This is the last working paper version of an article published in
the Review of Economics and Statistics, 2011, 93(3), p. 1053–1062.

Divisions within Academia: Evidence from Faculty Hiring and Placement

Marko Terviö*
Helsinki School of Economics

August 30, 2009

Abstract

I look for divisions to clusters among academic departments in three disciplines: economics, mathematics, and comparative literature. I define clusters as subsets of departments with unexpectedly little hiring across the cluster lines. The division within economics is by far the strongest, is consistent with anecdotal evidence about "Freshwater" and "Saltwater" schools of thought, and has been stable over time. There is also a significant division within comparative literature, but the hiring patterns between top mathematics departments are consistent with random matching. (A14,B29,I21,J44)

*Address marko.tervio@hse.fi. I wish to thank Enghin Atalay, Sascha Becker, Deepak Hedge, Clarice Li, and John Prins for excellent research assistance, Timothy Hampton, Michael Katz, David I. Levine, Johan Walden, and participants at NBER Higher Education Working Group for useful comments, and the Committee on Research at UC Berkeley for funding.

1 Introduction

The recent debate over the appropriate policy response to the financial crisis of 2008 has brought to surface old divisions among economists. Many disputes seem to be related to methodological differences among macroeconomists that go back to differing attitudes towards the contributions of Keynes.[1] Another, not entirely unrelated divide is between the proponents of structural and reduced-form methods of research in the field of industrial organization. In both cases most academic economists probably recognize that some departments are reputed in being in one camp or another. In this paper I ask whether there exists a significant division of economics departments into clusters that prefer to hire from the same cluster (the answer is yes), whether this division has changed since the 1980s (no), and whether economics is special in having such a split (qualified yes).[2]

I use data on faculty composition by Ph.D. origin from three academic disciplines: economics, comparative literature, and mathematics. Within each discipline, I compare all possible partitions of top departments into two clusters of equal size and pick the division that minimizes hiring across clusters. I measure the significance of the division against its bootstrapped distribution under the null hypothesis of random matching between the actual sets of positions and professors. I find that economics has a very significant division, which appears to be stable over time, and is consistent with what are commonly thought of as the "Freshwater" and "Saltwater" schools of thought even up to the relative strengths

[1]Blanchard (2008) argues that the division in macroeconomics has diminished over time; the response by Chari, Kehoe and McGrattan (2009) is unenthusiastic but not entirely in disagreement.

[2]Economists' labor market has been studied extensively, with focus on wages, research output, and career progression; see reviews by Colander (1989) or Ehrenberg (2003).

of attachment to the clusters by individual departments. By contrast, the apparent division in mathematics is not stronger than what would be likely to appear under random matching. In the end I analyze the division within economics in more detail and discuss potential causes for the split.

2 Data

Lists of professors in all three disciplines were obtained from departmental home pages in 2004. The data sources for Ph.D. origin were department web pages, personal cv's, the ProQuest dissertation database, and the mathematics genealogy project *www.genealogy.ams.org*. In addition, listings of economics professors in 1987 were obtained from an old graduate study guide.[3] All tenured and tenure-track faculty (assistant, associate, and full professors) for each academic department in the sample were included, except those who were cross-listed from other departments and whose title only included other disciplines.

The full sample consists of the faculty at 120 PhD-granting departments in Economics in 2004 and 92 in 1987, 40 in Mathematics, and 42 in Comparative Literature. For Economics, the 2004 data includes all 107 U.S. departments with Ph.D. programs as listed in National Research Council's 1995 study,[4] and a further 13 universities that each had at least 5 placements in the initial sample. The 1987 data includes all U.S. departments with a Ph.D. program included in the guide.

[3] *Guide to Graduate Study in Economics, Agricultural Economics, and Doctoral Programs in Business Administration in the United States and Canada.* Edited by Wyn F. Owen and Douglas A. Ruby, The Economics Institute, Boulder Colorado, 1989.

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

For comparative literature the sample includes all departments listed in the NRC study. For mathematics the sample was defined as follows: the 10 most effective Ph.D. programs as ranked by the NRC study were used as the seed; further U.S. programs were added step-by-step if they had at least 5 placements within the existing sample; this method converged at 40 departments.[5]

The main analysis is based on analyzing the hiring patterns between 16 top U.S.-based departments, where the subset of "top departments" is defined according to a measure of influence computed from the hiring/placement matrix of the full sample. This influence measure was introduced by Pinski and Narin (1976) to rank academic journals using citation data; here the hiring of a Ph.D. graduate from another department is analogous to a journal citing another journal. The method is described in more detail in the Appendix. This measure is notable for being, with a small modification, behind the PageRank algorithm used by Google to rank web pages.[6] It was first used in economics by Liebowitz and Palmer (1984) to rank economics journals, and recently by Amir and Knauff (2008) to rank the top 50 economics departments in the world.

3 Visual Cluster Analysis

Finding clusters or "cliques" is a common task in social network analysis. Theoretically, clusters are subsets of nodes (here: departments) in a network that are more connected (here: by hiring each others' graduates) to each other than to the

[5]The reason for limiting the sample departments in mathematics was finite research assistance resources.

[6]See Page and Brin (1998), and also Palacios-Huerta and Volij (2004) who show that this ranking method has theoretically attractive properties.

rest of the network. I first apply two standard exploratory methods of looking for clusters: multidimensional scaling (MDS) and agglomerative hierarchical clustering.

MDS is a method for projecting data points into a reduced number of dimensions (typically two), so that the distances between the points represent the relative dissimilarity of the corresponding data points.[7] The results of MDS are mapped in Figure 1 where interactions (defined as hires + placements) with other departments was used to define the data point for each department. To keep the plots readable only the top 20 departments are included in each discipline. (The rankings by influence are used in defining the "top" throughout). After removing the UK-based departments as outliers, the "eyeball test" suggests a division in economics that fits the anecdotal evidence about departments from Chicago to Rochester forming a “Freshwater” school of thought, where research methodology (and possibly ideology) is on average different from that prevalent at the “Saltwater” departments from Harvard to Berkeley. The horizontal dimensions appears to capture the "degree of salinity," but it is hard to see any particular interpretation for the vertical dimension.

The pattern of the MDS map in Comparative Literature is mostly consistent with perceived notions of departments that are closer to Yale being more “theoretical” as opposed to “traditional” in their approach.[8] Mathematics does not suggest an easily interpretable pattern.

Figure 2 shows dendrograms that illustrate the results of hierarchical agglom-

[7] See Appendix B for more on the methodology of MDS, and Eagly (1975) who used it to find clusters in the citation network of economics journals.

[8] Timothy Hampton, private communication.

erative clustering.[9] There each department is initially defined as its own "cluster" at the bottom of the hierarchy. Moving upwards in the tree, the two most similar clusters are always the next to be merged into a new cluster by a horizontal connecting line. The heights of the vertical lines capture the magnitude of the dissimilarity between the clusters. The same patterns that are visible in the MDS figures also show up in the dendrograms. In economics, roughly the same set of departments appears in one side in the horizontal dimension in both Figure 1 and 2. No similar pattern jumps out for mathematics. A casual comparison of the dendrograms across disciplines suggests that in economics there is a clearer division into two clusters that encompass almost all departments (the exception being CalTech). In comparative literature there are some clear differences in the clustering suggested by Figures 1 and 2, but the nearest neighbors in the dendrogram (those whose branches join first) also appear near each other in Figure 1.

Are the visually suggested clusters real or just an artefact of human pattern recognition? To find out I next use a nonparametric method to find clusters and then test them against the null hypothesis of random matching.

4 Nonparametric Cluster Analysis

Suppose we started from a prior definition of two clusters, that is, from a given partition of departments into two bins. The null hypothesis is that every position and professor had an equal chance of being matched. How likely is it that we would observe this proportion of cross-cluster movements under the null hypothesis? A simple χ^2-test of independence could be used to check whether the hiring

[9] See Appendix C for more on this methodology.

patterns in fact exhibit significant clustering. However, when the partition has been chosen precisely to make the division appear strong then the naive χ^2-test is biased towards finding clustering. After all, even under random matching it would be possible to find some partitions with relatively few cross-cluster hires. A better question is, is there a division that is deeper than we could expect to find due to random factors?

To obtain the correct distribution for the χ^2-statistic under the null hypothesis of no clustering I created rematchings, where in each rematching the entire actual population of professors and positions were randomly matched. Then, for each rematching, all possible partitions into two clusters of equal size were considered and the χ^2-statistic for the strongest possible partition was recorded. The resulting distribution of χ^2-statistics was then used to evaluate the significance of the strongest possible partition found in the actual sample.

The number of possible partitions grows exponentially in the number of departments so, to keep the bootstrap calculations manageable, the data is restricted to the 16 most influential departments in the US. Also, as self-hires are inevitably also within-cluster hires, the apparent preference for self-hiring would be confounded with clustering. Therefore self-hires are excluded from cluster analysis, both from the data and as a possibility in the rematchings. (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 are 1.2%, 2.5%, and 2.6%.)

The results of the cluster analysis are reported in Table 1. Dividing the top 16 departments into two clusters of 8 departments so as to minimize the proportion of cross-cluster hires leads to 33.9% of all hires in Economics to be cross-clusters in 2004 and 37.5% in 1987; in Mathematics this fraction is 41.8% and in Literature 38.7%. The division within economics is so deep that none of the $10,000$ rematchings produced a division as strong as the sample value in either year. Thus it can (conservatively) be concluded that the bootstrap p-value for the test against no division within economics is below 0.0001. It is also striking that the strongest partition in Economics is exactly the same in both 1987 and 2004.[10] By comparison, in mathematics the observed division is marginally statistically significant when taking as given the best partition, with a naive p-value of 0.068. In the random matching exercise such partitions or stronger resulted in more than 27.8% of the rematchings, so I conclude that there is no evidence for a division within mathematics. In comparative literature the clustering is statistically significant, but not as strong as in economics: the sample value of the χ^2 test statistic (or higher) resulted in about 6.2% of the rematchings.

The statistically strong division within economics does not imply near-isolation between the clusters. Even after taking into account the self-hires, a full 24% of faculty trained and hired by the top 16 departments obtained their Ph.D. across the divide. Unfortunately I don't have reliable data on the field of specialization; it is plausible that the division could be much stronger among macroeconomists than in other fields.

[10] The definition of top 16 departments is based on the 2004 ranking. Hiring data for Harvard and Caltech in 1987 is missing, and Pinski-Narin influence is not defined for departments with missing hiring data. (In terms of appendix A, matrix T would become reducible). However, they can still be included in the cluster analysis as their placements are observed in the hiring data of the other departments.

5 Close-up on the Division within Economics

A strict division to discrete clusters is only an abstraction, and in practice some departments are going to be more strongly part of some cluster while others are more neutral. (This is also why having the clusters be equal-sized is not a crucial assumption; the point of the clusters is to help uncover a particular dimension of heterogeneity.) Table 2 shows the strength of the attachment to the clusters in economics in 2004, defined as the proportion of interactions (hires plus placements) that a department has with Cluster 1 (the "Saltwater" cluster) out of its interactions with all departments in the US top 16. For brevity, I call this measure the "salt content." Columbia and Berkeley are the saltiest departments at 89.5% and 85.5% respectively. (In terms of hiring only, these departments are even more extreme, with 39 out of 40 hires at Berkeley coming from other Saltwater departments.) At the other end of the spectrum are Rochester and Minnesota, with 34.6% and 35% salt content respectively. These proportions must be compared to the average salt content of 65.7% within the top 16. Yale, Stanford, and Chicago are so close to the average that they appear neutral in terms of relative connectedness with the two clusters.

With one exception, the decomposition of interactions in Table 2 reveals that the partition holds up separately for hires and placements: either way, the saltiest departments are found in the Saltwater cluster. Chicago is an exceptional case because in its hiring it is closer to the other cluster; 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, Chicago's 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 from the data, most of the Freshwater-trained faculty at Chicago are excluded from this analysis. (The impact of including self-hires can be seen in Figure 3, where influence is plotted against salt content.) When only junior faculty are included then Chicago appears in line within the rest of Freshwater cluster, perhaps because many future self-hires are still doing their junior stints at other Freshwater departments.

The salt content for departments outside the US top 16 is defined the same way, as the proportion of interactions with Saltwater departments as a fraction of all interactions with the top 16. Table 3 lists the salt content for all 91 departments that have strictly positive influence in 2004. As an aside, Table 3 also lists bootstrapped confidence intervals for the ranking by influence. It shows that, below the top 10, rankings are quite approximate; for example, only 12 schools can "confidently" be placed in the top 20, and 25 in the top 40. The reason why influence does not closely reflect the relative number of placements is that a small number of placements at top departments (such as by Caltech and Penn State) convey more influence than a large number of placements at lower ranked departments.

The level of relative connectedness to the academic clusters can be measured for any institutions that employ PhDs in that discipline. As an example of independent interest, Table 4 shows the salt content at the banks of the Federal Reserve, defined as the average salt content of the alma mater of their research economists.[11] The 13 Feds (12 district banks and the Board of Governors) are also divided along a saltwater-freshwater dimension, by more than what could be expected if the existing set of Fed economists were matched randomly with the

[11]Data on the PhD origins of Fed economists was gathered from the Fed banks' websites in October 2007.

existing numbers of positions. The level of between-Fed variance in salt content found in 10,000 random rematchings was never as high as the actual sample value. As for the individual Feds, the highest salt content is found in Boston (which could be attributed to geographical proximity to prominent Saltwater departments) while Richmond is the least salty (which can not be attributed to geography).

6 Discussion

Could mere geography explain clustering in academic labor markets? It is plausible that the costs of hiring (informational or otherwise) are increasing in geographic distance. This should result in a tendency for some aggregate measure of distance of faculty movements to be minimized, which in turn would show up as geographic clustering. Surely this is the natural explanation for why the UK-based economics departments form an outlying group in the visual cluster analysis. However, in none of the disciplines is the strongest possible division based on an obvious split on a large geographical scale. Furthermore, the lack of a significant division within mathematics seems to rule out distance as a sufficient explanation for clustering. However, geography cannot be dismissed quite so easily, because distance could have a nonlinear impact, and the sets of top departments are not exactly the same in each discipline. Perhaps there is an advantage of being in the same metro area, but not much beyond that. Notably, all four within-metro-area pairs of departments in economics are in the same cluster (Harvard/MIT and Berkeley/Stanford in the Saltwater, and Chicago/Northwestern and Caltech/UCLA in the Freshwater cluster). However, this too fails to explain why mathematics is not divided, because there are also four within-metro-area pairs in mathematics; but three of them are split across the clusters (Columbia/NYU, Caltech/UCLA and Berkeley/Stanford; the exception is Harvard/MIT).

I conclude by proposing two possible (by no means mutually exclusive) driving forces for the strong clustering in economics that can at the same time be consistent with the lack of significant clustering in mathematics. The first is informational costs. It may be harder to objectively assess a job candidate's quality in economics than in mathematics, so personal contacts are more important in selecting interviewees and in evaluating job candidates—after all, mathematics is the ultimate objective discipline. Even if there were initially only random patterns in hiring propensities, the informational advantage from personal connections would then work to strengthen existing connections, because departments that are more connected by past movements of faculty are better informed of each others' job candidates and of the level of bias in their letters of recommendation.[12] There is not necessarily anything insidious about such "cluster bias" in hiring as it could be an optimal response to the information structure in this labor market.[13]

The second possible explanation for clustering is horizontal differentiation caused by a complementarity in methodology or "research style" within departments. Consider first the fact that hiring patterns are very hierarchical in that higher ranked departments place their graduates both laterally and at lower ranked universities, while movements upwards are more rare: Of all the faculty at the top 10 economics departments, 79.6% received their Ph.D. inside the top 10. For

[12]Even if this only affected junior hiring, it would spill over to the composition of senior faculty due to the insider advantage in getting tenure (documented in Oyer 2007).

[13]Simon and Warner (1992) found support for the hypothesis that the information flow within "old boy networks" allows workers and firms to be matched more efficiently.

mathematics this figure is 58.3% and for comparative literature 63.2%.[14] Such hierarchy can easily be explained by complementarities in research quality (e.g. due to peer externalities), as these tend to generate sorting by quality ("positive assortative matching") both among faculty and students. This can be described as vertical differentiation. If, in addition, there is a "horizontal" dimension to the differentiation between individuals, and if there are complementarities also along this dimension, then it would be efficient to also sort faculty to departments by horizontal qualities. According to this explanation, mathematics does not have a dimension of horizontal differentiation at least in the sense that would be subject to complementarities between faculty members.

There is some evidence for horizontal differentiation between departments in Colander (2005) who surveyed Ph.D. students at 7 top programs. He found that students at Chicago (the only Freshwater department in the survey) held significantly different policy opinions compared to students at other schools. For example, they had the least confidence in the stabilizing potential of fiscal policy, and the most concern that minimum wages increase unemployment. In terms of rating the importance of economic assumptions Chicago students were again different (having the highest percentage of students who checked "the neoclassical assumption of rational behavior" and "the rational expectations hypothesis" as very important and "price rigidities" as unimportant) but the magnitudes of these differences were not large. Ideology is a special case of horizontal differentiation (and somewhat uncomfortable for the self-image of economists); and it seems clear that ideology can hardly be a factor in mathematics. However, in Colander's data, the students in Chicago were not unusual by their distribution of political

[14] The influence measure of Pinski and Narin is indeed based on exploiting this phenomenon.

orientation.

Appendix on Methodology

Hiring/placement data is contained in a matrix where typical element M_{ij} is the number of current faculty at department i who obtained their Ph.D. at department j. These matrices are available as supplemental content.

A. Influence weights

The Pinski-Narin influence weights $p = (p_1, \ldots, p_n)$ are defined by

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

where $T_{ij} = M_{ij} / \sum_k M_{ik}$ is a typical element of the faculty-size normalized hiring matrix. If T is irreducible (as it is with our data) then p is equivalent to the dominant eigenvector of T. In practise, p is easiest to compute by invoking its interpretation as the limiting distribution of the Markov chain defined by T, as p is now equal to any row of $\lim_{R\to\infty} T^R$.

Brin and Page (1998) offer an intuitive interpretation for p.[15] To paraphrase their story of a random web surfer for the current application, suppose that all professors in an academic discipline participate 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 sends the tag to the department where she got her Ph.D., where it is given

[15] Their PageRank algorithm yields a slightly modified version of p that guarantees unique non-zero weights even when T is not irreducible (which is often the case when T represents the link structure between a set of web pages).

to a randomly selected current faculty member. The "winner" of the draw then sends the tag to his doctoral Alma mater, where another raffle takes place, and so on. Under repeated play, the probability that the tag is held by a current faculty member of department i approaches p_i.

Robustness The influence measure in Table 3 is based on nearly complete data on faculty at PhD-granting institutions in the US. I interpret the actual placements as realizations of random draws from underlying transition probabilities. As 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.[16] The median and the confidence intervals for the rank by influence show the degree to which the rankings are dependent on individual (sometimes lucky) placements. These were obtained by bootstrap, where each professor was treated as an observation, i.e., a combination of an alma mater and a current employer. The bootstrap used 10000 resamplings, where each resampling was a set of 3174 professors drawn with replacement from the actual population of 3174. The lower bounds indicates how many departments are outranked in a pairwise sense in at least 95% of resamplings (similarly 5% for the upper bound). For example, MIT ranked above Harvard in 54.9% of resamplings, while both ranked above all other departments over 99% of the time. Hence MIT and Harvard form a robust top 2 but their relative rank is not robust. In general, the rankings are much 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. (The lower bound is left empty for departments that didn't outrank anyone in at least 95% of the resamplings.) The

[16] For example, the most valuable placement in economics is to MIT, where it conveys $17.120/37 \approx 0.46$ percentage points of influence weight to the alma mater.

ranking by influence is better described as a pyramid than a pecking order.

B. Multidimensional scaling (MDS)

The $n \times n$ matrix of normalized interactions is defined by typical element $X_{ij} = (M_{ij} + M_{ji}) / \sum_h M_{ih}$. The rows of X represent observations (i.e., academic departments) in n-dimensional space. The dissimilarity between departments i and j is defined as the absolute value distance

$$D_{ij} = \sum_h |X_{ih} - X_{jh}| . \tag{2}$$

Define the matrix A with typical element $A_{ij} = -(1/2) D_{ij}^2$, the centering matrix $H = I - (1/n)ee'$, where e is the all-ones vector, and the contrast matrix $B = HAH$. Find the two largest eigenvalues of B, $\lambda_1 > \lambda_2$, and the corresponding eigenvectors, z_k, normalized so that $z_k' z_k = \lambda_k$, ($k = 1, 2$). Finally, the two-dimensional coordinates for the observations (depicted in Figure 1) are obtained as the rows of $(z_1 \; z_2)'$. Note that only the relative locations are determined—the maps are indeterminate with respect to rotation, reflection, and translation. For more information, see Chapter 14 in Mardia, Kent, and Bibby (1979), and Stata documentation for commands *mds* and *mdsmat.*

C. Agglomerative hierarchical clustering

Hierarchical cluster analysis is based on repeated application of the average linkage recurrence formula

$$D_{k(ij)} = \frac{n_i}{n_i + n_j} D_{ki} + \frac{n_j}{n_i + n_j} D_{kj}, \tag{3}$$

where n_i is the number of observations in group i and $D_{k(ij)}$ is the dissimilarity between cluster k and the new cluster formed by joining clusters i and j. Initially each observation is defined as a cluster, with pairwise dissimilarities D_{ij} defined by (2). Then the two most similar clusters are merged and defined as a new cluster, and the distances between the new cluster and the other clusters are defined by (3) and depicted as the height of the joining branch in the dendrogram; this step is repeated until there is only one cluster left. For more information, see Chapter 9 in Timm (2002), and Stata documentation for commands *cluster averagelinkage* and *cluster dendrogram*.

References

AMIR, RABAH AND MALGORZATA KNAUFF (2008): "Ranking Economics Departments Worldwide on the Basis of PhD Placement." *Review of Economics and Statistics*, 90(1), pp. 185–190.

BLANCHARD, OLIVIER (2008): The State of Macro. *NBER Working Paper* 14259.

BRIN, SERGEY AND LAWRENCE PAGE (1998): "The Anatomy of a Large-Scale Hypertextual Web Search Engine." *Computer Networks and ISDN Systems*, 30, 107–117.

CHARI, V V; PATRICK J KEHOE AND ELLEN R MCGRATTAN (2009): New Keynesian Models: Not Yet Useful for Policy Analysis. *American Economic Journal: Macroeconomics*, 1(1), pp. 242–266.

COLANDER, DAVID (1989): "Research on the Economics Profession." *Journal of Economic Perspectives* , 3(4), pp.137–148.

COLANDER, DAVID (2005): "The Making of an Economist: Redux." *Journal* *of Economic Perspectives* , 19(1), pp. 175–198.

EAGLY, ROBERT V (1975): "Economics Journals as a Communicating Network," *Journal of Economic Literature,* 13(3), pp. 878–888.

EHRENBERG, RONALD G (2003): "Studying Ourselves: The Academic Labor Market," *Journal of Labor Economics,* 21, pp. 267–287.

LIEBOWITZ STAN J AND JOHN P PALMER (1984): "Assessing the Relative Impacts of Economics Journals." *Journal of Economic Literature*, 22(1), pp. 77–88.

MARDIA, KANTI V; J T KENT AND J M BIBBY (1979): Multivariate Analysis. *London: Academic Press.*

OYER, PAUL (2007): "Is There an Insider Advantage in Getting Tenure?" *AER Papers & Proceedings*, 97, 501–505.

PALACIOS-HUERTA, IGNACIO AND OSCAR VOLIJ (2004): "Measurement of Intellectual Influence." *Econometrica*, 72(3), pp. 963–977.

PINSKI, GABRIEL AND FRANCIS NARIN (1976): "Citation influence for Journal Aggregates of Scientific Publications: Theory, with Application to the Literature of Physics." *Information Processing and Management*, 12, pp. 297–312.

SIMON, CURTIS J AND JOHN T WARNER (1992): "Matchmaker, Matchmaker: The Effect of Old Boy Networks on Job Match Quality, Earnings, and Tenure." *Journal of Labor Economics*, 10(3), pp. 306–330.

TIMM, NEIL (2002): Applied Multivariate Analysis. *New York: Springer.*

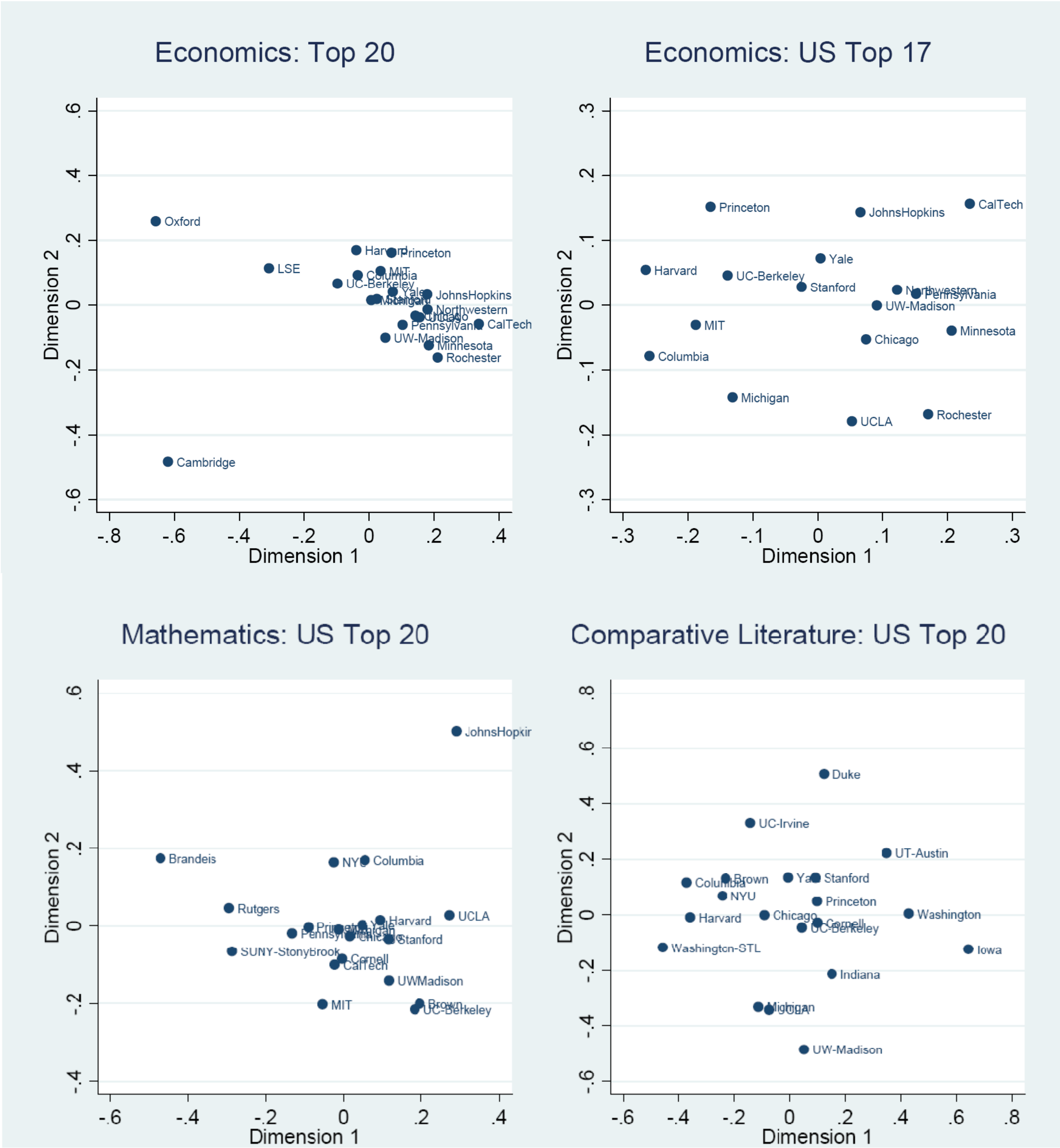

Figure 1. Hiring/placement patterns between top 20 departments, as illustrated by Multidimensional Scaling (MDS). Top right panel shows the analysis repeated for economics after removing the outliers (UK-based departments). Nearby data points indicate departments with similar hiring and placement patterns. See Appendix for details.

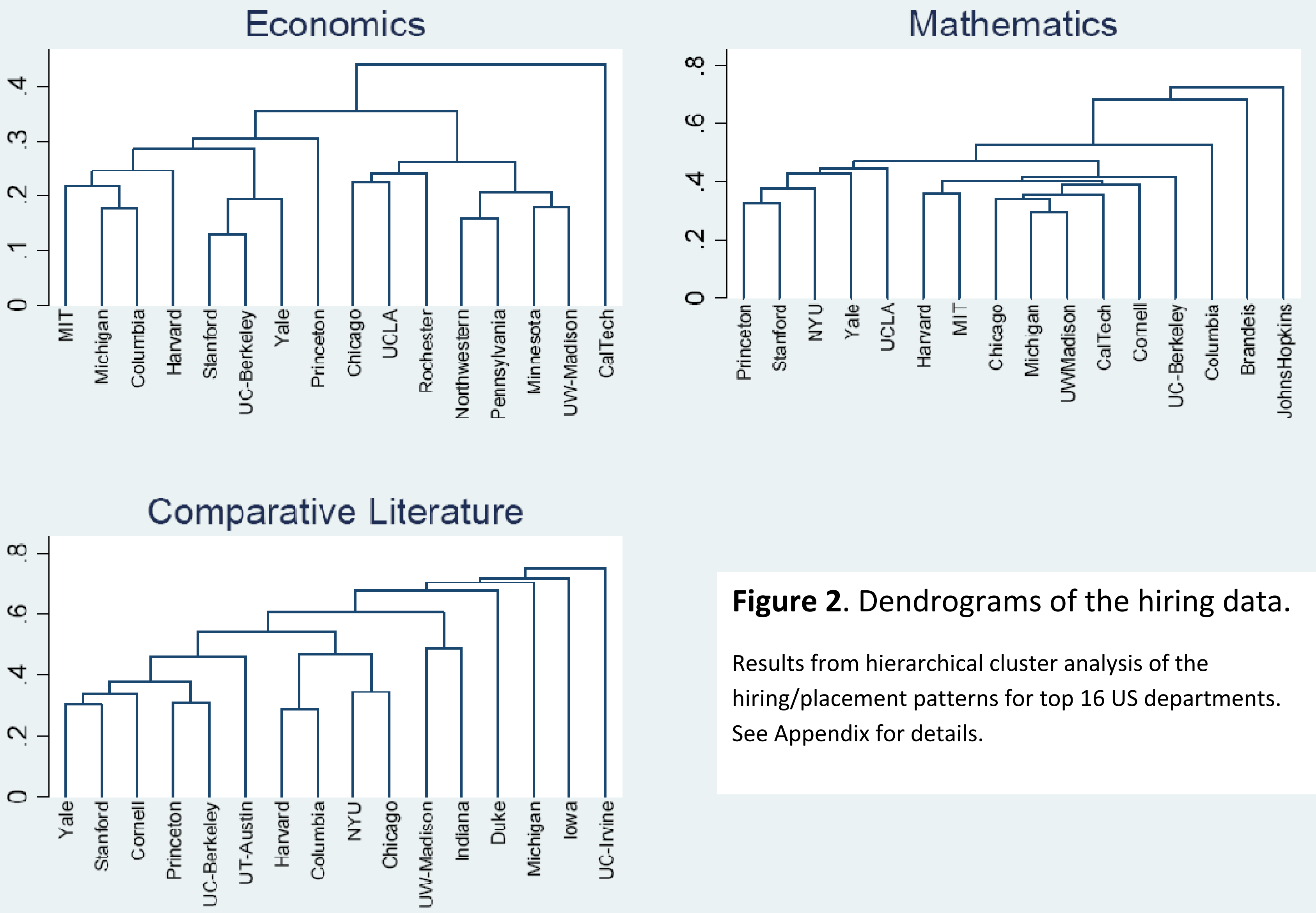

Figure 2. Dendrograms of the hiring data.

Results from hierarchical cluster analysis of the hiring/placement patterns for top 16 US departments. See Appendix for details.

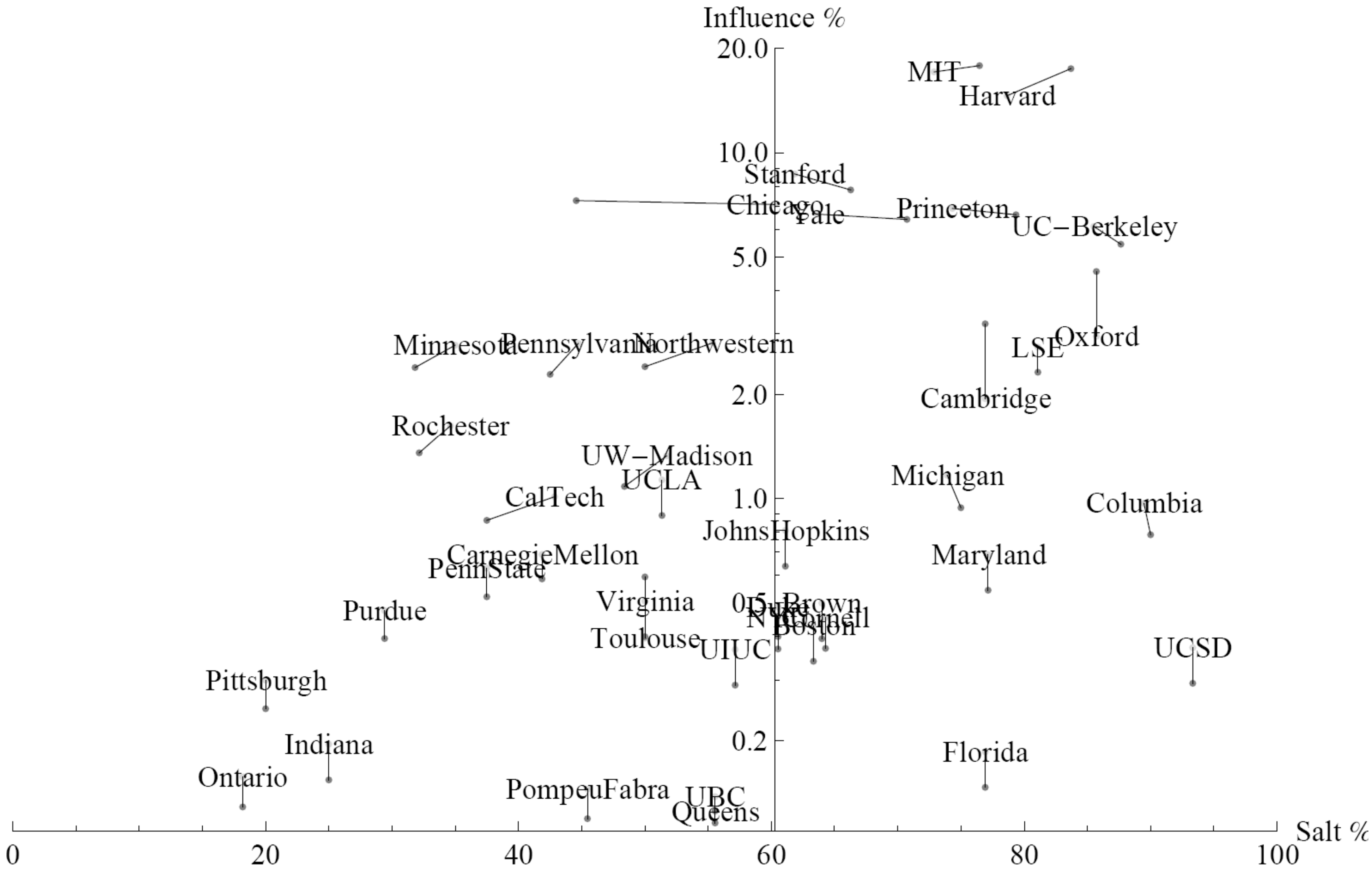

Figure 3. Influence and division within economics. Horizontal axis represents the proportion of US Top 16 placements and hires to/from Saltwater cluster, see Table 2. Vertical axis represents influence in the hiring network, in the sense of Pinski and Narin (1976). The connected dots show the results when self-hires are *not* excluded from the data.

Table 1. Testing for a partition of Top 16 US PhD-granting departments into two clusters

	Proportion cross-hires	Naïve p-value*	Bootstrapped p-value*	# Movers: C1->C1	# Movers: C1->C2	# Movers: C2->C1	# Movers: C2->C2
Economics (2004)	0,339	1,570E-08	< 0,0001	219	104	48	78
Economics (1987)	0,375	2,865E-06	< 0,0001	178	115	27	59
Mathematics	0,418	0,068	0,278	169	106	53	52
Comparative Literature	0,387	0,002	0,062	64	46	24	47

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

* χ^2-test (df=1) against the null of random matching across clusters. Bootstrap with 10,000 rematchings.

** Top 16 departments based on the influence ranking in 2004. The strongest partition is exactly the same in 1987 and 2004.

Table 2. Close-up on the clusters in Economics in 2004.

Rank by influence		# Interactions with US Top 16	Proportion with Saltwater cluster ("Salt content")		# Placements to US Top 16	Proportion to Saltwater cluster		# Hires from US Top 16	Proportion from Saltwater cluster		# Interactions with US Top 16 (juniors)	Proportion with Saltwater cluster		# Self-hires
	<u>Cluster 1 ("*Saltwater*")</u>													
19	Columbia	38	0,895	***	4	0,500		34	0,941	***	17	0,882	**	1
7	UC-Berkeley	69	0,855	***	29	0,690		40	0,975	***	21	0,905	***	6
2	Harvard	103	0,786	***	74	0,770	***	29	0,828	*	36	0,861	***	16
5	Princeton	74	0,743		38	0,684		36	0,806	*	24	0,625		9
16	Michigan	46	0,739		6	0,500		40	0,775		16	0,688		1
1	MIT	118	0,729		94	0,713	**	24	0,792		33	0,879	***	9
6	Yale	66	0,636		35	0,571		31	0,710		21	0,571		8
3	Stanford	76	0,618		43	0,558		33	0,697		30	0,600		5
	Cluster 1	*590*	*0,742*	***	*323*	*0,678*	***	*267*	*0,820*	***	*198*	*0,758*	***	*55*
	<u>Cluster 2 ("*Freshwater*")</u>													
4	Chicago	68	0,603		37	0,459	*	31	0,774		27	0,407	**	12
9	Northwestern	56	0,554		24	0,417	*	32	0,656		24	0,458	*	3
15	UW-Madison	29	0,517		6	0,333		23	0,565		9	0,111	***	1
17	UCLA	37	0,514	*	5	0,400		32	0,531		12	0,583		0
10	Pennsylvania	38	0,447	**	14	0,571		24	0,375	***	16	0,375	**	1
18	Caltech	14	0,429		5	0,200	*	9	0,556		5	0,600		1
11	Minnesota	40	0,350	***	23	0,174	***	17	0,588		11	0,182	***	2
14	Rochester	26	0,346	***	12	0,333	*	14	0,357	**	11	0,364	*	1
	Cluster 2	*308*	*0,494*	***	*126*	*0,381*	***	*182*	*0,571*	***	*115*	*0,391*	***	*21*
	US Top 16	*898*	*0,657*		*449*	*0,595*		*449*	*0,719*		*313*	*0,623*		*76*

***/**/* indicates 1%/5%/10% statistical significance of χ^2-test against the null of random matching with rest of US Top 16.

Self-hires are excluded everywhere except in the last column.

Interactions = Hires + Placements.

Juniors = Assistant and Associate professors.

Table 3. Economics: Results for departments with strictly positive influence in 2004.

Rank	University	Salt	*p-value*	Influence	*Md*	*C.I. 95%*	Placements	Hires	Self-hires		1987 Salt	1987 Influence
1	MIT	0,729	+ *0,005*	17,120	*1*	*(1,2)*	215	37	9	.	0,659	18,891
2	Harvard	0,786	+ *0,000*	14,616	*2*	*(1,2)*	214	47	16	.	0,662	
3	Stanford	0,618	*0,773*	8,682	*3*	*(3,6)*	156	42	5	.	0,633	10,588
4	Chicago	0,603	*0,991*	7,085	*5*	*(3,7)*	177	53	12	.	0,449	8,163
5	Princeton	0,743	+ *0,013*	6,902	*5*	*(3,7)*	117	53	9	.	0,750	11,593
6	Yale	0,636	*0,571*	6,646	*5*	*(3,7)*	134	45	8	.	0,774	10,799
7	UC-Berkeley	0,855	+ *0,000*	6,125	*6*	*(3,8)*	173	56	6	.	0,789	6,994
8	Oxford	0,857	+ *0,017*	2,947	*10*	*(7,18)*	49	42	19	.	0,800	
9	Northwestern	0,554	*0,457*	2,821	*10*	*(8,14)*	112	40	3	.	0,500	1,480
10	Pennsylvania	0,447	*0,051*	2,811	*10*	*(8,17)*	91	35	1	.	0,717	5,006
11	Minnesota	0,350	- *0,001*	2,779	*10*	*(8,14)*	100	25	2	.	0,581	4,570
12	LSE	0,811	+ *0,010*	2,743	*10*	*(8,16)*	45	54	3	.	0,667	
13	Cambridge	0,769	*0,219*	1,947	*13*	*(9,21)*	36	31	13	.	1,000	
14	Rochester	0,346	- *0,008*	1,624	*14*	*(10,22)*	58	20	1	.	0,345	1,969
15	UW-Madison	0,517	*0,350*	1,326	*16*	*(12,22)*	112	30	1	.	0,750	2,183
16	Michigan	0,739	*0,058*	1,166	*17*	*(11,28)*	70	47	1	.	0,759	2,479
17	UCLA	0,514	*0,270*	1,131	*18*	*(11,32)*	41	40	0	.	0,484	0,341
18	Caltech	0,429	*0,184*	1,012	*19*	*(11,36)*	18	14	1	.	0,000	
19	Columbia	0,895	+ *0,000*	0,968	*19*	*(14,29)*	65	38	1	.	0,744	5,658
20	Johns Hopkins	0,611	*0,939*	0,808	*21*	*(14,34)*	30	17	0	.	0,375	1,734
21	Carnegie Mellon	0,419	- *0,014*	0,690	*22*	*(16,34)*	29	56	4	.	0,143	
22	Maryland	0,771	+ *0,041*	0,689	*23*	*(14,40)*	24	39	0	.	0,786	0,729
23	PennState	0,375	*0,063*	0,629	*24*	*(13,75)*	15	24	1	.	0,353	0,016
24	Virginia	0,500	*0,350*	0,506	*26*	*(17,41)*	31	27	0	.	0,500	0,163
25	Brown	0,640	*0,700*	0,499	*26*	*(18,39)*	36	30	0	.	0,471	0,164
26	Duke	0,605	*0,970*	0,486	*27*	*(17,41)*	39	50	2	.	0,429	0,373
27	Purdue	0,294	- *0,009*	0,475	*27*	*(18,41)*	36	22	1	.	0,091	0,580
28	NYU	0,605	*0,970*	0,455	*27*	*(19,38)*	26	41	1	.	0,643	0,021
29	Cornell	0,643	*0,661*	0,454	*28*	*(19,37)*	50	35	1	.	0,519	0,838
30	Boston	0,633	*0,728*	0,430	*28*	*(18,49)*	14	33	0	.	0,880	0,124
31	Toulouse	0,500	*0,509*	0,396	*29*	*(20,39)*	22	28	9	.		
32	UCSD	0,933	+ *0,000*	0,371	*30*	*(20,40)*	35	34	0	.	0,833	1,783
33	UIUC	0,571	*0,710*	0,367	*30*	*(19,49)*	37	40	0	.	0,765	0,527
34	Pittsburgh	0,200	- *0,009*	0,299	*32*	*(21,52)*	16	24	1	.	0,643	0,005
35	Indiana	0,250	- *0,013*	0,196	*35*	*(22,74)*	20	21	0	.	0,588	0,110
36	Florida	0,769	*0,219*	0,186	*37*	*(23,81)*	10	18	0	.		
37	Western Ontario	0,182	- *0,000*	0,157	*37*	*(28,55)*	15	30	1	.	0,000	
38	Pompeu Fabra	0,455	*0,317*	0,145	*38*	*(28,69)*	6	48	1	.		
39	UBC	0,556	*0,686*	0,138	*38*	*(28,62)*	15	30	4	.		
40	Queens	0,556	*0,686*	0,125	*38*	*(31,51)*	19	29	4	.		
41	Iowa	0,438	*0,178*	0,113	*39*	*(33,51)*	23	23	2	.	0,294	0,029
42	CUNY	0,600	*0,977*	0,085	*42*	*(30,)*	10	62	5	.	0,000	
43	U-Washington	0,550	*0,633*	0,070	*44*	*(35,61)*	29	24	1	.	0,643	0,084
44	BC	0,632	*0,794*	0,068	*45*	*(32,)*	6	28	0	.	0,650	0,000
45	Michigan State	0,625	*0,820*	0,061	*45*	*(36,67)*	26	41	2	.	0,563	0,446
46	EUI	0,400	*0,356*	0,058	*46*	*(34,78)*	5	12	0	.		
47	Rice	0,500	*0,469*	0,055	*46*	*(36,82)*	8	19	1	.	0,556	0,140
48	SUNY-StonyBrook	0,750	*0,393*	0,051	*47*	*(36,72)*	9	14	0	.	0,556	0,001
49	Colorado	0,300	*0,051*	0,049	*49*	*(34,84)*	10	30	0	.	0,375	0,125
50	Toronto	0,730	*0,113*	0,039	*49*	*(39,68)*	8	61	3	.		
51	Iowa State	0,458	*0,150*	0,033	*51*	*(40,71)*	18	50	4		0,545	0,256
52	Tulane	0,250	*0,150*	0,030	*53*	*(38,)*	5	12	0		0,000	
53	Kentucky	0,250	- *0,042*	0,026	*56*	*(39,)*	5	19	1		0,250	0,103
54	UNC	0,571	*0,773*	0,026	*53*	*(41,67)*	27	30	1		0,700	0,209
55	Ohio State	0,500	*0,269*	0,026	*53*	*(42,69)*	25	36	0		0,679	0,054
56	Louisiana State	0,667	*0,820*	0,025	*56*	*(39,)*	4	14	1		0,200	0,031
57	GMU	0,375	*0,063*	0,019	*58*	*(41,)*	4	29	2		0,143	0,000
58	SUNY-Albany	0,267	- *0,008*	0,018	*59*	*(41,)*	5	22	1		0,500	0,030
59	UC-Davis	0,864	+ *0,012*	0,018	*57*	*(43,88)*	8	28	0		0,667	0,038

Table 3 continued.

Rank	University	Salt	p-	Influence	Md	C.I. 95%	Placements	Hires	Self-hires	1987 Salt	1987 Influence
60	Missouri-Columbia	0,364	*0,106*	0,016	*58*	*(44,83)*	6	19	0	0,000	
61	TexasAM	0,263	- *0,003*	0,015	*61*	*(44,76)*	19	31	1	0,438	0,011
62	Oregon	0,500	*0,609*	0,014	*62*	*(43,)*	3	18	0	0,250	0,066
63	WestVirginia	0,000	*0,219*	0,014	*62*	*(44,)*	3	16	0	0,000	
64	Hebrew	0,583	*0,894*	0,013	*60*	*(47,76)*	12	23	6	0,000	
65	USC	0,550	*0,633*	0,012	*65*	*(44,90)*	7	35	0	0,467	0,015
66	Arizona	0,636	*0,817*	0,011	*67*	*(44,)*	3	21	0	0,571	0,010
67	Claremont	0,000	*0,082*	0,011	*63*	*(45,)*	4	5	0	0,571	0,000
68	SouthCarolina	1,000	*0,104*	0,011	*63*	*(46,)*	1	16	0	0,750	0,000
69	Rutgers	0,350	- *0,021*	0,009	*63*	*(50,84)*	12	30	1	0,654	0,000
70	Washington-STL	0,688	*0,486*	0,009	*62*	*(52,74)*	21	21	0	0,538	0,009
71	VPI	0,375	*0,189*	0,008	*63*	*(51,78)*	12	15	0	0,333	0,011
72	WashingtonState	0,429	*0,348*	0,007	*65*	*(51,)*	4	12	0	0,500	0,137
73	UT-Austin	0,667	*0,519*	0,006	*67*	*(53,85)*	15	30	2	0,824	0,083
74	NC-State	0,286	- *0,016*	0,004	*71*	*(55,)*	9	27	1	0,357	0,008
75	UCSB	0,737	*0,231*	0,003	*71*	*(59,)*	9	29	0	0,500	0,016
76	SouthernIllinois	0,000	*0,082*	0,002	*72*	*(59,)*	4	10	0	0,000	
77	NewSchool	1,000	*0,159*	0,002	*73*	*(60,85)*	8	6	0	1,000	
78	Vanderbilt	0,250	- *0,004*	0,002	*72*	*(61,90)*	8	34	2	0,375	0,174
79	SMU	0,200	*0,066*	0,002	*74*	*(60,)*	4	18	0	0,000	
80	UMass-Amherst	0,938	+ *0,006*	0,002	*74*	*(60,)*	10	24	1	0,810	0,002
81	Kansas	0,200	- *0,009*	0,002	*82*	*(60,)*	7	19	0	0,267	0,000
82	Tennessee	0,000	*0,000*	0,001	*74*	*(63,)*	3	15	0	0,500	0,000
83	FloridaState	0,333	*0,178*	0,001	*79*	*(63,)*	4	32	0	0,000	
84	Auburn	0,000	*0,000*	0,001		*(64,)*	1	11	0	0,500	0,000
85	SUNY-Binghamton	0,889	*0,079*	0,000	*81*	*(68,)*	4	21	0	0,867	0,007
86	Syracuse	0,684	*0,465*	0,000	*78*	*(70,)*	11	30	3	0,500	0,002
87	Utah	0,700	*0,528*	0,000	*82*	*(70,)*	5	20	3	0,714	0,000
88	ArizonaState	0,250	- *0,042*	0,000		*(75,)*	3	30	0	0,286	0,000
89	UC-Riverside	0,818	*0,143*	0,000		*(76,)*	1	21	0	1,000	0,006
90	American	1,000	+ *0,015*	0,000		*(75,)*	7	23	3	1,000	0,000
91	SUNY-Buffalo	0,417	*0,189*	0,000	*85*	*(76,)*	6	18	1	0,000	
	Others (in sample)	0,561		0,398			32	515	13	0,568	1,295
	Others (out of sample)						173				
	All	0,602		100			3174	3174	202	0,608	100

Rank: ordering by Influence, as defined by Pinski and Narin (1976), but with self-hires excluded
A further 29 sample departments are unranked (have no influence) because they have no placements at any department with influence
Salt: proportion of interactions with "Saltwater" cluster out of all interactions with US top 16; see Table 2 for definitions
+/- significantly above/below sample mean, at 5% level
p-value of χ2-test against the null of equality with the sample mean
Bootstrap of 10,000 resamplings from the population of actual matches (PhD-origin current-employer pairs)
Md: median rank by influence
C.I.: quantiles 0.025 and 0.975 for the rank by influence
Empty values indicate resamplings where the university ended up unranked
Placements: Number of placements in the sample department
Hires: Number of current faculty with known PhD origin. Faculty with missing PhD origin (total 35 in 2004 and 16 in 1987) are excluded from all counts
Interactions: Hires from and placements to US Top 16 departments (excluding self-hires)
Self-Hires: Number of faculty with PhD from same department
Salt (1987): not defined for departments with no interactions with either cluster
Influence (1987): not defined for departments without hiring data

Table 4. Salt Content of Research Economists at the Federal Reserve Bank

Fed	N	Mean	St.dev	p-value
Atlanta	25	0,512	0,162	0,026
Board of Governors	105	0,643	0,137	0,000
Boston	15	0,688	0,109	0,006
Chicago	34	0,578	0,159	0,858
Cleveland	16	0,503	0,135	0,030
Dallas	25	0,496	0,190	0,015
Kansas City	12	0,637	0,194	0,262
Minneapolis	19	0,533	0,154	0,107
New York	56	0,643	0,139	0,006
Philadelphia	14	0,539	0,175	0,181
Richmond	18	0,440	0,116	0,000
San Francisco	19	0,647	0,130	0,104
St. Louis	22	0,492	0,218	0,006
*All**	380	0,587	0,166	
Feds	13	0,565	0,078	< 0.0001**

Mean: Average salt content of research economists by PhD origin (from Table 3).

p-value: Mann-Whitney test against the null that salt content is same as in the rest of sample.

*Not including 46 researchers with PhD origin either unknown or from outside the sample departments.

**Bootsrapped p-value against the null that between-Fed variation in salt content is due to random matching: The maximum between-group st.dev. in 10,000 random matchings was 0.0677.