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Is Economics a House Divided? Analysis of Citation Networks*

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Abstract

We investigate divisions within the citation network in economics using citation data between 1990 and 2010. We consider all partitions of top institutions into two equal-sized clusters, and pick the one that minimizes cross-cluster citations. The strongest division is much stronger than could be expected to be found under idiosyncratic citation patterns, and is consistent with the reputed freshwater/saltwater division in macroeconomics. The division is stable over time, but varies across the fields of economics.

Keywords: citations, clustering, influence, schools of thought

JEL Codes: A11, D85, I23

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1 Introduction

We ask whether the academic discipline of Economics is divided into clusters of universities where authors tend to cite authors from the same cluster more than could be expected under idiosyncratic differences in citation patterns. We use citation data between top economics journals from 1990 to 2010 to construct the citation matrix between authors' home institutions. We compare all possible partitions of top universities into two equal-size clusters. We find a significant division between top universities in this citation network, and it is consistent with what is commonly thought as the divide between "freshwater" and "saltwater" schools.

The likelihood of citing a paper by an author from another university in the same cluster is about 16% higher than the likelihood of citing a paper by an author from the other cluster. We assess the statistical significance of this division using simulations. In each simulated citation network, the likelihood of citation propensities is independent across university pairs, while average citation propensities and the distribution of pairwise deviations from average propensities at each university match their empirical counterparts. The division is statistically extremely significant, and is robust to considering different extents of "top universities" and time periods. However, there are significant differences across fields of economics, with macroeconomics and econometrics exhibiting the strongest division whereas finance and international economics exhibit rather weak division.

2 Data

2.1 Data Sources

We use the citation data of articles published in 102 economics journals between 1990 and 2010, where the set of top journals was taken from the classification by Combes and Linnemer (2010).[1] The data was obtained from Thomson Scientific's Web of Science, which is an online database pooling journal articles' data from major databases including Science Citation Index Expanded (SCI-EXPANDED), Social Sciences Citation Index (SSCI), Arts and Humanities Citation Index (A&HCI). Notes, editorials, proceedings, reviews, and discussions were not included. The resulting data cover $97,526$ unique articles with $34,431$ unique contact authors and 1187 unique affiliations associated with these contact authors.

Our data set contains information on articles cited in the reference sections of these articles. Data on cited articles consist of year of publication, name of journal and name

[1] For the list of journals and their summary statistics, see Table $A.1$ in the appendix.

of the contact author.[2]

2.2 Construction of the Citation Matrix

We use articles published between 1990 and 2010 and articles cited by them to construct a citation matrix between institutions. Data on contact authors of citing articles contain also their affiliation at the time of publication. However, author affiliations for cited articles are not directly observed. Hence we construct a career path for each author from 1977 to 2010 by using affiliation information of citing articles. For this task we also use data on articles published between 1977 and 1989, in order to enlarge the set of cited articles that can be matched with an author affiliation. If an author did not publish in our sample journals in a year then we use his or her next known affiliation; if no affiliation is observed between the cited year and 2010, then we use the last previously observed affiliation. Using this procedure, we are able to identify $36,189$ unique authors of a total of $1,662,212$ cited articles in the reference sections of $91,635$ unique articles written by $32,572$ unique authors. Authors of a total of $753,230$ cited articles could not be matched with an affiliation. The observed affiliations form a total of 1187 citing and 1192 cited institutions.

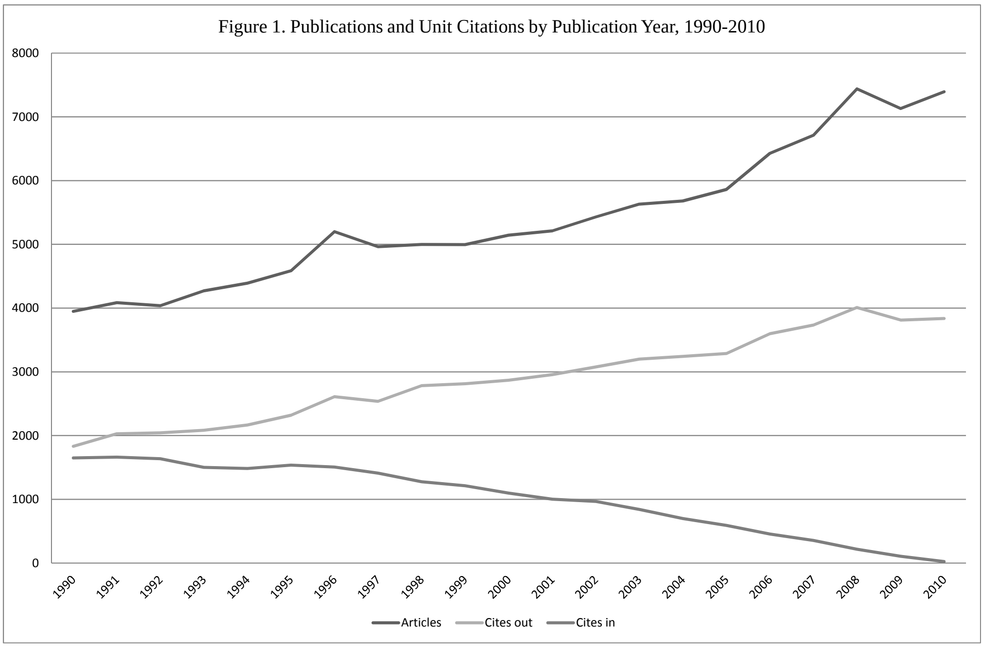
We measure citations in units, so that every article conveys one unit of citations, regardless of how many documents it cites. For example, if an article by an author from MIT cites 20 articles, and 4 of them by Harvard authors, then this counts as $4/20 = 0.2$ units of citations from MIT to Harvard.[3] Cited publications whose author cannot be matched with an affiliation are treated as authored at an institution called "Unknown".

Citation data is gathered in the aggregate citation matrix, which gives the sum of unit citations from all articles. The element at row i and column j is the sum of unit citations by authors from institution i to articles by authors from institution j. To analyze subsets of institutions we just keep the relevant submatrix of the aggregate citation matrix; when analyzing subsets of journals and publication years we restrict the underlying summation to subsets of articles.

Figure 1 shows the distribution of articles in our data by publication year. Steady increase in the annual number of articles reflects an increase in the number of journals as well as increase in articles per journal-year. Of the 102 journals in the set 79 were in existence in 1990 and 96 in 2000. The average number of articles published in a journal per year increased from 50 in 1990 to 54 in 2000, and to 73 in 2010. Figure 1 also shows the distribution of unit citations that are used in the construction of our

[2] For cited articles with multiple authors only the affiliation of the contact author is available.

[3] It would be ideal to also divide citations for multi-author documents proportionally between the authors, but observing only on the contact author affiliation precludes this.



citation matrix by publication year. The number of "Cites out" and "Cites in" in a given year refer the amount of unit citation for which an author affiliation could be identified, respectively for citations made and citations received.

3 Analysis

Our goal is to find out whether institutions can be divided into "clusters" within which authors cite each other more than could be expected under idiosyncratic citation patterns. The existence of discrete clusters is, of course, an abstraction; the point of this exercise is to uncover a dimension of differentiation in the citation patterns of institutions. Self-citations are a serious confounding factor, because citations within an institution are necessarily also within-cluster citations. Over 10% of cites in our data are institutional self-cites.[4] We ignore all self-citations, effectively replacing the diagonal elements of the citation matrix with zeroes.

To measure clustering we use a slightly modified version of Q-modularity of Girvan and Newman (2002).[5] For a given partition of institutions to clusters, Q measures the difference between the actual and expected proportion of cites between clusters,

[4]Note that we cannot distinguish between authors citing themselves, and authors citing their peers at the same institution, because we only have data on contact author affiliation.

[5]Newman (2004) shows that this method, although originally defined for binary networks, is also suitable for weighted networks.

where the expectation is calculated under independently distributed citation patterns. The strongest division in the network is that which maximizes modularity. Our additional normalization takes into account the impact of removing self-citations on expected citation patterns. Without this correction, the expectation benchmark would always predict a significant amount of self-citations. With the correction, expected self-citations are set to zero. Intuitively, the expected citation patterns are calculated under the hypothesis that authors at all institutions distribute their outbound non-self cites at a probability that depends only on target institution, not on sender institution. Analyzing proportions instead of cite counts also serves as a normalization that gives each institution equal weight in defining the strength of deviations from expectation, regardless of its share of all citations.

Denote the aggregate citation matrix for the set of n institutions by M. The normalized citation matrix T has typical elements

$$T_{ij} = M_{ij} / \sum_{h \neq i} M_{ih} \tag{1}$$

and we set $T_{ii} = 0$. Row i measures citations as proportions of outbound non-self cites from institution i. We define its expectation as the average fraction of non-self citations by departments other than i going to department j:

$$E_{ij} = \frac{1}{n-2} \sum_{h \neq i} T_{hj} \quad \text{for } h \neq j \tag{2}$$

and $E_{ii} = 0$, for $i = 1, \ldots, n$. Finally, the citation information that is used in the analysis is contained in the matrix of deviations from expected citation patterns $\Omega = T - E$.

Table 1 shows the unit citations between the top 20 academic institutions, i.e., the matrix M. The background colors represent a heat map of the pairwise deviations from expected citation patterns, i.e., the elements of Ω. If a row department cites a column department more (less) than expected then the corresponding element is red (blue), while darkness captures the magnitude of the deviation. Consider, for example, the element at first column and second row, 4.6. It is the sum of unit citations made by articles with a contact author at the University of Rochester to articles where the contact author is affiliated with the University of Minnesota. It could mean, for example, that there were 46 articles by Rochester authors that cited Minnesota authors, and that 10% of the citations in each of those articles referred to articles by Minnesota authors, giving a total of 4.6 unit citations. Moreover, the relatively dark shade of this cell reveals that 4.6 is clearly above the expected number of unit citations from Rochester to Minnesota, where the expectation is based on the total amount of (non-self) unit citations made and received by these two institutions in our data.

	Minnesota	Rochester	Penn	NYU	Carnegie Mellon	Northwestern	UCLA	Cornell	Wisconsin	Chicago	Michigan	UCSD	Yale	Stanford	Columbia	LSE	Harvard	Princeton	MIT	UC Berkeley
Minnesota	44.4	5.3	8.9	5.7	5.3	9.9	6.4	4.3	5.6	15.1	3.4	2.8	6.0	11.2	4.9	2.8	14.0	6.9	11.4	7.1
Rochester	4.6	44.2	7.9	5.4	5.6	11.7	4.8	2.5	2.7	16.7	6.1	4.1	8.3	11.0	3.6	3.0	12.8	6.9	8.7	4.6
Penn	9.6	13.4	90.2	12.7	9.4	22.2	10.4	6.7	10.5	40.5	9.8	4.8	15.0	23.3	14.1	5.9	36.0	19.9	26.2	13.7
NYU	7.9	15.2	18.5	72.7	8.1	20.6	12.3	6.7	8.4	34.8	8.1	7.4	11.5	22.3	16.0	7.3	32.5	19.5	24.0	13.4
Carnegie Mellon	2.6	3.6	5.8	4.1	26.2	5.9	3.8	4.1	2.5	12.2	3.7	1.7	5.9	11.3	3.9	1.5	10.0	5.1	7.3	4.2
Northwestern	8.3	15.3	20.7	10.5	9.7	105.1	11.3	7.0	10.4	36.5	9.6	8.3	14.4	29.8	10.6	7.1	32.0	20.7	29.5	15.2
UCLA	6.9	8.7	13.6	9.1	5.8	15.2	64.4	5.0	6.7	28.1	7.4	5.6	10.1	21.9	9.5	3.5	27.6	13.5	19.3	13.2
Cornell	6.4	6.4	9.4	7.0	4.8	11.0	7.8	64.9	8.2	18.8	8.5	5.8	10.6	14.9	6.4	5.8	18.8	13.3	15.4	11.6
Wisconsin	5.3	7.2	13.0	7.4	6.7	14.3	8.3	6.0	67.8	21.0	9.7	7.3	9.9	16.7	7.7	5.5	21.4	15.2	18.0	17.3
Chicago	6.2	12.7	18.2	11.1	9.3	24.3	14.0	7.9	9.8	135.8	11.7	8.9	18.5	26.1	10.7	5.8	46.8	22.7	35.0	15.3
Michigan	4.7	11.0	14.4	7.7	3.7	12.8	8.6	5.6	9.0	25.5	64.5	6.6	10.5	18.6	8.6	4.5	34.0	16.4	17.8	11.4
UCSD	2.3	6.4	6.3	3.3	3.3	8.5	4.3	2.0	4.8	11.4	4.9	40.6	8.2	9.9	3.3	3.0	13.9	10.1	9.9	7.5
Yale	5.6	5.6	11.5	5.7	4.3	12.9	7.5	3.5	6.2	18.0	6.5	5.2	80.0	17.4	8.4	7.0	22.6	13.6	16.8	10.9
Stanford	7.1	12.2	16.8	9.1	10.2	24.9	12.9	6.3	7.1	32.0	11.3	8.2	17.4	123.3	13.8	5.8	41.8	19.9	31.6	24.5
Columbia	4.8	10.0	13.9	9.3	6.7	14.8	8.2	4.5	7.0	29.2	8.9	5.8	13.5	24.1	67.1	5.0	36.3	22.0	24.5	13.3
LSE	3.9	6.8	9.6	7.7	4.2	10.7	4.6	3.9	6.3	18.0	4.9	7.1	11.4	15.0	6.3	65.4	24.3	16.8	23.5	10.8
Harvard	8.2	17.2	24.4	15.5	9.2	25.5	17.2	8.8	10.2	55.2	18.3	9.9	24.0	38.4	19.8	10.9	224.6	35.5	59.6	30.0
Princeton	4.4	8.8	9.2	6.1	5.4	15.3	5.3	5.7	7.1	22.9	6.6	6.6	13.6	21.8	9.9	7.4	30.3	69.0	27.0	11.5
MIT	5.4	10.6	17.8	7.4	5.0	16.2	9.7	6.3	7.5	35.8	11.1	8.4	16.3	25.9	12.1	8.4	50.5	27.6	127.8	18.5
UC Berkeley	6.4	7.0	16.0	9.7	6.5	17.7	9.8	5.9	7.5	27.1	10.8	7.1	18.1	34.7	11.7	5.3	45.1	24.0	36.4	120.1

Table 1. Unit citations from row to column department for the top 20 academic departments, 1990-2010. Colors depict deviations from expected citations patterns in the absence of clustering (excluding self−citations). Red depicts citations above and blue below expected intensity, darker shades depict stronger deviations. Institutions are ordered by the strength of their connection to the saltwater cluster.

We consider all partitions of the set of n institutions into two equal-sized clusters.[6] Formally, consider any partition of the set of n institutions into subset A and its complement. We measure the strength of the division as

$$Q(A|\Omega) = e_A' \Omega e_A + (l - e_A)' \Omega (l - e_A) \tag{3}$$

where e_A is the membership vector for subset A, equal to unity for members and zero for non-members, and l is a vector of ones. This measure gives the sum of total deviations from the expected proportion of normalized citations for within-cluster pairs of institutions. (Deviations add up to zero, so the amount of deviations for between-cluster pairs of institutions is necessarily just the negative of Q and can be omitted.)

We define the strongest division to be the partition of A to two clusters of $n/2$ institutions that maximizes (3).[7] Thus, for a set of n institutions, with n even, there are $c_n = \frac{1}{2}\binom{n}{n/2}$ distinct ways of dividing them to two equal-sized clusters. We use brute force to select the strongest of all possible partitions.

4 Results

There are authors from 1192 institutions in the data. To analyze their possible division we restrict the analysis to a subset of top institutions. We define the "top" by the ranking of institutions by influence in the network of citations using eigenvalue centrality; for details, see Pinski and Narin (1976).[8] Self-citations are removed before calculating influence. Table 2 lists the influence measure for the top 50 institutions by influence. Our main specification considers the division between the top 20 academic institutions. Selected summary statistics of the citation matrix are also reported in Table 2. Self-cites, which are excluded in the analysis, are reported separately. Cites to articles whose contact author could not be matched with an institution are listed as "cites to unknown". All cites are measured in units-per-citing-article, so the sum of outgoing cites, self-cites, and cites to unknown adds up to the total number of articles published by contact authors from each institution.

Clustering results The strongest division is depicted in the last columns of Table 2 for $n = 12, 16, 20, 24$. We call the cluster that includes Harvard "the Saltwater cluster" and the other "the Freshwater cluster." Most departments always show

[6] We will consider the possiblity of an arbitrary number of unevenly sized clusters when we apply two alternative clustering methods in the next section.

[7] There could, in principle, be several maximizers, but this never occurs in our data.

[8] Davis and Papanek (1984) provide an early study of department rankings based on citation counts. For rankings of academic journals using network influence, see Liebowitz and Palmer (1984), and *Eigenfactor.org*. Amir and Knauff (2008) and Terviö (2011) apply this method to data on PhD placement / faculty hiring data.

Table 2. Summary Statistics and Main Results for Top 50 Institutions, 1990-2010

	Institution	*Cites in*	*Cites out*	*Self-cites*	*Cites to Unknown*	*Unique Authors*	*Influence*	*Relative Salt*	*Strongest division for Top 24*	*Top 20*	*Top 16*	*Top 12*
1	Harvard	2.482,93	888,20	224,62	601,18	583	5,126	0,651	S	S	S	S
2	Chicago	2.042,52	582,97	135,78	349,25	368	4,292	-0,221	F	F	F	F
3	MIT	1.941,23	570,79	127,81	360,39	295	4,005	1,042	S	S	S	S
4	Stanford	1.652,42	609,57	123,34	414,09	441	3,516	0,126	S	S	S	S
5	Princeton	1.512,75	434,00	68,98	230,03	224	3,030	0,851	S	S	S	S
6	Northwestern	1.303,40	570,31	105,09	259,60	321	2,752	-1,147	F	F	F	F
7	Berkeley	1.248,10	662,44	120,08	454,49	480	2,501	1,352	S	S	S	S
8	Pennsylvania	1.126,74	588,49	90,16	295,35	343	2,340	-1,555	F	F	F	F
9	Yale	1.072,01	393,06	80,00	251,94	277	2,225	0,059	S	S	S	F
10	*Federal Reserve*	1.093,26	1.053,16	234,83	393,01	677	1,965	-1,508				
11	Columbia	867,85	492,04	67,13	269,83	338	1,729	0,196	S	S	S	S
12	Rochester	852,98	268,14	44,17	126,69	169	1,703	-1,982	F	F	F	F
13	Michigan	805,30	481,96	64,46	277,58	366	1,613	-0,538	S	S	F	F
14	NYU	821,24	566,06	72,70	232,24	293	1,547	-1,419	F	F	F	
15	UCLA	730,26	426,52	64,43	256,05	284	1,527	-0,986	F	F	F	
16	Wisconsin	732,28	522,95	67,82	318,22	352	1,393	-0,481	F	F	F	
17	LSE	753,41	450,93	65,38	240,68	305	1,283	0,625	S	S	S	
18	UCSD	694,68	256,96	40,56	127,47	135	1,246	-0,239	S	S		
19	Carnegie Mellon	567,71	200,28	26,16	123,56	165	1,150	-1,347	F	F		
20	Minnesota	545,43	303,93	44,38	216,68	249	1,084	-2,107	F	F		
21	Cornell	562,31	434,20	64,89	310,91	337	1,059	-0,586	F	F		
22	*World Bank*	545,06	469,50	120,39	346,12	407	0,963	0,932				
23	Illinois	489,97	464,64	63,36	308,01	326	0,940	-1,048	F			
24	Duke	417,44	385,02	47,53	212,45	263	0,854	-1,271	F			
25	Maryland	477,03	417,22	57,42	252,35	251	0,832	-0,020	S			
26	UBC	496,13	370,38	48,97	203,64	217	0,826	0,414	S			
27	Hebrew	395,34	201,61	43,34	144,05	135	0,782	-0,084				
28	Oxford	437,86	329,36	46,90	181,75	268	0,731	1,548				
29	Tel Aviv	365,07	215,30	31,53	103,17	108	0,705	-0,775				
30	Boston U	322,11	239,46	24,87	113,67	149	0,642	0,147				
31	Toronto	338,08	345,74	35,95	175,31	223	0,637	-0,619				
32	UC Davis	335,19	319,12	46,27	218,62	214	0,609	-0,039				
33	Ohio State	332,69	339,89	35,45	186,66	230	0,603	-1,035				
34	Texas-Austin	339,10	382,01	37,85	224,14	276	0,576	-1,168				
35	USC	294,50	254,58	25,37	139,05	164	0,571	-1,175				
36	Washington	304,01	230,31	24,12	129,58	174	0,562	-0,789				
37	Virginia	298,93	195,71	19,38	108,90	144	0,543	-0,530				
38	Penn State	300,33	304,04	30,63	170,33	209	0,542	-1,565				
39	*IMF*	304,92	353,73	45,87	143,39	291	0,512	0,760				
40	Michigan State	301,68	294,24	35,04	175,72	201	0,508	0,009				
41	Caltech	238,43	129,08	22,22	71,71	73	0,501	-1,439				
42	Indiana	280,42	244,60	23,71	135,69	173	0,480	-1,157				
43	Iowa	245,24	178,83	16,01	89,16	129	0,478	-2,399				
44	ANU	267,16	205,56	25,26	133,18	151	0,442	0,125				
45	UNC	236,50	291,13	31,72	180,15	245	0,436	-1,195				
46	Brown	226,44	205,73	23,66	99,61	91	0,428	-0,626				
47	Florida	242,49	196,30	21,05	117,65	155	0,424	-1,417				
48	UCL	234,70	213,26	22,93	82,82	114	0,421	0,683				
49	Arizona	239,10	217,00	34,02	155,98	192	0,412	-0,977				
50	Cambridge	246,18	190,01	28,51	113,48	173	0,406	1,265				
	Others (1142 institutions)	21.747,74	35.768,34	3.128,56	19.970,10	29934	35,546	0,020				
	All	54.708,65	54.708,65	6.130,65	30.795,70	42682	100	0,000				

Articles from all sample journals from 1990 to 2010. *Non-academic institutions in italics.*

Influence in the network of citations is calculated after dropping self-citations by institutions from the data.

"Relative salt" measures the propensity to cite members of Saltwater cluster relative to Freshwater cluster (with clusters defined for Top 20).

up in the same cluster. Chicago, Northwestern, Penn, and Rochester are always in the Freshwater cluster; MIT, Stanford, Princeton, Berkeley, and Columbia are always in the Saltwater cluster. The only institutions whose cluster membership varies by specification are Yale and Michigan. The division is the same as was found in hiring/placement data in Terviö (2011).[9]

The magnitude of the division can be illustrated by considering the relative propensities to cite within and between clusters. Among the top 20 academic institutions, the average number of unit citations between a pair of institutions in different clusters is 11.76, while the average for institution pairs in the same cluster is 13.67, that is 16.2% higher. Among the top 16 academic institutions, the average number of unit citations between a pair of institutions in different clusters is 14.91, while the average for institution pairs in the same cluster is 17.32, that is 16.1% higher.

We also applied two alternative clustering algorithms, the Louvain method (using the Pajek software package) and MapEquation (see Rosvall and Bergstrom (2011) for details). For $n = 24$ both methods yield the same division as our analysis, when restricted to yield two clusters of equal size. Without this restriction the Louvain method moves Michigan and UCSD to the Freshwater cluster, while MapEquation finds that the division to equal-size clusters is in fact optimal. For $n = 20$ Pajek finds the same clusters as we do, whereas MapEquation finds no division at all (i.e., just one cluster). Both algorithms find one cluster optimal for $n = 16$ and $n = 12$.

Strength of attachment The relative strength of attachment to the Salt and Freshwater clusters can be measured for any institution that hosts authors that publish in our sample of journal articles. More precisely, redefine Ω to include all departments and not just the top n. We define the "salt content" of department i as

$$S_i = \frac{e_i' \Omega e_S}{(l - e_i)' \, e_S} - \frac{e_i' \Omega e_F}{(l - e_i)' \, e_F}, \tag{4}$$

where e_i is the ith unit vector, and e_S and e_F are the membership vectors of Saltwater and Freshwater clusters. The divisors account for the removal of self-cites: top institutions are themselves members of a cluster, and have one less potential citation partner in their own cluster. Finally, "relative salt" is obtained by subtracting the mean salt content of all departments (0.385).

Table 2 lists the "relative salt" measure for the 50 most influential institutions. It measures the average deviation from the expected share of outgoing citations to Saltwater members in excess of the share going to members of the Freshwater cluster. True to name, the saltiest of saltwater schools appear to be Berkeley and MIT, while

[9] In Terviö (2011) the "top" was defined by PhD placement instead of citations, but using the exact same set of top 16 U.S. departments as there results in exactly the same clusters here.

Minnesota and Rochester are the freshest of the fresh. Chicago appears surprisingly "neutral" along with Stanford, Yale, and Colombia. Note that self-citations were removed from the analysis and Chicago is by far the most heavily cited Freshwater department, so a disproportionate share of its citations to the Freshwater cluster are ignored in the analysis. Outside academia, the Federal Reserve Bank appears quite "fresh" while World Bank and IMF are somewhat "salty."

The joint pattern of attachment to clusters and influence in the citation network is depicted in Figure 2. The rough pyramid shape of the scatter plot shows that more influential institutions appear to be less "partisan" in terms of the salt/fresh division.

5 Is the division statistically significant?

Given the large number of possible partitions, it would often be possible to find partitions where the division appears strong even for a random pattern of deviations. It could also be that the anecdotal evidence of a division in economics is based on people attributing meaning to essentially random variation. To test the statistical significance of the division, we have to take into account that the partition has been selected from the set of possible partitions precisely in order to maximize the strength of the apparent division. Our concern is not that we would find spurious clustering due to random variation at the level of citations or publications, but rather that we might confound a random collection of strong links between departments with clustering.

We measure the statistical significance of the division by comparing the strength of the strongest division found in the actual sample to its bootstrapped distribution. The bootstrap distribution is obtained by generating random permutations of the deviation matrix Ω and measuring the strength of the strongest division found for each permutation. In these permutations we randomly reorder the off-diagonal elements of Ω, separately for each column, treating all possible permutations as equally likely. These simulated deviation matrices describe a world where the average share of incoming citations is held fixed for each university, but deviations from average non-self citation patterns are idiosyncratic. In the simulation, the distribution of pairwise deviations Ω_{ij} is the same as in actual data, but a tendency to cite a particular institution more does not imply a tendency to cite another particular institution more.

The strongest partition under the random benchmark always appears "statistically significant" to a naive test that treats the strongest partition as given. We conducted $10,000$ simulations for each $n = 12, 16, 20$, and 2000 for $n = 24$. In all of these simulations there is only one instance where it is possible to find a division as strong as we find in the actual data, for $n = 16$. Therefore we conclude that the division is statistically very significant. This simulation also helps illustrate the 16% magnitude

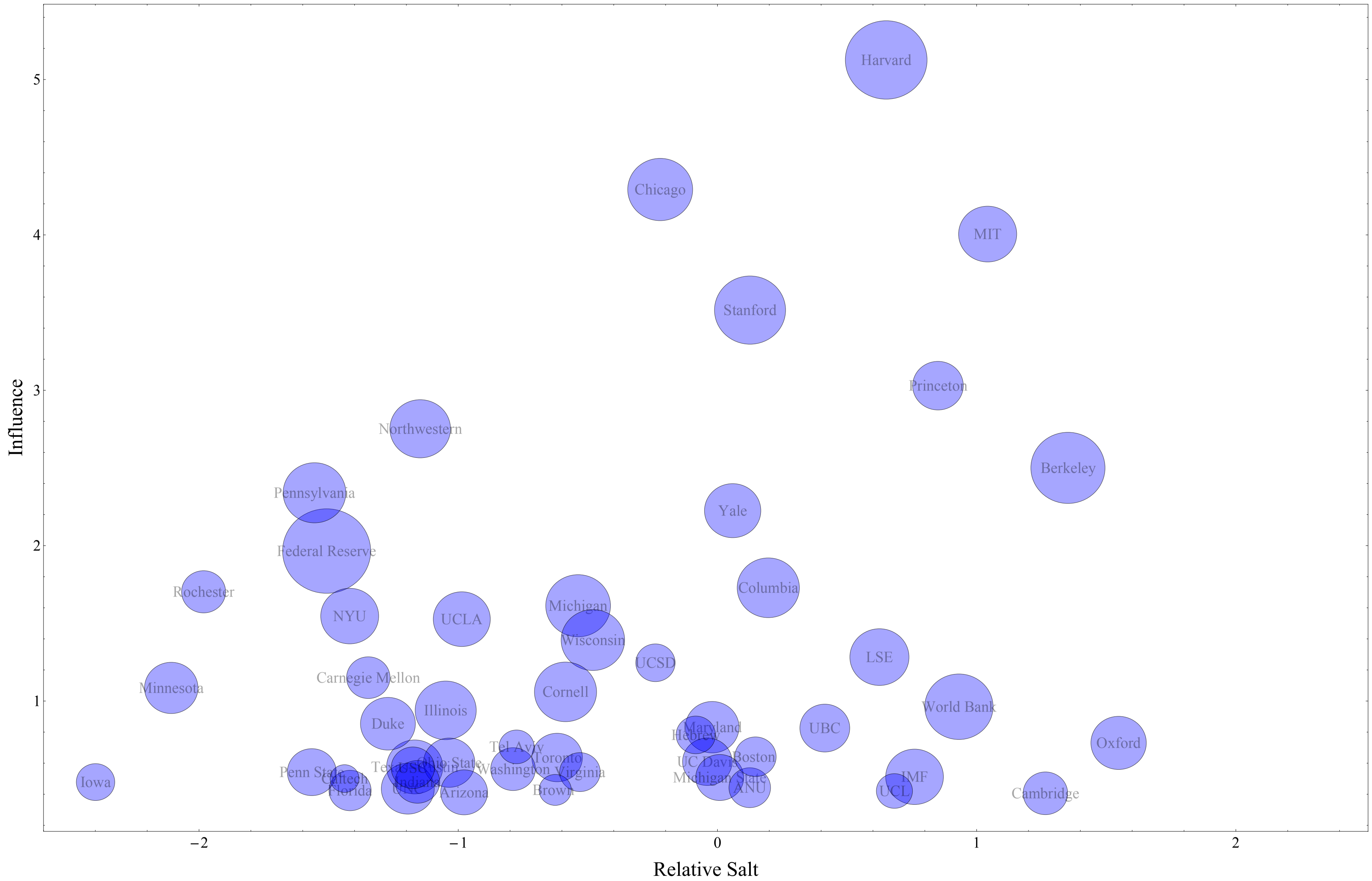
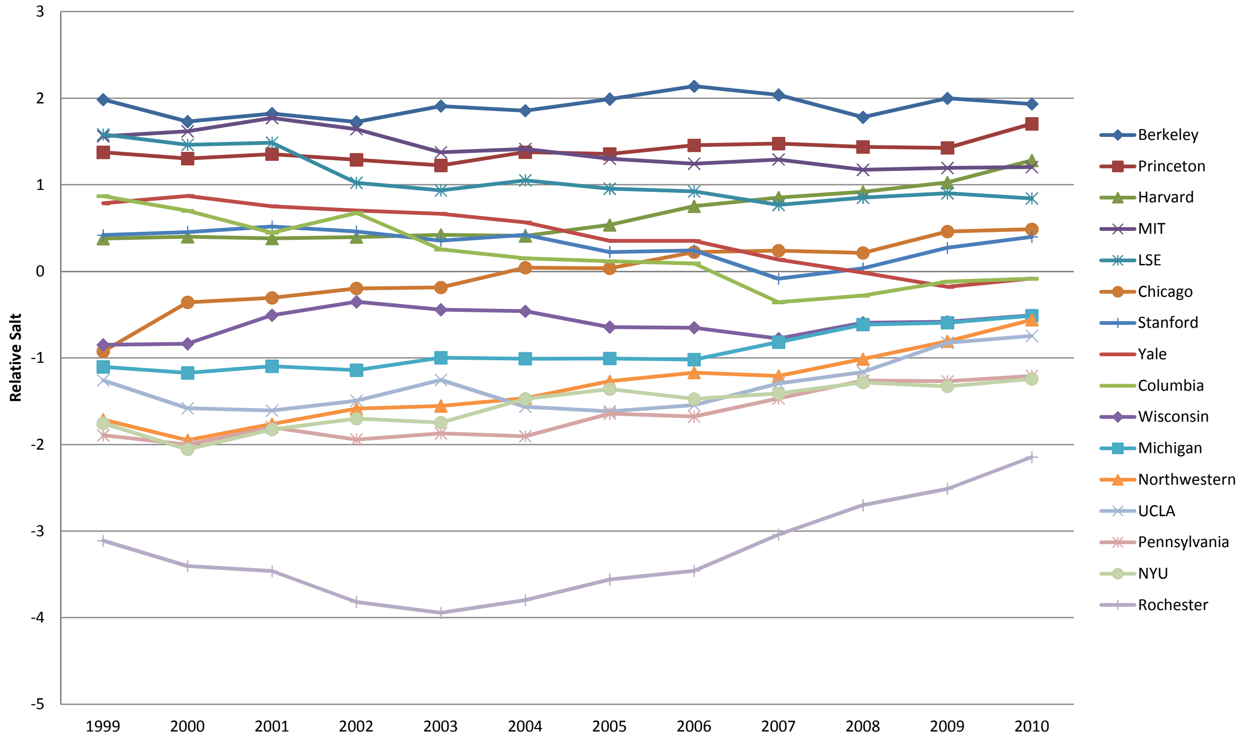


Figure 2. Relative strength of attachment to the clusters (more positive = more Saltwater than Freshwater) and influece in the citation network, for the 50 most influential institutions, 1990-2010. Bubble size is proportional to the number of unique authors.

Figure 3. Time series of the strength of attachment and cluster membership for academic institutions that form the top 16 for the whole period 1990-2010 (Last year of the 10-year moving window shown)



of the "excess" within cluster citations by showing how far it is in the tail. In these simulations the strongest partition results in a magnitude this large in 0.3% of the cases, the 95th percentile of the excess is 8.5%, and the 99th percentile is 13.1%.

6 Subsamples

Time periods We repeat the cluster analysis for a subset of citation years, using a rolling 10-year window starting from 1990-99 and ending in 2001-10, with the set of departments fixed at the top 16 academic departments as calculated for the whole time period. The clusters in the strongest division are exactly the same throughout the period, but there appears to be a secular trend towards a weaker division. The excess percentage of cites for within-cluster pairs (over between-cluster pairs) declines from 18.9% to 13.7% between the first and last window. After running 10000 simulations for each window, we find that the division is always statistically very significant, but with $p-$value increasing from 0 to 0.0009 over time.

The time series results are summarized in Figure 3, which plots the strength of

Table 3. Division by Field, 1990-2010

	Modified Q			Within Cluster Bias			
Field	P-Value	Actual	P_{95}	Actual	P_{95}	Citations	Articles
Macro/Monetary	0.000	1.350	0.877	32.6	11.5	82,995	3,764
Micro Theory	0.025	0.870	0.837	13.8	10.8	90,430	5,455
Industrial Org.	0.156	0.716	0.769	11.2	12.8	51,305	2,608
Econometrics	0.000	1.480	1.032	40.8	14.0	104,810	5,527
Labor	0.112	0.774	0.811	17.3	7.8	44,372	2,201
Growth/Dev.	0.058	1.139	1.149	24.0	13.7	61,463	3,376
Finance	0.191	0.455	0.499	2.8	10.2	104,398	3,801
Public	0.027	1.063	1.026	31.7	15.9	76,361	4,365
International	0.184	1.161	1.263	18.8	13.1	62,415	3,075
All 102 journals	0.000	0.642	0.400	16.1	8.5	1,662,212	91,635

attachment to saltwater cluster (as defined in that period) against the last year of the 10-year time window. A noticeable development is the increasing "saltiness" of Chicago. Towards the end of the period, Chicago has a higher relative propensity to cite authors at saltwater schools than the average of all institutions. Despite this, Chicago shows up in the Freshwater cluster in every time period, because it is so heavily cited by other Freshwater departments. Even though Chicago appears "more salty" than some of the Saltwater departments, an alternative partition where it switches places with a weakly attached Saltwater department would result in more cross-cluster citing and make the division weaker.

Fields We analyze the citations between the subset of 4 most influential field journals for nine fields, with journal fields defined by Combes and Linnemer (2010). Unfortunately we do not have the JEL codes by article, so we do not include articles in general interest journals. The definition of "most influential" journals is based on the same influence measure as for institutions in the previous section, calculated from the matrix of unit citations between all 102 journals in our data. See Table $A.1$ in the appendix for summary statistics by journal. We also list our influence measures for these journals so as to provide an alternative ranking based on the citation patterns between them.

Table 3 shows the strongest division in each field. The analysis is in each case conducted for the 16 most influential academic departments in the citation network of that field. We define the p-value as the fraction of simulations where the strongest division to two clusters is as strong or stronger as the one found in actual data. With all journals included this p-value is 0.0001. Among the fields, macroeconomics and

Table 4. Cluster Membership of Top Departments by Field, 1990-2010

	Macro / Money	*Econo-metrics*	*Micro Theory*	*Public*	*Growth / Dev.*	*Labor*	*Ind. Org.*	*Internt'l*	*Finance*	*General*	*All w/out Macro*	*Overall*
Harvard	**S**	**S**	**S**	**S**	**S**	**S**	**S**	**S**	**S**	**S**	**S**	**S**
Chicago	**F**	**F**	**F**	S	**F**	**F**	S	**F**	S	S	**F**	**F**
MIT	**S**	F	**S**	**S**	**S**	**S**	**S**	**S**	**S**	**S**	**S**	**S**
Stanford	**S**	**S**	**S**	F	F	F	F	F	**S**	**S**	**S**	**S**
Princeton	**S**	F	**S**	F	F	**S**	F	**S**	**S**	**S**	**S**	**S**
Northwestern	**F**	**F**	**F**	**F**		**F**	**F**	S	S	**F**	**F**	**F**
Berkeley	**S**	**S**	**S**	**S**	F	**S**	**S**	F	**S**	**S**	**S**	**S**
Pennsylvania	**F**		**F**	S	**F**	S	S	**F**	**F**	**F**	**F**	**F**
Yale	**S**	F	F	F	F	F	**S**	**S**	**S**	F	F	**S**
Columbia	**S**		F		F	**S**	F	**S**	F	**S**	**S**	**S**
Rochester	**F**		**F**	**F**				**F**	**F**	**F**	**F**	**F**
Michigan	S			S	**F**	**F**	**F**	S	**F**	**F**	S	**F**
NYU	**F**		S		S		**F**	**F**	**F**	**F**	**F**	**F**
UCLA	**F**	S		**F**	S	**F**	S	S	**F**	S	S	**F**
Wisconsin		S		S		**F**	**F**			**F**	**F**	**F**
LSE		F		**S**	**S**		**S**					**S**
UCSD		F	**S**	F				F			F	**S**
Carnegie M.	**F**	S		**F**						**F**		**F**
Minnesota	**F**	S	**F**									**F**
Cornell					S	S			**F**			**F**
	p=0.000	*p=0.000*	*p=0.025*	*p=0.027*	*p=0.058*	*p=0.112*	*p=0.156*	*p=0.184*	*p=0.191*	*p=0.003*	*p=0.003*	*p=0.000*

Note: We list top 20 departments from the overall ranking and find the division among top 16 departments in each field (see Table A2 for field rankings).
S is defined as the cluster with Harvard in it.
Each field is made of citations going out from top 4 field journals (see Table A1 for journal rankings).
There are departments that are ranked top 16 in some fields although they are not placed in top 20 in the overall ranking. These are left out of this table.
Cluster membership is bold+underlined if it is the same as in the full data for top 20 departments.
P-values (last row) give the statistical significance of the division.
General: citations going out from top 5 general interest journals (Econometrica, AER, JPE, QJE, REStud).
All w/out Macro: top 4 journals from all fields put together excluding Macro/Money journals. This group consists of 32 journals in total.

econometrics have the strongest division, at $p = 0.000$. Micro theory (0.025), public economics (0.027), and growth/development (0.058) also exhibit a clear division, while the remaining fields show only weak evidence for a division.[10] In terms of the excess likelihood of citing same-cluster authors, the highest "biases" are found in econometrics (40.8%) and macroeconomics (32.6%), while for a moderately clustered field like micro theory this "bias" is only 13.8%. To illustrate the size of these bias measures we also list the 95th percentile of the same measure in the simulations under the random benchmark; they vary between 8% and 16% by field.

Table 4 shows the variation in the cluster membership of top departments across fields, and highlights the differences from the Saltwater-Freshwater division found in the overall sample (as seen in Table 2). Clearly there is significant variation in the memberships across fields, even if we only considered those where the division is statistically significant. Some groups of departments like Berkeley-Harvard-MIT and Chicago-Northwestern-Rochester are quite consistently found together, whereas Stanford, Yale, Columbia, and Michigan appear very inconsistent in their affiliations. The seemingly random affiliation of the latter departments is consistent with the fact that they are only weakly attached to their cluster in the main analysis (i.e., they have "relative salt" close to zero, see Figure 2). Since our clustering method forces all departments to belong to one cluster or another it is not surprising that weakly attached departments swing about rather randomly between clusters. The real outlier among the fields is econometrics, where the division is significant and yet looks very different from that found in the full sample (e.g., it is the only field where MIT is not on the same side with Harvard). The division in macroeconomics is almost identical to the overall division. This raises the question whether the overall division is driven by the division in macro. For this reason we construct a sample that combines the field data but leaves out macro. The second to last column of Table 4 shows that the resulting division is almost identical to the overall division. Moreover, we analyse top five general interest journals and find a division very similar to the overall division. Divisions that we find in both cases (top five general interest and all fields excluding macro) have high statistical significance (p-value is 0.003 for both).

7 Conclusion

Stanford economist Robert E. Hall first came up with the freshwater/saltwater term in the 1970s, based on the then workplaces of a group of leading macroeconomists with a distinctive style of research: Robert E. Lucas at Chicago, Thomas Sargent

[10] Table A.2 in the appendix provides more detail on the influence and cluster membership of the top departments in each field.

at Minnesota, and Robert Barro at Rochester.[11] More recently, Gregory Mankiw (2006) has argued that the freshwater/saltwater division had become an issue of the past already by the 1990s, because "(...) science progresses retirement by retirement. As the older generation of protagonists has retired or neared retirement, it has been replaced by a younger generation of macroeconomists who have adopted a culture of greater civility" (p. 38). We don't have a measure of civility, but, in terms of the citation flows between economics departments, the Saltwater/Freshwater division is clearly not yet a matter of the past.

The network of citations in economics in articles published during the 1990s and 2000s exhibits a division where authors are significantly less likely to cite articles by authors at universities across the divide. The division adheres to the common notions of "Freshwater" and "Saltwater" schools. We find a 16% excess likelihood of citing same-cluster authors, which is statistically very significant, but, in terms of magnitude, very far from having two isolated schools of thought. When restricting the citations to top field journals, the strongest divisions are found in macroeconomics and econometrics. Citation data cannot reveal whether the divisions are based on methodological or ideological differences, but it seems clear that a purely geographical explanation would not work. Some of the divisions may be explained by a tendency to cite former colleagues and mentors, as the same division has earlier been found (Terviö 2011) in the network of Ph.D. placements. Hiring networks and specialization could conceivably explain divisions in a field like econometrics where it would be harder to argue for ideological reasons behind the clustering.

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APPENDIX- Table A1. Summary Statistics and Influence by Journal, 1990-2010

Rank	Journal Title	Articles	Cites In	Cites Out	Self Cites	Cites to Other	Influence	Top Field
1	Econometrica	995	3071,69	297,64	150,66	541,71	11,137	
2	American Economic Review	3222	2751,80	959,97	244,78	1748,25	9,668	
3	Journal of Political Economy	857	1895,59	305,10	63,24	481,66	7,635	
4	Quarterly Journal of Economics	783	1476,68	258,37	50,08	471,55	5,923	
5	Review of Economic Studies	778	1036,27	348,94	46,79	379,27	4,734	
6	Journal of Finance	1373	1245,49	538,25	255,60	576,15	4,708	Finance
7	Journal of Economic Theory	1764	981,51	671,10	209,00	875,90	4,503	Theory
8	Journal of Financial Economics	1018	867,63	426,41	163,89	427,71	3,712	Finance
9	Journal of Econometrics	1721	781,87	586,13	153,10	956,77	2,770	Econometrics
10	Journal of Monetary Economics	1130	748,34	462,90	103,98	555,12	2,606	Macro/Money
11	Rand Journal of Economics	766	536,83	323,02	66,45	376,53	1,904	IO
12	Review of Economics and Statistics	1195	646,46	458,65	38,82	689,53	1,846	
13	Journal of Public Economics	1500	598,69	536,08	124,04	833,89	1,764	Public
14	Journal of Economic Perspectives	753	418,99	161,28	16,32	516,40	1,621	
15	Review of Financial Studies	762	340,58	400,31	49,37	312,32	1,607	Finance
16	International Economic Review	964	431,28	448,29	31,67	482,04	1,592	
17	Economic Journal	1449	608,13	526,92	51,66	824,42	1,591	
18	Journal of Economic Literature	75	440,67	17,58	1,10	53,32	1,529	
19	Games and Economic Behavior	1291	270,67	494,48	94,43	674,09	1,349	Theory
20	Journal of the American Statistical Assoc.	2231	321,31	80,22	232,33	1631,45	1,289	Econometrics
21	Economics Letters	4261	389,55	1926,21	157,95	2001,84	1,210	
22	European Economic Review	1504	417,39	572,00	44,11	801,89	1,147	
23	Journal of Labor Economics	555	286,83	222,88	33,30	294,82	1,089	Labor
24	Journal of International Economics	989	400,76	375,90	90,94	517,17	1,063	International
25	Journal of Business & Economic Statistics	786	291,34	323,55	33,50	414,95	0,998	Econometrics
26	Journal of Business	481	241,70	238,15	18,98	220,87	0,946	
27	Journal of Human Resources	609	261,85	182,79	32,70	380,51	0,915	Labor
28	Econometric Theory	789	128,46	253,62	57,48	455,91	0,778	Econometrics
29	Journal of Law & Economics	449	193,87	123,18	19,26	289,56	0,756	
30	Journal of Money Credit and Banking	956	262,49	406,03	46,13	487,84	0,751	Macro/Money
31	Journal of Mathematical Economics	888	154,60	267,44	65,13	530,44	0,733	Theory
32	Journal of Ec. Dynamics & Control	1485	223,62	596,44	62,11	790,46	0,717	Macro/Money
33	Journal of Financial and Quant. Analysis	648	171,71	360,01	27,26	259,73	0,685	Finance

Table A1 (continued)

Rank	Journal Title	Artciles	Cites In	Cites Out	Self Cites	Cites to Other	Influence	Top Field
34	Economic Inquiry	951	180,50	306,32	13,15	587,53	0,588	
35	American Political Science Review	598	134,05	39,34	44,58	419,08	0,567	Public
36	Public Choice	1535	141,09	373,79	132,74	961,47	0,535	Public
37	Journal of Econ. Behavior & Organization	1512	156,23	535,27	57,43	869,31	0,519	Theory
38	Journal of Development Economics	1059	197,26	356,39	47,37	621,24	0,493	Growth/Dev
39	Industrial & Labor Relations Review	605	126,36	148,42	40,73	393,85	0,480	Labor
40	Journal of Applied Econometrics	688	149,65	305,67	17,05	363,28	0,466	
41	Journal of Law Economics & Organization	412	96,07	125,92	17,47	261,60	0,452	
42	Brookings Papers on Economic Activity	193	78,60	45,50	2,79	136,71	0,438	Macro/Money
43	International Journal of Game Theory	593	99,02	164,08	44,83	330,09	0,429	
44	Journal of Urban Economics	935	180,10	282,70	104,14	534,16	0,420	
45	Journal of Accounting & Economics	475	76,78	97,14	67,28	299,58	0,416	
46	Journal of Industrial Economics	495	151,06	205,38	22,68	260,94	0,400	IO
47	Canadian Journal of Economics	1109	157,26	463,04	35,67	586,29	0,398	
48	Economica	631	134,75	270,08	13,23	342,69	0,358	
49	Social Choice and Welfare	849	78,83	246,92	66,52	508,56	0,342	
50	Journal of Banking & Finance	1849	112,01	732,80	125,43	959,77	0,339	
51	Journal of Environ. Ec. and Management	844	273,22	254,19	83,08	497,73	0,325	
52	Journal of Risk and Uncertainty	451	94,33	132,35	40,57	265,08	0,318	
53	Oxford Economic Papers	691	140,15	266,95	18,05	398,01	0,313	
54	National Tax Journal	732	93,68	139,45	59,95	468,60	0,309	Public
55	Scandinavian Journal of Economics	641	118,45	266,88	16,34	347,79	0,304	
56	International Journal of Industrial Org.	953	120,04	429,75	40,86	475,40	0,302	IO
57	Journal of Economic History	435	63,50	52,33	21,63	328,04	0,286	
58	Review of Economic Dynamics	351	59,82	170,70	8,14	170,16	0,283	
59	Journal of Health Economics	853	119,46	188,51	63,63	566,86	0,267	
60	Oxford Bulletin of Economics and Statistics	652	135,50	265,42	18,32	359,26	0,267	
61	Amer. Journal of Agricultural Economics	2140	195,83	421,21	244,94	1295,85	0,260	
62	Journal of Econ. & Management Strategy	394	66,08	178,08	11,40	202,52	0,241	IO
63	Journal of International Money and Fin.	962	104,85	412,23	51,59	490,19	0,227	International
64	Regional Science and Urban Economics	645	89,16	229,29	34,90	363,81	0,208	
65	Journal of Economic Growth	126	62,77	54,32	5,41	66,27	0,202	Growth/Dev
66	Economic Theory	1303	42,13	547,12	9,71	701,17	0,191	
67	Econometric Reviews	117	51,00	49,96	3,13	62,91	0,190	
68	Review of Income and Wealth	434	41,43	95,62	16,79	293,59	0,150	

Table A1 (continued)

Rank	Journal Title	Artciles	Cites In	Cites Out	Self Cites	Cites to Other	Influence	Top Field
69	World Development	1655	84,01	183,20	65,26	1132,54	0,150	Growth/Dev
70	Land Economics	628	131,39	161,31	39,99	409,70	0,146	
71	Applied Economics	3195	79,76	1079,06	109,70	1932,24	0,139	
72	Journal of Comparative Economics	593	41,07	155,98	31,60	388,42	0,136	
73	Explorations In Economic History	325	27,86	58,49	9,29	248,22	0,123	
74	Economics of Education Review	661	35,76	165,33	40,50	430,18	0,112	
75	Econ. Development and Cultural Change	536	59,15	121,14	15,44	369,43	0,111	Growth/Dev
76	Journal of Financial Intermediation	235	29,57	122,93	5,71	106,36	0,110	
77	Mathematical Finance	273	37,21	47,15	15,46	183,39	0,108	
78	Macroeconomic Dynamics	347	29,21	172,18	4,43	165,40	0,102	
79	Labour Economics	432	39,73	188,20	7,44	236,36	0,092	Labor
80	Journal of Population Economics	525	34,71	188,07	15,70	316,23	0,091	
81	Journal of Risk and Insurance	513	42,88	139,60	55,45	306,95	0,090	
82	Journal of the European Economic Assoc.	323	19,28	134,57	1,94	174,49	0,088	
83	International Tax and Public Finance	379	40,66	157,94	12,40	205,66	0,083	
84	Journal of Regulatory Economics	456	30,34	143,91	23,63	275,46	0,069	
85	World Economy	830	26,36	128,73	25,56	518,71	0,068	International
86	Journal of Real Estate Finance and Econ.	547	25,53	158,90	35,79	336,31	0,067	
87	Energy Journal	402	29,66	78,14	21,43	263,43	0,065	
88	Environmental & Resource Economics	726	57,81	246,94	26,31	439,75	0,062	
89	Journal of Productivity Analysis	375	32,13	100,89	22,58	246,53	0,055	
90	Water Resources Research	4928	29,26	52,15	885,94	3556,91	0,054	
91	Journal of Economic Psychology	604	19,94	109,03	24,27	392,70	0,052	
92	Health Economics	868	30,69	175,07	47,98	590,95	0,044	
93	Economic History Review	259	11,08	15,64	13,45	191,90	0,042	
94	Experimental Economics	138	12,29	66,63	2,78	68,59	0,033	
95	Resource and Energy Economics	302	23,76	103,10	4,50	185,40	0,028	
96	Ecological Economics	1429	31,96	193,34	68,89	990,77	0,028	
97	Southern Economic Journal	1164	11,00	350,01	2,13	705,86	0,026	
98	Insurance Mathematics & Economics	900	14,48	77,02	124,96	586,02	0,022	
99	Journal of Economic Geography	119	8,56	32,42	3,20	74,38	0,019	
100	Industrial and Corporate Change	188	6,01	29,17	5,52	130,31	0,013	
101	Journal of Common Market Studies	294	5,89	13,68	9,78	171,55	0,009	International
102	Economy and Society	246	1,10	2,96	5,59	106,45	0,001	
	Total		28155,80	28155,80	6222,29	53080,91	100,000	

APPENDIX- Table A2. Influence and Division by Field, 1990-2010

Macroeconomics/Monetary Economics

Rank	*Institution*	*Influence*	*Cluster*
1	Federal Reserve	6,748	
2	Chicago	5,404	F
3	Harvard	5,001	S
4	Princeton	4,409	S
5	MIT	4,280	S
6	Northwestern	3,215	F
7	Stanford	3,184	S
8	Columbia	3,165	S
9	Rochester	2,898	F
10	Pennsylvania	2,895	F
11	Carnegie Mellon	2,298	F
12	NYU	2,249	F
13	Berkeley	1,961	S
14	Yale	1,797	S
15	Minnesota	1,705	F
16	UCLA	1,221	F
17	Michigan	1,206	S
18	UCSD	1,200	
19	IMF	1,104	
20	Virginia	1,035	

Significance of division: p = 0.000

Microeconomic Theory

Rank	*Institution*	*Influence*	*Cluster*
1	Northwestern	5,6225	F
2	Stanford	4,9160	S
3	Harvard	4,5609	S
4	MIT	3,0671	S
5	Chicago	2,6729	F
6	Pennsylvania	2,6345	F
7	Berkeley	2,6283	S
8	Hebrew	2,3405	S
9	Princeton	2,2235	S
10	Yale	1,9789	F
11	Rochester	1,6796	F
12	Caltech	1,6352	F
13	Columbia	1,2958	F
14	UCSD	1,2892	S
15	Minnesota	1,2812	F
16	NYU	1,2608	S
17	Carnegie Mellon	1,2550	
18	UCLA	1,2513	
19	Tel Aviv	1,2202	
20	LSE	1,1743	

Significance of division: p = 0.025

Industrial Organization

Rank	*Institution*	*Influence*	*Cluster*
1	Stanford	5,5790	F
2	Harvard	5,5658	S
3	MIT	5,0191	S
4	Berkeley	3,8157	S
5	Northwestern	3,8119	F
6	Chicago	3,4647	S
7	Princeton	3,0156	F
8	Yale	2,7202	S
9	Pennsylvania	1,7994	S
10	Michigan	1,6604	F
11	LSE	1,6439	S
12	UCLA	1,4305	S
13	Columbia	1,3893	F
14	Oxford	1,3638	F
15	NYU	1,3060	F
16	Wisconsin	1,1362	F
17	UBC	1,0537	
18	Carnegie Mellon	1,0098	
19	Boston U	0,8990	
20	Toulouse	0,8909	

Significance of division: p = 0.156

Cluster column denotes members of the strongest division between freshwater (F) and saltwater (S) clusters for 16 most influential academic departments by field.

Table A2 (continued)

Econometrics				*Labor Economics*				*Growth and Development*			
Rank	*Institution*	*Influence*	*Cluster*	*Rank*	*Institution*	*Influence*	*Cluster*	*Rank*	*Institution*	*Influence*	*Cluster*
1	Harvard	4,0812	S	1	Chicago	6,0248	F	1	World Bank	6,6918	
2	Yale	4,0494	F	2	Harvard	5,7762	S	2	Harvard	5,2555	S
3	Chicago	3,2981	F	3	MIT	3,9138	S	3	MIT	3,2398	S
4	Stanford	3,0671	S	4	Princeton	3,7586	S	4	Chicago	2,8572	F
5	Wisconsin	2,7577	S	5	Michigan	2,8488	F	5	Princeton	2,8380	F
6	UCSD	2,5052	F	6	Cornell	2,6335	S	6	Stanford	2,2975	F
7	Berkeley	2,4271	S	7	Northwestern	2,2136	F	7	Berkeley	2,1822	F
8	MIT	2,4249	F	8	Stanford	2,1601	F	8	Pennsylvania	2,1374	F
9	Princeton	2,0573	F	9	Columbia	2,0402	S	9	Yale	1,8715	F
10	Minnesota	1,8980	S	10	Berkeley	1,9212	S	10	Oxford	1,7516	S
11	LSE	1,7210	F	11	Wisconsin	1,7542	F	11	IMF	1,6168	
12	Australian Natl U	1,4065	F	12	Pennsylvania	1,6850	S	12	Columbia	1,6053	F
13	UCLA	1,3731	S	13	Illinois	1,3616	F	13	UCLA	1,4137	S
14	Northwestern	1,2735	F	14	Yale	1,3361	F	14	LSE	1,2300	S
15	Carnegie Mellon	1,2575	S	15	UCLA	1,3359	F	15	Sussex	1,1414	S
16	Washington	1,1755	S	16	Michigan State	1,1199	S	16	NYU	1,0910	S
17	Rochester	1,1570		17	Rand	1,0766		17	Cornell	1,0385	S
18	N Carolina State U	1,1018		18	LSE	1,0264		18	Michigan	1,0201	F
19	Pennsylvania	1,0981		19	Federal Reserve	0,9765		19	Maryland	1,0175	
20	Federal Reserve	1,0876		20	Rochester	0,9166		20	Northwestern	0,9900	
Significance of division: p = 0.000				*Significance of division: p = 0.112*				*Significance of division: p = 0.058*			

Cluster column denotes members of the strongest division between freshwater (F) and saltwater (S) clusters for 16 most influential academic departments by field.

Table A2 (continued)

Finance

Rank	*Institution*	*Influence*	*Cluster*
1	Chicago	7,8673	S
2	Harvard	5,1636	S
3	MIT	4,1508	S
4	Pennsylvania	3,7895	F
5	NYU	3,6090	F
6	Stanford	3,4444	S
7	Rochester	3,1435	F
8	UCLA	3,0611	F
9	Northwestern	2,8458	S
10	Princeton	2,2709	S
11	Columbia	2,0991	F
12	Michigan	1,9926	F
13	Berkeley	1,9176	S
14	Yale	1,6008	S
15	Federal Reserve	1,5739	
16	Cornell	1,4666	F
17	Duke	1,4440	F
18	Illinois	1,4170	
19	USC	1,3899	
20	Ohio State	1,2346	

Significance of division: $p = 0.191$

Public Economics

Rank	*Institution*	*Influence*	*Cluster*
1	Harvard	6,1096	S
2	Stanford	3,6090	F
3	Chicago	3,1788	S
4	Princeton	3,0292	F
5	MIT	2,9096	S
6	Michigan	2,6438	S
7	Northwestern	1,8147	F
8	Rochester	1,7341	F
9	Yale	1,7076	F
10	Berkeley	1,6974	S
11	Carnegie Mellon	1,6327	F
12	Pennsylvania	1,6069	S
13	Wisconsin	1,5837	S
14	UCLA	1,5698	F
15	UCSD	1,5403	F
16	LSE	1,3275	S
17	Maryland	1,2446	
18	Columbia	1,1431	
19	Federal Reserve	1,1407	
20	Caltech	1,1369	

Significance of division: $p = 0.027$

International Economics

Rank	*Institution*	*Influence*	*Cluster*
1	Harvard	4,7528	S
2	MIT	4,1995	S
3	Columbia	3,6099	S
4	Princeton	3,5515	S
5	Chicago	3,2578	F
6	Berkeley	3,1833	F
7	Federal Reserve	3,1302	
8	IMF	2,9166	
9	Stanford	2,4534	F
10	World Bank	2,2068	
11	Pennsylvania	2,0556	F
12	Northwestern	1,8857	S
13	Yale	1,8760	S
14	NYU	1,6134	F
15	Michigan	1,5766	S
16	UCLA	1,4886	S
17	UCSD	1,4779	F
18	Rochester	1,3049	F
19	UBC	1,0187	F
20	Tel Aviv	1,0149	

Significance of division: $p = 0.184$

Cluster column denotes members of the strongest division between freshwater (F) and saltwater (S) clusters for 16 most influential academic departments by field.