	88	0.0013	98	0.0000
Fordham	73	0.0000	79	0.0023	92	0.0000	98	0.0000
Idaho	64	0.0016	87	0.0000	92	0.0000	98	0.0000
Utah	71	0.0004	82	0.0019	92	0.0000	98	0.0000
Colorado St	73	0.0000	87	0.0000	84	0.0021	98	0.0000
Mississippi	73	0.0000	87	0.0000	78	0.0034	98	0.0000
Catholic	73	0.0000	87	0.0000	92	0.0000	98	0.0000
Dallas	73	0.0000	87	0.0000	92	0.0000	98	0.0000
Florida Intl	73	0.0000	87	0.0000	92	0.0000	98	0.0000
Loyola	73	0.0000	87	0.0000	92	0.0000	98	0.0000
Mississippi St	73	0.0000	87	0.0000	92	0.0000	98	0.0000
Missouri-Kansas City					73	0.0000	98	0.0000
Missouri-St Louis	73	0.0000	87	0.0000	92	0.0000	98	0.0000
Nebraska-Omaha			73	0.0000	87	0.0000	98	0.0000
Nevada	73	0.0000	87	0.0000	92	0.0000	98	0.0000
Northeastern	73	0.0000	87	0.0000	92	0.0000	98	0.0000
Old Dominion	73	0.0000	87	0.0000	92	0.0000	98	0.0000
Rutgers-Newark	73	0.0000	87	0.0000	92	0.0000	98	0.0000
Southern			87	0.0000	92	0.0000	98	0.0000
Texas Tech	73	0.0000	87	0.0000	92	0.0000	98	0.0000
Texas-Dallas	73	0.0000	87	0.0000	92	0.0000	98	0.0000
U Miami			73	0.0000	87	0.0000	98	0.0000
Western Michigan	73	0.0000	87	0.0000	92	0.0000	98	0.0000
Clark Atlanta					73	0.0000	89	0.0011

Note: Missing values indicate departments that have no faculty from other institutions or that have placed no faculty at other institutions for the time period shown.

Placement Success Rates

In all analyses so far we have used the raw number of placements to estimate the strength of a tie from the sending department to the receiving department. The intuition is that the more students a department can place in other prestigious departments, the more central to the discipline it will be. But another way to think about placement is how well students in a department do on average when they go on the market. To determine this, we also need to know the total number of Ph.D.s produced by each department. We compile these data using statistics drawn from the National Science Foundation, the National Academy of Sciences, and the Department of Education's National Center for Education Statistics.

We can incorporate information that controls for production by letting a_{ij} indicate the number of candidates that the ith department places in the jth department, divided by the total number of Ph.D.s produced by department i, and then apply the same methodology described above to determine placement and hiring capacity scores. This means that departments that place a high proportion of their students at other institutions will tend to have high scores. Table 3 shows the results of this procedure.

Notice that Cal Tech's department skyrockets to the top of the list. This is interesting, because in Figures 1 and 3 we saw that Cal Tech's department is relatively peripheral to the full network. Although it clearly has a high batting average with its students, its small size keeps it from having a larger impact on the discipline. Similarly, departments at UCSD, SUNY Stony Brook, and UC Irvine seem to do exceptionally well in placing the average student, suggesting they have more influence on the network than the small sizes of their graduate programs would indicate.

Discussion

We believe that the methods for analyzing patterns of placement in the political science social network convey a considerable amount of information about the core-periphery structure of the discipline. However, we would emphasize that

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Table 3
Production-Adjusted Placement Scores

Department	Rank	Score	Department	Rank	Score	Department	Rank	Score
Cal Tech	1	0.9634	Ohio St	44	0.0092	Kansas	86	0.0013
UCSD	2	0.1485	Kentucky	45	0.0087	North Texas	86	0.0013
Stanford	3	0.0799	Oklahoma	46	0.0086	Texas-Arlington	86	0.0013
SUNY Stony Brook	4	0.0672	Purdue	47	0.0083	West Virginia	90	0.0012
Harvard	5	0.0599	Penn	48	0.0081	George Mason	91	0.0011
Rochester	6	0.0587	Florida St	49	0.0078	Alabama	92	0.0010
Yale	7	0.0519	Syracuse	50	0.0074	SUNY Albany	92	0.0010
Michigan	8	0.0516	Wisconsin-Milw.	50	0.0074	Arizona St	94	0.0009
UC Irvine	9	0.0503	Arizona	52	0.0073	Case Western	94	0.0009
Northwestern	10	0.0459	Washington St	53	0.0070	UC Riverside	94	0.0009
UCLA	11	0.0423	Oregon	54	0.0068	Northern Arizona	97	0.0008
Chicago	12	0.0412	Delaware	55	0.0067	Southern Illinois	97	0.0008
Emory	13	0.0389	Nebraska	56	0.0065	Wayne St	99	0.0007
Berkeley	14	0.0388	Denver	57	0.0064	GWU	100	0.0006
Iowa	15	0.0356	Brandeis	58	0.0062	Colorado St	101	0.0005
Princeton	16	0.0351	Howard	59	0.0061	Northern Illinois	101	0.0005
Wash U St Louis	17	0.0342	Texas A&M	60	0.0060	Missouri	103	0.0004
MIT	18	0.0334	Massachusetts	61	0.0056	Va. Commonwealth	103	0.0004
Minnesota	19	0.0297	U Washington	62	0.0055	Tennessee	105	0.0003
UC Davis	20	0.0294	Georgetown	63	0.0053	Utah	105	0.0003
Cornell	21	0.0275	South Carolina	63	0.0053	Virginia Tech	105	0.0003
Illinois-Urbana	22	0.0269	UC Santa Barbara	65	0.0048	Fordham	108	0.0002
UNC	23	0.0266	Virginia	66	0.0043	Idaho	108	0.0002
Houston	24	0.0258	Carnegie Mellon	67	0.0040	Temple	108	0.0002
Rice	25	0.0225	Florida	68	0.0038	Clark Atlanta	111	0.0001
Wisconsin	26	0.0222	NYU	69	0.0036	Auburn	112	0.0000
Colorado	27	0.0208	Hawaii	70	0.0029	Catholic	112	0.0000
Columbia	28	0.0204	Penn St	71	0.0028	Dallas	112	0.0000
Vanderbilt	29	0.0196	American	72	0.0022	Florida Intl	112	0.0000
Texas	30	0.0176	SUNY Buffalo	72	0.0022	Loyola	112	0.0000
New Orleans	31	0.0157	Connecticut	74	0.0021	Mississippi	112	0.0000
Michigan St	32	0.0153	SUNY Binghamton	74	0.0021	Missouri-K.C.	112	0.0000
Duke	33	0.0152	Maryland	76	0.0020	Missouri-St. L.	112	0.0000
Cincinnati	34	0.0142	Miami U	77	0.0019	Nebraska-Om.	112	0.0000
Indiana	35	0.0135	CUNY	78	0.0018	Nevada	112	0.0000
Brown	36	0.0133	Illinois-Chicago	78	0.0018	Northeastern	112	0.0000
Johns Hopkins	37	0.0132	USC	78	0.0018	Old Dominion	112	0.0000
Boston U	38	0.0124	New Mexico	81	0.0017	Rutgers-Newark	112	0.0000
Boston Coll	39	0.0120	Notre Dame	81	0.0017	Texas Tech	112	0.0000
Pittsburgh	40	0.0118	Claremont Grad	83	0.0016	Texas-Dallas	112	0.0000
Tulane	41	0.0104	New School	83	0.0016	U Miami	112	0.0000
Kent St	42	0.0095	Louisiana St	85	0.0014	W. Michigan	112	0.0000
Rutgers	42	0.0095	Georgia	86	0.0013			

our use of the terms core and periphery is not meant to have the pejorative connotations that sometimes go with that dichotomy as it is used, for example, in world systems modeling (e.g., Wallerstein 2004). It is often the case that the core is viewed as having a level of dominance over the periphery and of having an exploitative relationship with it (e.g., with core nations buying primary goods cheaply from peripheral countries while making it expensive for the peripheral countries of the world economy to modernize).[11] Here we follow Borgatti and Everett (1999) in thinking about core-periphery networks in neutral terms, merely as one where the core has greater density of connections within itself than with the periphery, with more connections coming from the core to the periphery than vice versa, and where peripheral elements are only loosely connected to one another.[12]

As noted earlier, it is apparent from Figures 1 and 3 that political science is characterized by a set of highly interconnected departments that hire each other's students. The heart of this exchange network includes the generally high-Ph.D.-producing departments referred to by Masuoka, Grofman, and Feld (2007b) as the "big eight," those at Berkeley, Chicago, Columbia, Harvard, Michigan, Princeton, Stanford, and Yale; as well as departments such as those at UCLA, Cornell, and Wisconsin. Comparing Figures 1 and 3 further reveals how remarkably little change has occurred in the centrality of the very top departments in the network over time, although some other departments have become (marginally) more central and others (marginally) more peripheral, with only a few departments exhibiting substantial shift in relative location.[13]

Notes

* We are indebted to Clover Behrend-Gethard for bibliographic assistance.

1. Other important types of networks that have been characterized in core-periphery terms are citation networks (e.g., by scholar or by journal or by country) and import-export networks.

2. Reputation or status of a department has been found to play a significant role in political scientists' perceptions about the quality of that department's graduate students, thus influencing the ability of a Ph.D. to be hired. As early as the 1960s, scholars had identified a core set of institutions whose students dominated the majority positions on political science faculties. According to Somit and Tanenhaus (1964, 4): "Although all graduate departments seem to socialize students in essentially the same fashion and impose much the same requirements, the particular department at which a student takes his doctorate matters a great deal. That source of a man's doctorate is a status symbol that tends to mark him for life." This hiring pattern may also have long-term ripple effects since alumni tend to have a more favorable view of their own department and may be biased toward hiring other alumni on their faculties (Grofman, Feld, and Masuoka 2005). For a more detailed discussion on social status and the practice of homophily, please see Blau 1964; McPherson, Smith-Lovin, and Cook 2001; Podolny 2005.

3. There is a direct parallel here with ranking methods involving tournament competitions, e.g., to rank chess players or football teams. We would not want merely to count victories, but to assess the caliber of the opponent being beaten. Methodologies similar to what is used here have been devised for that purpose (see e.g., Batchelder and Bershad 1979).

4. We will later exclude same department-placements from our empirical analyses, so the main diagonal will contain all zeros.

5. Although there are *n* nonzero solutions to this set of equations, in practice the eigenvector corresponding to the principal eigenvalue is used (Bonacich 1987).

6. This method has recently been used to analyze Supreme Court precedents in the network of judicial citations (Fowler and Jeon 2007; Fowler et al. 2007).

7. It is important to note that this data cannot be used to study departments that do not have graduate students.

8. In contrast to typical social network and citation data, our Ph.D.-placement network contains *loops* where the same node points to itself (Harvard Ph.D.s who were hired by Harvard, for example). Including these loops in the placement and hiring capacity score calculations is mathematically feasible, and one might argue that these observations should be retained like any other because they contain additional information about the scholars and departments in question. However, we suspect that it is probably easier for a school to hire its own, so these self-placements may not be unit homogenous with other-placements. Thus, we exclude them from the data. Of course this is not to say that loops cannot be used to effectively increase the reputation and identity of a department. The building of the Chicago School under Charles Merriam is an example of how loops may positively influence a department's reputation (Heaney and Hansen 2006).

9. However, this data does not tell us about retention length since they indicate only the job held in 2002. Nor is data about previous hires in this dataset. We might also note that top schools may be able to "afford" to "hire from anywhere" without those choices being reflected in any lowering of their prestige, since it is likely that it will be assumed that if they did hire x there must be something about x that was worthy of the hire, regardless of the institution from which x received his or her Ph.D.

10. Node placement was generated by the Kamada-Kawai algorithm, which specifies that connected nodes have zero energy at a fixed finite length that is inversely proportional to the strength of the tie (like a spring at rest). The algorithm then iteratively tries to reduce the amount of energy in the whole system with different placements of nodes.

11. Also see Forbes (1984). Other pejorative uses of the term "core-periphery structure" are found in some of the urban geography literature, which distinguishes areas where jobs are abundant, and standards of living high, from areas that are more peripheral.

12. Feld, Bisciglia, and Ynalvez (2003) show that there are multiple types of core-periphery networks and that Ph.D. exchange in sociology can be modeled as what they call a *network of vertical ties*, but, since our interest in this paper is primarily in visualization, we will neglect such further complications. Work in progress by a subset of the present authors reveals that political science also can be characterized as a network of vertical ties.

13. We conducted a number of sensitivity analyses. Generating scores for a sub network of Ph.D.s 2000–2005 did not alter the scores much from the ones shown for 1993–2005. We also tried eliminating any institution that had not placed at least one Ph.D. at one of the other institutions in the network. This had very little effect on the overall scores.

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APPENDIX

Table A1
Ph.D. Students Placed at Other U.S. Ph.D.-Granting Institutions (1960–2002) and Department Size (2002)

Department	Placements	Faculty	Department	Placements	Faculty	Department	Placements	Faculty
Harvard	278	47	Penn. St.	17	24	Tennessee	4	20
Berkeley	208	60	USC	17	38	Alabama	3	11
Chicago	198	32	Georgia	16	43	Auburn	3	18
Yale	176	50	Colorado	15	32	Boston Col.	3	18
Columbia	174	61	Denver	15	9	Delaware	3	27
Michigan	172	50	Houston	15	28	Miami U.	3	26
Princeton	143	40	Oklahoma	15	26	New Orleans	3	13
Stanford	107	41	UC Santa Barbara	14	30	Northern Illinois	3	28
Wisconsin	101	47	Emory	14	26	Wayne St.	3	21
Minnesota	92	34	Rice	14	19	Case Western	2	7
UCLA	86	64	Notre Dame	13	37	Clark Atlanta	2	3
Indiana	82	49	Arizona	12	45	Colorado St.	2	19
M.I.T.	78	27	UC Davis	12	32	George Mason	2	46
Northwestern	77	37	Connecticut	12	30	Georgia St.	2	24
Cornell	75	29	Massachusetts	12	26	North Texas	2	20
North Carolina	73	53	Wisconsin-Milwaukee	12	29	Saint Louis	2	5
Johns Hopkins	59	23	CUNY Grad.	11	14	Temple	2	18
Ohio St.	59	48	Vanderbilt	11	16	Texas-Arlington	2	17
Syracuse	56	29	Boston U.	10	23	Utah	2	23
Washington U.	47	28	Carnegie Mellon	10	47	Virginia Tech	2	14
Duke	46	38	SUNY Binghamton	10	22	West Virginia	2	19
Rochester	44	16	SUNY Buffalo	10	15	Catholic	1	16
Iowa	42	27	Purdue	10	32	Dallas	1	9
Illinois-Urbana Champaign	38	41	South Carolina	10	37	Fordham	1	20
Texas	36	36	Tulane	10	19	Idaho	1	6
Michigan St.	35	50	Brandeis	9	15	Mississippi St.	1	11
Virginia	33	44	G.W.U.	9	44	Mississippi	1	16
American	31	74	Brown	8	17	New Mexico	1	19
U. Washington	28	39	UC Irvine	8	27	SUNY	1	0
UCSD	27	35	Hawaii	8	27	Northeastern	1	19
NYU	27	29	Kansas	8	37	Northern Arizona	1	17
U. Penn.	27	27	New School	8	10	Texas-Dallas	1	18
Pittsburgh	27	29	SUNY Albany	8	30	Virginia Commonwealth	1	14
Florida St.	25	30	Cincinnati	7	22	Western Michigan	1	25
Georgetown	25	41	Texas A&M	7	38	Florida Intl	0	16
Florida	22	36	Arizona St.	6	29	Loyola	0	18
SUNY Stony Brook	22	24	Howard	6	16	U. of Miami	0	5
Rutgers-New Brunswick	22	42	Louisiana St.	6	20	Missouri-Kansas City	0	8
Claremont	21	11	Missouri-Columbia	6	28	Missouri-St. Louis	0	22
Maryland	21	48	UC Riverside	5	15	Nebraska-Omaha	0	10
Kentucky	20	20	Southern Illinois	5	27	Nevada	0	14
Caltech	19	6	Washington St.	5	19	Old Dominion	0	10
Oregon	19	22	Kent St.	4	24	Rutgers-Newark	0	17
Illinois-Chicago	18	23	Nebraska-Lincoln	4	18	Southern-Baton Rouge	0	6

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Table A2
Predicting Reputation Rankings with Social Network Measures

	Dependent Variable: Log *U.S. News and World Report* Rank in 2005						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Log Placement Capacity Rank	0.888		0.786	0.552	0.801	0.552	0.792
	(0.043)		(0.064)	(0.130)	(0.065)	(0.175)	(0.067)
	0.000		0.000	0.000	0.000	0.002	0.000
Log Hiring Capacity Rank		0.727	0.135	0.146	0.062	0.147	0.113
		(0.062)	(0.064)	(0.063)	(0.094)	(0.064)	(0.100)
		0.000	0.037	0.023	0.509	0.024	0.262
Placements				–0.005			
				(0.003)			
				0.041			
Faculty Size					–0.006		
					(0.006)		
					0.288		
Log Outward Eigenvector Centrality Rank						0.234	
						(0.162)	
						0.151	
Log Inward Eigenvector Centrality Rank							0.022
							(0.076)
							0.768
Intercept	0.440	1.070	0.310	1.312	0.689	0.266	0.287
	(0.172)	(0.249)	(0.180)	(0.517)	(0.399)	(0.182)	(0.196)
	0.011	0.000	0.089	0.012	0.086	0.147	0.145
Adjusted R-Squared	0.767	0.511	0.773	0.778	0.773	0.775	0.771

Note: OLS regressions of the log *U.S. News and World Report* department rank. Notice that the log placement rank generates an adjusted *r*-squared of 0.767 (Model 1) compared to 0.511 for the log hiring capacity rank (Model 2). Both of these variables are included in Model 3. Although the hiring capacity rank differs significantly from 0, the overall fit only barely increases by 0.006 over Model 1. This and the large difference in coefficients both suggest that the placement capacity rank is a much better predictor of reputation rankings than the hiring capacity rank. Models 4–7 add additional social network variables, including raw counts of placements and faculty, and inward and outward eigenvector centrality. The eigenvector centrality variables are not significant in Models 6 and 7 and the faculty size variable in Model 5 fails to improve fit over Model 3. Adding raw placements in Model 4 does improve fit by a tiny amount (0.005) and the coefficient is barely significant, but the placement rank variable continues to be strongly significant. This suggests that there is a lot of information on reputation reflected in the placement rank that is not present in the raw quantity of placements.