Network Analysis of Three Academic Labor Markets

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Abstract

The academic labor market is analyzed as a citation network, where departments gain citations by placing their Ph.D. graduates into the faculty of other departments. The aim is to measure the distribution of influence and the possible division into clusters between academic departments in three disciplines (economics, mathematics, and comparative literature). Departmental influence is measured by a method similar to that used by Google to rank web pages. In all disciplines, the distribution of influence is significantly more skewed than the distribution of academic placements, due to a strong hierarchy of schools in which movements are seldom upwards. This hierarchy is strongest in economics. It is also found that, in economics, there are clusters of departments that are significantly more connected within than with each other. These clusters are consistent with anecdotal evidence about "Freshwater" and "Saltwater" schools of thought. There is a similar although weaker division within comparative literature, but not within mathematics. (A11, A14, L14, Z13).

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1 Introduction

The labor force in academia forms a self-sustaining network. The faculty at PhD-granting university departments consists of graduates of other PhD-granting departments. There appear to be two important structures in this network. First, universities can quite robustly be ranked by influence in any academic discipline, so that the flows of PhDs are horizontal and downwards but seldom much upwards in this ranking. Second, in some disciplines, there are "clusters" of universities that are much more connected than could be expected by (geographic) distance, perhaps due to different schools of thought, or inertia created by the importance of personal relations in hiring. In this paper we analyze the structure of these networks in three academic disciplines: economics, mathematics, and comparative literature.[1]

We will quantify the vertical hierarchy by an influence measure introduced by Pinski and Narin (1976) to rank academic journals using citation data. Palacios-Huerta and Volij (2004) have shown that this method (which they call the Invariant method) is the unique way of ranking journals while satisfying a set of theoretically desirable properties. This measure is also, with a small modification, behind the PageRank algorithm used by Google to rank web pages—introduced in Page and Brin (1998)—but it has not previously been applied to labor market data.[2] In our application the hiring of a Ph.D. graduate from another department is roughly analogous to a document citing another document. Besides generating the rankings by influence for the three disciplines under study, we show that in all of them the pecking order goes beyond what would be expected just from the (already very uneven) distribution of professors by Ph.D. origin. Economics turns out to have the strictest hierarchy of the three disciplines.

[1]For an introduction into concepts and models in the economics of social networks, see Jackson (2005).

[2]In another economic application, Fryer and Torelli (2005) use this method to construct a measure for the popularity of individuals in a social network.

The second set of issues studied in this paper concerns clustering. Clusters in a network are subsets of nodes that are more connected to each other than to the rest of the network. The detection of clusters or "cliques" is a standard task in social network analysis.[3] In most applications the social network is described by binary valued links, for example representing whether two individuals have at least one coauthored publication. The academic hiring network is extremely dense in the binary sense—many departments are directly connected in that at least one faculty member was trained by the other department. For example, between the US top 10 departments in economics, all but two of the possible links exist; even within top 40 most of the possible links exist. As a result, all departments in the academic hiring network are connected, if not directly, then at least through other departments.[4] Instead of reducing the hiring network into binary links, it is most fruitfully analyzed as a network of "citations" which forms, in the jargon of graph theory, a "weighted directed graph." Here the strength of a link from node i to j to is defined as the proportion of the faculty at department i that was trained at department j.[5]

To analyze the possible clustering, we first apply a standard visual method, namely multidimensional scaling (MDS). This is basically for data exploration purposes. In the resulting graphs, nearby data points represent departments with similar hiring and placement patterns. Next we use a method which considers all possible divisions of the departments into two clusters (of given size) and picks the strongest division in terms of minimizing the number

[3]See, e.g., Scott (2000), for a textbook treatment of social network analysis.

[4]By contrast, Goyal, van der Leij, and Moraga-González (2006) find that only 40% of economists who have ever published a coauthored paper are connected in the network of coauthorships.

[5]Citation analysis has been applied to find clusters in the network of citations between journals. For example, Pieters and Baumgartner (2002) find that 42 Economics journals divide into 7 clusters roughly by subfield. Copic, Jackson, and Kirman (2005) develop a new likelihood-based method which divides the same journals into 19 clusters.

of cross-cluster hires. The drawback of both of these methods is that there are always bound to be groups of departments that seem to form a cluster, even if there were only random differences in hiring patterns. This would not be a problem if one were simply looking for the best way to partition the data into clusters, but our null hypothesis is that there is no clustering at all. Therefore we generate artificial data sets under the null hypothesis of random matching between departments and professors, while keeping the numbers of positions and placements by each department at their true values. The statistical significance of the observed clustering is measured by comparing the distribution of a measure of the strength of clustering in the simulated data set to its actual value. We find that there is a very significant division into clusters among top departments in economics, and the strongest possible division is along the lines of what are commonly thought as the "Freshwater" and "Saltwater" schools of thought. By contrast, the apparent division in mathematics is not stronger than what would be likely to appear under random matching.

2 Data

The data comes from three academic disciplines: economics, mathematics, and comparative literature. The lists of professors were taken from the departmental home pages in 2004. For economics, the data includes the faculty at all 107 departments with Ph.D. programs listed in National Research Council's 1995 study.[6] A further 13 mostly foreign programs that each had at least 5 placements in the initial sample were also included. For comparative literature the sample includes all still-existing departments listed in the NRC study and the University of Toronto (a total of 43 programs). For mathematics the sample includes 41 top U.S. programs. The initial top 10

[6] Research-Doctorate Programs in the United States: Continuity and Change. National Research Council, National Academy of Sciences, Washington, D.C., 1995.

was defined as the 10 programs with the most effective Ph.D. programs as ranked by the NRC study. Further U.S. programs were added step-by-step if they had at least 5 placements within the existing sample.[7] The data sources were department web pages, personal cv's, the ProQuest dissertation database, and the mathematics genealogy project *www.genealogy.ams.org*.

The data includes all tenured and tenure-track faculty (assistant, associate, and full professors[8]) for each academic department in the sample. The sample sizes in terms of the numbers of professors are 3209 in economics, 1939 in mathematics, and 771 in comparative literature. The judgmental part of data gathering was the dealing with cross affiliations. As a general rule, faculty members were not included if the title included only disciplines other than the one under study. For example, a "Professor of Finance" listed at an economics department home page was not included, but a "Professor of Finance and Economics" was included. Where cross-affiliated faculty were given in a separate list they were not included, regardless of titles. Finally, we did not drop faculty known to have degrees from other fields from the analysis. Degree fields are often not available, probably because it is usually understood that the degree is in the same discipline as the department.[9]

3 Vertical Structure: Influence in Academia

There is a strong sense of hierarchy in academia. Movements of faculty between universities are commonly described as being moves up or down. Few

[7] This method "converged" after 40 departments; in addition Syracuse was added by mistake despite having only 4 placements in the sample.

[8] For UK departments it includes also readers and lecturers.

[9] In total we know of 106 Economics professors in the sample that have a Ph.D. in another discipline. The most significant inflows from other disciplines that appear in the data are 18 degrees in Business or Management and 11 in Finance. For Comparative Literature, 99 professors report a degree in something other than Literature. For Mathematics, the field of degree was not recorded even when mentioned.

issues raise as much controversy as the ranking of departments. In this paper the purpose is not to try to rank departments by some universal definition of quality, but to measure the influence of departments in the training of an academic discipline. What is an influential academic department? One answer is: a department that places Ph.D. students at influential departments. This circular-sounding question about influence, when asked recursively, yields a sensible measure of influence, as was shown by Pinski and Narin (1976).

Journal citations have been counted probably since academic journals began, but a simple tally of citations is clearly an unsatisfactory method for measuring the influence of an article or a journal as not all citations are equally valuable. Garfield (1972) introduced the "impact factor" which amounts to asking the "circular-sounding" question just once—it values journals by the average number of citations that its articles amass.[10] The drawback of the impact factor approach is that it can attribute high impact for members of "cliques" of journals that cite each other intensively, even if the clique itself is not much cited by the rest of the discipline. To correct for this problem, Pinski and Narin took the idea of endogenously determined weights for citations from different journals to its logical conclusion.

The structure of the network is, for the purposes of this paper, fully described by the hiring matrix M, where M_{ij} is the number of faculty at department i who did their Ph.D. at department j. The faculty-size normalized hiring matrix is denoted by T, with typical element $T_{ij} = M_{ij}/\sum_k M_{ik}$. By construction, the matrix T satisfies the properties of a probability transition matrix. The Pinski-Narin influence weights are in fact equivalent to the limiting probability distribution of the Markov chain described by T. One advantage of these weights is that they provide an additive measure of influence, as the long-run probability of being in either of two particular "states" is the sum of the individual probabilities.

[10] Pieper and Willis (1999) use the impact factor method to rank Economics Ph.D. programs.

Let's denote the Pinski-Narin influence weights p_i for departments $i = 1, \ldots, n$ in the sample. Each of the influence weights p_j is a weighted average of all influence weights p_i, where the weights are given by the fraction of faculty at department i who got their Ph.D. from department j:

$$p_j = \sum_{i=1}^{n} T_{ij} p_i \quad \text{and} \quad \sum_{j=1}^{n} p_j = 1. \tag{1}$$

If T is irreducible (more of which below), then the influence weights are equivalent to the dominant eigenvector of the transition matrix. However, the most convenient way for actually computing the influence weights uses the interpretation of p as the limiting distribution of the Markov chain defined by T.[11]

The PageRank algorithm used by the search engine Google is based on a slightly modified version of the Pinski-Narin influence weights. Its creators, Page and Brin (1998), give a tangible (if somewhat contrived) interpretation for the influence measure using the "random surfer" model. To paraphrase Page and Brin for the current application, suppose that the whole of an academic discipline participates in an E-mail version of "tag - you're it." The game starts with a randomly selected professor being the holder of the tag. She will hold the tag for a day, then send it to the department where she got her Ph.D., where it is again given to a randomly selected current faculty member. After holding the tag for a day, that faculty member in turn will send the tag to his doctoral Alma mater, where another raffle takes place, and so on. When this game has been going on for long, then the probability that the tag is held by a current faculty member of department i approaches the Pinski-Narin influence weight of department i.

The modification introduced by Page and Brin was meant to allow the computation of (non-zero) influence weights for all nodes even when the tran-

[11] By the Perron-Frobenius theorem, if T is irreducible, then p is equal to (any row of) $\lim_{R \to \infty} T^R$.

sition matrix is not irreducible—a practical concern for the network of web pages.[12] In terms of the above "tag game" analogy, if the transition matrix is not irreducible then the tag can get permanently stuck in a subset of departments—in an extreme case in a single department—because all of the faculty in the subset have Ph.D.'s from that same subset. This would leave all other departments with zero influence weight. However, this is not a practical problem with academic labor market data. The subset of departments where the tag eventually gets stuck (in Markov chain terminology, "the absorbing chain") includes most of the discipline, and we view the resulting zero influence weight for the other departments as a feature, not as a bug. It is also in principle possible to have a transition matrix that defines two or more separate absorbing chains, but this too is not a problem with our academic labor market data.

Results

The Pinski-Narin influence weights computed for economics, mathematics, and Comparative literature are listed in the first columns of Tables 1-3. Of the 120 departments in economics data, 91 end up with a non-zero weight. (A further 17 departments have placements but in zero-weight departments only, and thus end up with a zero weight.) The order of rankings by influence is quite similar to many previous rankings, such as the ranking by program effectiveness in the NRC study.[13] A surprisingly low rank by influence in the Pinski-Narin sense, compared to perceived department quality, is simply due to a small number of placements in top programs. Of course, a department

[12] PageRanks differ from Pinski-Narin influence weights only by replacing T with $\delta T + (1-\delta)E$, where E is a matrix with $1/n$ in every element (giving equal probability of transiting to every state), and δ is a real number slightly less than one.

[13] For economics, similar rankings have been obtained, for example, with weighted-page methods based on the Ph.D. alma mater of top-journal authors, see Kocher and Sutter (2001) and the working paper version of Coupe (2003). For the application of various ranking methods, see e.g., Dusansky and Vernon (1998) and Lubrano et al (2003).

without a strong Ph.D. program could be of arbitrarily high quality in terms of research, but the purpose here is not to rank departments by quality but to measure a very narrow and precise definition of influence.

Robustness to outliers The influence measures in Tables 1–3 are not strictly speaking estimates, because they are calculated based on (almost) the full universe of data. Yet one question that remains is how dependent the measured influence weights might be to a few strokes of luck. We can interpret the actual placements by departments as realizations of random draws from some underlying probabilities of transitions. Since the influence is very unevenly divided, one or two placements in a top program can increase the ranking of an otherwise weak department quite a bit.[14] We study the robustness of the influence measures by a bootstrap exercise, where each professor in the sample was treated as an observation. The influence weights were calculated for 1000 resamplings of actual placement data, using, without loss of generality, only the data for departments that have a non-zero influence weight. Tables 1-3 report selected percentiles from the bootstrapped distribution of influence weights. The robustness of pairwise influence rankings is depicted by giving the rank of the highest department that a department outranks in at least 90% of the resamplings. For example, in economics, MIT and Harvard form a robust top 2 but their relative rank is not robust: MIT had a higher influence weight than Harvard in only 54.9% of resamplings, whereas compared to Stanford (rank 3) both were more influential over 99% of the time. In mathematics, Princeton and Harvard form a robust number one and two respectively. Empty values refer to departments that don't outrank anyone in 90% of the resamplings. In general, the rankings are less robust for lower ranked departments, as well as for a few departments whose influence is largely based on a small number of top placements.

[14]The most valuable placement in Economics is to MIT, where it conveys $17.860/37 = 0.48$ points of influence weight to the alma mater.

Self-hiring Tables 1-3 also report the influence weights calculated from various restricted hiring matrices. The first restriction is the exclusion of self-hires. It is not clear how, if at all, the hiring of one's own graduates should be adjusted for in the measurement of influence. If we were attempting to measure the influence of authors, then there would be a good reason to discount references to one's own work. But when hiring one's own graduates, the departments still need to put their money where their mouth is, so a self-link in a labor market is certainly more informative than a self-link by an author or even a journal. On the other hand, a department with a good placement record clearly benefits in terms of its influence weight by hiring more of its own graduates—especially if this happens at the expense of close competitors in the ranking. In the analysis with "no self-hires" the diagonal elements in M—the self-hires—are replaced with zeros. This results in a distribution of influence weights that is somewhat less skewed than was obtained using the full sample. In economics, a few top departments with significant self-hiring lose several places in the ranking, notably Cambridge (9th to 13th) and Toulouse (21st to 31st). (These ranks are not shown in the tables.) In mathematics and comparative literature the removal of self-hires has remarkably little effect on the ordering of departments by influence–probably because the hiring of own graduates seems to be more prevalent in Europe and these samples include only American departments to begin with.

Trends It would be interesting to know how the relative influence of departments has changed or is changing over time. Unfortunately we don't have historical data, and the data on the year of Ph.D. completion has too many missing values. However, we do have the current academic rank, which we use to divide the sample professors into "seniors" and "juniors" by the very rough and inclusive definition of calling all but full professors "juniors."[15] Tables 1-3 list the influence weights for samples restricted into juniors, and

[15] For the UK departments, Readers and Senior Lecturers were also defined as "seniors."

also for juniors with the self-hires excluded. For the top departments in any discipline, the effect of including only juniors is most striking on Oxford and Cambridge in economics, and is indicative of them having diminished in influence. When the departments are ranked by their influence using the juniors-only hiring matrix, they fall from 8th and 9th to 20th and 39th respectively. Further down, Johns Hopkins falls from 20th to 49th. Near the top, Chicago is clearly stronger in the junior sample, rising to form a clearly separate top 3 together with Harvard and MIT. In mathematics the major change is that Princeton and Harvard swap places at the top.

Hierarchy The most conspicuous feature of the network of the academic labor market is the strong hierarchy in hiring and placement. The strength of the pecking order is illustrated in tables 4-6, which show hiring matrices where batches of ten departments, ordered by the influence weight, are aggregated into groups. It is striking how much less upward than downward movements there are, as seen by comparing the upper and lower triangles of these matrices. The exclusivity (someone might say inbreeding) at the top is stronger in economics than in mathematics or comparative literature. At the top 10 economics departments, 79.6% of the faculty received their Ph.D. at a top 10 department, and 96.4% within the top 40. For mathematics these figures are 58.3% and 74.6%, and for comparative literature 63.2% and 79.9%. For a more detailed look, the hiring/placement data is tabulated in the Appendix, tables A.1-A.3 (for economics only the 40 most influential departments are shown). In total, the fraction of faculty who have moved up—who have a Ph.D. from a department with a lower influence weight than their current department—is 12% in economics, 17% in mathematics, and 15% in comparative literature.

Note that if the existing distribution of faculty by department of origin were divided evenly between the departments, then the influence weights for each department would simply equal their respective proportions of all placements. In fact, the distribution of influence weights is more skewed than the distribution of faculty by Ph.D. origin–which itself is already very skewed. In economics, 43.6% of all faculty in the sample universities received their PhDs in the top 10 programs, but the combined influence weight for the top 10 is 79%. For mathematics these figures are 46.6% and 76.8%, and for comparative literature 54.4% and 86%. The higher concentration of influence is due to the hierarchical nature of the network: top departments rarely hire from lower departments, whereas the lower departments not only hire from the top both also from each other. (Of course, the "top departments" are defined endogenously using roughly this same criterion!) The largest proportion of faculty at any level comes from the top group, but this proportion is generally lower at less influential departments, and only slightly over 20% at the unranked departments.

Extension to out-of-sample departments The relatively large share of placements coming from out of sample departments in mathematics (23.6%) and comparative literature (18.7%) is a potential concern, especially for any comparisons with economics. (A department is "out of sample" if we do not have data on the PhD origins of its current faculty). Could it be that hiring at the top appears more concentrated in economics merely because influential departments that form an important part of the network in mathematics are missing from our sample? To investigate this possibility, we introduce a simple extension to the Pinski-Narin influence weights that allows us to measure the influence of out-of-sample departments within the network of sample departments. Using the information on the Ph.D. origins of all professors in the sample departments, it is possible to divide the unit measure of influence between all departments that have placed faculty in the sample departments.

The extension of influence weights to out-of-sample departments is best understood in terms of the tag game analogy. Note that faculty from out-of-sample departments could not be part of the random draw, because the tag would leave the network and the game would end there. However, if the game has a last stage then the tag can be sent to an out-of-sample university in that last stage. The extended influence weights correspond to the probability of the tag ending up in any of the departments in that last stage, after the in-sample tag game has been going on for "infinitely" long. Mathematically, the extended influence weights are then defined by

$$\hat{p}_j = \sum_{i=1}^{n} \hat{T}_{ij} p_i, \tag{2}$$

where the plain influence weights p_i for the in-sample departments are calculated as before in (1), and where $\hat{T}$ is now the (non-square) hiring matrix that includes columns for the out-of-sample departments. Clearly the extended influence weights will be strictly positive for all departments that have placed faculty in any of the sample departments with non-zero Pinski-Narin influence weights.

The extension of influence weights does not cause significant differences in economics or comparative literature, as there are relatively few placements by out-of-sample universities at the top universities.[16] However, for mathematics, the picture is altered significantly, and is reported in Table 7. This is because the sample of mathematics departments excludes all non-US universities (due to almost universal lack of cv's in the web) and a few of them turn out to be highly influential in the US. The ranking by extended influence weights even brings two non-US universities into the top 10: Moscow State (8th) and Cambridge (10th).

Table 8 reports the distribution of placements and influence (extended in a manner just described), again aggregated into groups of ten departments, but now ordered by the extended influence weight. This makes only a small

[16] In Comparative Literature, the only notable change is the appearance of Johns Hopkins as the 8th most influential program, now years after the department was disbanded. In Economics, the highest out-of-sample appearance is UCL at 33rd.

difference to the distribution of placements by group. However, the distribution of influence becomes more even in mathematics and literature now that out-of-sample departments are allowed to absorb their share of the influence. This suggests that the influence weights calculated with the standard method would have lead us to significantly overestimate the concentration of influence in mathematics, due to the lack of data on current faculty at foreign mathematics departments. Comparative literature shows almost as high a concentration of influence within the top 10 as economics, but taking into account that comparative literature is a significantly smaller discipline, we conclude that, among our sample of three disciplines, economics is the most top-heavy in terms of the distribution of influence.[17]

4 Horizontal Structure: Clusters in Academia

4.1 Visual Exploration

The objective of Multidimensional Scaling (MDS) is to create a map of the data where similar data points are located close to each other. If the data only had as many dimensions as the map then the data would be simple to depict as a scatter plot, but with more dimensions in the data some kind of a projection is needed. MDS is basically a method for obtaining such a projection in a way that minimizes the squared errors between pairwise distances between the data point markers on the map and the corresponding pairwise dissimilarities between data points.[18]

In our application the data point for department i consists of its vector of interactions (hires + placements) with other departments, normalized by

[17] In total, there are 217 economics departments, 231 mathematics departments, and 115 literature departments with at least one placement in the data.

[18] For details on MDS, see for example Chapter 9 in Timm (2002). For an application of MDS see Eagly (1975), who used it to uncover clusters in the citation data between 18 economics journals.

the total number of interactions for i. Data points that are near each other in the MDS maps represent departments with similar hiring and placement patterns, and clusters are literally suggested by clusters of nearby data points in the map. Departments with unusual hiring patterns show up as outliers. The directions of the axes and the scales of the MDS map do not have any economic interpretation, and any rotation of the map would represent the same map.[19] The most significant dimension of variation captured by the MDS is depicted along the horizontal axes throughout.

Figure 1 shows the results for the top 20 most influential economics departments. By far the largest differences in hiring patterns are between UK and US departments, due to a much larger fraction of faculty trained in the home continent in both countries. The presence of this "Atlantic dimension" is unsurprising and easily explained by geographic factors. More interestingly, the other axes of variation could reasonably be called the "salinity dimension." It fits the anecdotal evidence about departments from Chicago to Rochester forming a somewhat different "Freshwater" school of thought compared to the "Saltwater" departments from Harvard to Berkeley. Figure 2 shows the results of the analysis with only the data from the top 16 US departments (this is also the sample of departments that will be analyzed in detail in the next section). Now the salinity dimension comes into clear view along the horizontal axis, while the vertical dimension does not seem to have an obvious interpretation. It looks like most departments could be roughly divided into two clusters, with the Saltwater schools in the left and the Freshwater schools in the right.

Figure 3 shows the results from economics with more departments added to the analysis. The salinity dimension still remains, but other variation in hiring patterns starts to become more significant and the figures start getting

[19] We use the absolute value difference dissimilarity measure. Similar results are obtained with the squared difference measure, but it tends to result in less readable plots due to relatively larger distances between outliers and the main group of observations.

unwieldy due to the cluttering of data points. Again, non-US departments show up as outliers, so they are removed from the analysis for Figure 4. This again brings up the left-right salinity dimension. The results for mathematics are shown in Figures 5 and 6. There is no obvious presence of clusters, although a few departments are somewhat outliers from the main group of departments. The results for comparative literature, Figures 7 and 8, suggest a possible division between a periphery of large state schools and a core of mostly private top universities.

4.2 Finding and Testing Clusters

The drawback of the visual approach is that it does not tell us whether there is statistically significant clustering in the data. The "eyeball tests" tell us that economics seems to have clustering, but is the division into "Freshwater" and "Saltwater" camps real or just an artefact of human pattern recognition? To answer this question we compare the observed strength of the partition of departments into two clusters with its simulated distribution under the null hypothesis of no clusterization, taking into account that the partition into clusters has been chosen to maximize the measured strength of the division in the first place.

Suppose we started from a prior definition of two clusters, that is, from a given partition of the departments into two bins. The null hypothesis would be that every position and every professor had an equal chance of being matched, taking as given the sample values for the number of positions and PhD graduates by clusters. How likely is it that, under the null hypothesis, we would observe this 2×2 matrix of hires and placements? A simple χ^2-test of independence could be used to check whether these clusters in fact exhibit statistically significant "home-bias." An unexpectedly small number of between-cluster movers would show up as a large value for the χ^2-test statistic, suggesting a rejection of the null.

However, this simple χ^2-test would provide a misleading test for the presence of clustering. The reason is that the partition into clusters has in practice been chosen to make the partition appear strong. Even if the null hypothesis of random matching were true it would be possible to find partitions with relatively few cross-cluster hires. Thus the test for the presence of clustering should take into account that the test statistic is not based on an ex ante given partition, but to one that results in the best partition in the sense of minimizing the cross-cluster movements. Even in the case of the freshwater-saltwater division, where we have a prior idea of at least some of the departments belonging to different schools of thought, this "prior knowledge" could be based on casual observations about some departments being more connected than others. The point is that there is always some way to divide the departments into two groups that seem to be more connected than random, and we may start believing in that particular division as being "caused" by something or the other. The question is, is there a division that is deeper than could be expected due to random factors?

To derive the corrected distribution for this "extreme value" χ^2-statistic under the null hypothesis of no clustering we resorted to a simulation. In the simulation, the number of positions at each department was fixed at its true level, as was the total number of placements by each department. In each draw of the simulations, the actual population of professors and positions were matched randomly, the partition that minimizes cross-cluster hires was found, and the resulting χ^2-statistic recorded.

For simplicity, the number of possible clusters is pinned down at two in this analysis. In economics, to focus on the more interesting and subtle school-of-thought division within the discipline, we concentrate on US departments only. The number of possible partitions explodes when adding more departments. To make the bootstrap calculations manageable, the data is restricted to the 16 most influential departments. Also, because self-hires are inevitably also within-cluster hires, a preference for self-hiring would be confounded with clustering in the following analysis. Therefore self-hiring will henceforth be excluded, both from the data and as a possibility in the simulations.[20]

The random matching matrices (resamplings) were generated by adding all professors sequentially to the open positions, so that the probability of placement at any given department was proportional to the number of yet unfilled positions. For each resampling the departments were partitioned into two clusters of 8 departments so that the number of cross-cluster hires was minimized. The resulting "naive" χ^2-test statistic against the null of random matching was recorded. Finally, the resulting cumulative distribution function of the generated χ^2-test statistics was evaluated at the actual sample value of the χ^2-test statistic for the best partitioning.

The results from the search for the strongest partition are reported in Table 9. The division within economics was found to be so deep that none of the 5000 resamplings produced a χ^2-test statistic even nearly as large as the sample value. Thus we can (conservatively) say that the corrected p-value for the test against no division in economics is below 0.0002. By comparison, in mathematics the observed division is only marginally statistically significant even when taking as given the best partition (with a naive p-value of 0.068). Dividing the top 16 math departments into two bins of 8 departments so as to minimize the proportion of cross-cluster hires still leads to 42% of cross-hires. Under the random matching exercise such partitions or stronger result in more than 25% of the resamplings, so we can conclude that there is no evidence for a division within mathematics. In comparative literature the clustering is statistically significant, but not as clearly as in economics. There the sample value of the test statistic (or higher) results in about 1% of the resamplings.

[20] The proportion of home-grown faculty is 6.7%, 7.1%, and 9.9% in economics, math, and literature respectively. The expected proportions under random matching would be 1.2%, 2.5%, and 2.6%.

4.3 Close-up on the Clusters in Economics

The division into discrete clusters is of course an abstraction, and in practice some departments are inevitably more strongly part of a given cluster, while others are more neutral. Table 10 shows the strength of individual departments' attachment to the clusters in the strongest possible partition in economics. The relative connectedness to the two clusters is measured by the proportion of interactions (hires plus placements, but self-hires excluded) that a department has with Cluster 1 (the Saltwater cluster) out of interactions with all departments in the US top 16—this could be called a measure of "salinity." Columbia and Berkeley are the saltiest departments, with 89.5% and 85.5% of interactions with other saltwater departments. At the other end of the spectrum are Rochester and Minnesota, with 34.6% and 35% saltwater interactions respectively. These proportions must be compared to the average proportion 65.7%, which would result in expectation under random matching within the top 16. Yale, Stanford, and Chicago are so close to the average that they could be considered neutral in terms of relative connectedness with the two clusters.

A decomposition of interactions into hires and placements reveals that the partition holds up quite nicely: ranked separately, the saltiest departments both in terms of placements and hires are found in Cluster 1. However, Chicago is an exceptional case, because in terms of hiring it is closer to the other cluster than to its own. Its appearance in the Freshwater cluster is entirely due to the high proportion of its placements that have ended up at more hard-core Freshwater departments. However, the relatively high proportion of hires from the Saltwater cluster (77.4%, compared with the average proportion of 71.9%) is due to the exceptionally strong influence of Chicago within the Freshwater cluster: since self-hires are excluded in the analysis, most home-cluster faculty are in fact not included in its tally.

Finally, Table 10 also shows the strength of attachment to the clusters by department calculated from the junior data only (defined as assistant and associate professors). The results are quite similar to the full sample; it certainly does not seem that the division would be on the wane. Now even the anomalous Chicago appears to be in line within the Freshwater cluster, perhaps because, in the junior sample, many future self-hires are still currently doing stints at other Freshwater departments and thus are counted in the interactions.

5 Conclusion

In this paper we measured the properties of the citation network defined by movements of faculty between departments in three academic disciplines: economics, mathematics, and comparative literature. We found that the influence of departments as defined by Pinski and Narin (1976)—aka the Google PageRank approach—is highly concentrated, even more so than the number of placements. As a result of this exercise, a purely mechanical ranking of PhD programs by influence was obtained for each discipline. A type of a confidence interval for the ranking was calculated by bootstrapping with the actual population of professors and positions.

We also explored the clustering of university departments within disciplines, that is, the existence of groups of departments that are more connected by hiring and placement within the group than between groups. Economics exhibits the strongest division into clusters of the disciplines under study. It is possible to divide the top departments in economics so that (excluding self-hires) roughly two thirds of hires are from within cluster, and one third from outside. This division is consistent with anecdotal evidence about "Freshwater" and "Saltwater" schools of thought, even up to the relative strength of attachment of cluster members to their own cluster. Likewise, comparative literature exhibits a statistically significant division into clusters, but not as strong as economics. There is also an apparent division within mathematics, but upon closer inspection it turned out that this division is not significantly stronger than the strongest division that could be expected to appear under a null hypothesis of random matching between the professors and positions in the data.

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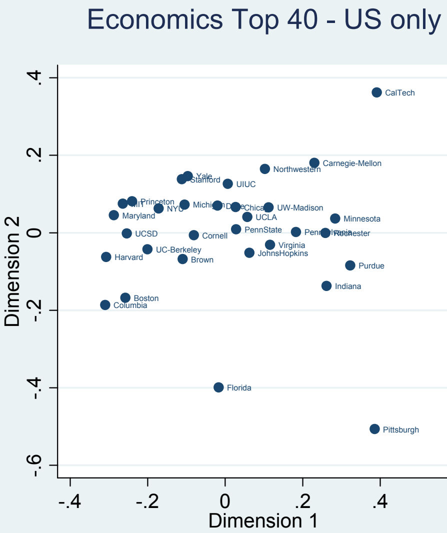
Figure 1

Figure 2

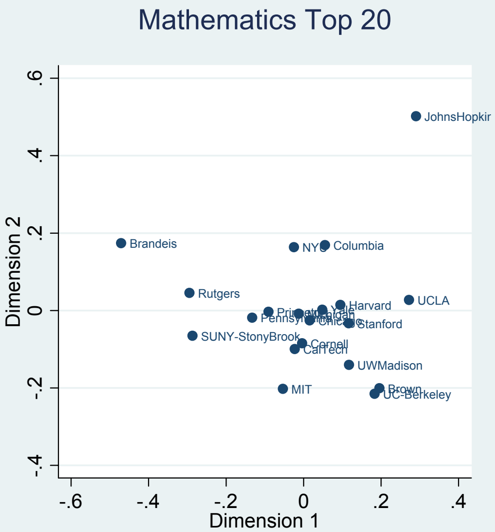
Classical MDS

Figure 3



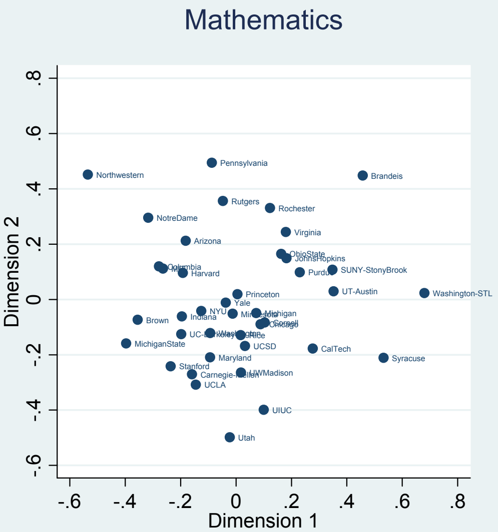
Classical MDS

Figure 4



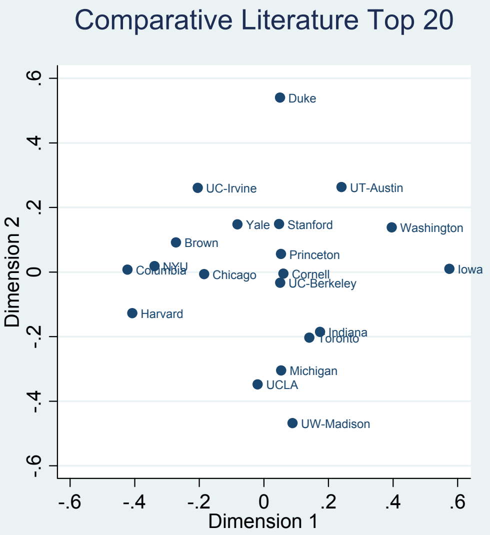
Classical MDS

Figure 5



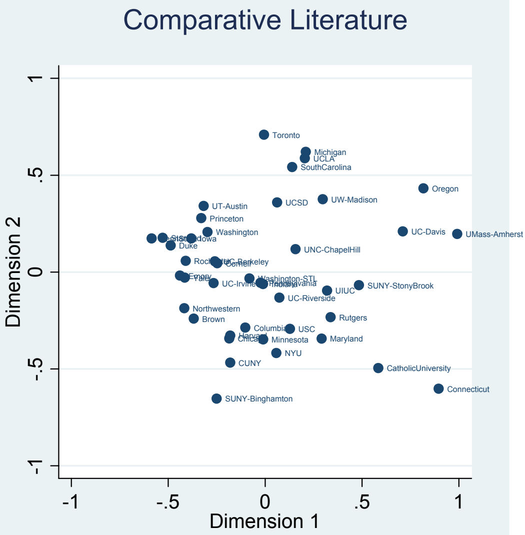
Classical MDS

Figure 6



Classical MDS

Figure 7



Classical MDS

Figure 8

Table 1. Economics

Pinski-Narin influence weights %

Rank by influence	University	Influence weight	Bootstrap results: 5%	Bootstrap results: 50%	Bootstrap results: 95%	Bootstrap results: Beats pairwise 90%	Restricted samples: no self-hires	Restricted samples: with juniors only	Restricted samples: with juniors, no self-hires	# Faculty	# Placements
1	MIT	17.860	14.397	17.709	21.773	3	17.120	13.319	13.457	37	215
2	Harvard	17.495	13.335	17.345	22.116	3	14.617	13.463	12.556	47	214
3	Stanford	7.806	5.525	7.703	10.198	9	8.682	9.990	10.278	42	156
4	Chicago	7.272	4.955	7.181	9.785	9	7.086	12.223	10.363	54	177
5	Princeton	6.617	4.519	6.540	8.971	9	6.903	7.197	7.933	53	117
6	Yale	6.413	4.360	6.311	8.695	9	6.647	5.485	6.045	45	134
7	UC-Berkeley	5.440	3.787	5.330	7.067	10	6.125	5.301	5.393	56	173
8	Oxford	4.537	2.047	4.461	7.973	14	2.947	1.190	0.500	54	49
9	Cambridge	3.202	1.432	3.114	6.046	14	1.947	0.088	0.063	37	36
10	Northwestern	2.408	1.577	2.365	3.342	14	2.821	4.264	4.699	40	112
11	Minnesota	2.394	1.463	2.331	3.462	14	2.780	1.911	2.107	26	100
12	LSE	2.320	1.231	2.251	3.629	15	2.743	2.682	2.815	56	45
13	Pennsylvania	2.287	1.078	2.210	3.668	15	2.812	1.808	1.992	35	91
14	Rochester	1.354	0.613	1.293	2.248	20	1.624	1.687	1.860	20	58
15	UW-Madison	1.078	0.561	1.046	1.671	25	1.320	1.246	1.373	30	110
16	Michigan	0.940	0.355	0.878	1.727	29	1.165	1.267	1.319	47	70
17	UCLA	0.893	0.265	0.831	1.664	32	1.132	1.261	1.390	40	41
18	CalTech	0.865	0.168	0.789	1.902	35	1.012	0.388	0.428	14	18
19	Columbia	0.786	0.342	0.757	1.334	32	0.968	1.006	1.109	40	65
20	Johns Hopkins	0.638	0.224	0.606	1.135	35	0.808	0.018	0.020	17	30
21	Toulouse	0.594	0.197	0.558	1.255	35	0.396	2.073	1.143	28	22
22	Carnegie-Mellon	0.586	0.209	0.549	1.027	35	0.690	1.315	1.304	57	29
23	Maryland	0.544	0.136	0.512	1.045	35	0.689	1.607	1.771	39	24
24	PennState	0.520	0.001	0.483	1.446	73	0.629	1.145	1.262	24	15
25	Duke	0.400	0.081	0.368	0.793	39	0.486	0.601	0.663	50	39
26	Virginia	0.400	0.098	0.369	0.796	39	0.506	0.275	0.303	27	31
27	Purdue	0.395	0.093	0.358	0.802	40	0.475	0.051	0.056	22	36
28	Brown	0.394	0.106	0.368	0.760	37	0.500	0.082	0.090	30	36
29	Cornell	0.370	0.142	0.343	0.676	37	0.454	0.316	0.349	35	50
30	NYU	0.368	0.126	0.346	0.660	37	0.455	1.012	1.115	41	26
31	Boston	0.339	0.039	0.306	0.719	42	0.430	2.033	2.241	33	14
32	UCSD	0.293	0.085	0.268	0.569	41	0.371	0.316	0.349	34	35
33	UIUC	0.290	0.047	0.266	0.620	43	0.367	0.278	0.306	40	37
34	Pittsburgh	0.248	0.025	0.219	0.560	45	0.300	0.556	0.613	26	16
35	Indiana	0.155	0.001	0.140	0.429	73	0.196	0.000	0.000	21	20
36	Florida	0.147	0.001	0.120	0.412	67	0.186	0.082	0.090	18	10
37	Western Ontario	0.129	0.020	0.114	0.294	50	0.158	0.148	0.151	31	15
38	UBC	0.126	0.012	0.106	0.310	55	0.138	0.060	0.057	32	15
39	Pompeu Fabra	0.119	0.006	0.104	0.282	57	0.145	0.334	0.344	48	6
40	Queens	0.116	0.034	0.105	0.231	50	0.125	0.096	0.098	29	19
41	Iowa	0.098	0.028	0.088	0.198	50	0.114	0.140	0.154	23	23
42	CUNY	0.073	0.000	0.061	0.231		0.085	0.000	0.000	62	10
43	U-Washington	0.058	0.012	0.050	0.124	58	0.070	0.003	0.003	25	29
44	BC	0.054	0.000	0.046	0.160	84	0.068	0.128	0.141	28	6
45	Michigan State	0.050	0.005	0.042	0.120	63	0.061	0.000	0.000	41	26

46	Rice	0.046	0.004	0.039	0.114	69	0.055	0.000	0.000	19	8
47	EUI	0.046	0.001	0.036	0.122	74	0.058	1.104	1.216	12	5
48	SUNY-StonyBrook	0.040	0.003	0.032	0.101	72	0.051	0.148	0.163	14	9
49	Colorado	0.038	0.000	0.029	0.121	88	0.049	0.004	0.004	30	10
50	Toronto	0.033	0.005	0.028	0.074	69	0.040	0.004	0.005	61	8
51	IowaState	0.029	0.003	0.024	0.070	72	0.033	0.003	0.003	50	18
52	Tulane	0.023	0.000	0.016	0.078		0.030	0.000	0.000	12	5
53	Kentucky	0.022	0.000	0.014	0.073	87	0.026	0.000	0.000	19	5
54	LouisianaState	0.021	0.000	0.014	0.075		0.025	0.000	0.000	14	4
55	UNC	0.021	0.004	0.017	0.052	73	0.026	0.020	0.022	30	27
56	OhioState	0.020	0.003	0.017	0.046	74	0.026	0.044	0.049	36	25
57	GMU	0.017	0.000	0.011	0.059		0.019	0.025	0.025	29	4
58	SUNY-Albany	0.015	0.000	0.010	0.051		0.018	0.110	0.111	22	5
59	Hebrew	0.014	0.001	0.011	0.038	75	0.013	0.006	0.005	24	12
60	UC-Davis	0.014	0.000	0.011	0.038	79	0.018	0.022	0.025	29	8
61	Missouri-Columbia	0.013	0.000	0.010	0.037	84	0.016	0.044	0.048	19	6
62	TexasAM	0.012	0.001	0.007	0.039	82	0.015	0.000	0.000	31	19
63	Oregon	0.011	0.000	0.006	0.041		0.014	0.000	0.000	18	3
63	WestVirginia	0.011	0.000	0.006	0.041		0.014	0.000	0.000	16	3
65	USC	0.009	0.000	0.003	0.037	88	0.012	0.002	0.002	35	7
66	Arizona	0.009	0.000	0.002	0.036		0.011	0.002	0.002	21	3
67	Claremont	0.008	0.000	0.005	0.029		0.011	0.000	0.000	5	4
68	SouthCarolina	0.008	0.000	0.005	0.029		0.011	0.000	0.000	16	1
69	Rutgers	0.007	0.000	0.005	0.021	84	0.009	0.000	0.000	30	12
70	Washington-STL	0.007	0.001	0.005	0.018	80	0.009	0.000	0.000	21	21
71	VPI	0.007	0.000	0.005	0.017	82	0.008	0.000	0.000	15	12
72	WashingtonState	0.006	0.000	0.004	0.017		0.007	0.000	0.000	12	4
73	UT-Austin	0.005	0.000	0.003	0.015	86	0.006	0.009	0.009	30	15
74	NC-State	0.003	0.000	0.001	0.011	88	0.004	0.000	0.000	27	9
75	UCSB	0.002	0.000	0.001	0.007	88	0.003	0.000	0.000	29	9
76	SouthernIllinois	0.002	0.000	0.001	0.006	87	0.002	0.003	0.003	10	4
77	NewSchool	0.002	0.000	0.001	0.006	88	0.002	0.000	0.000	6	8
78	Vanderbilt	0.002	0.000	0.001	0.005	88	0.002	0.000	0.000	34	8
79	SMU	0.001	0.000	0.001	0.005		0.002	0.004	0.004	18	4
80	UMass-Amherst	0.001	0.000	0.001	0.005		0.002	0.000	0.000	24	10
81	Kansas	0.001	0.000	0.000	0.005		0.002	0.000	0.000	19	7
82	Tennessee	0.001	0.000	0.001	0.004		0.001	0.000	0.000	15	3
83	FloridaState	0.001	0.000	0.000	0.004		0.001	0.000	0.000	32	4
84	Auburn	0.001	0.000	0.000	0.003		0.001	0.000	0.000	11	1
85	Syracuse	0.000	0.000	0.000	0.001	88	0.000	0.000	0.000	30	11
86	SUNY-Binghamton	0.000	0.000	0.000	0.001		0.000	0.000	0.000	21	4
87	Utah	0.000	0.000	0.000	0.001		0.000	0.000	0.000	20	5
88	ArizonaState	0.000	0.000	0.000	0.000		0.000	0.000	0.000	30	3
89	American	0.000	0.000	0.000	0.000		0.000	0.000	0.000	23	7
90	UC-Riverside	0.000	0.000	0.000	0.000		0.000	0.000	0.000	21	1
91	SUNY-Buffalo	0.000	0.000	0.000	0.000		0.000	0.000	0.000	18	6
NR	29 Departments get no rank: Alabama,Cincinnati,Clark,Clemson,ColoradoSchool,ColoradoState,Connecticut,Fordham, Georgetown,Georgia,GeorgiaState,GWU,Hawaii,Houston,Howard,Lehigh,Nebraska,Northeastern,NorthIllinois, NotreDame,Oklahoma,RPI,Temple,UIC,NewHampshire,UtahState,UT-Dallas,UW-Milwaukee,Wyoming.									517	32
	Total 120 Departments									*3209*	*2999*

Table 2. Mathematics

Pinski-Narin influence weights %

Rank by influence	University	Influence weight	Bootstrap results: 5%	50%	95%	Beats pairwise 90%	Restricted samples: no self-hires	with juniors only	with juniors, no self-hires	# Faculty	# Placements
1	Princeton	23.612	18.253	23.598	31.071	2	17.172	11.084	11.953	39	175
2	Harvard	14.138	10.370	14.033	18.303	3	14.359	14.160	15.270	33	121
3	UC-Berkeley	9.334	6.327	9.222	12.580	5	9.658	9.083	8.707	68	127
4	MIT	7.153	5.042	7.057	9.577	6	6.329	10.760	7.736	50	123
5	Chicago	5.483	3.294	5.342	7.895	8	6.460	3.153	3.400	37	82
6	Stanford	4.731	2.759	4.596	6.985	10	5.161	4.955	5.343	32	78
7	NYU	4.216	2.030	4.055	6.674	11	4.714	4.614	4.975	65	58
8	Columbia	3.220	1.678	3.133	4.977	16	3.387	4.852	4.906	39	42
9	UCLA	2.658	1.119	2.519	4.522	19	3.134	1.695	1.636	70	40
10	CalTech	2.219	0.786	2.074	4.095	23	2.514	1.502	1.620	15	27
11	Yale	2.078	1.234	2.023	2.982	21	2.550	3.202	3.453	27	51
12	Cornell	2.052	0.992	1.956	3.280	21	2.518	1.730	1.865	39	46
13	Michigan	1.786	0.817	1.702	2.964	23	2.094	2.471	2.460	65	41
14	JohnsHopkins	1.718	0.188	1.579	3.670	30	1.976	2.297	2.477	19	9
15	Brandeis	1.687	0.369	1.564	3.579	27	1.923	0.600	0.431	15	15
16	UWMadison	1.412	0.710	1.354	2.174	24	1.701	1.692	1.824	61	38
17	Rutgers	1.215	0.118	1.146	3.013	38	1.385	1.368	1.148	75	19
18	SUNY-StonyBrook	1.195	0.088	1.107	2.873	38	1.390	2.731	2.946	22	9
19	Brown	1.173	0.578	1.124	1.898	24	1.233	2.893	2.427	43	38
20	Pennsylvania	1.078	0.237	1.009	2.219	31	1.203	2.032	1.643	29	17
21	UIUC	0.943	0.241	0.880	1.984	34	1.049	1.513	1.489	69	29
22	Rice	0.888	0.311	0.837	1.645	31	0.990	0.104	0.112	12	15
23	Minnesota	0.820	0.407	0.779	1.324	28	0.969	0.755	0.814	63	42
24	Northwestern	0.564	0.138	0.527	1.109	36	0.660	1.185	1.278	28	11
25	UTAustin	0.522	0.168	0.494	0.963	36	0.611	1.487	1.604	61	12
26	Washington	0.516	0.177	0.480	0.950	36	0.610	0.695	0.710	62	19
27	Carnegie-Mellon	0.428	0.085	0.394	0.852	38	0.526	1.105	1.192	34	9
28	Maryland	0.391	0.142	0.363	0.709	38	0.470	1.058	1.141	60	16
29	MichiganState	0.388	0.092	0.349	0.781	38	0.455	1.093	1.178	67	9
30	OhioState	0.326	0.044	0.270	0.797	40	0.370	0.713	0.695	97	14
31	Purdue	0.321	0.086	0.294	0.623	40	0.379	0.383	0.384	65	14
32	Indiana	0.310	0.103	0.281	0.582	38	0.380	0.297	0.320	49	18
33	Virginia	0.270	0.024	0.242	0.652	41	0.317	0.023	0.025	29	7
34	NotreDame	0.242	0.020	0.219	0.612		0.271	0.779	0.840	40	9
35	Washington-STL	0.223	0.009	0.195	0.531		0.260	0.325	0.350	23	5
36	Arizona	0.187	0.027	0.166	0.410	41	0.215	0.339	0.332	73	9
37	UCSD	0.183	0.065	0.168	0.337	40	0.219	0.253	0.251	49	13
38	Syracuse	0.116	0.008	0.088	0.315		0.142	0.390	0.421	31	4
39	Utah	0.114	0.031	0.104	0.230		0.134	0.388	0.383	60	9
40	Rochester	0.049	0.011	0.043	0.106		0.060	0.132	0.143	27	6
41	UC-Irvine	0.042	0.008	0.037	0.088		0.051	0.111	0.120	32	5
	Total 41 departments									*1874*	*1431*

Table 3. Comparative Literature

Pinski-Narin influence weights %

Rank by influence	University	Influence weight	Bootstrap results 5%	Bootstrap results 50%	Bootstrap results 95%	Beats pairwise 90%	Restricted samples: no self-hires	Restricted samples: with juniors only	Restricted samples: with juniors, no self-hires	# Faculty	# Placements
1	Yale	26.884	18.579	26.707	40.014	2	19.854	17.178	18.924	16	90
2	Harvard	13.773	6.325	13.406	23.028	6	12.323	10.477	8.656	17	65
3	Princeton	10.909	4.807	10.627	17.912	8	10.574	10.331	11.381	19	45
4	UC-Berkeley	7.477	4.199	7.170	10.853	8	8.526	17.109	12.565	19	68
5	Stanford	7.462	2.664	7.198	12.757	9	8.902	10.974	12.089	17	38
6	Columbia	6.228	2.501	5.868	10.313	10	6.866	6.489	7.148	41	36
7	NYU	5.367	1.375	5.066	9.819	13	6.937	8.349	9.197	14	17
8	Iowa	2.892	0.138	2.612	6.914	24	3.239	0.928	0.876	20	10
9	Michigan	2.810	0.707	2.594	5.477	17	3.352	3.089	2.978	18	15
10	Cornell	2.169	0.572	1.979	4.102	22	2.803	0.236	0.260	32	27
11	UW-Madison	2.003	0.376	1.779	4.186	22	2.589	0.196	0.216	9	21
12	UT-Austin	1.774	0.416	1.586	3.754	22	1.940	0.792	0.873	15	16
13	Chicago	1.333	0.248	1.172	2.886	22	1.579	0.275	0.303	13	18
14	UC Irvine	0.996	0.060	0.822	2.429	30	1.287	3.046	3.356	18	5
15	Duke	0.960	0.040	0.786	2.369	30	1.158	4.140	4.561	24	7
16	Indiana	0.905	0.095	0.737	2.249	29	1.105	0.343	0.314	19	18
17	UCLA	0.847	0.219	0.756	1.746	27	0.948	0.495	0.454	17	17
18	Brown	0.710	0.117	0.614	1.540	29	0.872	0.596	0.657	26	12
19	Washington	0.687	0.154	0.586	1.478	28	0.800	1.431	1.351	23	13
20	Toronto	0.648	0.000	0.502	2.006		0.456	0.158	0.175	18	11
21	Washington-STL	0.640	0.000	0.484	1.996		0.745	0.000	0.000	23	4
22	UNC-Chapel Hill	0.356	0.005	0.240	1.043	35	0.414	0.000	0.000	14	8
23	Minnesota	0.341	0.015	0.267	0.875	33	0.440	0.904	0.996	16	6
24	Pennsylvania	0.290	0.000	0.233	0.728	35	0.364	0.981	1.081	45	5
25	Northwestern	0.281	0.000	0.209	0.819		0.363	0.000	0.000	12	3
26	SUNY-Stony Brook	0.250	0.000	0.137	0.866		0.324	0.065	0.072	9	1
27	Rutgers	0.211	0.000	0.167	0.610		0.273	0.463	0.511	18	2
28	UCSD	0.192	0.017	0.149	0.463	35	0.248	0.053	0.058	16	4
29	Oregon	0.149	0.000	0.117	0.415		0.192	0.000	0.000	12	2
30	USC	0.147	0.000	0.083	0.484		0.191	0.762	0.839	17	3
31	UIUC	0.107	0.000	0.068	0.307		0.120	0.141	0.111	29	7
32	Maryland	0.097	0.000	0.029	0.347		0.083	0.000	0.000	4	4
33	Emory	0.042	0.000	0.021	0.141		0.054	0.000	0.000	20	3
34	Rochester	0.035	0.000	0.020	0.123		0.046	0.000	0.000	16	2
35	CUNY	0.017	0.000	0.008	0.061		0.019	0.000	0.000	32	6
36	UC Davis	0.012	0.000	0.000	0.052		0.016	0.000	0.000	9	2
NR	7 Departments get no rank: Catholic University, Connecticut, Umass-Amherst, Penn State, South Carolina, SUNY-Binghamton, UC-Riverside.									84	4
	Total 43 departments									*771*	*615*

Table 4. Economics hiring by group - sorted by influence

% of all hires by the Row group from the Column group

	Top 10	11.-20.	21.-30.	31.-40.	41.-50.	51.-60.	61.-70.	71.-80.	81.-91.	Unranked*	Out of Sample	Of all hires
Top 10	79.6	11.2	4.3	1.3	0	0	0	0	0	0	3.6	14.0
11.-20.	62.3	19.9	7.2	4.0	1.2	0.3	0	0	0	0	5.0	10.1
21.-30.	46.6	24.7	10.8	5.1	3.7	2.0	0.9	0	0	0	6.3	11.1
31.-40.	42.7	19.9	5.5	10.7	4.6	1.6	1.6	0	0	0	13.4	9.7
41.-50.	37.9	27.4	10.2	7.6	6.4	1.9	1.0	1.9	0.3	0	5.4	9.9
51.-60.	38.0	21.7	10.3	5.7	2.3	10.6	3.8	3.4	0.8	0	3.4	8.3
61.-70.	33.5	20.3	14.6	7.5	4.7	4.2	4.7	5.2	1.4	0	3.8	6.7
71.-80.	39.0	20.0	10.2	6.3	3.4	4.4	3.4	5.9	1.0	0	6.3	6.5
81.-91.	22.1	19.2	11.7	7.9	6.7	5.4	6.3	7.9	8.8	0	4.2	7.6
Unranked*	21.4	18.1	14.0	5.8	8.5	6.8	5.0	5.0	4.5	6.2	4.7	16.2
Of all placements	43.6	19.8	9.7	5.9	4.2	3.6	2.5	2.6	1.6	1.0	5.5	100
Influence	79.0	13.6	4.6	2.0	0.5	0.2	0.1	0.0	0.0	-	-	

*29 universities

Table 5. Mathematics hiring by group - sorted by influence

% of all hires by the Row group from the Column group

	Top 10	11.-20.	21.-30.	31.-41.	Out of Sample	Of all hires
Top 10	58.3	10.5	5.8	1.1	24.3	23.9
11.-20.	50.6	15.7	7.3	4.6	21.8	21.1
21.-30.	39.8	15.9	11.6	6.3	26.4	29.5
31.-41.	40.2	18.0	11.9	8.6	21.3	25.5
Of all placements	46.6	15.1	9.4	5.3	23.6	100
Influence	76.8	15.4	5.8	2.1	-	

Table 6. Comparative Literature hiring by group - sorted by influence

% of all hires by the Row group from the Column group

	Top 10	11.-20.	21.-30.	31.-43.	Out of Sample	Of all hires
Top 10	63.2	13.4	3.3	0	20.1	20.1
11.-20.	51.4	22.3	6.3	0.6	19.4	19.4
21.-30.	56.9	16.0	6.1	4.4	16.6	16.6
31.-43.	45.0	22.0	4.7	9.9	18.3	18.3
Of all placements	54.4	18.3	5.0	3.7	18.7	100
Influence	86.0	10.9	2.9	0.3	-	

Table 7. Mathematics: Extended influence weights, %

Rank by Ext. influence	Rank by influence	University	Extended influence weight	# Placements
1	1	Princeton	17.764	172
2	2	Harvard	10.973	118
3	3	UC-Berkeley	7.457	126
4	4	MIT	5.707	121
5	5	Chicago	4.161	80
6	6	Stanford	3.618	77
7	7	NYU	3.054	58
8		Moscow State	2.669	35
9	8	Columbia	2.548	42
10		Cambridge	2.407	26
11	9	UCLA	2.008	40
12	10	Cal Tech	1.677	27
13	12	Cornell	1.664	46
14		Tel Aviv	1.651	15
15	11	Yale	1.633	50
16	13	Michigan	1.461	40
17		Oxford	1.381	9
18	14	Johns Hopkins	1.313	8
19	15	Brandeis	1.230	14
20	16	UW-Madison	1.126	38
		Other out-of-sample (180 depts)	19.207	358
		Other in-sample (24 depts)	5.292	374
		Total	*100*	*1874*

Table 8. Extended influence weights and the concentration of influence

	% of total	1.-10.	11.-20.	21.-30.	31.-40.	Others
Economics	Placements	43.6	19.8	9.7	4.3	22.6
	Ext.Influence	76.7	13.0	4.3	2.4	3.5
Mathematics	Placements	46.3	15.5	9.7	2.8	25.6
	Ext.Influence	60.4	15.2	7.7	5.0	11.7
Comparative Literature	Placements	54.0	13.5	12.6	3.6	16.4
	Ext.Influence	74.3	11.2	6.0	3.7	4.8

Table 9. Testing for partition into two clusters.

Discipline	Chi2	Naïve p-value of Chi2	Bootstrap p-value of Chi2	Cross-hires, % of total	# Movers: C1 → C1	# Movers: C1 → C2	# Movers: C2 → C1	# Movers: C2 → C2	# Resamplings	Max. value of Chi2 in resamplings
Economics	31.964	1.57E-08	< 0.0002	33.9	219	104	48	78	5000	18.779
Mathematics	3.332	0.068	0.257	41.8	169	106	53	52	2000	15.814
Comp.Literature	9.015	0.003	0.009	38.7	45	24	46	66	2000	18.552

Partitions that minimize % cross-hires:

Economics	C1	MIT, Harvard, Stanford, Princeton, Yale, UC-Berkeley, Michigan, Columbia
	C2	Chicago,Northwestern,Minnesota,Pennsylvania,Rochester,UW-Madison,UCLA,CalTech
Mathematics	C1	Princeton, Harvard, UC-Berkeley, MIT, NYU, UCLA, Yale, Michigan
	C2	Chicago, Stanford, Columbia, CalTech, Cornell, JohnsHopkins, Brandeis, UW-Madison
Comparative Literature	C1	Yale, Harvard, Stanford, Columbia, NYU, UT-Austin, Chicago, Duke
	C2	Princeton, UC-Berkeley, Iowa, Michigan, Cornell, UW-Madison, UC-Irvine, Indiana

Self-hires excluded.

Table 10. Close-up on the clusters in Economics.

University	# Interactions with US Top 16	Proportion of Interactions with C1		# Placements to US Top 16	Proportion of Placements to C1		# Hires from US Top 16	Proportion of Hires from C1		# Self-hires	# Interactions with US Top 16 (juniors)	Proportion of Interactions with C1 (juniors)	
Cluster 1													
Columbia	38	0.895	***	4	0.500		34	0.941	***	1	17	0.882	**
UC-Berkeley	69	0.855	***	29	0.690		40	0.975	***	6	21	0.905	***
Harvard	103	0.786	***	74	0.770	***	29	0.828	*	16	36	0.861	***
Princeton	74	0.743		38	0.684		36	0.806	*	9	24	0.625	
Michigan	46	0.739		6	0.500		40	0.775		1	16	0.688	
MIT	118	0.729		94	0.713	**	24	0.792		9	33	0.879	***
Yale	66	0.636		35	0.571		31	0.710		8	21	0.571	
Stanford	76	0.618		43	0.558		33	0.697		5	30	0.600	
Cluster 1	*590*	*0.742*	***	*323*	*0.678*	***	*267*	*0.820*	***	*55*	*198*	*0.758*	***
Cluster 2													
Chicago	68	0.603		37	0.459	*	31	0.774		12	27	0.407	**
Northwestern	56	0.554		24	0.417	*	32	0.656		3	24	0.458	*
UW-Madison	29	0.517		6	0.333		23	0.565		1	9	0.111	***
UCLA	37	0.514	*	5	0.400		32	0.531		0	12	0.583	
Pennsylvania	38	0.447	***	14	0.571		24	0.375	***	1	16	0.375	**
Caltech	14	0.429	*	5	0.200	*	9	0.556		1	5	0.600	
Minnesota	40	0.350	***	23	0.174	***	17	0.588		2	11	0.182	***
Rochester	26	0.346	***	12	0.333	*	14	0.357	**	1	11	0.364	*
Cluster 2	*308*	*0.494*	***	*126*	*0.381*	***	*182*	*0.571*	***	*21*	*115*	*0.391*	***
US Top 16	*898*	*0.657*		*449*	*0.595*		*449*	*0.719*		*76*	*313*	*0.623*	

Stars indicate statistically significant differences compared to random matching: *** 1%, ** 5%, and * 10% level.

Interactions = Hires + Placements. Self-hires are excluded from all calculations.

Juniors = Assistant and Associate professors.

Appendix

Table A.1. Hiring in Economics (Top 40 only).

	Hired | Placed	MIT	Harvard	Stanford	Chicago	Princeton	Yale	UC-Berkeley	Oxford	Cambridge	Northwestern	Minnesota	LSE	Pennsylvania	Rochester	UW-Madison	Michigan	UCLA	Cal Tech	Columbia	Johns Hopkins	Toulouse	Carnegie-Mellon	Maryland	PennState	Duke	Virginia	Purdue	Brown	Cornell	NYU	Boston	UCSD	UIUC	Pittsburgh	Indiana	Florida	Western Ontario	UBC	Pompeu Fabra	Queens	Other (80 depts)	Other (out sample)	Missing or no Ph.D.	Total hired
1	MIT	9	10	4	2	3	2	0	2	0	0	0	1	2	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	37
2	Harvard	14	16	3	3	1	2	3	1	1	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47
3	Stanford	4	8	5	5	3	5	3	0	1	1	3	0	0	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	42
4	Chicago	8	5	3	12	3	2	2	0	1	0	3	0	2	0	1	0	1	0	1	1	0	1	1	0	0	1	1	0	0	0	2	0	0	0	1	0	0	0	0	0	0	1	1	54
5	Princeton	14	5	3	3	9	2	3	0	1	2	0	3	0	1	0	0	1	0	2	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	2	0	53
6	Yale	6	2	4	2	6	8	4	0	0	4	0	2	2	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	45
7	UC-Berkeley	15	10	6	0	3	5	6	2	1	0	1	0	0	0	0	0	0	0	0	0	0	1	2	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	2	0	56
8	Oxford	0	3	2	1	2	1	3	19	3	0	0	4	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	12	54
9	Cambridge	0	2	0	0	0	0	3	2	13	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	6	6	37
10	Northwestern	5	3	7	5	3	1	0	0	1	3	4	0	0	0	1	1	0	1	1	0	1	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	40
11	Minnesota	3	1	0	3	1	3	2	0	0	1	2	0	1	2	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	1	26
12	LSE	3	8	4	0	3	2	4	7	3	1	0	3	1	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	2	0	1	9	2	56
13	Pennsylvania	2	1	2	1	1	3	0	1	0	4	5	3	1	2	1	0	1	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	0	0	0	1	0	0	0	1	1	0	35
14	Rochester	2	0	1	5	2	0	0	0	0	1	2	0	0	1	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	20
15	UW-Madison	2	1	2	2	0	3	3	0	0	4	1	1	2	1	1	2	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	1	0	0	0	30
16	Michigan	5	11	2	2	7	3	3	1	0	3	0	0	4	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	0	0	0	0	0	0	1	0	0	0	0	0	47
17	UCLA	4	6	2	3	2	2	1	1	0	4	3	1	1	2	1	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	2	1	0	40
18	Cal Tech	1	0	2	1	0	1	1	0	0	0	1	0	0	1	0	0	1	1	0	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	14
19	Columbia	9	11	2	0	3	1	4	0	0	0	0	0	0	2	0	2	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	2	40
20	Johns Hopkins	2	1	1	1	0	3	1	0	0	1	0	0	0	0	1	2	0	0	0	0	0	0	0	0	1	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	17
21	Toulouse	3	2	0	0	0	0	0	1	0	0	0	1	1	0	0	0	0	1	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	9	0	28
22	Carnegie-Mellon	3	2	4	3	1	2	1	0	0	2	0	0	2	1	7	4	1	4	0	0	1	4	0	0	1	1	1	0	1	0	0	0	0	1	0	1	0	1	0	2	5	0	1	57
23	Maryland	5	4	4	3	3	3	3	0	0	0	0	0	1	0	2	0	1	0	2	2	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	2	1	0	39
24	PennState	0	1	0	2	3	0	1	0	0	2	0	1	0	3	3	0	0	0	0	0	1	0	0	1	0	0	0	0	1	0	0	2	1	0	0	0	0	0	0	0	0	2	0	24
25	Duke	4	6	3	4	4	3	1	0	0	4	3	0	1	1	2	0	0	0	0	0	0	1	0	0	2	0	0	0	0	0	0	2	0	0	0	1	0	0	1	0	5	2	0	50
26	Virginia	3	1	1	2	2	1	0	0	0	1	0	1	0	1	1	2	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	5	1	0	27
27	Purdue	2	0	0	0	0	0	1	0	0	1	2	0	1	2	1	2	0	1	0	1	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	4	2	0	22
28	Brown	1	5	2	4	0	1	2	0	1	1	0	0	1	0	1	0	2	0	3	3	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	1	0	30
29	Cornell	2	1	2	2	2	3	4	1	0	5	0	1	0	1	0	1	1	0	0	1	0	0	0	1	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	1	3	0	35
30	NYU	1	2	3	5	5	3	2	0	1	1	0	1	3	1	2	0	0	0	5	0	0	0	0	0	0	0	0	0	3	1	0	1	0	0	0	0	0	0	0	0	0	1	0	41
31	Boston	6	5	1	1	0	1	2	0	0	4	0	2	1	1	2	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	33
32	UCSD	10	3	4	1	1	3	6	0	1	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	1	0	34
33	UIUC	1	3	5	3	2	4	3	0	0	4	2	0	1	1	1	1	1	0	0	0	0	1	0	0	1	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	1	3	0	40
34	Pittsburgh	0	1	0	0	0	0	0	0	0	0	3	0	0	1	1	0	1	0	1	0	0	0	0	0	0	0	1	1	0	0	0	1	0	1	1	0	0	0	0	0	9	2	2	26
35	Indiana	0	0	0	1	1	2	0	0	0	0	2	1	2	1	1	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0	1	0	0	0	3	2	0	21
36	Florida	2	1	0	1	0	3	0	0	0	0	0	0	0	1	1	2	0	0	2	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	0	2	0	0	18
37	Western Ontario	0	1	1	4	0	2	0	0	0	2	3	1	3	1	2	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	3	4	1	31
38	UBC	0	1	2	0	2	0	4	0	0	5	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	0	0	0	0	1	4	0	3	2	0	2	32
39	Pompeu Fabra	1	2	2	1	0	0	0	1	0	2	3	2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	2	0	3	0	0	0	0	0	0	1	0	4	23	0	48
40	Queens	0	0	1	1	5	1	3	1	0	0	4	0	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	1	1	0	4	0	2	0	29
	Other (80 depts)	63	69	66	88	34	53	94	9	8	49	53	15	56	28	72	47	27	6	45	17	5	15	20	12	29	25	28	27	33	17	6	20	33	9	18	7	8	7	2	7	441	81	5	1754
	Total placed	215	214	156	177	117	134	173	51	36	112	100	45	91	58	110	70	41	18	65	30	22	29	24	15	39	31	36	36	50	26	14	35	37	16	20	10	15	15	6	19	493	175	35	3209

Table A.2. Hiring in Mathematics

Hired | Placed	Princeton	Harvard	UC-Berkeley	MIT	Chicago	Stanford	NYU	Columbia	UCLA	CalTech	Yale	Cornell	Michigan	JohnsHopkins	Brandeis	UWMadison	Rutgers	SUNY-StonyBrook	Brown	Pennsylvania	UIUC	Rice	Minnesota	Northwestern	UT-Austin	Washington	Carnegie-Mellon	Maryland	MichiganState	OhioState	Purdue	Indiana	Virginia	NotreDame	Washington-STL	Arizona	UCSD	Syracuse	Utah	Rochester	UC-Irvine	Out of Sample	Missing	Total hired
1 Princeton	11	4	1	0	2	1	2	0	1	1	0	0	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	1	40
2 Harvard	8	5	7	1	0	1	0	2	0	0	0	1	1	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	1	34
3 UC-Berkeley	4	12	8	6	4	1	2	2	4	1	2	0	1	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	17	0	68
4 MIT	8	11	1	12	1	1	0	0	2	2	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	7	1	51
5 Chicago	7	3	2	3	1	2	1	1	0	0	0	2	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	5	42
6 Stanford	3	4	0	2	3	3	1	1	0	1	0	0	3	0	1	1	0	0	2	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	5	37
7 NYU	12	4	1	3	0	6	4	3	0	0	4	0	0	0	0	0	0	0	1	1	0	0	2	1	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	0	20	2	67
8 Columbia	5	3	0	2	1	1	1	4	0	1	0	0	0	0	1	0	1	1	0	1	0	1	0	0	1	0	1	1	2	0	0	0	0	0	0	0	0	0	0	0	0	11	0	39
9 UCLA	6	4	10	0	2	4	6	1	2	1	2	0	1	0	0	3	0	0	1	0	1	1	2	0	0	2	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	19	1	71
10 CalTech	2	1	1	0	1	0	0	0	1	1	1	2	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	2	0	15
11 Yale	8	1	2	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	9	1	28
12 Cornell	4	3	4	3	4	2	1	0	0	0	0	0	1	0	1	1	0	0	1	0	1	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	10	0	39
13 Michigan	8	2	5	5	4	0	2	0	0	1	2	1	2	0	1	0	1	0	1	0	1	0	0	1	1	3	0	0	0	0	1	0	1	0	0	1	0	0	1	0	0	20	0	65
14 JohnsHopkins	3	0	2	1	1	3	0	3	0	0	0	0	0	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	2	21
15 Brandeis	5	0	1	2	2	0	1	0	0	0	2	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	15
16 UWMadison	4	4	7	4	3	2	3	1	1	1	2	5	2	0	0	1	0	0	2	1	1	0	3	0	1	0	0	1	1	0	0	1	0	1	0	1	1	1	0	0	0	6	5	66
17 Rutgers	7	5	4	7	4	1	5	3	0	0	4	2	1	0	1	0	4	1	0	0	0	0	0	0	0	1	0	1	0	1	1	1	0	0	0	0	1	1	0	0	0	19	0	75
18 SUNY-StonyBrook	0	0	1	3	2	1	0	1	1	0	2	1	0	0	0	2	0	1	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	1	0	0	0	3	0	22
19 Brown	2	6	4	3	1	1	1	1	2	0	2	1	1	1	0	0	0	0	5	0	1	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	8	3	46
20 Pennsylvania	3	5	1	2	4	0	2	1	0	0	0	1	0	0	0	0	0	0	0	2	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	1	30
21 UIUC	5	1	2	6	3	2	0	1	2	3	1	3	5	1	0	5	0	1	0	0	5	0	0	0	0	2	1	3	0	0	0	0	0	0	0	0	0	0	1	0	0	16	5	74
22 Rice	1	3	1	0	0	1	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	12
23 Minnesota	7	3	2	5	6	4	5	1	0	0	2	2	2	0	1	3	0	0	0	1	1	1	2	0	0	0	0	0	0	1	0	1	0	0	0	0	1	0	1	0	1	10	4	67
24 Northwestern	1	5	3	5	0	3	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	7	0	28
25 UT-Austin	6	1	5	1	5	3	1	0	1	1	2	1	2	0	1	3	0	0	1	0	1	1	0	0	2	0	0	0	0	1	0	0	2	0	0	0	0	0	0	1	1	18	0	61
26 Washington	9	4	2	11	0	7	1	0	1	0	1	2	1	0	0	3	1	0	1	0	2	0	2	0	0	2	0	0	0	0	0	0	0	0	1	0	1	0	2	0	0	8	0	62
27 Carnegie-Mellon	2	1	1	1	0	2	0	0	1	0	0	2	0	0	0	0	1	0	6	0	2	0	2	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	11	0	34
28 Maryland	5	1	9	3	2	3	3	2	3	0	1	1	0	0	0	1	2	1	4	0	1	1	2	0	0	2	1	1	0	0	0	0	0	0	0	0	1	0	0	1	0	9	6	66
29 MichiganState	0	1	4	2	1	2	3	3	2	0	0	0	3	0	0	1	1	0	1	0	0	1	2	2	0	0	3	2	2	0	1	3	0	2	0	1	1	0	2	0	0	21	0	67
30 OhioState	4	3	3	4	3	1	1	2	0	2	5	1	1	0	1	1	1	0	2	0	1	0	4	1	0	0	0	0	0	4	2	1	0	1	1	1	1	0	0	0	0	45	0	97
31 Purdue	6	4	2	3	6	2	0	3	3	2	0	4	3	2	0	0	0	0	0	0	1	1	6	0	0	0	0	0	0	1	2	1	0	1	0	0	0	1	0	0	1	10	2	67
32 Indiana	3	0	5	3	1	1	3	0	1	0	2	1	8	0	1	1	1	1	1	1	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	2	0	0	0	0	10	0	49
33 Virginia	1	2	2	1	3	0	0	0	0	0	6	0	0	0	0	1	0	0	1	0	0	0	1	0	1	0	0	0	1	0	0	1	1	0	0	0	1	0	0	0	0	6	2	31
34 NotreDame	2	2	2	4	0	1	1	0	0	1	0	1	1	0	0	1	2	1	3	3	0	0	1	0	0	0	0	1	1	0	1	0	0	3	0	0	0	0	0	2	0	6	1	41
35 Washington-STL	1	1	3	0	3	1	0	1	0	2	1	2	0	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	3	0	23
36 Arizona	4	4	3	7	2	1	1	4	2	1	1	0	0	0	0	3	2	0	1	0	1	0	1	1	0	0	0	2	0	1	0	1	1	0	0	3	1	0	0	1	1	23	1	74
37 UCSD	2	2	5	3	2	7	0	0	2	1	2	2	0	0	0	0	0	0	1	2	2	0	1	0	1	2	0	0	0	1	0	1	0	0	0	0	1	0	0	0	1	8	2	51
38 Syracuse	0	0	1	0	1	1	0	0	0	0	2	3	1	0	1	1	0	0	1	1	2	1	4	0	0	0	0	1	0	0	0	2	0	0	0	0	0	0	0	0	0	8	0	31
39 Utah	2	2	6	1	1	3	3	1	4	3	0	3	0	0	0	1	0	0	0	0	2	1	1	0	1	2	1	0	0	1	1	1	0	0	0	0	0	0	2	0	0	17	10	70
40 Rochester	3	3	1	2	2	1	0	0	0	0	1	0	1	1	1	0	0	0	0	0	1	1	1	1	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	5	1	28
41 UC-Irvine	1	1	3	2	1	2	3	0	3	0	0	1	0	0	1	0	0	0	0	1	0	0	2	0	0	1	0	0	0	1	1	1	0	0	0	1	0	0	0	0	0	6	3	35
Total placed	175	121	127	123	82	78	58	42	40	27	51	46	41	9	15	38	19	9	38	17	29	15	42	11	12	19	9	16	9	14	14	18	7	9	5	9	13	4	9	6	5	443	65	1939

Table A.3. Hiring in Comparative Literature.

	Hired | Placed	Yale	Harvard	Princeton	UC-Berkeley	Stanford	Columbia	NYU	Iowa	Michigan	Cornell	UW-Madison	UT-Austin	Chicago	UC-Irvine	Duke	Indiana	UCLA	Brown	Washington	Toronto	Washington-STL	UNC-Chapel Hill	Minnesota	Pennsylvania	Northwestern	SUNY-Stony Brook	Rutgers	UCSD	Oregon	USC	UIUC	Maryland	Emory	Rochester	CUNY	UC-Davis	UC-Riverside	South Carolina	SUNY-Binghamton	Penn State	UMass-Amherst	Connecticut	Catholic University	Out of sample	Missing	Total hired
1	Yale	6	2	2	0	2	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	16
2	Harvard	2	4	0	1	0	2	3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	17
3	Princeton	4	0	4	0	1	2	0	0	2	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	19
4	UC-Berkeley	6	3	4	2	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	19
5	Stanford	5	0	1	2	1	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	17
6	Columbia	6	9	1	3	1	5	0	0	0	1	0	1	1	1	0	0	1	2	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	41
7	NYU	2	2	0	1	1	2	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	14
8	Iowa	1	0	1	0	1	0	0	2	0	2	2	1	1	0	0	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	20
9	Michigan	0	1	1	4	1	0	0	1	1	0	0	0	0	0	1	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	18
10	Cornell	4	2	2	4	0	1	1	0	0	0	1	1	1	1	0	0	1	0	2	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	3	32
11	UW-Madison	0	1	2	3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	9
12	UT-Austin	5	1	0	1	1	0	0	0	0	0	1	2	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	15
13	Chicago	3	3	0	1	1	1	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	13
14	UC-Irvine	3	0	1	1	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	8	1	18
15	Duke	4	0	1	0	2	1	0	0	0	0	0	0	0	0	1	0	0	0	2	0	0	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	24
16	Indiana	2	0	1	3	0	0	1	1	0	1	3	0	1	0	0	1	2	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	19
17	UCLA	0	1	3	3	2	2	0	0	1	0	0	1	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	17
18	Brown	4	3	1	2	2	2	1	0	1	0	1	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	5	1	26
19	Washington	3	0	1	3	2	0	0	2	0	1	0	3	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	23
20	Toronto	0	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	1	0	0	5	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	4	18
21	Washington-STL	1	1	0	2	1	4	0	0	2	0	0	0	0	1	0	2	0	1	1	0	2	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	3	0	23
22	UNC-Chapel Hill	0	1	2	1	0	0	0	0	0	1	0	0	1	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	4	0	14
23	Minnesota	1	2	0	1	0	2	1	0	1	0	1	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	2	0	16
24	Pennsylvania	6	6	4	5	5	0	0	0	0	2	0	0	1	0	1	1	0	1	0	0	0	2	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	8	1	45
25	Northwestern	2	0	0	1	1	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	3	0	12
26	SUNY-Stony Brook	1	1	0	2	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	9
27	Rutgers	4	5	0	4	0	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	18
28	UCSD	1	2	3	1	2	0	0	0	0	1	1	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	16
29	Oregon	0	0	1	4	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	12
30	USC	2	1	2	1	0	0	2	0	0	2	0	0	1	0	0	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	2	0	17
31	UIUC	0	1	1	5	1	0	1	0	1	1	0	0	2	0	0	2	0	1	1	0	0	0	0	0	0	0	0	0	0	1	3	1	0	0	1	0	0	0	0	0	0	0	0	5	1	29
32	Maryland	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	4
33	Emory	6	0	1	1	1	1	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	20
34	Rochester	0	0	0	1	1	1	0	0	0	6	2	0	0	0	0	0	0	0	1	0	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	16
35	CUNY	2	3	0	0	0	7	2	1	0	2	1	0	1	0	0	0	1	1	0	1	0	0	0	0	1	0	0	0	0	0	1	0	0	0	4	0	0	0	0	0	0	0	0	4	0	32
36	UC-Davis	0	0	1	2	0	1	0	0	0	0	0	0	0	0	0	2	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	9
37	UC-Riverside	1	3	1	0	1	0	0	1	0	0	0	0	1	1	0	0	0	2	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	13
38	South Carolina	0	1	0	0	2	0	0	0	1	0	1	1	0	0	0	1	1	0	0	2	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	3	0	16
39	SUNY-Binghamton	1	0	0	0	0	0	1	0	0	1	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	1	12
40	Penn State	1	0	0	0	3	1	0	0	2	1	1	1	1	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	1	0	0	0	4	0	20
41	UMass-Amherst	0	3	2	2	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	10
42	Connecticut	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
43	Catholic University	1	1	0	1	0	0	0	0	0	0	0	0	1	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	1	10
	Total placed	90	65	45	68	38	36	17	10	15	27	21	16	18	5	7	18	17	12	13	11	4	8	6	5	3	1	2	4	2	3	7	4	3	2	6	2	1	1	0	1	0	0	1	141	15	771