Business Analytics in the 21st Century from the Perspective of Academic Journals

by

Qiang Ruan

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Abstract

Do research trends in business and statistics predict or even reflect the emergence of analytics in business practice and programs in the 21st century? My dissertation explores the answer to this question from several perspectives.

The first and second essays explore knowledge sharing among statistics and business academic journals. Both essays use citation and abstract data from 24 business journals and 12 statistics journals for the years 2000, 2005, 2010, and 2015 from the Web of Science. The first essay employs multidimensional scaling with factor analysis simple structure groups to analyze both citations and abstracts. The similarity of citations among statistics and probability and other business disciplines seems to have changed somewhat from 2000 to 2015, but the changes are not substantial. Journals from different disciplines are more likely to share research interests in 2015 than previously.

Analysis of the citing and cited data based on disciplines and topic modeling also are used to describe how the different disciplines either influence or are influenced by other disciplines during the emergence of business analytics. Journals in accounting and ISOM are more likely to cite other disciplines than be cited by other disciplines. On the other hand, economics, finance, and probability are more likely to be cited by other disciplines. These three disciplines are more likely to "teach" than “learn”. The citing and cited patterns are not so evident in other disciplines.

The second essay applies network analysis and log-multiplicative models to reexamine communications among statistics and business journals. UCINET and LEM are the tools used in this research. In this essay, we find that the rise of business analytics seems to have promoted and increased communication among different disciplines, but the changes are not pronounced. The

influence of statistics journals as storers (citing) remains low and stable for the four years, the impact of statistics journals as sources (cited) starts high and increases in the four years we selected. We also discuss the influence of other disciplines.

The third paper focuses on studying the landscape of data science research from a network perspective. Like previous essays, Web of Science provides the source of data in our research: we extract publication information related to data science from 1960 to February 2020. The paper presents descriptive statistics of the most cited journals, the most cited authors, and the most productive authors. We also use exponential Random Graph Models (ERGM) to analyze the citation network regarding paper quality and the number of authors of the paper. Statistics journals are influential in data science studies as they provide fundamental background for this new rising subject. Publications with fewer keywords, more pages, and more authors, and publications with funding support are more likely to be cited by articles about the same topic.

This research finds that since the emergence of business analytics, knowledge sharing between statistics and academic business disciplines has increased but not substantially. Moreover, in the landscape of data science, the journals that publish the most are not statistics journals, but the most cited authors are statisticians.

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Chapter 1: Introduction

The development of data science and its application in business analytics has affected our life in different ways. Stores use it to target customers with marketing, websites apply it to recommend videos for online users, and some scientists update the data of the world pandemic disease Covid-19 with it. While it is well applied in real life, how does business analytics influence academic research, especially in the business school? We use the following framework to explore this question.

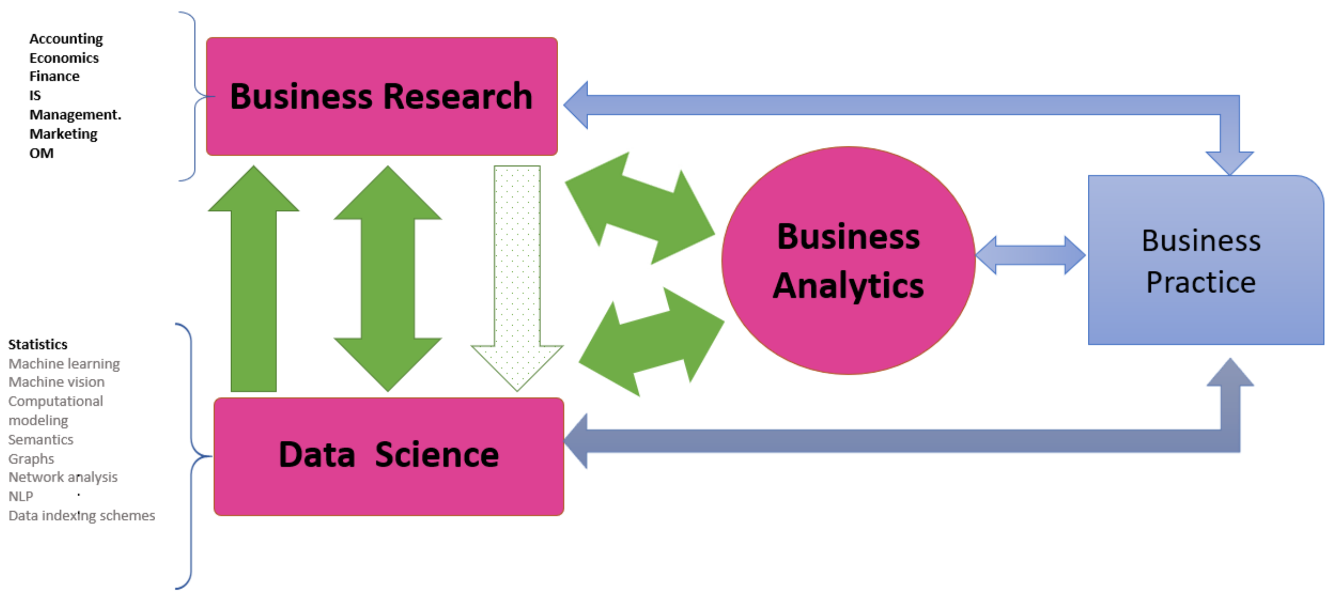


Figure 1.1 The Framework of the Dissertation

In Figure 1.1, seven disciplines comprise business research: accounting, finance, economics, information system (IS), management, marketing, and operations management (OM). Many disciplines have contributed to data science, such as statistics, machine vision, computational modeling, graphs, network analysis, and others.

Business analytics is an important tool used in business practice and research. Both business research and data science, including statistics, have contributed to the development of business analytics. Also, we suggest that, business analytics has enhanced knowledge and technology sharing between business and statistics. For example, more and more business researchers use python and R packages to solve accounting, finance, economics, information system and operations management, (ISOM), (management, and marketing problems. In essay 1 and 2 of this dissertation, we use citation analysis, text analytics, network science, and the log-multiplicative model to explore patterns of academic connections between statistics and business journals and whether or not these patterns have changed in the 21st century with the emergence of business analytics.

Data science in our framework has affected business analytics and been affected by business and statistics. In Essay 3, we observe the influence of business and statistics journals, publications, and authors on data science. We use both descriptive statistics and network analysis with exponential random graph models to explore the landscape of data science.

Chapter 1 presents the framework of this dissertation. It shows the relationships among business research, data science (statistics), and business analytics in this dissertation. Chapter 2 explores the similarities among statistics and business journals using citation analysis and text analytics. We use multidimensional scaling and factor analysis to identify knowledge sharing among journals. In Chapter 3 we use network analysis and the log-multiplicative model to explore the knowledge sharing further. Chapter 4 presents the landscape of data science from a perspective of business and statistics research. Chapter 5 gives a general conclusion of the dissertation.

Chapter 2: Essay 1: Similarities Among Statistics and Business Journals: Citation Analysis and Text Analytics

2.1 Introduction

Today scholars in business school not only need to be able to understand business disciplines but also need to have a deep understanding of statistics to build models and conduct experiments. The breakthrough technologies that have led to the emergence of business analytics depend upon applications of statistics. Instead of just using traditional software such as SAS and SPSS, scholars are writing codes in R to create their models, for example. They also use text analysis to obtain a deeper understanding of documents at a faster pace.

In this research, we would like to see if the communication of different business disciplines in the academic world with statistics and probability journals has changed since the year 2000. The knowledge disseminated from statistics and probability may inspire business scholars to push their discipline forward. On the other hand, applications of business analytics and other statistical tools may encourage statisticians to develop new theories in attempting to solve real-world problems.

Back to this essay, we want to examine communication in the academic world among statistics and business journals. Do different disciplines communicate more at the emergence of business analytics in the 21st Century? In this essay, we would like to examine the academic interactions among statistics and business disciplines using both citation and abstract data from Web of Science. We have chosen accounting, finance, economics, information systems, and operations management (ISOM), management, and marketing as business disciplines and statistics and probability as statistics related disciplines. These disciplines are widely used in previous literature when studying business disciplines and statistics disciplines.

To examine the communication among the journals, we extract both citation frequencies and abstracts data from the Web of Science. Twenty-four top business journals and twelve top statistics journals are selected to examine the communication patterns in the years 2000, 2005, 2010, and 2015. We use citation analysis and abstract text analysis in this essay. Based on our analysis, there are more cross citing patterns and shared research interests among business and statistics journals in 2015 than previously. Also, economics acts like a link connecting statistics and other business disciplines. Several journals, such as *the Journal of Business and Economic Statistics*, more frequently cross cite and have shared interests as indicated by citations and abstracts.

2.2 Literature Review

2.2.1 Knowledge Diffusion and Transfer

Knowledge diffusion reviews how ideas spread within and among disciplines and promote progress in science and art. For example, the Chern-Simons theory in mathematics has contributed to condensed matter research and string theory, which are important research areas in modern physics. Borgman and Furner (2002) focus on bibliometrics as a measure of scholarly communication and knowledge diffusion in academia. There are two types of knowledge diffusion: emitting knowledge outside of the academic disciplines and assimilating knowledge within the academic disciplines. Holsapple and Lee-Post (2010) investigate knowledge diffusion by examining the actual publishing behaviors of all full-time, tenured operations management (OM) researchers at a sizable set of leading research universities in the United States. They look at both the proportion of benchmark faculty members who have published in a journal and the number of articles published by benchmark faculty members in the journal. Tabak et al. (2012) state that knowledge dissemination models seek to facilitate the deployment and utilization of evidence-based approaches to improve the health care in practice. They compare existing models and develop an inventory of models used in dissemination and implementation (D&I) research. Meredith et al. (2011) state that one way to research knowledge generation and diffusion in the business disciplines is to look at published studies in "top-level" academic journals. They have used citation analyses and the opinion of recognized experts to evaluate knowledge diffusion and transfer. Landry et al. (2007) differentiate technology transfer and knowledge transfer. According to them, technology is the tool for conducting research, while knowledge incorporates principles and theories. In this essay, we are looking at how the tool transfer (business analytics) is associated with the knowledge diffusion among statistics and business disciplines.

Economics and business have applied statistical models in their research to promote the development of these disciplines for a long time. We would like to see how knowledge dissemination is changing among statistics and business disciplines at the emergence of business analytics in the 21st Century.

We use citation analysis and text analytics to describe knowledge diffusion among statistics and business journals. Citation analysis is a valuable tool to review citing behavior and scientist/journal influence. Text analytics can retrieve, extract, and summarize information from massive texts.

2.2.2 Citation Analysis

Citation analysis has a long history. Citation research begins in the 1920s when Gross and Gross (1927) use reference analysis to help librarians prepare chemistry books for students to pursue advanced work. They use reference frequency of the *Journal of the American Chemical Society* in 1926 as a tool to measure the importance of cited journals. Many papers followed this approach (Smith (1981); Moed, H. F. (2006); Bornmann and Daniel (2008); Moed (2010)) in citation analysis.

Garfield (1972) uses citation frequency to evaluate journals, considering both academic fields and years and comes up with the 'impact factor' of journals, which assesses the influence and quality of journals (Nierop (2010); Arnold and Fowler (2010)). Pinski and Narin (1976) use a cross citing matrix between journals to find citation influence. They also consider the citing journal prestige. Petersen and Aase (2010) use a meta-analysis approach to analyze operation management journal rankings based on five ranking studies in the discipline. Mingers (2015) uses factor analysis to process cross citation data to identify sub-fields in business and management research.

At first, researchers studied information exchange within disciplines such as economics, psychology, and physics, etc. (Cason and Lubotsky (1936); Eagly (1975); Nerur et al. (2006); Landry et al. (2007)). However, some researchers explore not only intradisciplinary but also interdisciplinary communications of disciplines. For example, Pieters and Baumgartner (2002) investigate how economics journals communicate within this field and with other social science and business journals. Biehl et al. (2006) use multidimensional scaling of correlations and factor analysis to explore how information flows among business journals in different disciplines. They find that most business academics published in non-overlapping disciplines, except for finance, economics, strategic management, and organizational behavior and human resources.

Analysis of the citations in statistics and probability journals did not come to researchers' attention until recently. Altman and Goodman (1994) analyze statistical article citations in the biomedical literature to investigate statistical methods transfer into medical journals. Stigler (1994) studies intradisciplinary and interdisciplinary communications of statistics journals. Theoharahis and Skordia (2003) evaluate perceptions of statistics journals, which is a subjective quality measure, and find that perceptions are highly correlated with citation frequency and impact factor. Nierop (2009) explains the reason statistics journals have low impact factors by examining citation diffusion patterns of statistics journals. Varin et al. (2016) use the Bradley-Terry model to reveal uncertainty in statistics journal rankings.

2.2.3 Text Analytics

As technology developed rapidly in the twentieth century, information became too much to handle. Scholars proposed using data mining to analyze texts. Feldman and Dagan (1995) suggested categorizing texts with similar concepts to extract information and discover knowledge in databases (KDD), which solved the problem of dealing with unstructured texts. According to Hotho et al. (2005), text mining is information extraction, text data mining and KDD process, indicating that we are trying to use text mining to extract useful information and apply machine learning and statistics to explore text patterns.

Text analytics has become a valuable tool to conduct interdisciplinary studies recently. Scholars have used text analytics to analyze abstracts and full papers to explore research interests among different academic fields. Fisher et al. (2010) find that text analytics and information retrieval are essential tools in business research and have room to grow. Indulska et al. (2012) also use text analytics to examine abstracts of information systems, management, and accounting journals to reveal how academic topics change in 25 years. They use Latent Semantic Analysis (LSA) to identify the relative conceptual drift and data mining to identify the core concepts.

2.2.3.1 Topic Modeling

Topic modeling is a statistical tool for exploring the latent structure of a collection of documents (Boyd-Graber et al. (2014)). The original topic model is Latent Dirichlet Allocation (LDA), which assumes that each document in a corpus is distributed over multiple topics, and each topic is distributed over words (Blei et al., 2003). Scholars have developed more topic models to improve text mining since then. Alghamdi and Alfalqi (2015) categorize topic models based on whether they consider an essential factor, time, or not. Probabilistic Latent Semantic Analysis (PLSA) (Hofmann (1999)), Latent Dirichlet Allocation (LDA) (Blei et al., 2003), Correlated Topic Model (CTM) (Blei and Lafferty(2007)), Syntactic Topic Model (Boyd-Graber and Blei (2009)), and Structural Topic Model (Roberts et al. (2014)) don't consider time. Topic models that consider how topics change over time include Dynamic Topic Modeling (DTM) (Blei and Lafferty (2006)), and Topics Over Time (TOT) (Wang and McCallum (2006).), etc.

Scholars have applied these topic modeling methods in many fields such as political science (Roberts et al. (2014), biology (Lee et al. (2016)), scientific studies (He et al. (2009); He et al. (2010); Nallapati et al. (2008); Wang and Blei (2011)), and social networks (McCallum et al. (2005); Hong and Davison (2010)). Yan (2015) uses information revealed by topics to analyze the research impact, dynamics, and diffusion by looking at the 50 topics labeled by the top five words that have the highest associations with each topic. He finds that the correlation between impact and popularity is not statistically significant in operations management research.

2.3.Motivation

The motivation for this work is to examine how research in statistics is influencing and influenced by research in business disciplines as business analytics has emerged in the twenty first century. The development of data science has enabled research in business practice to apply analysis at a faster speed and lower cost. As scholars in business disciplines, we also incorporate business analytics in our study. How will the application of business analytics affect the knowledge diffusion among statistics and business disciplines? Does the emergence of business analytics motivate scholars in business disciplines to have a deeper understanding of statistics and make more references to statistics journals? Can statistics enhance its models by extracting information from business disciplines and citing more articles from the business disciplines? We are interested in exploring whether the knowledge diffusion patterns among statistics and business disciplines have changed due to the development of business analytics.

To achieve our goal, we are looking at communications among statistics journals and business journals. Previous studies show that the relationship between journals in the same discipline is strong. We will investigate the relationship among statistics journals and other business journals by applying citation analysis and text analytics methods. Moreover, we want to find if the citation pattern and the research interest has changed in the 15 years between 2000 and 2015 as business analytics develops.

As citation data only give us the citing and cited numbers, we cannot see how the content and research trend change. Knowing that connection exists among statistics journals and business journals cannot show what connects them, not to mention why the connection changes. To understand the relationship better, we look at abstracts of these journals to find the topics that they are interested in and how often this interest is mutual. Also, we use text analytics to find whether journals from different disciplines are sharing the same research interest in more recent years than before.

2.4.Research Methods

We collect both citation and abstract data from Journal Citation Reports at Web of Science. To understand the change of communication patterns, we extract citation counts and abstracts of 36 top journals for the years 2000, 2005, 2010, and 2015. Since Web of Science doesn't have 2000 data of *Production and Operations Management*, we use 2001 data instead.

We have followed previous studies (Porter and Rafols (2009); Hric et al. (2017)) to use snapshots of articles in these 36 journals in four separate years to retrieve the knowledge diffusion among statistics and business disciplines. In our preliminary analysis, when data were pooled into four groups of five-year windows, changes through time were blurred by the pooling effect.

2.4.1 Selecting Journals

Based on the lists in Theoharakis and Skordia (2003), we select *the American Statistician; Annals of Probability; Annals of Statistics; Biometrics; Journal of Royal Statist Soc, Ser A&B; Statistical Science; and Technometrics*. Based on Eakin et al. (2005), we select the *Journal of Business and Economics Statistics*. Van Nierop (2009) helps us choose *J of Royal Statist Soc, Ser C*. The suggestions to use *Biometrika* and the *Journal of Statistical Planning and Inference* came when presenting preliminary results to the Joint Statistical Meetings of the American Statistical Association.

For business journals, we choose those used to determine the 'Intellectual capital score' for business schools in *Bloomberg Business Week*'s MBA rankings. We also use the *Financial Times* to choose journals that count for its research rank. As a result, we have 24 business journals and 12 statistics journals (See Table 1.)

2.4.2 Citation Frequency Analysis

Firstly, we conduct a citation analysis by looking at citing and cited data among journals in different disciplines. The citation frequencies imply the strength of the relationship among journals. Thus, we create two 36x36 asymmetric matrices reflecting the counts of cross citations between pairs of 36 journals for each of the four years. We build a 36-by-36 matrix with citing journals in the row and cited journals in the columns for each year. We also create a 36-by-36 matrix with cited journals in the row and citing journals in the columns for each year. Then we use Python, SAS, and NCSS to analyze citation data. We first use Python to transform the citation frequency matrices into cosine distance matrices for both cited-citing datasets and citing-cited datasets. Next, we use principal components factor analysis in SAS to get rotated factor loadings with a minimum eigenvalue of 1. Thus, we determine the groups of journals that load together on a factor. Then, we use SAS to analyze the cosine distance matrices and get non-metric multidimensional scaling (MDS) results for 36 journals. After putting non-metric MDS data in NCSS, we draw the scatter plots of 36 journals. We have analyzed citations for the four years separately.

After looking at the specific relationship of journals, we look at the relationships of disciplines. We would like to see if a change in communication patterns among different disciplines emerges. For example, is statistics more likely to "learn" from other disciplines or "teach" other disciplines in the four years? We want to explore the communication trend using citation datasets of disciplines. In the MDS maps of Figures 1, 2, and 6, we use red to represent accounting, blue to represent economics, green to represent finance, purple to represent ISOM, orange to represent management, yellow to represent marketing, sky blue to represent probability and pink to represent statistics. In our matrices, we have all the data of citing-cited, cited-citing, and the averages for eight disciplines.

2.4.3. Abstract Text Analytics

After conducting Citation Frequency Analysis, we use text analytics to analyze abstracts of the 36 journals. By looking at term frequencies in abstracts of these journals, we can reveal the research interest shared by journals within and among disciplines.

We first pool the words in abstracts of 36 journals in Python. We preprocess the texts by converting the texts to lowercase, removing punctuation and digits, removing stopwords (e.g., 'the,' 'a'), and lemmatizing words. We use a Term Frequency-Inverse Document Frequency (TFIDF) vectorizer to create the document-term matrix, which shows the term frequencies in a collection of documents. In our case, we generate 36 x N asymmetric matrices with frequencies of words used by journals. Next, we convert the document-term matrix to a 36 x 36 cosine distance matrix, and we use principal components factor analysis in SAS to get rotated factor loadings with a minimum eigenvalue of 1. We can see the groups that factor analysis has determined for each journal by looking at abstracts. Again, we use SAS to analyze the cosine distance matrix and get non-metric MDS results for 36 journals. After putting non-metric MDS data in NCSS, we get the scatter plots of 36 journals. We have analyzed abstracts for four years separately.

2.4.3.1 Topic Modeling

Latent Dirichlet Allocation (LDA), which is a Bayesian model, uses latent topics to present the contents of texts. Latent Semantic Analysis (LSA) uses singular value decomposition (SVD) to find the frequencies of terms in documents in a term-document matrix. Non-negative Matrix Factorization (NMF) factorizes a term-document featured matrix into a term featured matrix, and a document featured matrix to learn topics. Dynamic Topic Model (DTM)), an extension to LDA, is the only one among the four models that considers the time when learning topics in the documents. We present the results of LDA for your review in this essay.

2.5. Findings/Data

2.5.1 Data Source

In this essay, we have used 36 journals from 8 disciplines for the years 2000, 2005, 2010, and 2015 to conduct the research. The following figure shows the names, abbreviations, and disciplines of these selected journals.

Name	Abbreviation	Discipline	Name	Abbreviation	Discipline
Accounting Review	ACR	Accounting	Strategic Management Journal	SMJ	Management
Journal of Accounting Research	JAR	Accounting	Journal of Consumer Research	JCR	Marketing
American Economic Review	AER	Economics	Journal of Marketing Research	JMR	Marketing
Econometrica	EM	Economics	Journal of Marketing	JOM	Marketing
Journal of Econometrics	JOE	Economics	Marketing Science	MKS	Marketing
Review of Economics and Statistics	RES	Economics	Annals of Probability	ANP	Probability
Journal of Finance	JF	Finance	American Statistician	AMS	Statistics
Journal of Financial Economics	JFE	Finance	Annals of Statistics	AS	Statistics
Review of Financial Studies	RFS	Finance	Journal of the American Statistical Association	ASA	Statistics
Decision Sciences	DS	ISOM	Journal of Business & Economic Statistics	BES	Statistics
Information Systems Research	ISR	ISOM	Biometrics	BIO	Statistics
Management Science	MGS	ISOM	Biometrika	BMK	Statistics
MIS Quarterly	MISQ	ISOM	Journal of Statistical Planning and Inference	JSPI	Statistics
Operations Research	OPR	ISOM	Journal of the Royal Statistical A	RSSA	Statistics
Production and Operations Management	POM	ISOM	Journal of the Royal Statistical B	RSSB	Statistics
Academy of Management Journal	AMJ	Management	Journal of the Royal Statistical C	RSSC	Statistics
Academy of Management Review	AMR	Management	Statistical Science	SSC	Statistics
Administrative Science Quarterly	ASQ	Management	Technometrics	TEM	Statistics

Table 2.1 Selected Journals and their Abbreviations and Disciplines

We find that these journals have made 22,154 references, 28,005 references, 39,442 references, 45,166 references among themselves in the years 2000, 2005, 2010, and 2015, respectively. Statistics journals cite business journals 481 times, 789 times, 1066 times, and 927 times in the years 2000, 2005, 2010, and 2015, respectively. On the other hand, business journals cite statistics journals 750 times, 772 times, 1096 times, 1856 times in the years 2000, 2005, 2010, and 2015, respectively.

2.5.2 Citation Frequency Analysis

Below are the results from the methodology previously described where factor loadings are indicated by the enclosures, and disciplines by color on the MDS maps.

2.5.2.1 Citation: Citing-Cited

In Citation Frequency Analysis, we first use citing-cited matrices to find the cited similarities. We can see that principal component factor analysis loads journals onto seven factors in 2000 and six factors in 2005, 2010, and 2015. Accounting and finance journals load on separate factors in 2000. Still, they load together in the other three years, indicating that accounting and finance journals are cited by similar journals more in later years than in 2000. Also, except for the *Journal of Business and Economic Statistics*, all other journals loaded with journals in the same discipline in 2000. In all the other three years, we can see that journals may cross load on two factors. The cross-loaded journal links the two disciplines. In 2005, the *Journal of Econometrics* loaded with both the economics journals on one factor and the statistics journals on another factor. In 2015, both the *Journal of Econometrics* and the *Journal of Business and Economics Statistics* were loaded with economics and statistics journals, indicating these two journals link economics and statistics disciplines in research from a citing-cited perspective.

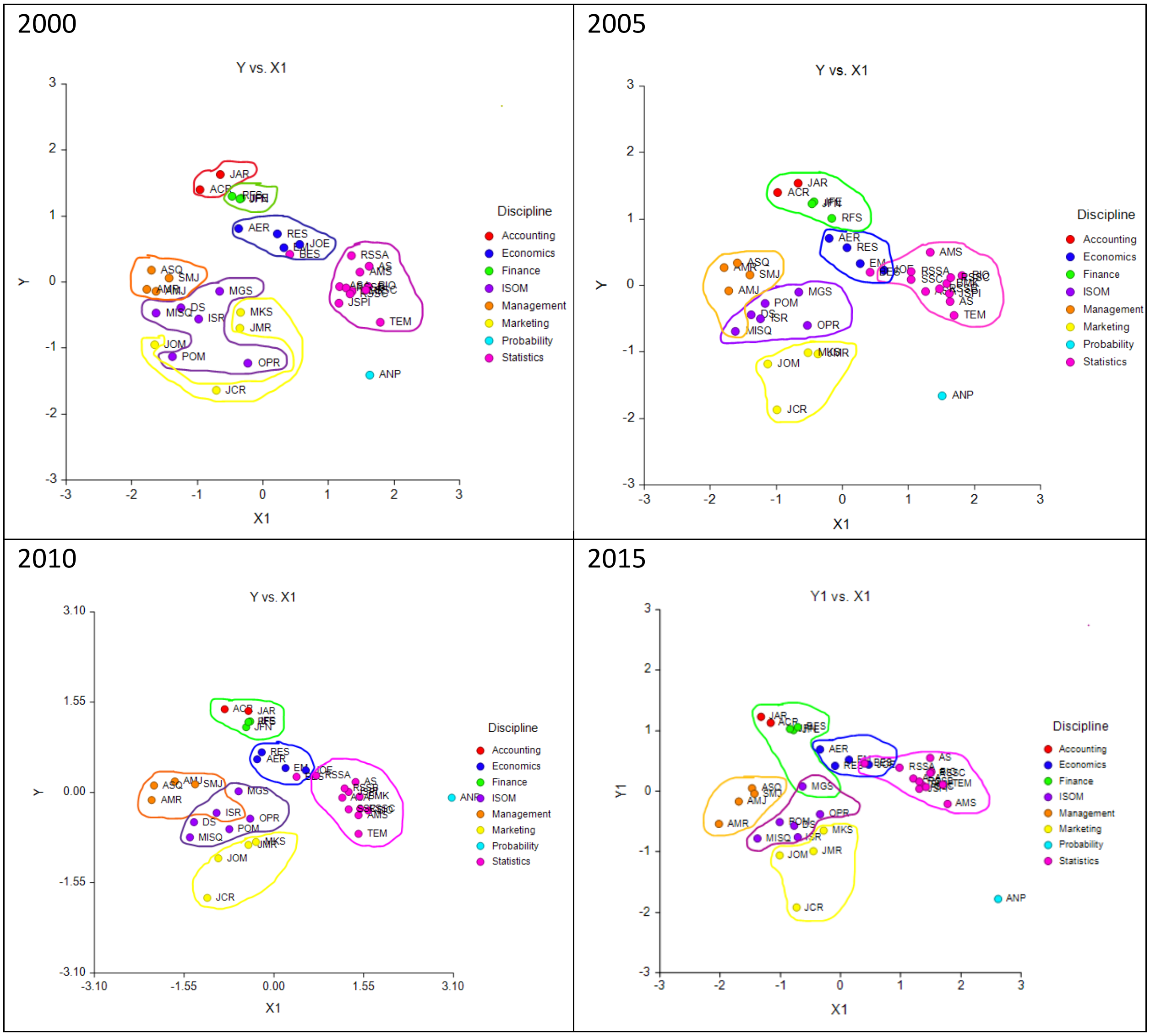


Figure 2.1. Structural Equivalence of journals based on Non-Metric MDS and Principal Component Factor Analysis results for Citing-Cited Citation Counts Data

Further, we can see that one discipline may link other disciplines. For example, economics is a link between journals in statistics and journals in accounting and finance. Also, the citation frequency MDS maps indicate that ISOM links management and marketing in all four years. ISOM even linked with accounting and finance and marketing in 2015. *Management Science* loads with both the accounting and finance category and ISOM category in 2015. The citation maps show more communication between different disciplines in 2015 than previously.

2.5.2.2 Citation: Cited-Citing

Next, we use cited-citing matrices to find the citing similarities between journals in Citation Frequency Analysis. We can see that principal component factor analysis loads journals onto eight factors in 2000 and 2005. In 2010 and 2015, journals load onto six factors. In 2000 and 2005, accounting and finance journals load on different factors, but they load together in 2015. In 2010, accounting journals do not load on any factor. This indicates that accounting and finance journals share more citing similarities in 2015 than in the other three years. The *Journal of Business & Economic Statistics* loads with economics journals in all four years, indicating that JBES is citing similar journals as economics journals. All other statistics journals are citing similar journals in all four years. *American Economics Review* cross loads with both finance journals and economics journals, linking the two disciplines from a cited-citing perspective. *The American Statistician* also cross loads linking statistics journals and economics journals in 2015.

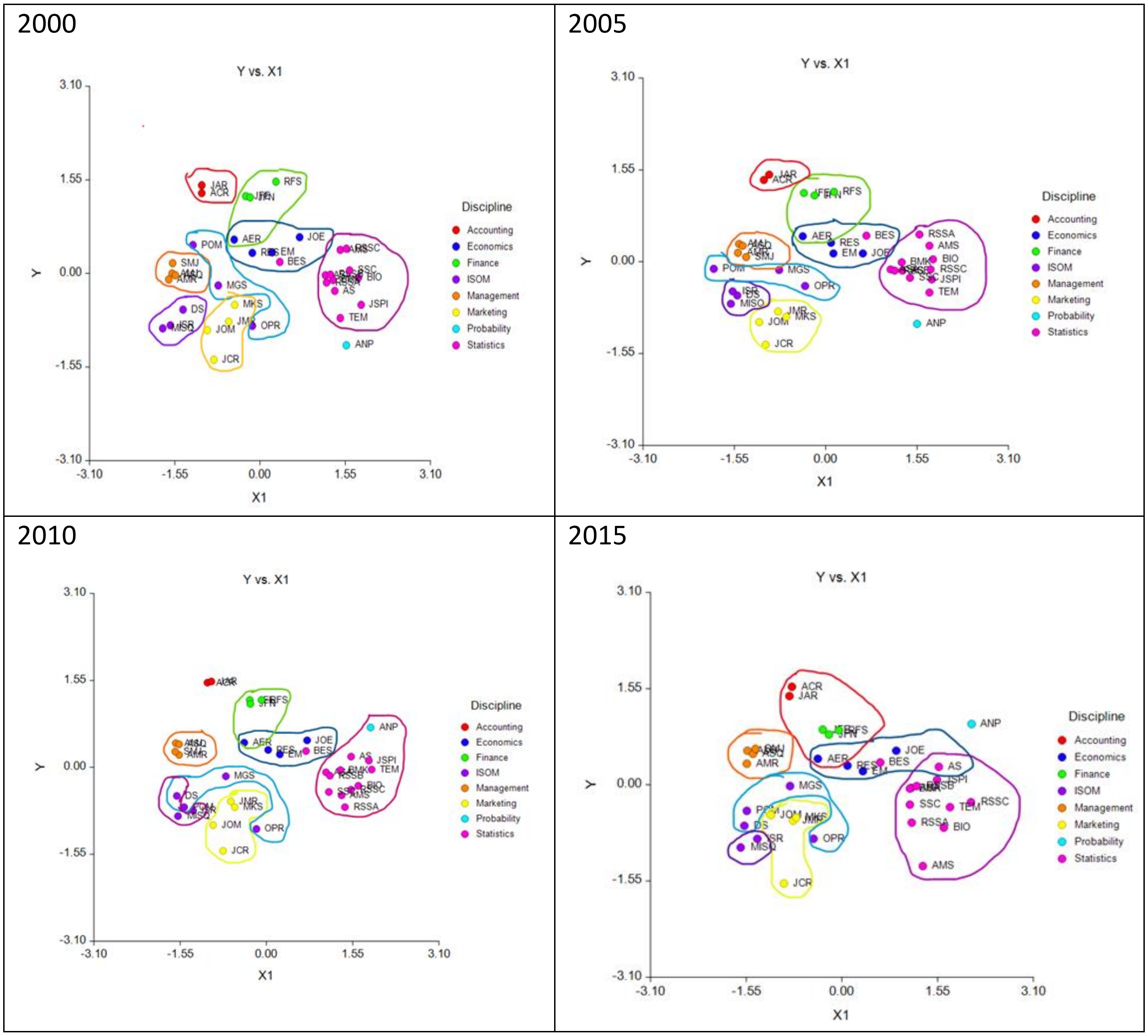


Figure 2.2. Structural Equivalence of journals based on Non-Metric MDS and Principal Component Factor Analysis results for Cited-Citing Citation Counts Data

Management journals fall in one group, indicating these journals are citing similar journals in all four years, similarly for marketing journals. For ISOM journals, *Productions and Operations Management*, *Operations Research* and *Management Science* are grouped in all four years. *Decision Sciences* cites similar journals as these three journals in 2010 and 2015. In 2000 and 2005, The citing pattern of *Decision Sciences* is identical to that of *MIS Quarterly* and *Information Systems Research*. In 2010, *Decision Sciences* acted like a link connecting the ISOM journals.

The results of Average Citing-Cited data are consistent with the citing-cited and cited-citing findings. We have put these results in the Appendix for your review.

2.5.2.3 Citation: Disciplines

In this section, we combine the journal citing-cited frequencies and cited-citing frequencies into eight disciplines in each of the four years and compare the self-citing behavior of the disciplines to interdisciplinary citing patterns. We first use the citing-cited frequency matrix for different journals to create the citing-cited frequency matrix for different disciplines. Next, we use the frequency table to create the relative frequency table for different disciplines as relative frequency can help us in comparing the citation patterns. After creating the citing-cited relative frequency matrices for different disciplines in all four years, we use the same method to get the cited-citing relative frequency matrices. In the end, we get the difference of cited relative frequency and citing relative frequency for different disciplines for four years. Below is Table 2 with the results.

As we can see, journals in Accounting and ISOM are more likely to cite other journals in later years than in 2000. Economics, finance, and probability journals are more likely to be cited than to cite generally. The difference between cited and citing increases until 2015 when the difference decreases somewhat for probability and substantially for economics. Marketing journals are more likely to cite than to be cited at a decreasing rate until 2015 when it is somewhat more likely to be cited. Management journals cite more in 2000 and 2015 while they are cited more in 2005 and 2010. Statistics journals are cited more in 2000 and 2015 while they cite other journals more in 2005 and 2010.

Discipline	2000	2005	2010	2015
Accounting	6.22%	18.69%	14.60%	19.07%
Economics	-9.24%	-18.02%	-22.43%	-7.89%
Finance	-2.08%	-3.32%	-4.12%	-14.83%
ISOM	13.83%	22.06%	25.24%	28.16%
Management	2.89%	-1.42%	-2.71%	2.94%
Marketing	9.22%	3.31%	2.18%	-6.47%
Probability	-13.50%	-26.99%	-34.71%	-30.04%
Statistics	-3.19%	0.95%	0.47%	-7.62%

Table 2.2 Differences of Cited Minus Citing Relative Frequencies of Eight Disciplines

Figure 2.3 below depicts the differences in Table 2.2 for the four years. From this figure, we can see that journals in accounting and ISOM are more likely to cite other disciplines than be cited by other disciplines. On the other hand, economics, finance, and probability are more likely to be cited by other disciplines than to cite other disciplines. These three disciplines are more likely to "teach" the other disciplines listed. The citing and cited patterns are not so evident in other disciplines.

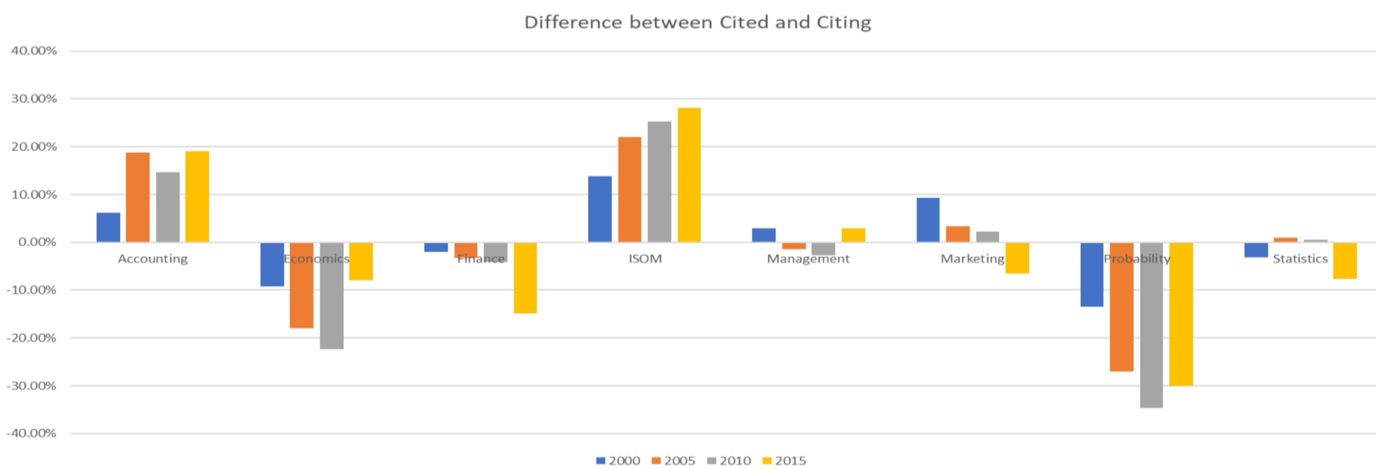


Figure 2.3 Differences between Cited and Citing Relative Frequencies of Eight Disciplines

After reviewing the differences between self-cited and self-citing relative frequencies of eight disciplines, we want to find whether the cited and citing relationships between statistics and business disciplines have changed in these four years.

In this table, we present the difference of cited and citing relative frequencies between statistics and the other seven disciplines. Accounting journals in 2000, as an example, never cite statistics journals (0%), while statistics journals cite accounting journals twice (0.026%). We then use 0% (out of 7,901 times that statistics was cited, none are from journals of accounting) minus 0.026% (out of all 7,632 times that statistics is citing, 2 are citations of accounting journals) to get the -0.026%. In this way, we have calculated all the differences between cited and citing relative frequencies for all disciplines for four years. As we can see, statistics journals are more likely to teach economics than to learn from it in 2015. Statistics' relationships with these disciplines in other years are not so obvious.

Discipline	2000	2005	2010	2015
Accounting	-0.026%	0.000%	0.126%	0.080%
Economics	2.762%	0.029%	-0.434%	6.384%
Finance	-0.428%	-0.530%	-1.123%	-0.867%
ISOM	0.354%	-0.019%	0.535%	1.681%
Management	0.127%	0.147%	0.155%	0.428%
Marketing	0.816%	0.274%	1.086%	0.703%
Probability	-0.415%	-0.847%	-0.818%	-0.785%

Table 2.3 Differences between Statistics Cited and Statistics Citing Relative Frequencies based on Statistics

Figure 2.4 depicts the information in Table 2.3. We can see that there are salient changes in the pattern of citations for statistics with respect to economics compared to other disciplines. On the other hand, finance, management, marketing, and probability are not changing much. The citing and cited patterns are not so obvious in other disciplines.

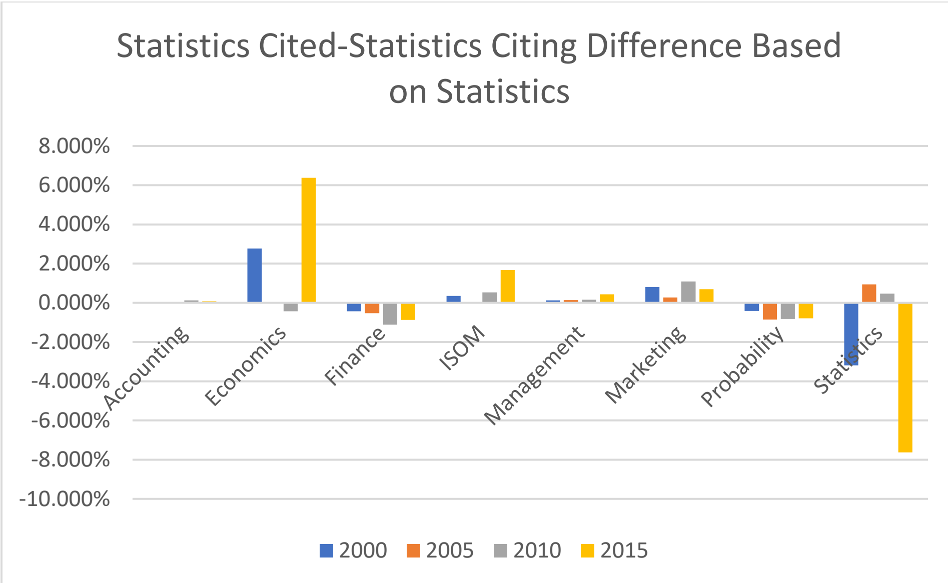


Figure 2.4 Differences between Statistics Cited and Statistics Citing Relative Frequencies based on Statistics

In this table, we present the difference of cited and citing relative frequencies between statistics and the other seven disciplines in another way. Taking accounting journals in 2000 as an example, they never cite statistics journals (0%), while statistics journals cite accounting journals twice (0.477%). We use 0% (out of 454 times that accounting cites, none are citations of statistics journals) minus 0.477% (out of 419 times that accounting was cited, 2 citations are by statistics journals) to get the -0.0477%. In this way, we have calculated all the differences of cited and citing relative frequencies between statistics and the other seven disciplines for four years.

	2000	2005	2010	2015
Accounting	-0.477%	0.000%	0.676%	0.341%
Economics	10.798%	5.503%	5.047%	11.981%
Finance	-0.930%	-1.123%	-1.625%	-0.686%
ISOM	1.000%	-0.415%	0.530%	1.846%
Management	0.256%	0.312%	0.294%	0.593%
Marketing	3.096%	0.667%	2.251%	1.639%
Probability	-7.208%	-26.453%	-27.519%	-20.921%
Statistics	3.190%	-0.946%	-0.473%	7.623%

Table 2.4 Differences between Statistics Cited and Statistics Citing Relative Frequencies based on Other Disciplines

As we can see, from this perspective Statistics journals are more likely to teach economics than to learn from it in all four years. They are more likely to learn from probability in all four years. Statistics' relationships with other disciplines are not so apparent in all four years.

Figure 2.5 offers a visualization of the information we get from Table 2.4.

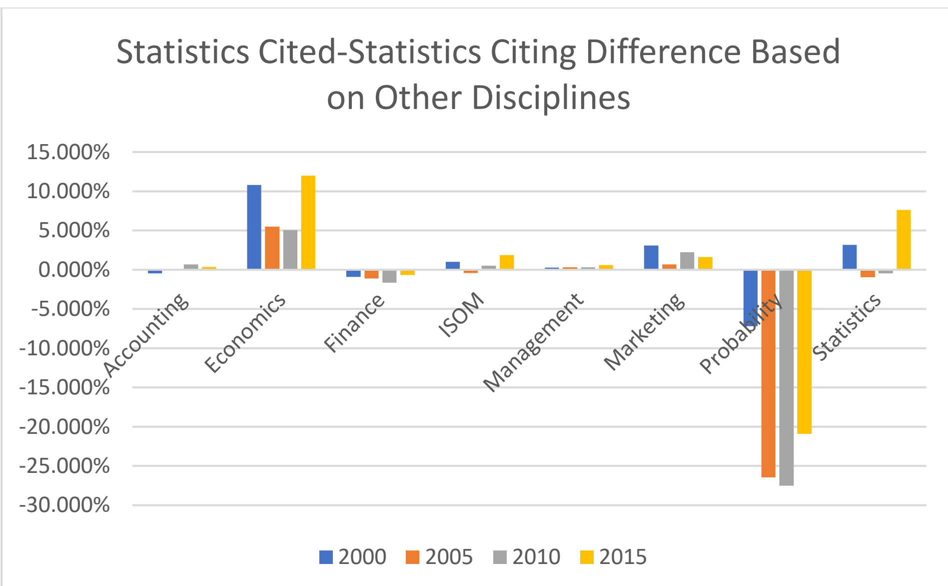


Figure 2.5 Differences between Statistics Cited and Statistics Citing Relative Frequencies Based on Other Disciplines

2.5.3 Abstract Text Analytics

2.5.3.1 Text Analytics: Factor Analysis and Multidimensional Scaling

In Abstract Text Analysis, we can see that principal component factor analysis categorizes journals into seven groups all four years. Journals in different disciplines share more research interest in more recent years than previously. The results are consistent with those of Citation Frequency Analysis. When journals cross load on factors associated with more than one discipline, it is because frequencies of words used in abstracts are similar. We can assume when journals in different disciplines share the same research interest, they tend to review literature in other areas, and communications among these disciplines become more frequent.

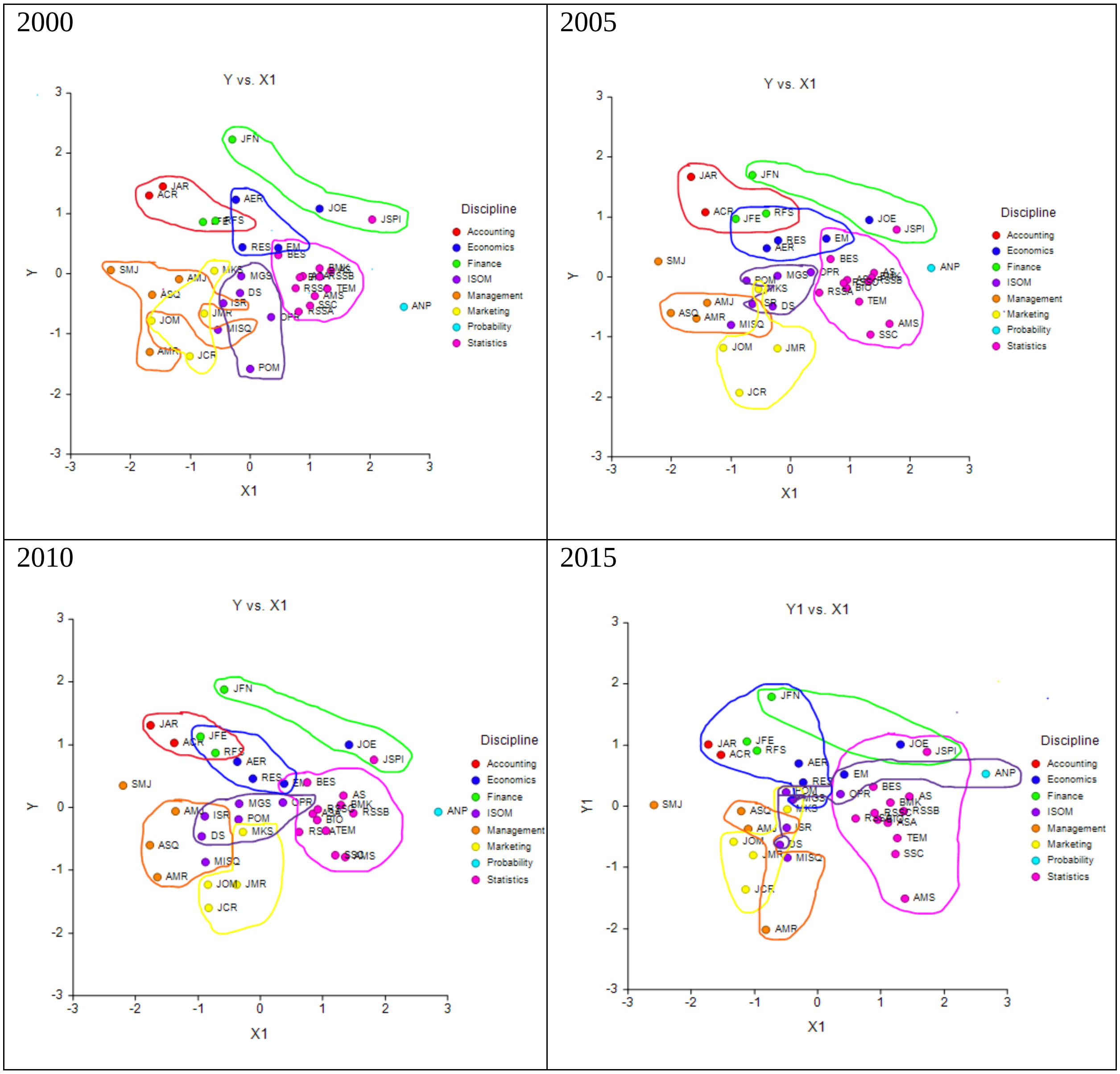


Figure 2.6. Structural Equivalence of journals based on Non-Metric MDS and Principal Component Factor Analysis results for Abstract Data

In 2000, most journals share the same research interest with journals of the same disciplines. That is to say, based on research interest, most journals of the same disciplines load on the same factor. There are only several exceptions. Accounting and finance journals load on a single factor. The *Journal of Finance*, *Journal of Econometrics* and *Journal of Statistical Planning and Inference* load together on a single factor. *Econometrica* cross loads with economics and statistics journals.

MIS Quarterly loads with management journals. *Information System Research* cross loads with ISOM and management journals.

Based upon their factor loadings, journals appear to share more research interest in later years. In 2005, Finance journals like the *Journal of Financial Economics* and *Review of Finance Studies* share the research interest with not only accounting journals but also economics journals. *Journal of Finance*, *Journal of Econometrics* and *Journal of Statistical Planning and Inference* share the same research interest. *MIS Quarterly* shares research interests with management journals. *Econometrica* shares research interest with economics and statistics journals.

In 2010, the *Journal of Financial Economics* and *Review of Finance Studies* share research interest with not only accounting journals but also economics journals. *Econometrica* shares research interest with economics and statistics journals. *Journal of Finance*, *Journal of Econometrics* and *Journal of Statistical Planning and Inference* continue to load together on a single factor. *MIS Quarterly* shares interests with management journals. *Decision Sciences* and *Information System Research* share research interests with information systems and management journals. *Marketing Science* shares research interest with ISOM and marketing journals,

In 2015, the MDS map becomes more chaotic, indicating the research interests of journals from different disciplines are more diverse. Accounting journals (*Journal of Accounting Research* and *Accounting Review*), finance journals (*Journal of Financial Economics*, *Journal of Finance* and *Review of Financial Studies*), economics journals (*American Economic Review* and *Review of Economics* and *Statistics*), and an ISOM journal (*Management Science*) load together on one factor. All the marketing journals share research interest with ISOM journals (*Production and Operations Management, Management Science*, *Information System Research*, and *Decision Sciences*). *Information System Research* also shares research interest with management journals except for the *Strategic Management Journal*. Statistics journals share research interest with economics journals (*Journal of Econometrics and Econometrica*) and an ISOM journal (*Operations Research*). *Production and Operations Management, Operations Research,* and *Decision Sciences* share research interest with *Econometrica* and *Annals of Probability*.

5.3.2 Topic Modeling

After examining the results of our topic models, we find that topics don't change much over the years; some disciplines share the same topics with other disciplines. We illustrate this finding with the word clouds in Figures 7, 8 and 9. The topics in accounting, economics, and statistics don't change much from 2000 to 2015 in the overall picture. However, accounting has focused more on earnings and analyst in 2015 than before. Economics has focused more on trade and parameter in 2015 than before. Statistics does not change its focus. Also, accounting shared topics such as firm and market with economics while economics shared topics such as model and estimate with statistics. The results are consistent with previous findings, indicating that economics acts like a link connecting business disciplines and statistics.

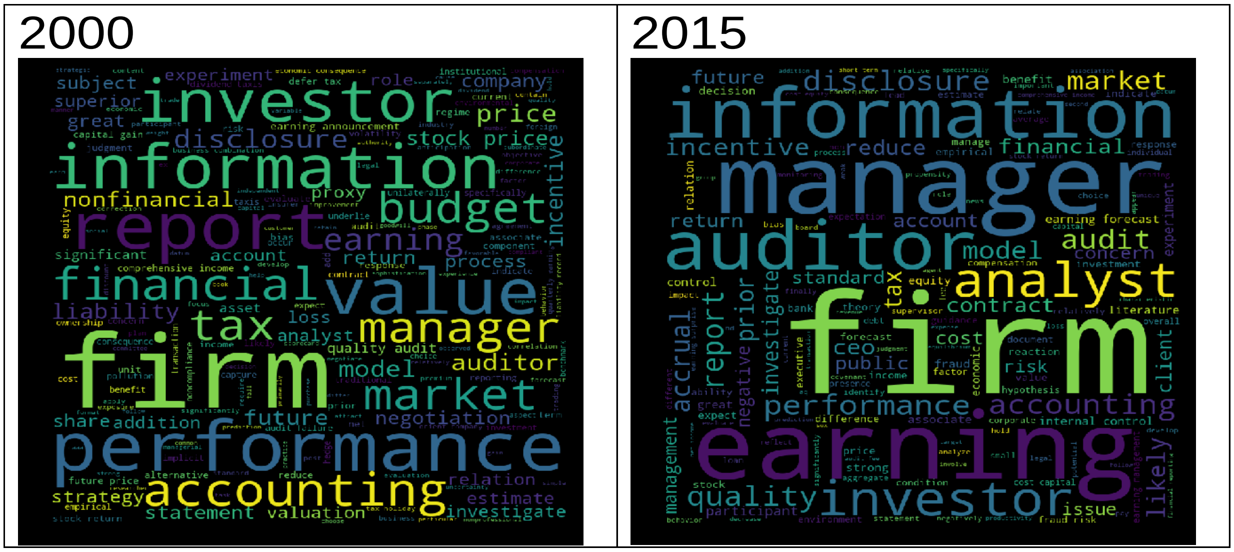


Figure 2.7 Accounting LDA Topics

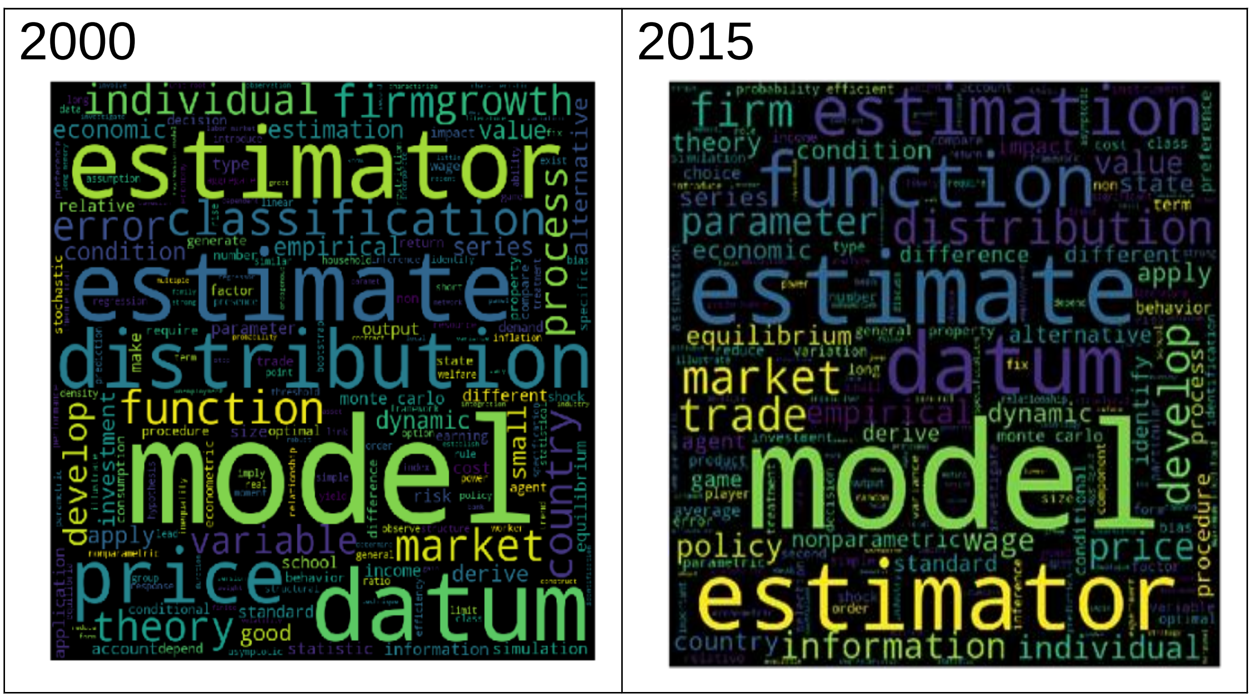


Figure 2.8 Economics LDA Topics

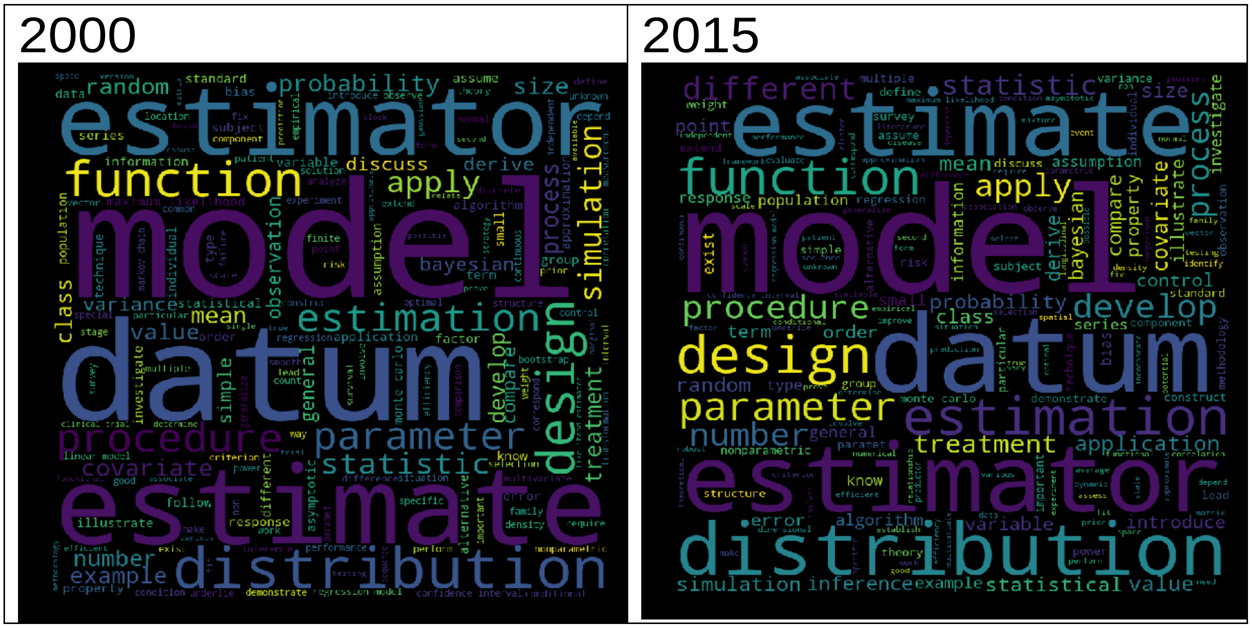


Figure 2.9 Statistics LDA Topics

2.6 Discussion/Conclusion(s)

To summarize, we can see more similarities in citing patterns among business and statistics journals in 2015 than previously. From factor analysis with both citing-cited and cited-citing perspectives, economics journals link journals in statistics to journals in accounting and finance. Also, ISOM is a link connecting economics and marketing. The *Journal of Econometrics* and the *Journal of Business and Economics Statistics* cross load with economics and statistics journals, indicating these two journals link economics and statistics disciplines in research. Meanwhile, from a cited-citing perspective, the *American Economics Review* is connecting finance and economics while *Decision Sciences* links information systems journals with operations management journals within ISOM.

As we can see, journals in accounting and ISOM are more likely to be influenced by other disciplines in later years than in 2000. Finance, marketing, and probability are more likely to influence other disciplines overall. Statistics journals are more likely to affect other disciplines more in 2000 and 2015 while they are more likely to be influenced by other disciplines in 2005 and 2010.

Using abstract text analysis, we can see that the *Journal of Finance*, *Journal of Econometrics*, and *Journal of Statistical Planning and Inference* share the same research interest in all four years. These three journals share the same research interest with other journals only in 2015 out of the four years considered.

Some disciplines that share a research interest communicate more. For example, accounting and finance share the same research interest, and cite each other more often. In 2015, accounting and finance journals were sharing more research interest with ISOM journals, and the citation analysis gives consistent results as accounting and finance journals are grouped with *Management Science* in the Citation Frequency MDS map. However, other disciplines share the same research interest but do not communicate frequently. For example, ISOM and marketing share the same research interest but are not citing each other. We find similarities from the text analysis of abstracts for these two disciplines but cannot see a similar pattern from the Citation Frequency Analysis. In 2015, we have more cross-loadings among different factor disciplines than in previous years. The *Journal of Econometrics* and *Journal of Statistical Planning and Inference* load with statistics; *Annals of Probability* loads with *Econometrica* and operations management journals.

We have chosen to use 2000, 2005, 2010, and 2015 for our analysis, but we haven't assessed the possibility that the variation from year to year in our results is random. In future research, we can use 2020 data to test the robustness of the results. Also, we may conduct a correspondence analysis to see if the results are consistent with the factor analysis and multidimensional scaling.

Regarding both citations and abstracts, the communications among statistics and probability and other business disciplines seems to have changed somewhat from 2000 to 2015, but the changes are not substantial.

Chapter 3 Essay 2: Connections Among Statistics and Business Journals: Network Analysis

3.1 Introduction

We have already discussed why we want to explore knowledge sharing among statistics and business journals at the emergence of business analytics in the first essay. This essay continues the study by using both a citation network analysis and the log-multiplicative model.

We use the citation data from 24 top business journals and 12 top statistics journals for the years 2000, 2005, 2010, and 2015, the same dataset we use in essay 1. We use UCINET to analyze the citation network. We calculate and present density, degree centralization, closeness centralization, and betweenness centralization, which are major centrality measures. Also, UCINET can group journals in a network by faction function. The network analysis allows us to observe the changes in the knowledge sharing pattern and the grouping by factions. We also compare the results of citation analysis and abstract analysis from essay 1 and citation network analysis from essay 2.

Next, we use the log-multiplicative model to discuss the influence of journals as storers (citing journals) and sources (cited journals) for the four years. We use LEM software (Log-linear and event history analysis with missing data using the EM algorithms) to find the scores and ranks of the journals as storers and sources. Thus, we can find the changes in journal influences at the emergence of business analytics.

In 3.2, we review literature related to network science, citation network analysis, and log-multiplicative model. In 3.3, we present the motivation of this essay. In 3.4, we describe our research methods. In 3.5, we show the findings. In 3.6, we make some conclusions based on the findings.

3.2. Literature Review and Background

3.2.1 Network Science in the Literature

Network Science has a long history. It was first used by the Swiss mathematician Leonhard Euler to solve the Konigsberg bridge problem in 1736. Network science mainly used graph theories from mathematics in the next two hundred years. More recently, many other disciplines have contributed to network science. For example, network science used algorithms from computer science, mapping subcellular from biology, and analytical tools from physics (Borgatti, S. P., Mehra, A., Brass, D. J., & Labianca, G., (2009); Kjaerulff, U. B., & Madsen, A. L., (2008); Borgatti, S. P., & Li, X., (2009); Borgatti, S. P., & Halgin, D. S., (2011); Lewis, (2011); Kacanski, S., & Lusher, D., (2017)). Scholars have conducted research on network theory and more importantly made it an application tool exploring relationships among nodes through links (Hanneman, R. A., & Riddle, M. (2005); Scott, J., Wasserman, S., & Carrington, P. J., (2005); Marin, A., & Wellman, B., (2011); Borgatti, S. P., Everett, M. G., & Johnson, J. C. (2018)).

According to the United States National Research Council (2006), network science is *'the study of network representations of physical, biological, and social phenomena leading to predictive models of these phenomena*.' As scientists develop network science from different disciplines, many disciplines have applied this new technique in recent years. According to Lewis (2011), network science studies nodes and links in a system and their dynamic behaviors. Network science is used in the following subfields:

Subfields	Social Network Analysis	Collaboration Networks	Synthetic Emergent Systems	Physical Science Systems	Life Science Systems
Applications		Citation Analysis; Marketing; Online Social Networks	Power Grids; Internet	Phase Transition; Percolation Theory; Ising Theory	Epidemics; Metabolic Processes; Genetics

Table 3.1 Network Application in Academic Subfields

In this paper, we focus on collaboration networks. We apply network science to analyze the relationship among journals from statistics and business disciplines in the years 2000, 2005, 2010, and 2015. Different from previous statistics papers, we are using network science to analyze both citation and abstract data of these 36 journals. Scholars have developed multiple tools such as UCINET, R packages, and Python packages (Borgatti, S. P. (2011); Borgatti, S. P., Everett, M. G., & Johnson, J. C. (2018)). In this essay, we will use UCINET to analyze the networks among 36 journals for four years.

3.2.2 Background of Fundamental Metrics for Network Science

To understand network analysis, we need to first understand some fundamental concepts. We use a simple network example to illustrate them.

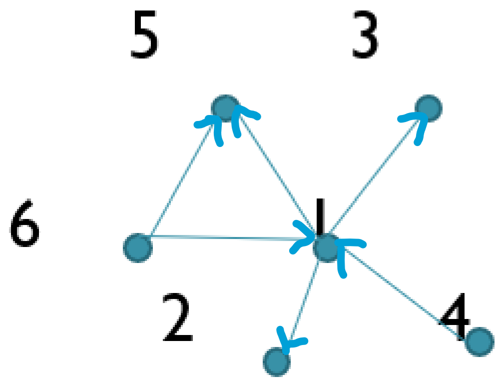


Figure 3.1 Simple Network Example

Figure 3.1 represents a simple network. We will use it to illustrate the concepts of networks. We can see that points 1, 2, 3, 4, 5, and 6 are individuals or collectives that appear in a network, and we study the links among these individuals or collectives. We refer to these points as nodes, actors, or vertices interchangeably. The connections between nodes in a network are called ties. Here we have a directed network, meaning that there is a direction in the relationship. The undirected network does not consider direction. For example, the citation network is a directed network as we identify whether paper A cites paper B or B cites A when there is a tie between A and B. The co-authorship network is undirected as the author C and author D are coauthors and write the same paper when there is a tie between them. We can also get an edgelist (Table 3.2) or a matrix (Table 3.3) based on the relationship presented in Figure 3.2

Node 1	Node 2
1	2
1	3
1	5
4	1
6	1
6	5

Table 3.2 Simple Network Example (Edgelist)

	1	2	3	4	5	6
1	0	1	1	0	1	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	1	0	0	0	0	0
5	0	0	0	0	0	0
6	1	0	0	0	1	0

Table 3.3 Simple Network Example (Matrix)

Four major network characteristics are used to measure the network: density; degree centralization; degree centrality; closeness centrality, and betweenness centrality.

Density, which is the proportion of all possible ties that are present. We use the sum of existing ties divided by the number of all possible ties to calculate it. In our example, the network has 6 existing ties and the number of all possible ties is 30 (6*(6-1)=30). Thus, the density =6/30 =0.2. Density informs about the speed of diffusion among the nodes. If we have higher density, then we will have a network with more links among nodes.

Degree centralization measures how well a node holds ties in a network. The higher degree centralization, the more the network is dependent on a small number of actors. UCINET measures the degree centralization and closeness centrality, as shown below.

degree centralization $=\frac{\sum(\text{Cmax}-\text{C(node i)}}{\text{Maximum Degree Value}}$

Where Cmax=maximum degree centrality in the network

C(node i)=degree of node i

In our simple example, as node 1 has the most directed to ties (3), we have degree centralization =((3-3)+(3-0)+(3-0)+(3-1)+(3-0)+(3-2))/((6-1)*(6-2))=0.6, and we can get the same result in UCINET. We can also use both equations and UCINET to calculate closeness centrality and betweenness centrality.

The closeness centrality is the sum of geodesic (shortest path) distances between a node and other nodes. If we have higher closeness centrality, then the node we measure is less central. When we are using the UCINET to measure the closeness centrality, we are using

closeness centrality$=\frac{\sum(\text{Cmax}-\text{C(node i)}}{\text{Maximum Closesness Value}}$

Where Cmax=maximum closeness centrality in the network

C(node i)=closeness of node i

The betweenness centrality measures how frequently one node appears in the geodesic path between two nodes in a network. If we have higher betweenness centrality, then the node we measure is more crucial in connecting other nodes. UCINET measures the betweenness centrality of the network as follows:

closeness centrality=$\frac{\sum(\text{Bmax}-\text{B(node i)}}{\text{Maximum Betweenness Value}}$

where Bmax=maximum betweenness centrality in the network

B(node i)=betweenness of node i

As this essay employs directed networks, we need to take indegree and outdegree into consideration. Indegree of node A counts the number of times nodes in the network direct to node A, and outdegree of node A counts the number of times A directs to nodes in the network. Incloseness and Outcloseness, and inbetweenness and outbetweenness also take the directions into consideration.

Thus, we can get the results in Table 3.4 for our sample network.

	OutDeg	Indeg	OutClo	InClos	Between
1	0.6	0.4	0.556	0.455	0.25
2	0	0.2	0.333	0.455	0
3	0	0.2	0.333	0.455	0
4	0.2	0	0.5	0.333	0
5	0	0.4	0.333	0.5	0
6	0.4	0	0.556	0.333	0

Table 3.4 Simple Network Example Descriptive Statistics

In this essay, we use factions to group the network nodes. Given a partition of a binary network of adjacencies into n groups, then a count of the number of missing ties within each group summed with the ties between the groups gives a measure of the extent to which the groups form separate clique like structures. The routine uses a tabu search minimization procedure to optimize this measure to find the best fit. Tabu Search is a neighborhood search method that accepts a move if no better move is available, and doesn’t go back to already visited solutions ((Hanneman, R. A., & Riddle, M. 2005; Borgatti, S. P., Everett, M. G., & Johnson, J. C. 2018).

3.2.3 Log-Multiplicative Model

We use the log-multiplicative model to explore the influence of journals as storers and sources. When analyzing data with rows as citing journals and columns as cited journals, we can see that the journals becomes storers when they cite other journals. On the other hand, when analyzing data with rows as cited journals and columns as citing journals, we can see that journals become sources of knowledge when they are cited by other journals. In this way, we are trying to find the influence of journals as storers and sources.

The log-multiplicative mode we are using is from Baumgartner and Pieters (2002) and Nerur et al.(2016):

$$\log F_{sr} = \mu + \mu_s^S + \mu_s^R + \delta_{sr} + \sum_{m=1}^{M} \xi_s^m \psi^m \xi_r^m$$

where S is the row (citing);

R is the column (cited);

F_{sr} is the intersection of row and column;

μ is the standard log-linear parameter;

In this equation, μ_s^S and μ_s^R are the main parameters, representing the storer of knowledge and the source of the knowledge.

We use the software LEM (J.K. Vermunt, 1997) to analyze the influence ranks of the 36 journals for four years. The name LEM stands for ‘Log-linear and event history analysis with missing data using the Expectation-Maximization algorithm’ This software can help us understand the influence of journals by using the log-multiplicative model.

3.3. Motivation

The motivation for this essay is to use network science to build research networks among statistics and business disciplines in the 21st century. As business analytics has emerged in recent years and played a more critical role in research, we want to see if this new research focus has changed the networks among the 36 statistics and business journals we are studying.

We now explore the following questions from the perspective of network science. How does the emergence of business analytics affect the communication networks among statistics and business journals? Does the emergence of business analytics motivate scholars in business disciplines to make more references to statistics journals? Can statistics enhance its models by extracting information from business disciplines and citing more articles from them?

To achieve our goal, we are looking at communications among statistics journals and business journals. Previous studies show that the relationship between journals in the same discipline is strong. We will investigate the relationship between statistics journals and other business journals by applying network science methods. Moreover, we want to find if the citation pattern changes over the 4 years as business analytics develops.

3.4. Research Methods

3.4.1 Selecting journals

We collect both citation and abstract data from Journal Citation Reports at Web of Science. We have a thorough description of the journal selection in the first essay. Below are the journals that we have selected:

Name	Abbreviation	Discipline	Name	Abbreviation	Discipline
Accounting Review	ACR	Accounting	Strategic Management Journal	SMJ	Management
Journal of Accounting Research	JAR	Accounting	Journal of Consumer Research	JCR	Marketing
American Economic Review	AER	Economics	Journal of Marketing Research	JMR	Marketing
Econometrica	EM	Economics	Journal of Marketing	JOM	Marketing
Journal of Econometrics	JOE	Economics	Marketing Science	MKS	Marketing
Review of Economics and Statistics	RES	Economics	Annals of Probability	ANP	Probability
Journal of Finance	JF	Finance	American Statistician	AMS	Statistics
Journal of Financial Economics	JFE	Finance	Annals of Statistics	AS	Statistics
Review of Financial Studies	RFS	Finance	Journal of the American Statistical Association	ASA	Statistics
Decision Sciences	DS	ISOM	Journal of Business & Economic Statistics	BES	Statistics
Information Systems Research	ISR	ISOM	Biometrics	BIO	Statistics
Management Science	MGS	ISOM	Biometrika	BMK	Statistics
MIS Quarterly	MISQ	ISOM	Journal of Statistical Planning and Inference	JSPI	Statistics
Operations Research	OPR	ISOM	Journal of the Royal Statistical A	RSSA	Statistics
Production and Operations Management	POM	ISOM	Journal of the Royal Statistical B	RSSB	Statistics
Academy of Management Journal	AMJ	Management	Journal of the Royal Statistical C	RSSC	Statistics
Academy of Management Review	AMR	Management	Statistical Science	SSC	Statistics
Administrative Science Quarterly	ASQ	Management	Technometrics	TEM	Statistics

Table 3.5 Selected Journals and their Abbreviations and Disciplines

3.4.2 Network Analysis

Firstly, we conduct a citation network analysis by looking at citing and cited data among journals in different disciplines. The citation frequencies imply the strength of the relationship among journals. Thus, we create two 36x36 asymmetric matrices reflecting the counts of cross citations between pairs of 36 journals for each of the four years. We build a 36-by-36 matrix with citing journals in the row and cited journals in the columns for each year. We also create a 36-by-36 matrix with cited journals in the row and citing journals in the columns for each year. Then we use UCINET to analyze citation data. We first transform the citation frequency matrices, which are the raw data, into correlation matrices for both cited-citing datasets and citing-cited datasets. Next, we analyze the network characteristics for the raw data matrices and the correlation data matrices. Then, to graphically describe the network characteristics we use Netdraw in UCINET to visualize the networks we have for the raw data and the correlations. In this way, we can see whether changes occur in networks among different disciplines by looking at both the characteristics and the graphs. For example, is statistics more influential as a storer or a source in the four years? We want to explore the network changes using citation datasets from the disciplines.

3.5. Findings

3.5.1 Network Metrics Based on Correlations

Correlation				
Characteristics	2000	2005	2010	2015
Density	0.37	0.386	0.381	0.408
Degree Centralization	0.304	0.227	0.323	0.264
Closeness	0.4213	0.3555	0.4389	0.3608
Betweenness	0.2109	0.1436	0.1551	0.1395

Table 3.6 Network Metrics Based on Correlations

To measure the centrality of the network, we look at the degree centralization. The degree centralizations are 0.304, 0.227, 0.323, and 0.264 in 2000, 2005, 2010, and 2015, showing that the overall centralization has fluctuated within a narrow range in these four years, indicating that the centrality doesn't change much in these years. The average degree (Appendix Table B 49) has increased from 12.944 to 14.278, which is consistent with that observation.

Next, we find that the closeness metrics from UCINET are 0.4213, 0.3555, 0.4389, and 0.3608 from 2000 to 2015, indicating that the closeness of the networks seems to fluctuate randomly.

For the betweenness, we can see that metrics are 0.2109, 0.1436, 0.1551, and 0.1395. A downward trend would show that two journals are less likely to communicate through a third journal in later years.

5.2 Network Metrics Based on Raw Data

Raw Data					
Characteristics		2000	2005	2010	2015
Density		0.381	0.417	0.492	0.508
Degree Centralization	Indegree	0.0001	0.0001	0	0.0001
	Outdegree	0.0001	0.0001	0	0.0001
Closeness	Incloseness	0.5465	0.6982	0.5927	0.5427
	Outcloseness	0.475	0.4431	0.4085	0.4969
Betweenness		0.1473	0.1083	0.834	0.571

Table 3.7 Network Metrics Based on Raw Data

As our raw data have directions (citing/cited), we have indegree and outdegree as well as Incloseness and Outcloseness. We can get more information using raw data than correlation data

When we are using raw data, we can see that the density changes become more obvious than when we are using the correlation data. The densities are 0.381, 0.417, 0.492, 0.508 in 2000, 2005, 2010, and 2015, showing that the density has increased in these four years. The average degree (Appendix Table B 50) has increased from 13.333 to 17.778, which is consistent with that observation.

Next, we find that the indegrees and outdegrees are basically 0 in all four years, indicating the variance in the network is negligible. Little centralization appears in the network.

For closeness, we can see that the in-closeness metrics are 0.5465, 0.6982, 0.5927, and 0.5427, and the out-closeness metrics are 0.475, 0.4431, 0.4085, and 0.4969. In-closeness metrics appear to be more variable than out-closeness metrics.

For betweenness, the metrics are 0.2109, 0.1436, 0.1551, and 0.1395, which is somewhat decreasing from 2000 to 2015. This is consistent with findings for the correlation matrix.

3.5.3 Network Graphs Based on Correlations

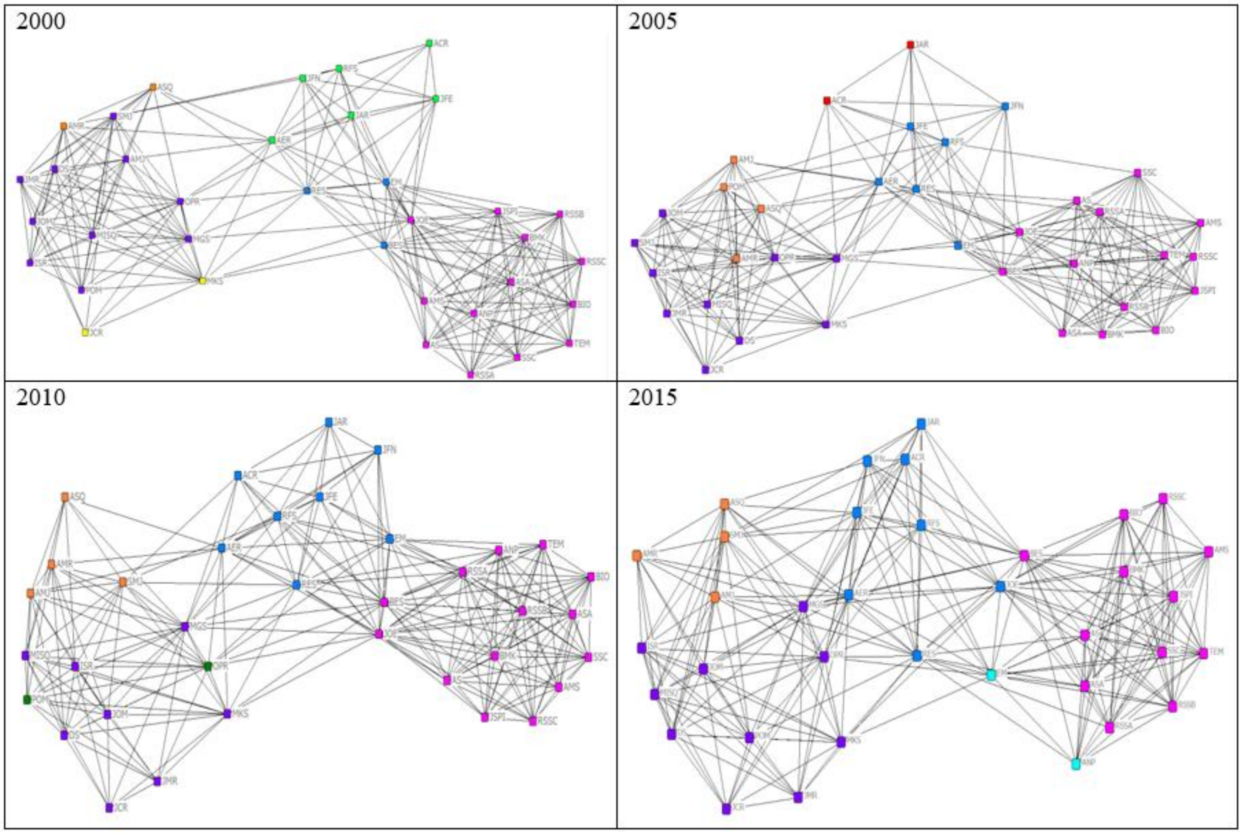


Figure 3.2 Networks for All Eight Disciplines with Correlation Data

When we use the UCINET to draw the network with the correlation data, we use the faction function to group the journals in the network. We can see that the results are quite consistent with what we have found in the citation analysis using multidimensional scaling with factor analysis. Economics is generally positioned between business on one side and statistics on the other.

In 2000, we can see that all the accounting journals and finance journals are grouped with an economics journal *the American Economics Review*. Economics journals *Review of Economics Study* and *Econometrica* are grouped with the *Journal of Business and Economics Statistics*, a statistics journal. The economics journal, *Journal of Econometrics*, is grouped with statistics journals. Management journals, *Administrative Science Quarterly* and *Academy of Management Review*, are in the same group. Marketing journals, *Journal of Consumer Research* and *Marketing*

Science, are in the same group. Other journals in the marketing, management, ISOM disciplines are in the same group.

In 2005, accounting journals are in the same group. Finance journals are in the same group with economics journals. All the economics journals except *Journal of Econometrics* are in the same group. The *Journal of Econometrics* is grouped with all the statistics journals. All the management journals are in the same group. Marketing journals and ISOM journals fall in the same group.

In 2010, , we can see that all the accounting journals and finance journals are grouped with economics journals: *the American Economics Review*, *Review of Economics Study*, and *Econometrica*. The *Journal of Econometrics* again is grouped with all the statistics journals. All the management journals are in the same group. *Production and Operations Management* and *Operations Research* are in the same group. Marketing journals and other ISOM journals fall in the same group.

In 2015, we can see that all the accounting journals and finance journals are grouped with economics journals: *the American Economics Review*, *Review of Economics Study*, and *Journal of Econometrics*. *Econometrica* is grouped with a statistics journal, the *Annals of Probability*. All other statistics journals are in the same group. All the management journals are in the same group. Marketing journals and ISOM journals fall in the same group.

3.5.4 Network Graphs Based on Raw Data

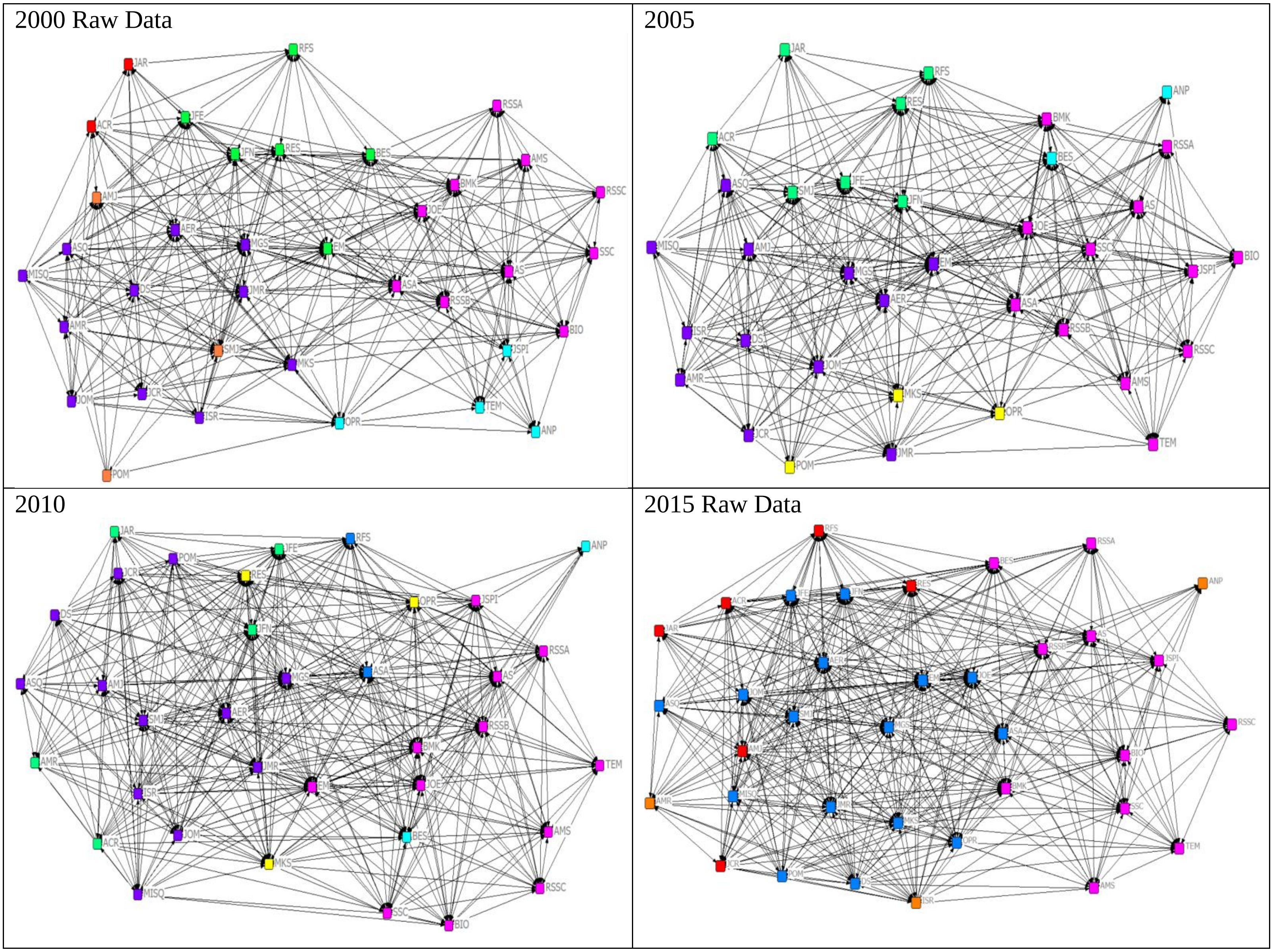


Figure 3.3 Networks for All Eight Disciplines with Raw Data

Using the raw data, we have more ties and directed ties but a more confusing picture than using the correlation data. In the dataset, the row represents the citing journals and the column represents the cited journals. If A points to B with an arrow, it means that B cites A. If the arrow is on both sides of the connection between A and B, it means that A cites B and B cites A. We can see that most journals are reciprocally citing other journals in all four years, and we are using the faction to divide journals into groups.

In 2000, we find that accounting journals are in the same group, Finance journals are in the same group with an economics journal *Econometrica* and a statistics journal *Journal of Business and Economics Statistics*. The *Journal of Econometrics* is in the same group with most statistics journals. Statistics journals, *Journal of Statistical Planning and Inference* and *Technometrics*, and *Annals of Probability* are in the same group with an ISOM journal *Operations Research*. *Production and Operations Management* is in the same group with management journals, *Academy of Management Journal* and *Strategic Management Journal*. *American Economics Review*, an economics journal, is in the same group with all other management, ISOM, and all the marketing journals.

In 2005, we find that accounting journals and finance journals are in the same group a management journal, *Strategic Management Journal*, and an economics journal, *Review of Economics and Statistics*. The *Annals of Probability* and the *Journal of Business and Economics Statistics* are in the same group. The *Journal of Econometrics* is in the same group with statistics journals. *Marketing Science* is in the same group with ISOM journals, *Operations Research* and *Production and Operations Management*. The rest of the management journals, economics journals, marketing journals and ISOM journals are in the same group.

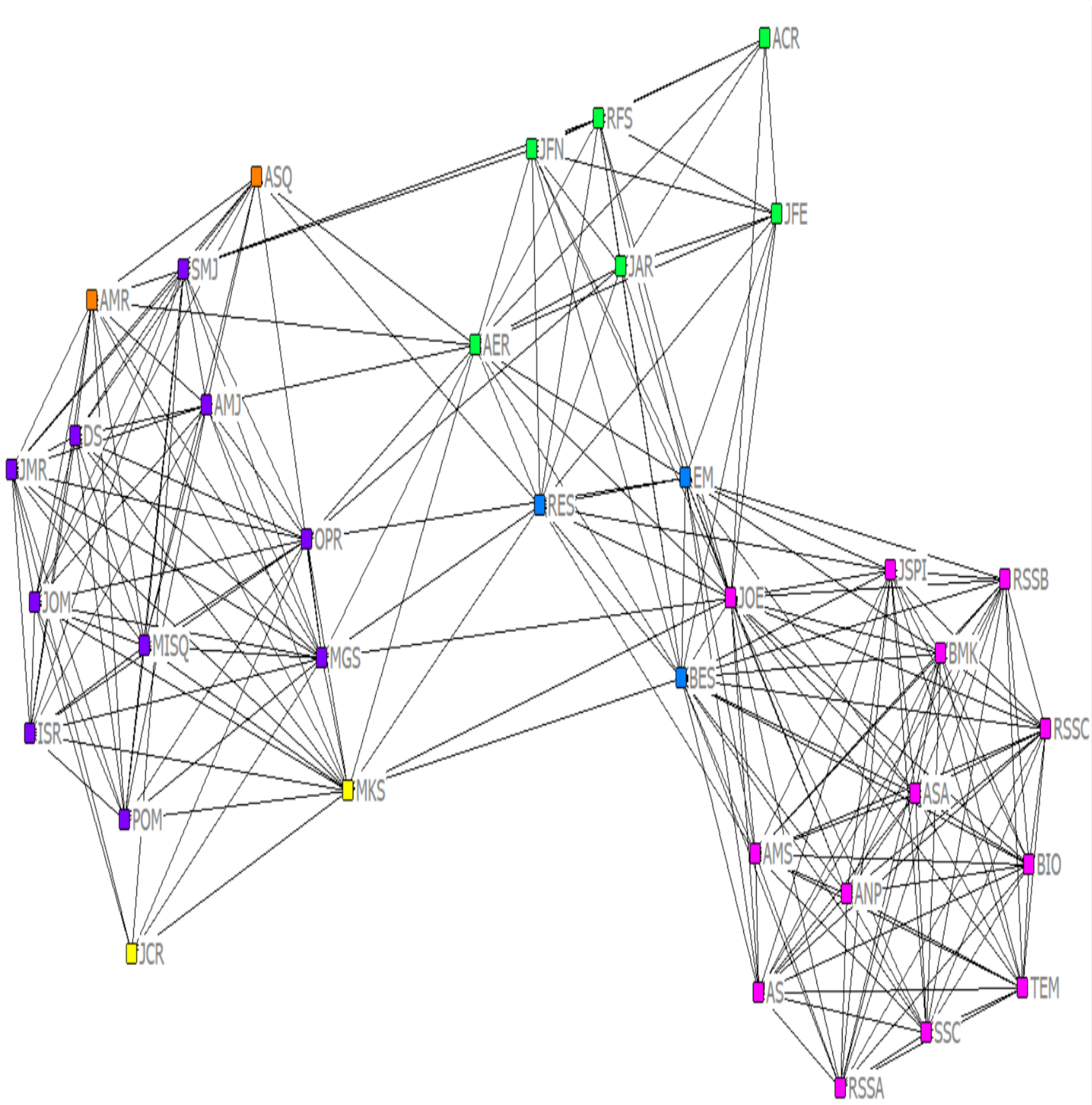
In 2010, we find that accounting journals and finance journals, *Journal of Finance Economics* and *Journal of Finance* are in the same group with a management journal, *Academy of Management Review*. An economics journal, *Review of Economics and Statistics*, is in the same group with an ISOM journal, *Operations Research*, and an marketing journal, *Marketing Science*. The *Journal of Econometrics* and *Econometrica* are in the same group with statistics journals. The *Review of*

Finance Studies is in the same group with the *Journal of the American Statistical Association*. The *Annals of Probability* and the *Journal of Business and Economics Statistics* are in the same group. The rest of the management journals, marketing journals and ISOM journals are in the same group with an economics journal, *American Economics Review*.

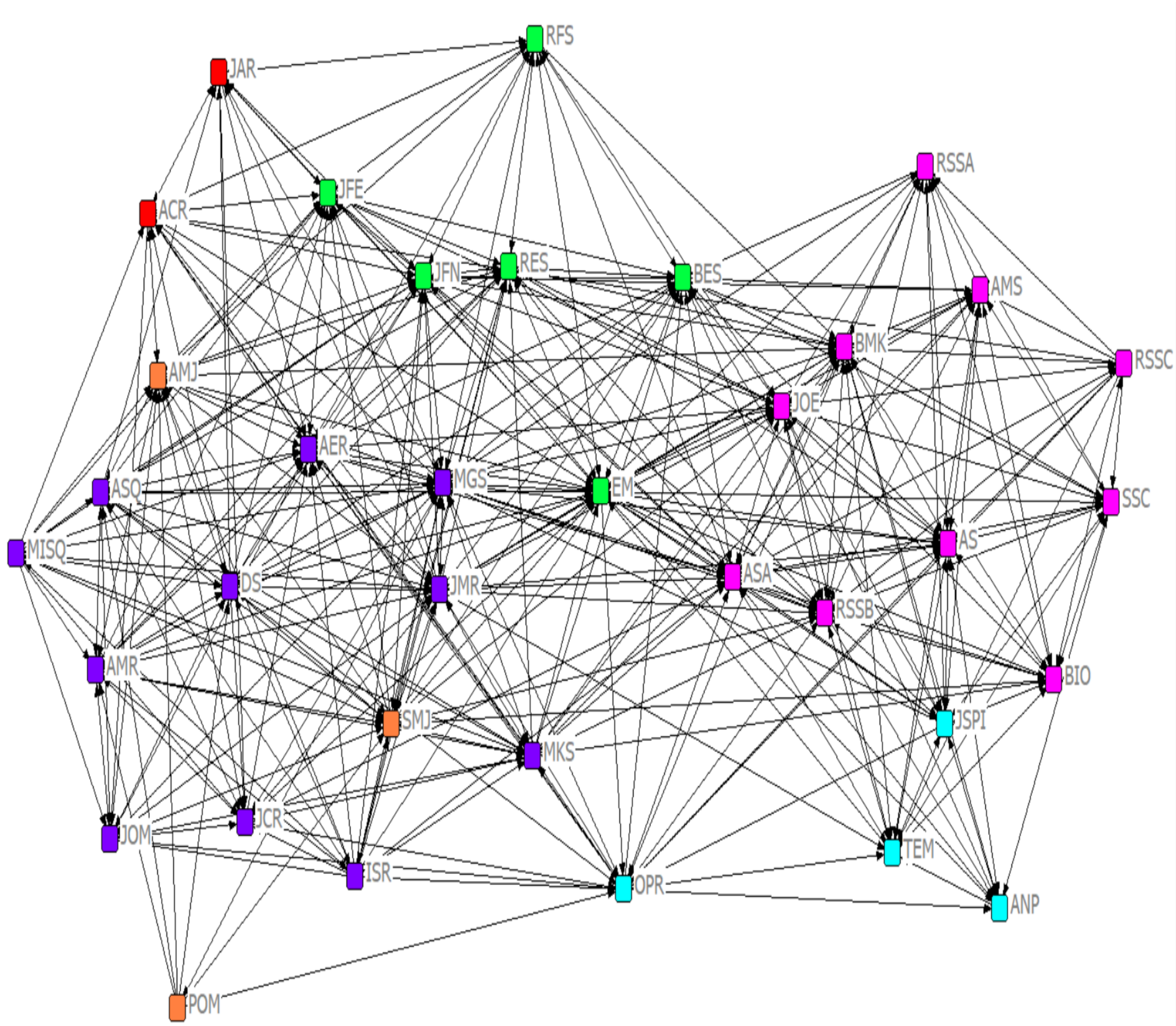
In 2015, we find that accounting journals are in the same group with a finance journal, *Review of Finance Studies*, a statistics journal, *Review of Economics and Statistics*, a management journal, *Academy of Management Journal*, and a marketing journal, *Journal of Consumer Research*. The *Annals of Probability*, a management journal, *Academy of Management Review*, and an ISOM journal, *Information System Research*, are in the same group.

Most statistics journals are in the same group. The *Journal of the American Statistical Association* in the same group with the rest of the management journals, marketing journals, ISOM journals and economics journals.

2000 Correlation Network

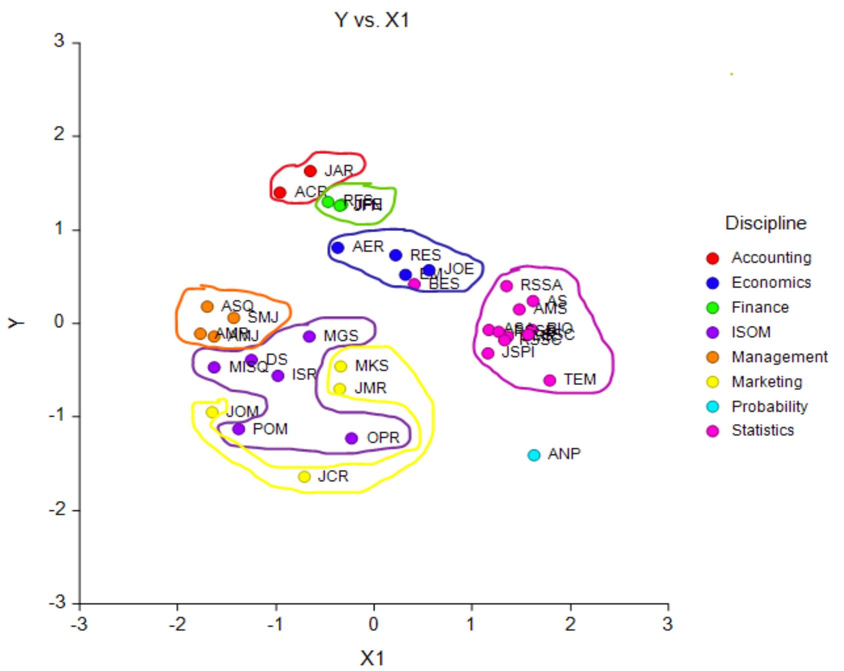


2000 Raw Data Network

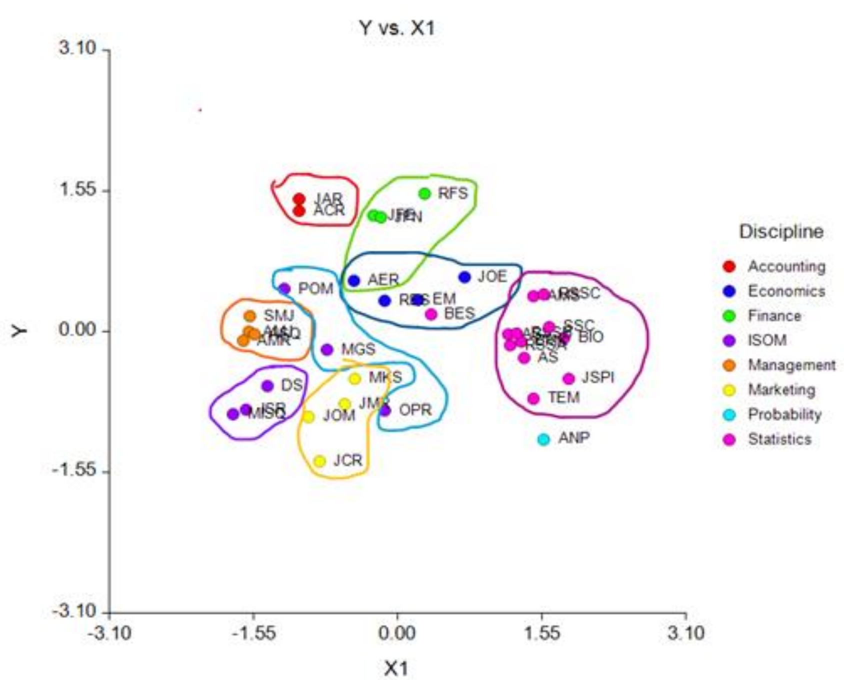


2000 MDS with Factor Analysis

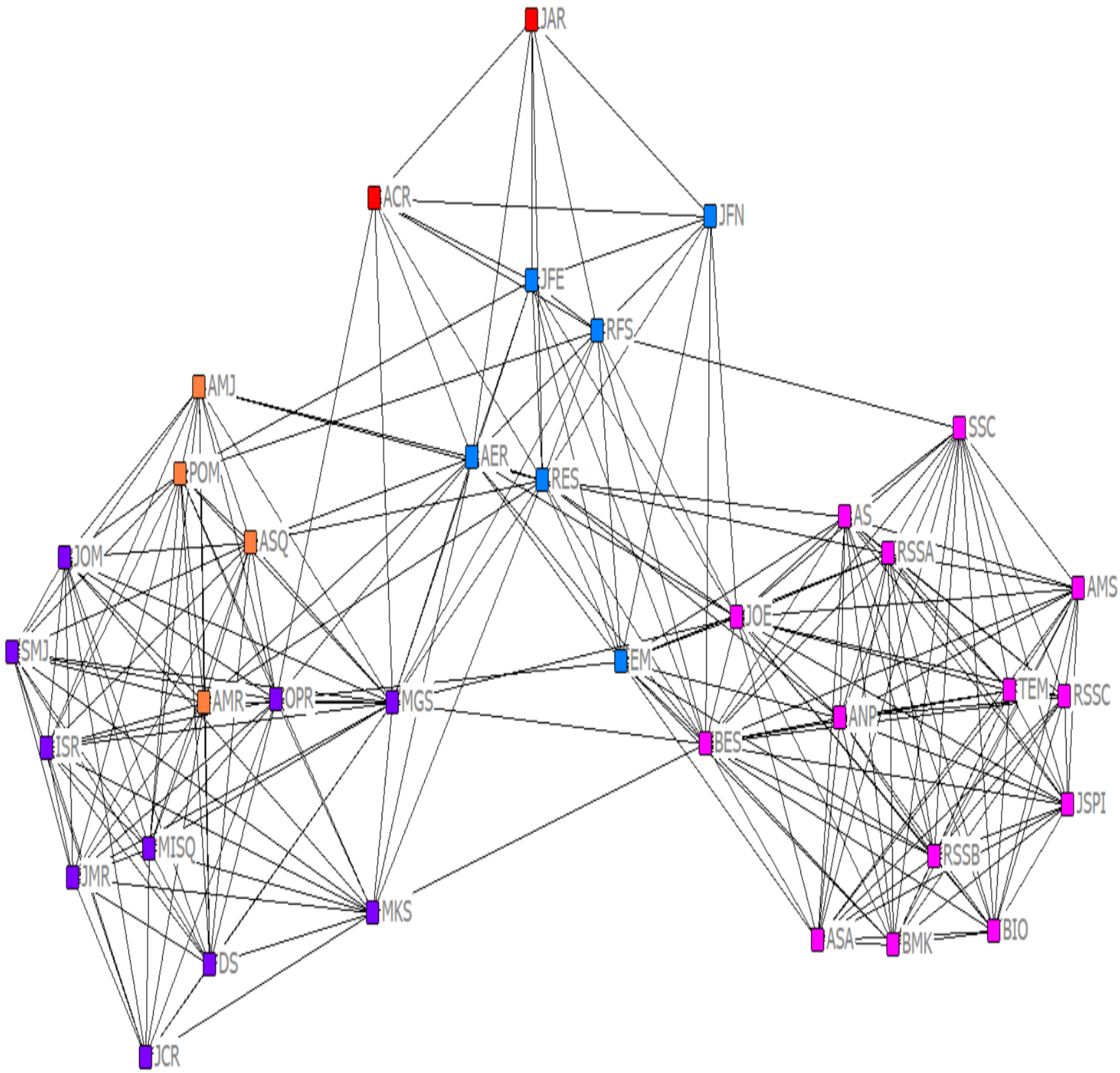
Citing-Cited



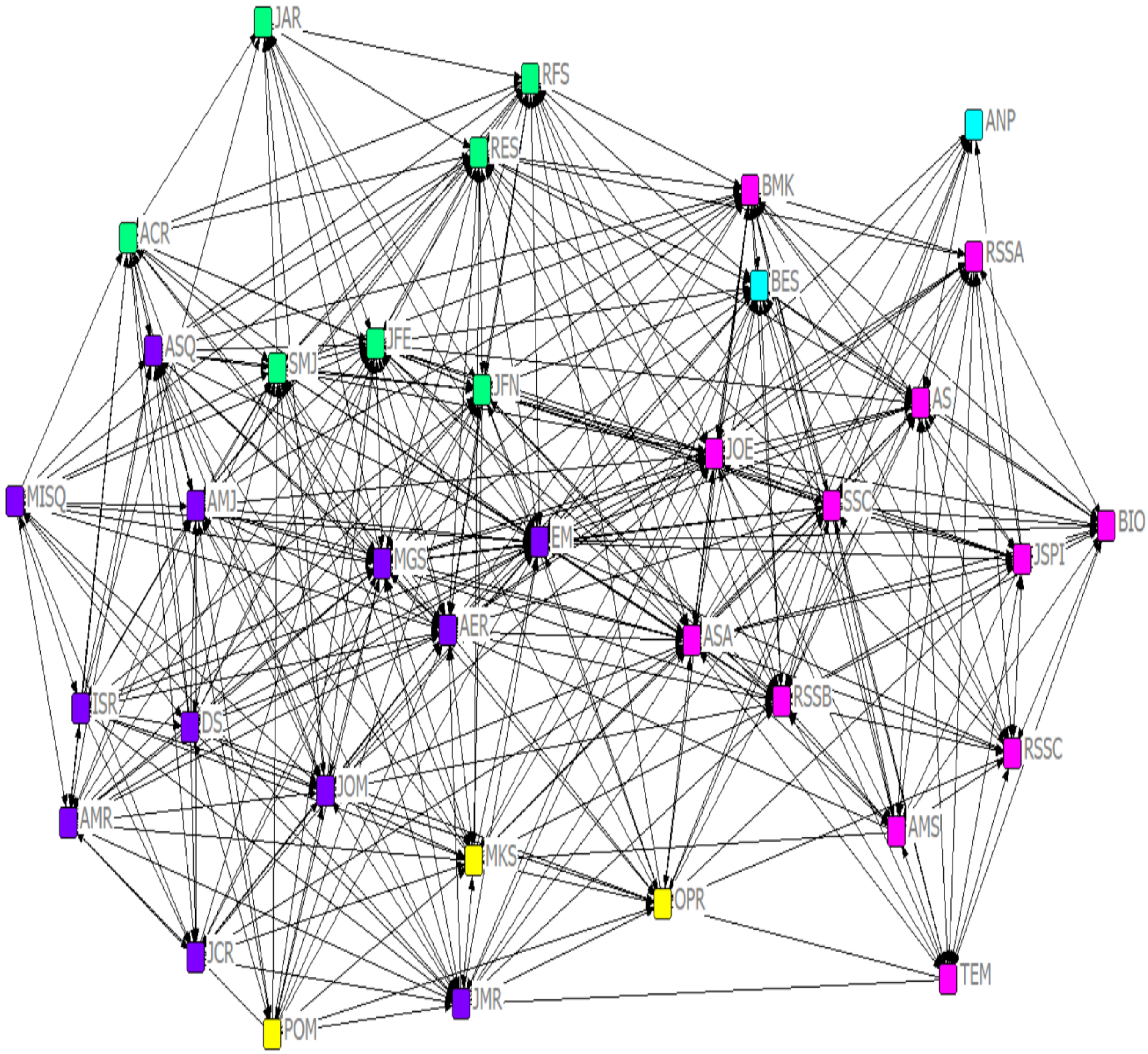
Cited-Citing



2005 Correlation Network

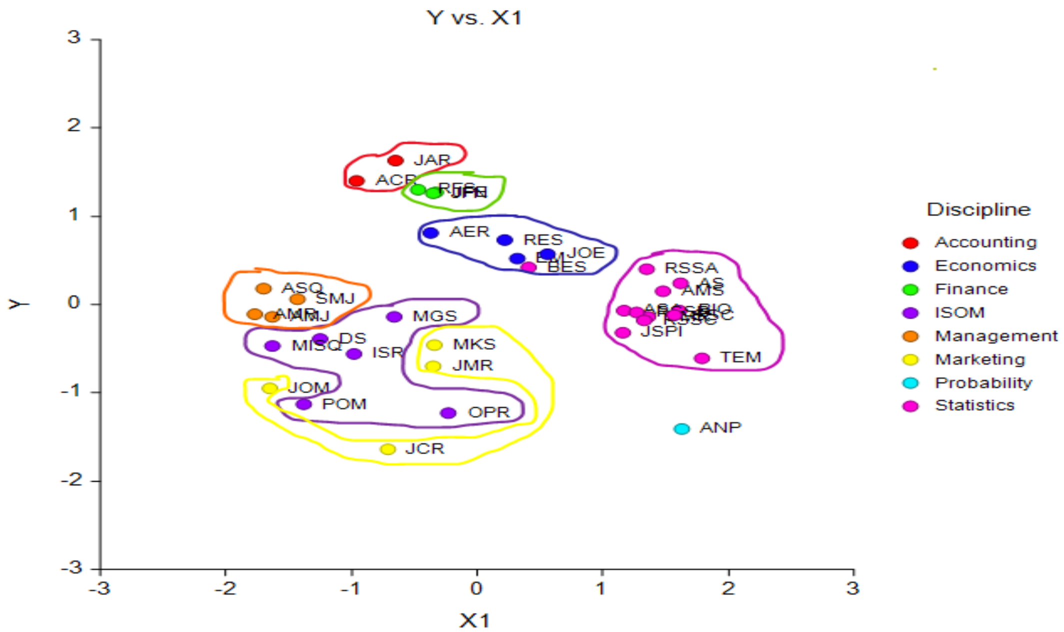


2005 Raw Data Network

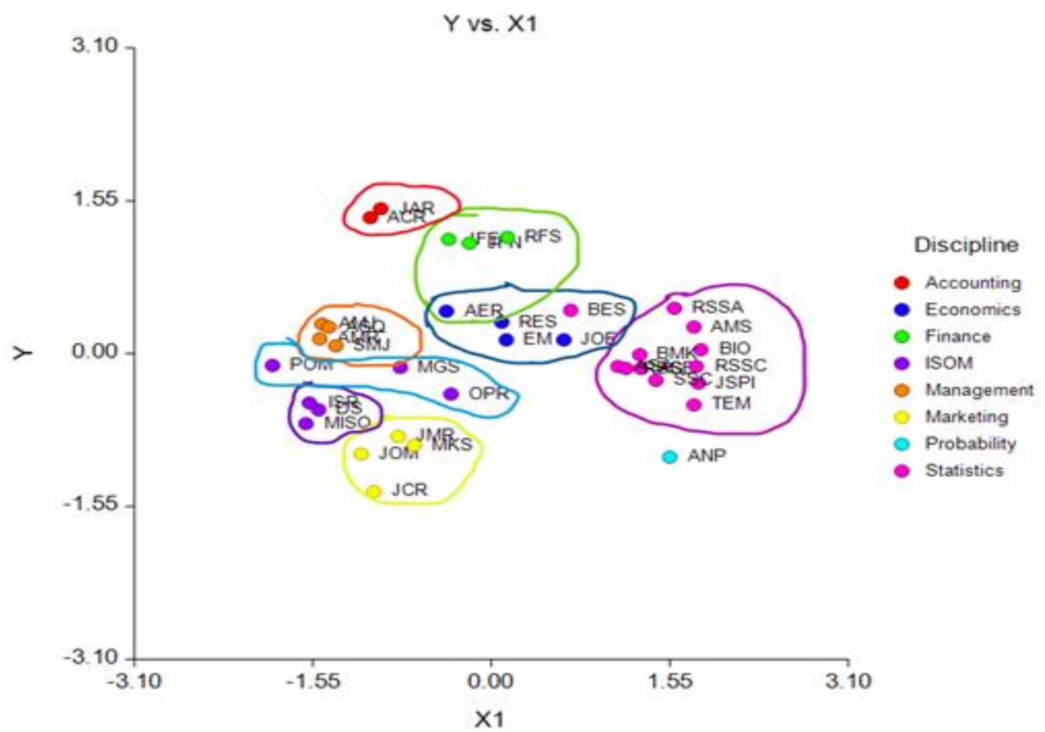


2005 MDS with Factor Analysis

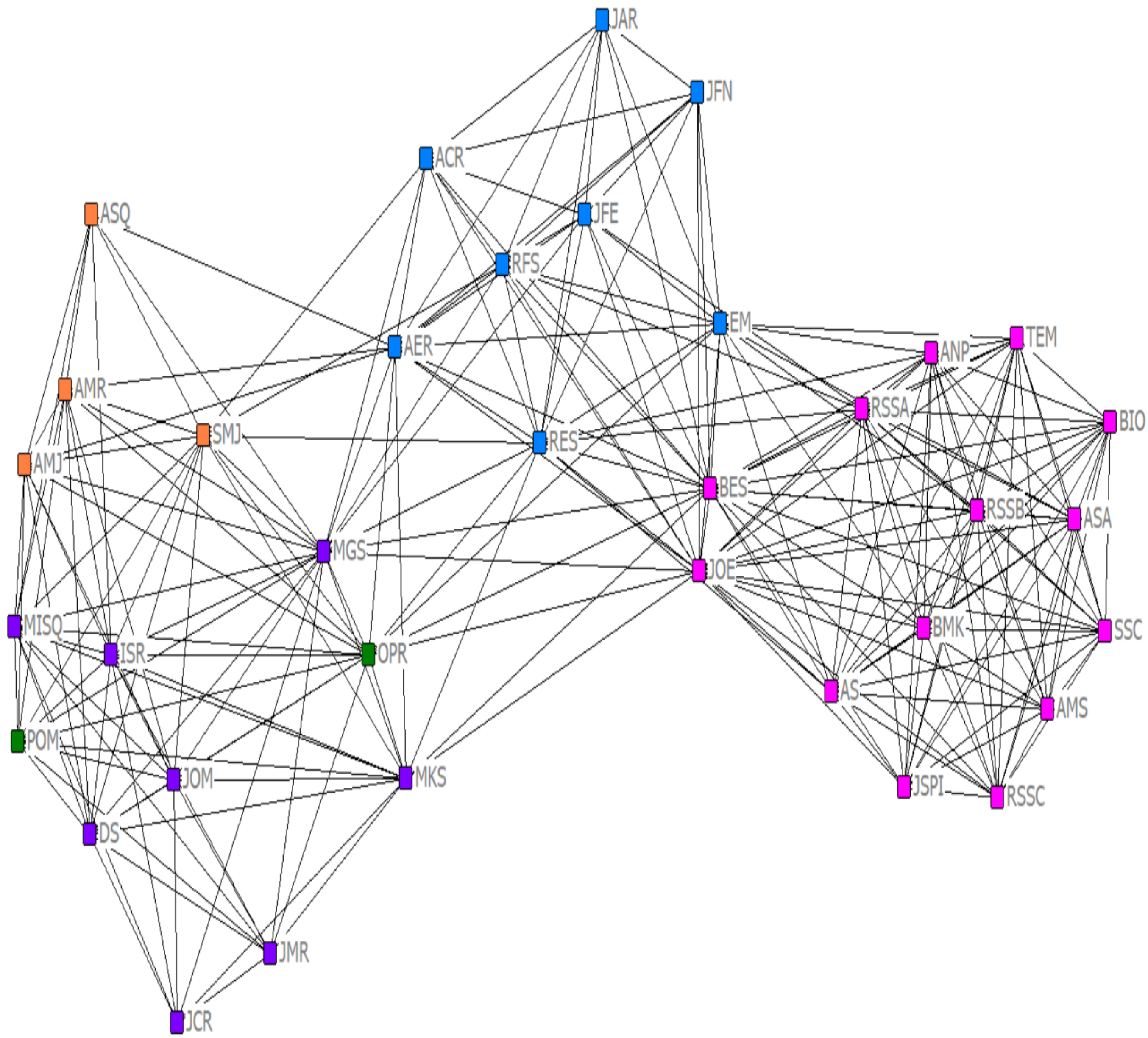
Citing-Cited



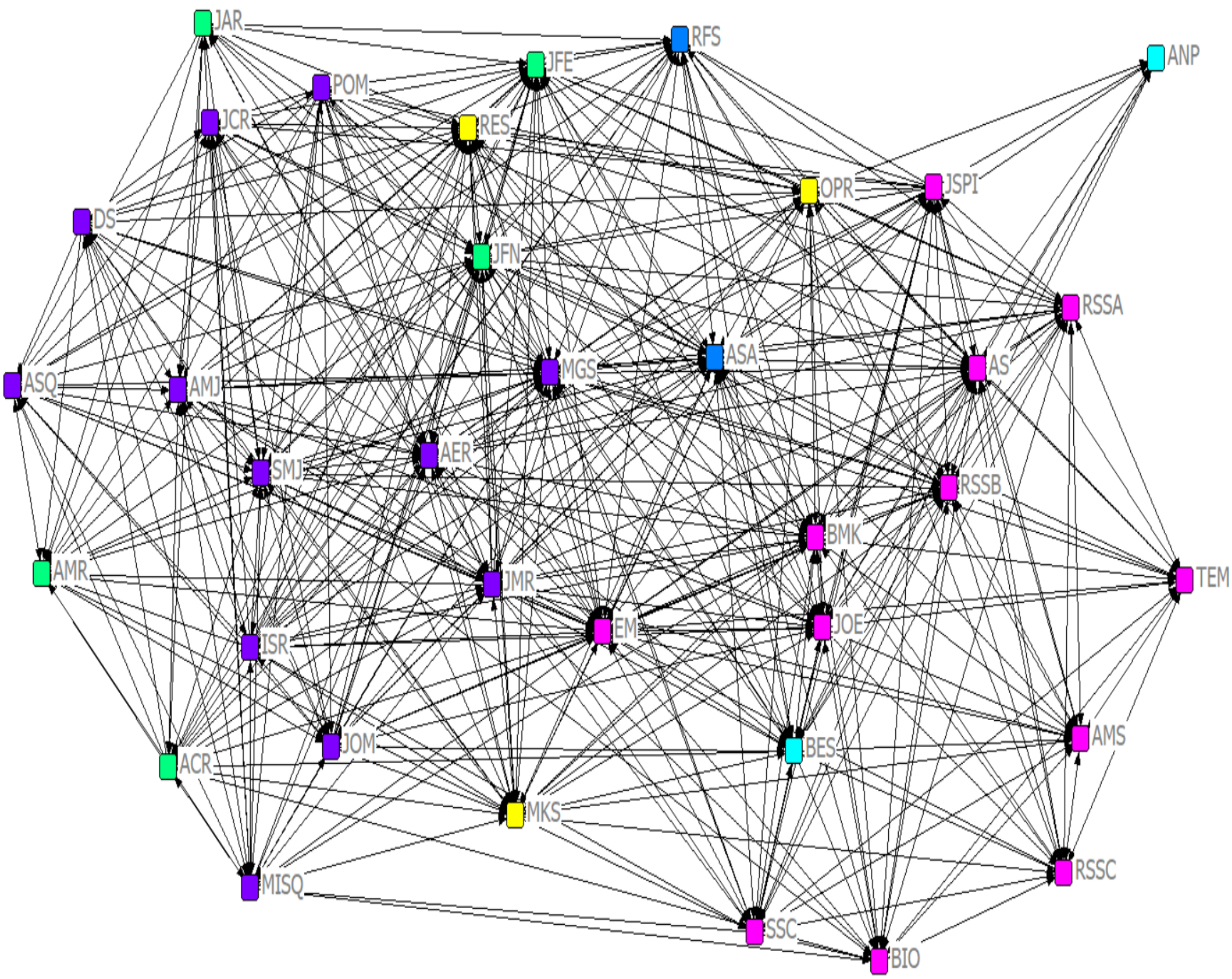
Cited-Citing



2010 Correlation Network

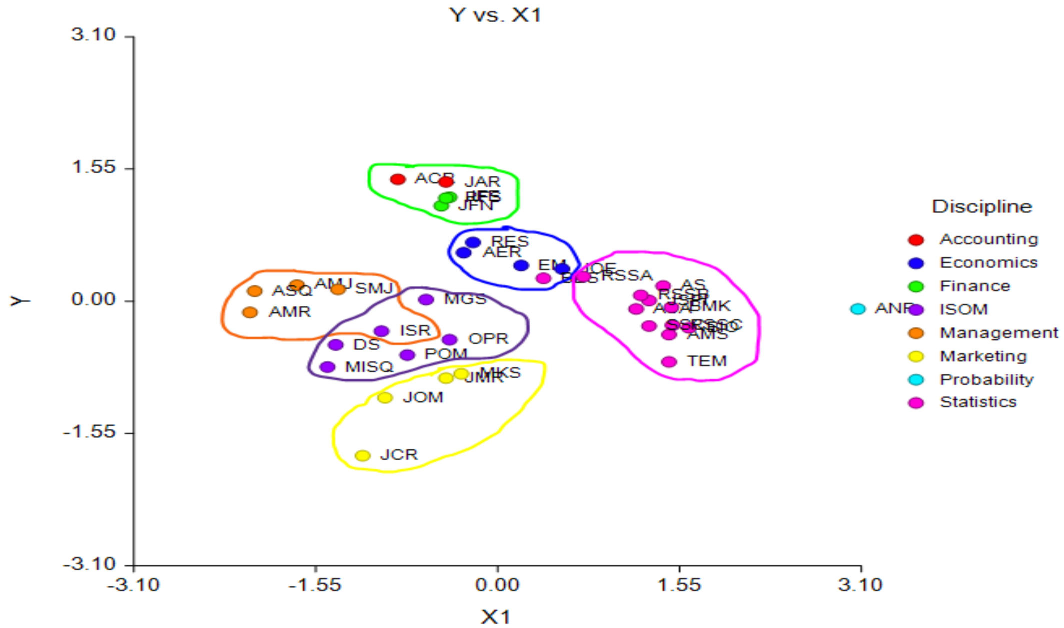


2010 Raw Data Network



2010 MDS with Factor Analysis

Citing-Cited



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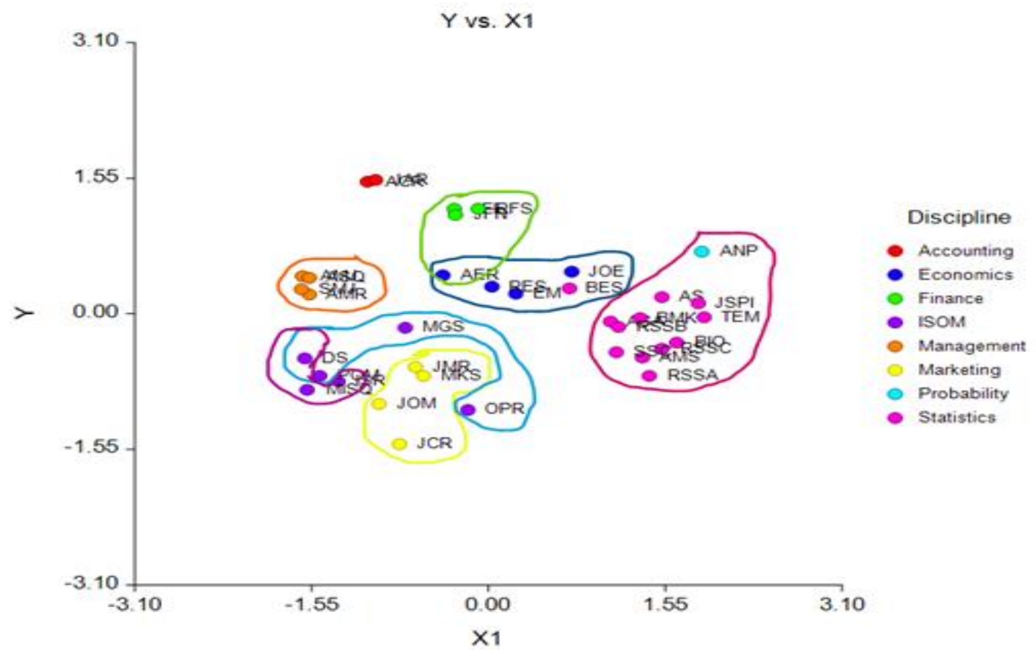
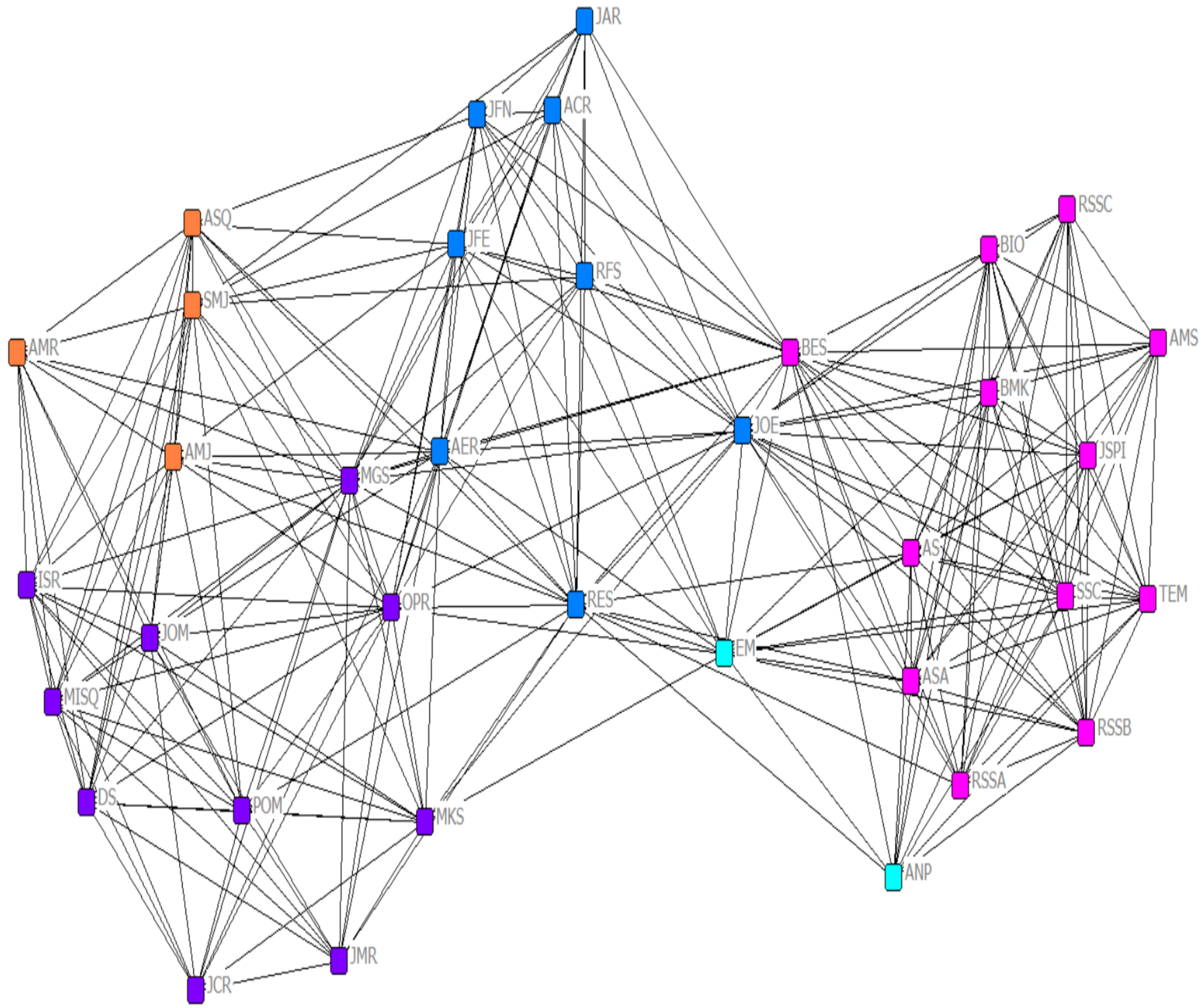
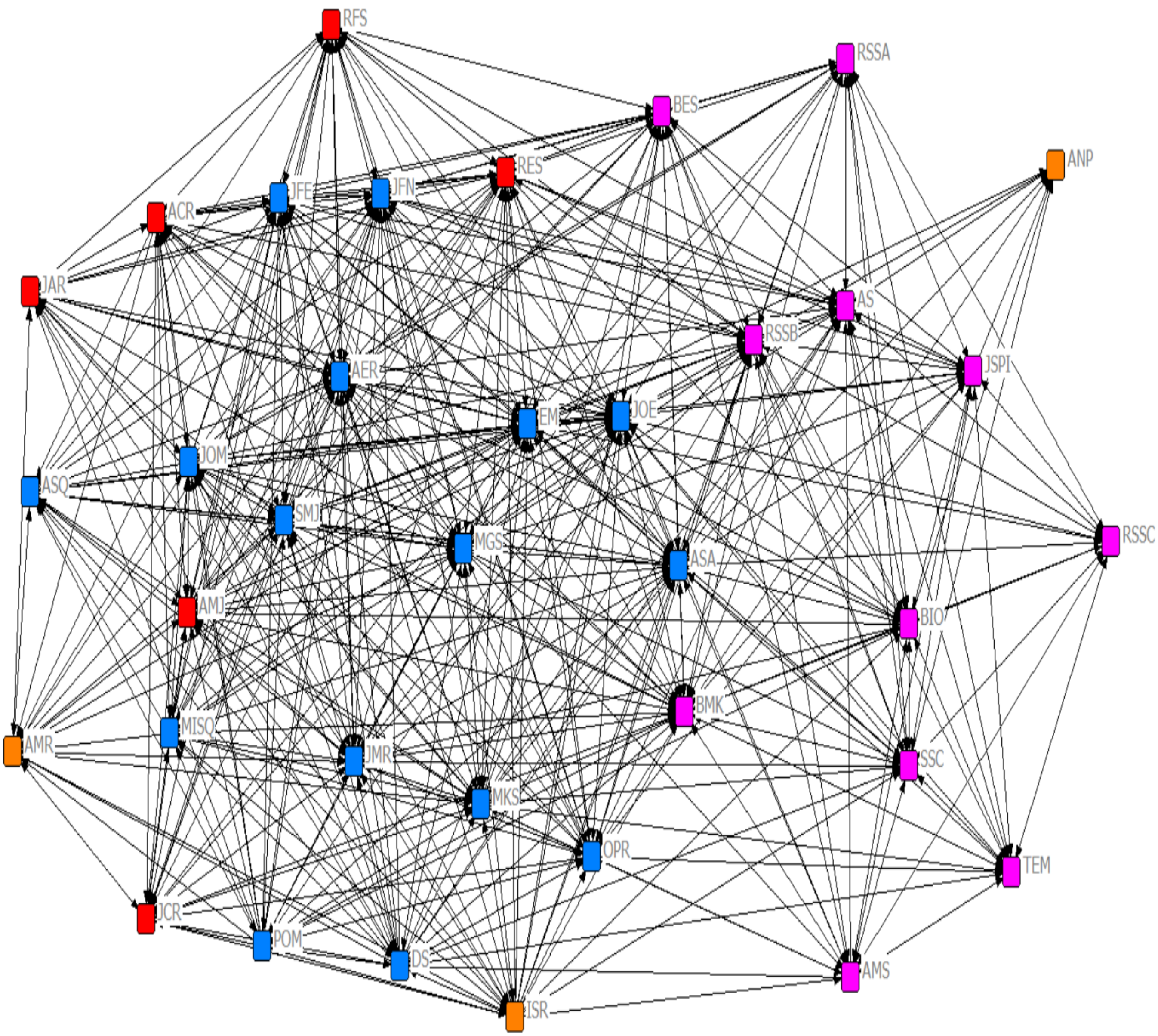


2015 Correlation Network

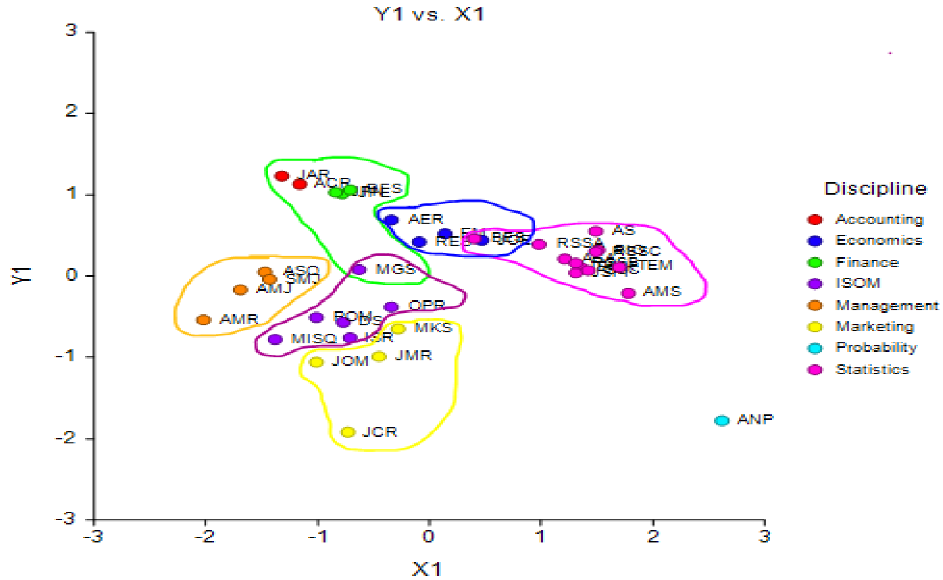


2015 Raw Data Network



2015 MDS with Factor Analysis

Citing-Cited



Cited-Citing

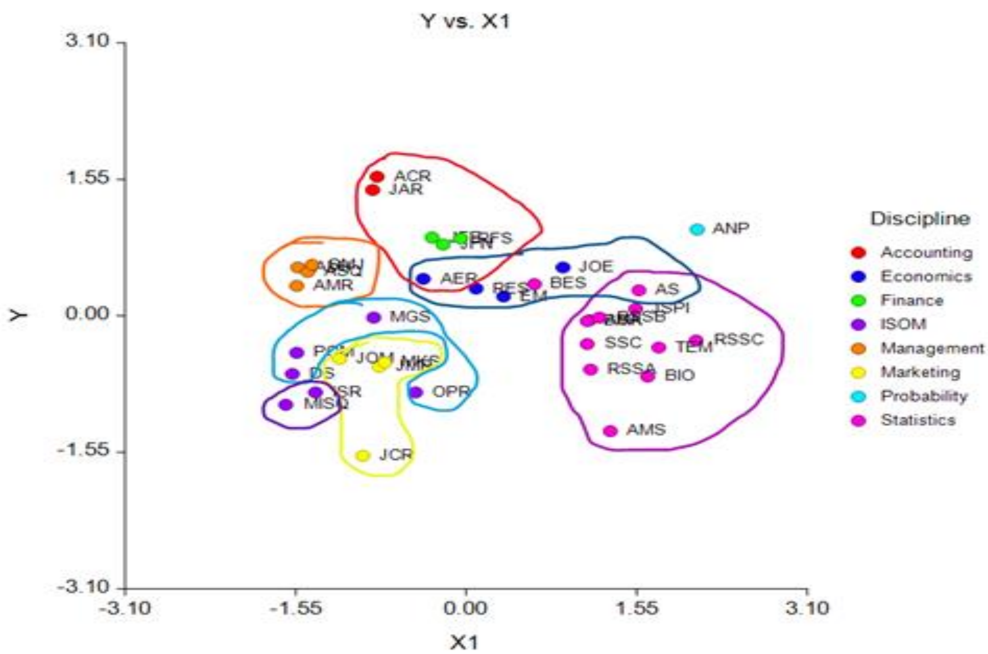


Figure 3.4 MDS Maps with Factor Analysis, Correlation Networks, and Raw Data Networks for 2000, 2005, 2010, and 2015.

From above graphs, we can see that the results of MDS maps with factor analysis are quite consistent with those of networks. Economics links statistics with business disciplines. The networks again suggest that the disciplines share more knowledge and research interests in 2015 than previously.

3.5.5 LEM Scores of Journals as Storers and Sources

Row (Citing)								
	2000		2005		2010		2015	
Journal	Value	Rank	Value	Rank	Value	Rank	Value	Rank
ACR	4.7359	13	4.7254	5	5.6799	2	7.0828	3
AER	5.0658	10	4.054	11	4.3388	16	6.0132	14
AMJ	3.8165	17	4.6637	6	3.1602	18	4.7364	19
AMR	3.5871	19	4.2116	9	1.186	23	2.353	23
AMS	-4.6352	29	-3.9162	28	-7.9434	33	-16.3669	35
ANP	-33.8913	36	-22.3468	36	-36.3338	36	-48.6598	36
AS	-11.5645	34	-4.7395	29	-3.4551	27	-4.642	27
ASA	-2.4948	25	-2.7709	25	-3.0773	26	-4.6406	26
ASQ	3.0765	20	3.9739	12	0.244	24	3.5595	21
BES	1.7674	24	2.1175	20	1.269	22	1.9776	24
BIO	-4.7205	30	-6.9422	34	-9.1264	34	-10.7352	33
BMK	-5.6385	31	-5.1461	31	-6.0217	31	-6.3898	30
DS	4.6552	15	3.2276	14	4.1793	17	5.9838	15
EM	2.0689	23	1.7681	22	2.1206	20	3.681	20
ISR	4.6677	14	2.4527	17	4.4272	13	5.9557	17
JAR	5.0885	9	4.1196	10	4.8289	11	6.343	12
JCR	5.3544	7	-3.2301	27	5.0503	10	6.4104	11
JFE	5.2356	8	5.0004	4	5.5805	5	7.32	2
JFN	6.0476	2	5.0835	3	5.1126	9	6.4861	10
JMR	5.912	3	2.0641	21	5.6362	3	6.6209	8
JOE	2.502	22	1.3205	23	1.7548	21	3.1717	22
JOM	5.3798	6	2.1641	19	5.1279	8	6.5036	9
JSPI	-6.3239	33	-6.3992	32	-3.7071	28	-6.361	29
MGS	6.1348	1	5.1828	1	5.953	1	7.8036	1
MISQ	4.5026	16	3.1663	15	4.3467	15	5.9757	16
MKS	5.4693	5	2.8387	16	5.4529	6	6.7366	6
OPR	5.7725	4	4.2559	7	5.4329	7	6.6237	7
POM	3.7454	18	3.5567	13	4.7248	12	6.9368	4
RES	2.8642	21	2.3495	18	2.99	19	4.8949	18
RFS	4.9859	12	4.2343	8	5.6295	4	6.8713	5
RSSA	-3.783	26	-2.924	26	-2.4942	25	-4.0548	25
RSSB	-4.2986	27	-5.0818	30	-4.5419	29	-6.1767	28
RSSC	-4.4811	28	-6.6633	33	-7.5909	32	-11.695	34
SMJ	5.0119	11	5.147	2	4.4245	14	6.32	13
SSC	-6.0859	32	-2.4782	24	-5.1084	30	-7.4727	31
TEM	-19.5304	35	-9.0395	35	-9.2501	35	-9.1669	32

Table 3.8 LEM Scores of Journals as Storers

Table 3.8 presents the scores of journals as storers, the higher the score, the more influential the journal is as a storer. We can see that *Management Science* ranks first as a storer for all four years. *Journal of Finance and Economics*' influence is somewhat increasing and ranks second in 2015. Statistics journals are not as influential storers as are business journals in all four years for the journals we selected.

Column (Cited)								
	2000		2005		2010		2015	
Journal	Value	Rank	Value	Rank	Value	Rank	Value	Rank
ACR	3.4922	18	4.3297	12	4.1114	14	4.8418	14
AER	6.5222	5	6.6055	4	6.3341	4	7.3241	4
AMJ	-22.8201	35	-0.261	24	-19.88	36	-23.3675	35
AMR	-25.4046	36	-1.4215	27	-19.4895	34	-25.4777	36
AMS	4.2144	14	2.79	17	2.6156	19	2.0593	21
ANP	-0.1442	27	-5.1167	29	-0.8226	26	0.5121	23
AS	4.9353	13	4.7328	10	5.3093	8	7.2551	5
ASA	6.3461	6	5.3142	8	5.695	7	7.1926	6
ASQ	-21.4815	34	-0.2409	23	-19.8212	35	-23.0162	34
BES	5.556	10	5.1826	9	4.8882	10	6.3918	11
BIO	5.0921	12	1.7507	20	2.7668	18	4.2682	17
BMK	5.7369	8	3.9936	14	4.5598	12	6.4338	10
DS	-4.9844	30	-5.1782	30	-6.8326	32	-5.0795	30
EM	7.4833	1	7.1769	1	7.0818	1	8.3441	1
ISR	-5.9824	32	-7.9196	31	-5.9809	30	-9.0742	31
JAR	3.8612	15	4.5257	11	4.3431	13	4.7185	16
JCR	0.0683	26	-24.2037	36	-1.2947	27	-2.0416	27
JFE	6.9366	3	6.6117	3	6.5443	3	7.0458	7
JFN	7.3126	2	7.0378	2	6.9223	2	7.4824	3
JMR	0.8059	25	-13.3505	34	-0.1372	25	-0.7856	26
JOE	6.5744	4	6.1342	5	6.1981	5	7.7974	2
JOM	-2.2438	28	-14.9633	35	-2.7825	29	-3.3437	28
JSPI	2.6674	20	0.4302	21	3.3651	15	4.9168	13
MGS	1.7207	23	2.0869	19	1.364	23	-0.0692	24
MISQ	-5.7602	31	-8.6384	32	-6.8157	31	-10.6075	32
MKS	1.423	24	-9.5987	33	0.7147	24	-0.2794	25
OPR	3.3747	19	3.3987	15	2.3819	20	1.7265	22
POM	-4.431	29	-1.5969	28	-2.1527	28	-3.4596	29

RES	5.6231	9	5.5714	7	5.2944	9	6.4781	9
RFS	6.1376	7	5.8342	6	6.0533	6	6.9555	8
RSSA	3.8059	16	3.1921	16	2.813	17	4.2572	18
RSSB	5.3666	11	4.2289	13	4.6919	11	6.2507	12
RSSC	2.3849	21	0.2465	22	1.9324	22	2.6454	20
SMJ	-20.3069	33	-0.7292	26	-15.3607	33	-16.9603	33
SSC	3.7547	17	2.6923	18	3.3378	16	4.7381	15
TEM	2.3631	22	-0.6481	25	2.052	21	3.9268	19

Table 3.9 LEM Scores of Journals as Sources

Table 3.9 presents the scores of journals as sources, the higher the score, the more influential the journal is as a source. We can see that *Econometrica*, the journal that links statistics and business, is the most influential source for all four years. *Journal of Finance*'s influence is high as a source. Statistics journals are more influential as sources than as storers in all four years for the journals we selected. For example, the *Journal of the American Statistical Association* ranks 6, 8, 7, 6 among sources and ranks 25, 25, 26, 26 among storers in 2000, 2005, 2010, and 2015. Also, the influence seems to increase for statistics journals. For example, *the American Statistician* increases from the 13th rank to the 5th rank from 2000 to 2015.

3.6 Discussion/Conclusion(s)

Based on our network analysis and LEM scores of the citation data, we can answer some of our original questions. Business analytics seems to promote and increase communication among different disciplines, but the changes are not as apparent as we expected. The emergence of business analytics seems to motivate business scholars to have a deeper understanding of statistics. The influence of statistics journals as storers remains low and stable, and the influence of statistics journals as sources remains high in the four years we selected. Thus, statistics may not cite and extract much information from business disciplines but may highly influence them. The communication patterns among statistics and business journals are quite stable. *Journal of Econometrics, Econometrica* (economics journals), and the *Journal of Business and Economics Statistics* (statistics journals) link statistics and business journals.

We find that the results of essay 1 and essay 2 are generally consistent. In factor analysis, journals of the same disciplines load on the same factor most of the time. In network analysis, statistics journals are in the same faction group. Economics and finance are in the same group, ISOM, management, and marketing fall in the same group. However, for the raw data the network grouping pattern is not clear. Still, statistics seems to be the source of knowledge in the analysis of both essays, the teacher in essay 1, the source in essay 2.. The learning is not reciprocal with business, though. Economics is the link between business and statistics in both essays.

In the future, we may extend the research by incorporating more data. We may use data from 1980 to 2020 to have a better picture of how the emergence of business analytics has influenced the knowledge sharing of statistics and business disciplines. Also, more journals may be included in the dataset. For example, the *Journal of Statistical Software* published articles about statistical software and algorithms. It may give us some other perspective of knowledge sharing among statistics and business journals. Thus, we may find other journals that connect business and statistics serving as an essential link in communication among journals.

Chapter 4: Essay 3 The Landscape of Data Science: Perspective from Citation Network Analysis

4.1 Introduction

Tukey (1962) first came up with the concept of "data science" in the last century. Since then, multiple disciplines such as statistics, computer science, and even architecture have contributed to creating the new discipline of data science. Data science is widely applied nowadays in business and academia. This essay focuses on mapping the landscape of data science from an academic business perspective and observing, in particular, the prominence (or lack thereof) of statistics in that landscape. Previous papers on data science are more likely to explore the application or the history of statistics, leaving the relationships among authors and publications which comprise the landscape of data science not well understood. In this paper, we discuss the journals, articles, and authors that have most contributed to the development of data science from network analysis. Thus, we have an overview of the landscape of data science for the business academy in the last 60 years.

To obtain the data for this analysis, we extract citation information for all the articles related to data science in statistics and business disciplines (Statistics and Probability; Business; Business Finance; Economics; Management; Information Science; Operations Management). We find that the articles range from 1960 to 2020. We have 19,353 publications and 300,712 references for these publications in our dataset. A large amount of data makes our research more informative than previous studies.

We use network citation analysis to study data science in the business academy, following the method of An and Ding (2018) when they explore the landscape of "Causal Inferences." We present both detailed descriptive statistics and ERGM (exponential random graph models) results. The descriptive statistics show us the most prolific journals, and most cited journals, articles, and authors. Besides, we present some centrality measures of the networks we created. In the end, we use ERGM to analyze the networks, and, in an effort to find what might affect the influence of these articles, we look at the number of keywords, the number of authors, the number of pages, and whether the paper has funding. From this analysis, we find that statistics has an essential spot in the landscape of data science in business.

In 4.2, we review literature related to citation network analysis, network science, and data science. In 4.3, we present the motivation of this essay. In 4.4, we describe our research methods. In 4.5, we present our findings. In 4.6, we make some conclusions and discussions based on the findings we have.

4.2 Literature Review

In the literature review, we are discussing previous researches from citation network analysis, network science: ERGM and data science perspectives.

4.2.1 Citation Network Analysis

In Chapters 2 and 3, we have presented how citation network analysis can help us understand communication among disciplines at the emergence of business analytics. In this essay, we are examining how citation analysis can help us overview the development of data science and how statistics and business may influence or be influenced by it.

How can we use citations to analyze the landscape of one academic field? Previous studies have given us some guidance. Ji and Jin (2016) investigate the citation networks and coauthorship and for statisticians from the perspectives of centrality, community structures, and productivity, patterns, and trends. Digital object identifier (DOI), which is defined by the International Organization for Standardization (ISO), is unique identifier assigned for each online publication. They use DOI to identify different papers, which is also applied in our essay to identify publications. The article also raises questions about how to set standards to evaluate network models. (Karwa and Petrović, (2016); Wang, S., & Rohe, K., (2016).) This paper also inspires scholars to An and Ding (2018) use exponential random graph models (ERGM) to examine citation networks by considering covariates such as paper quality, length, and the number of authors homophily such as the same field and shared authors, and network structures. They also explore a citation network among the most prolific authors.

4.2.2 Network Science: ERGM

In previous essays, we have discussed a network science definition (United States National Research Council (2006)) and how it is applied in multidisciplinary research studies. For example, Nerur et al. (2008) use multidimensional scaling, factor analysis, and pathfinder analysis (a psychometric scaling method) to evaluate individual scholar's influence while Leydesdorff (2007) uses the betweenness centrality to study scientific journals.

In this paper, we will focus on the ERGM method applied by An and Ding (2018), previously developed in the following publications. Wasserman and Robins (2005) state that dependence graphs can be used to distinguish among distributions. They define dependence graphs as a "graph of nodes whose edges signify pairs of random variables that are assumed to be conditionally dependent (given the value of all other variables)." Robins et al. (2007) "*provide an introductory exposition of the formulation and application of exponential random graph models for social networks and present the underlying logic and derivation of these models*." Based on the fundamental concepts, Hunter et al. (2008) have implemented ERGM in R (statnet). They write, "*Attribute information is easily incorporated into an ERGM (Fienberg and Wasserman 1981). Suppose we wish(original article) to examine the impact of p exogenous attributes represented by an* $n \times n \times p$ *array, X, whose* ijk^{th} *element is the value of the* k^{th} *attribute for the potential edge represented by the Bernoulli random variable* Y_{ij}. *Note that this construction allows the attributes to be functions of nodal covariates*." Provost and Fawcett (2013) state that data science can help business industry have a better understanding of data, thus boost their size and profits. How to apply data science into business research and practice becomes a hot topic (Kohavi et al. (2002)).Many more scholars explain how we can use ERGM to analyze networks from different perspectives (Snijders, T. A. (2002); Hunter and Handcock (2006); Butts, C. T. (2008); Morris et al. (2008); Goodreau et al. (2009); Ding, Y. (2011); Lusher et al. (2013))

4.2.3Business Analytics and Data Science

Borne (2018) refers Analytics as the product of machine learning and data science. In the twentieth century, analytics has become an essential tool in business practice and academic research in the 21st century data analytics. Scholars use data analytics to develop models and explore research questions in their field. Cao (2017) states that Data analytics is the multidisciplinary science of quantitatively and qualitatively examining data. It can be used to draw new conclusions or insights (exploratory or predictive), or extract and prove (confirmatory or fact-based) hypotheses about that information for decision-making and action.

Data Science first appeared in the 1960s. Tukey (1962) comes up with the idea that data analysis can be viewed as "new science" as it has (1) intellectual content, (2) organization in an understandable form, and (3) reliance upon the test of experience as the ultimate standard of validity. Naur (1974): defines data science as "*the science of dealing with data, once they have been established, while the relation of the data to what they represent is delegated to other fields and sciences*." Many more scholars have expended this discipline through published books and articles e.g. (Loukides (2011), Donoho, D. (2017).; Kelleher and Tierney (2018)).

4.3 Motivation

The motivation is to analyze the landscape of data science in the 21^{st} century from a perspective of academic areas in business and statistics. The development of data science has changed people's way of handling data. Nowadays, more and more scholars in business and statistics have used python, r, and other data science related software to process and analyze the data. In this case, we would like to explore the landscape of data science. What are the journals publishing the most data science papers? Are they also influential and cited most by other journals.? Who are the most prolific and influential authors in data science? What are academic areas influencing and influenced by data science the most in our selected areas?

To answer these questions, we overview data science development in business and statistics. Previous studies have used systematic reviews to learn data science development. We use descriptive statistics of citation networks and Exponential Random Graph Models (ERGM) to provide more information on this topic.

4.4 Research Methods

4.4.1 Data Collection

We extract publication information related to data science from Web of Science. The keywords used to search "data science" articles were suggested by panel of academic scholars. We are presented in Table 4.1:

Search Terms	
Artificial Intelligence	NLP
Business Analytics	Predicted Analytics
Data Mining	Supervised Learning
Data Science	Text Analytics
Deep Learning	Text Mining
Machine Learning	Unsupervised Learning

Table 4.1 Search Term Used in the Web Of Science

We have collected data from these areas: Statistics and Probability; Business; Business Finance; Economics; Management; Information Science; Operations Management. We didn't limit the time that these papers published, and we have publications ranging from 1960 to 2020, Feb.

In this paper, I use DOI to identify different papers and match references the publications have cited to papers in the publication results as each paper have a unique DOI For example, if a reference DOI and a publication DOI are matched, it means that the reference paper and the publication are the same paper. Thus, we can include the reference that shares the same DOI in the publication in the network analysis.

4.4.2 Network Analysis

4.4.2.1 Descriptive Statistics

We first use python to preprocess the data. The detailed description can be found in essay 1. Then we present descriptive statistics of prolific journals, most cited journals, most prolific authors, most cited authors, and influential articles. most prolific journals are journals that publish the greatest number of articles related to data science. Most cited journals receive citations related to data science the most often. Most prolific authors are authors who publish the highest number of articles related to data science.

4.4.2.2 Network Analysis

Next, we use R to do network analysis. We first present basic network statistics such as density, centralization, and reciprocity. Then we provide the information of centrality measures and correlations of the centrality measure of core and full networks. The full network includes all publications, and those references appear in the publications. The core network includes only those publications whose references appeared in the publications, meaning the core network removes publication that does not cite or be cited by other publications in our dataset.

After presenting the descriptive statistics of the network, we use the R network and ERGM to build models with full, and core networks, taking sender's effect, receiver's effect, and the network structure into consideration. Key words number, publication page, author number, and funding support are the covariates considered. These are all binary variables. If the number of the keywords is more than the average in our dataset, we code it as 1, otherwise 0. The publication page and author number are coded the same way. If the publication has funding support, we code it as 1, otherwise 0. We find these four covariates for citing papers and use them as the sender's effect, and we find these four covariates for cited articles and use them as the receiver's effect in our model. We use GWESP to illustrate the structure effect in the models.

The most prolific authors' network (50 most prolific authors) is also built but is only presented in the appendix. We will discuss why this network of authors is problematic in the findings.

4.5 Findings

Journal with most publications	Publications
EXPERT SYSTEMS WITH APPLICATIONS	2375
BIOINFORMATICS	872
DECISION SUPPORT SYSTEMS	377
EUROPEAN JOURNAL OF OPERATIONAL RESEARCH	322
JOURNAL OF THE AMERICAN MEDICAL INFORMATICS ASSOCIATION	322
IEEE-ACM TRANSACTIONS ON COMPUTATIONAL BIOLOGY AND BIOINFORMATICS	221
INFORMATION PROCESSING & MANAGEMENT	203
INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH	196
SCIENTOMETRICS	189
FUZZY SETS AND SYSTEMS	185
CHEMOMETRICS AND INTELLIGENT LABORATORY SYSTEMS	148
JOURNAL OF COMPUTATIONAL BIOLOGY	138
TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE	126
ANNALS OF OPERATIONS RESEARCH	115
INTERNATIONAL JOURNAL OF GEOGRAPHICAL INFORMATION SCIENCE	115
JOURNAL OF INFORMATION SCIENCE	102
JOURNAL OF THE ASSOCIATION FOR INFORMATION SCIENCE AND TECHNOLOGY	98
COMPUTATIONAL STATISTICS & DATA ANALYSIS	97
JOURNAL OF THE AMERICAN SOCIETY FOR INFORMATION SCIENCE AND TECHNOLOGY	97
JOURNAL OF THE OPERATIONAL RESEARCH SOCIETY	88
INTERNATIONAL JOURNAL OF INFORMATION TECHNOLOGY & DECISION MAKING	86
COMPUTERS & OPERATIONS RESEARCH	85
STATISTICAL ANALYSIS AND DATA MINING	78
COMPUTERS ENVIRONMENT AND URBAN SYSTEMS	73
INFORMS JOURNAL ON COMPUTING	72
SAFETY SCIENCE	63
JOURNAL OF GLOBAL OPTIMIZATION	57
IEEE SYSTEMS JOURNAL	56
INTERNATIONAL JOURNAL OF SYSTEMS SCIENCE	56
JOURNAL OF MANUFACTURING SYSTEMS	56

Table 4.2 Journal with Most Publications on Data Science

In table 4.2, we can see that the journals with most publications on data science is Expert Systems with Application, a journal introducing systems/techniques. ISOM journals rank high in journals journal with most publications on Data Science. We can see *European Journal of Operational Research, International Journal of Production Research, Scientometrics, Information Processing and Management, Annals of Operations Research,* and *Journal of Information Science* etc. are in the list. Statistics journals such as *Statistical Analysis and Data Mining* also appeared in the list, but most of these journals are not in statistics or other business areas.

Journal most cited	References
EXPERT SYST APPL	11378
BIOINFORMATICS	5095
EUR J OPER RES	4628
LECT NOTES COMPUT SC	4536
MACH LEARN	4235
DECIS SUPPORT SYST	4040
NUCLEIC ACIDS RES	3207
J MACH LEARN RES	3136
J AM STAT ASSOC	2907
COMMUN ACM	2698
MANAGE SCI	2680
IEEE T KNOWL DATA EN	2541
LECT NOTES ARTIF INT	2400
SCIENTOMETRICS	2393
P NATL ACAD SCI USA	2294
ANN STAT	2291
SCIENCE	2227
BMC BIOINFORMATICS	2097
NATURE	2032
INT J PROD RES	2013
IEEE T PATTERN ANAL	2003
J FINANC	1862
J AM MED INFORM ASSN	1854
ARTIF INTELL	1783
INFORM SCIENCES	1715
J AM SOC INF SCI TEC	1701
INFORM PROCESS MANAG	1693
MIS QUART	1666
PATTERN RECOGN	1661
TECHNOL FORECAST SOC	1643

Table 4.3 Most Cited Journals in Data Science

In table 4.3 shows the journal that is most cited in Data Science is again Expert Systems with Application, a journal introducing systems/techniques. ISOM journals also rank high in journals that are most cited in Data Science. We can still see the *European Journal of Operational Research*, *International Journal of Production Research*, and *Scientometrics*, etc. are in the list. However, some top journals such as ISOM journals *Management Science* and *MIS Quarterly* appears in the list. Statistics journals such *Journal of American Statistics Association*, and *Annals of Statistics* also appeared in the list. Also, other business journals such as *Journal of Finance* also appeared in the list, indicating that people try to apply data science in the finance area.

Next, we are discussing the authors' descriptive statistics. Before that, I want to make it clear that I have put both the most prolific authors list (Appendix Table C1) and the network (Appendix Figure C1) in the appendix. The reason is that we find most people on the list are for example, Asian people without their full names. The system is very likely to categorize people with the same abbreviated names as the same person. In this case, the prolific author list could be very misleading. We are not going to discuss this identification problem further but present to results for the readers' review.

Rank	Authors	Cited	Rank	Authors	Cited
1	BREIMAN L	2053	26	JAIN AK	395
2	AGRAWAL R	1413	27	BISHOP CM	369
3	HAN J	1123	27	WITTEN IH	369
4	HASTIE T	1001	29	LECUN Y	366
5	QUINLAN JR	980	30	ZHANG Y	365
6	SALTON G	660	31	CHANG CC	355
7	JOACHIMS T	608	32	FRIEDMAN J	344
8	VAPNIK V	601	32	WITTEN I	344
9	FRIEDMAN JH	539	34	FAYYAD U	337
10	QUINLAN J R	538	34	HAND DJ	337
11	BLEI DM	536	36	HALL M	331
12	KOHONEN T	524	37	LIU H	328
13	LIU B	512	38	PEARL J	325
14	FREUND Y	494	39	FAYYAD UM	313
15	TIBSHIRANI R	491	40	CRISTIANINI N	310
16	CORTES C	490	41	GLOVER F	307
17	KOHAVI R	476	42	CHEN HC	305
18	ZADEH LA	471	43	FAMA EF	295
19	KOSTOFF RN	461	44	FELDMAN R	280
20	VAPNIK V N	437	45	PANG B	276
21	EFRON B	432	46	MITCHELL TOM M	274
22	SCHOLKOPF B	426	47	ALTMAN EI	271
23	PAWLAK Z	417	47	BENGIO Y	271
24	LIU Y	400	49	LEYDESDORFF L	269
25	YANG Y	396	50	LEE S	267

Table 4.4 Most Cited Authors in Data Science

Table 4.4 presents authors that are most cited in Data Science. We can infer which author it is and what publications the author has from their last names. For example, the author that is most cited is Leo Breiman, with publications such as *Random Forests, Classification and Regression Trees*, and *Prediction Games and Arcing Classifiers*, etc. These papers provide theory support for data science and are still influencing it. From the name list, we can see what an influential role the statisticians have played in data science. When data scientists try to come up with new models, they need to go back to statistics papers to find theoretical evidence.

Rank	Author	Article	Citations	Total Citations
1	L Breiman	Random Forests	785	51022
2	M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. Witten	The WEKA data mining software: an update	256	19486
3	Agrawal, R., Imielinski, T., & Swami, A.	Database mining: a performance perspective	230	2068
4	Sebastiani, F.	Machine learning in automated text categorization	200	9658
5	L Breiman	Bagging Predictors	196	22109
6	LA Zadeh	Fuzzy sets	195	84757
7	McKenna, K. Y., Green, A. S., & Gleason, M. E.	Relationship formation on the Internet: What's the big attraction?	191	2014
8	Porter, M	An algorithm for suffix stripping	190	10757
9	Pang, B., & Lee, L	Opinion Mining and Sentiment Analysis	189	8834
10	Deerwester, S., Dumais, S. T., Furnas, G. W., Landauer, T. K., & Harshman, R.	Indexing by latent semantic analysis.	184	14782
11	Chang, C. C., & Lin, C. J.	LIBSVM: A library for support vector machines	182	41841
12	Burges, C. J.	A tutorial on support vector machines for pattern recognition	176	20741
12	LeCun, Y., Bengio, Y., & Hinton, G.	Deep learning	176	19921
14	Guyon, I., & Elisseeff, A.	An introduction to variable and feature selection	174	13643
15	Freund, Y., & Schapire, R. E.	A decision-theoretic generalization of on-line learning and an application to boosting.	172	17437
16	Friedman, J. H.	Greedy function approximation: a gradient boosting machine	164	8348
17	Salton, G., & Buckley, C.	Term-weighting approaches in automatic text retrieval	161	9865
18	Krizhevsky, A., Sutskever, I., & Hinton, G. E.	Imagenet classification with deep convolutional neural networks.	159	49878
19	Altman, E. I.	Financial ratios, discriminant analysis and the prediction of corporate bankruptcy.	157	16764
20	Fisher, Ronald A.	The use of multiple measurements in taxonomic problems	150	16313
20	Jain, A. K., Murty, M. N., & Flynn, P. J.	Data clustering: a review.	150	15619

Table 4.5 Most Cited Papers in Data Science

Table 4.5 presents the top 20 most cited papers in data science. We can see that some classic statistics papers such as *Random Forests*, *Bagging Predictors*, *Fuzzy sets*, and *An introduction to variable and feature selection*. These papers provide statistics support for data science development. When data scientists develop or use new data science programs, they can use statistics to build their packages and explain their results. On the other hand, we can see that data scientists try to cite papers that directly related to data science. For example, some most papers such as *The WEKA data mining software: an update*, *Database mining: a performance perspective*, *Machine learning in automated text categorization*, and *Opinion Mining and Sentiment Analysis* are more related to data science than other disciplines. It shows that data science has become an independent discipline from statistics, computer science, and information system, etc. Also, the table shows us that scholars from other disciplines are applying data science in their research. For example, *Financial ratios, discriminant analysis and the prediction of corporate bankruptcy* is a paper from the finance and accounting field yet is well-cited in data science.

Full citation network				Core citation network			
I. Basic network statistics				i. Basic network statistics			
Density	8.33E-06	Transitivity	0.000275791	Density	0.000226821	Transitivity	0.07292537
Centralization	0.00197336	Isolates	12016	Centralization	0.005922375	Isolates	0
Reciprocity	0.00098235	Components	19347	Reciprocity	0.001556496	Components	8321
II. Summary Information of the centrality measures				II. Summary Information of the centrality measures			
	Indegree	Outdegree	Betweenness		Indegree	Outdegree	Betweenness
Min	0	0	0	Min	0	0	0
Mean	2.306	2.306	71.48	Mean	2.159	2.159	81.57
Max	167	107	28539.8	Max	167	107	38600
SD	5.885745	3.856309	602.974	SD	5.722425	3.196297	752.8741
Skewness	10.46761	8.013094	25.91031	Skewness	10.73516	9.02001	28.87858
III. Spearman rank correlations of the centrality measures				III. Spearman rank correlations of the centrality measures			
	Indegree	Outdegree	Betweenness		Indegree	Outdegree	Betweenness
Indegree	1			Indegree	1		
Outdegree	-0.21	1		Outdegree	-0.24	1	
Betweenness	0.61	0.42	1	Betweenness	0.63	0.38	1

Table 4.6 Descriptive Statistics of Full and Core Citation Networks

Table 4.6 I shows that density, centralization, reciprocity, and transitivity are very small for both full and core citation networks. The results indicate that both full and core networks are very sparse. If node A and node B have a reciprocal relationship, the edge exists from A to B and from B to A. Otherwise, they do not have a reciprocal relationship. The reciprocity is very low, as papers do not cite mutually. Due to the forward citing patterns, articles can only cite those published before it, not vice-versa. The transitivity means that when node A and node B have a link, and node B and node C have a link, then A and C have a link. In our essay, the transitivity is about 7% for the core citation network, indicating that 7% of papers are citing what their references cite.

Table 4.6 II presents indegree, outdegree and betweenness. Indegree shows how many citations the publication receives and outdegree shows how many times the publication is cited. Betweenness indicates how often different disciplines cite the publication. The full network shows that publications receive about 2.3 citations, while the most cited publication is cited 167 times. Among the publications, the publication cites the most cites 107 references. The centrality measure of the core network is very similar.

Table 4.6 III presents the correlations of the centrality measures. Betweenness has a positive correlation with indegree and outdegree, but indegree and outdegree have a weak negative correlation, indicating that the publication cites many references is not necessarily well cited by other paper, or vice versa.

Monte Carlo MLE Results:											
	Model 1 Full Network				Model 2 Core Network				Model 3 Core Network		
	Estimate	Std. Error			Estimate	Std. Error			Estimate	Std. Error	
edges	-8.37766	0.015098	***		-8.54147	0.021799	***		-8.76381	0.026466	***
Sender's Effect											
nodefactor.key1.1	0.064568	0.012019	***		-0.00376	0.010011			-0.00177	0.010571	
nodefactor.fund1.1	-0.08446	0.014107	***		0.090729	0.010684	***		0.073172	0.017612	***
nodefactor.page1.1	0.005734	0.011172			-0.02286	0.010126	*		-0.0237	0.016195	
nodefactor.author_number1.1	0.017889	0.012307			0.007594	0.011128			0.037664	0.01571	*
Receiver's Effect											
nodefactor.key2.1	-0.03002	0.016495	.		-0.04706	0.010648	***		-0.00213	0.016762	
nodefactor.fund2.1	-0.04148	0.032382			0.12506	0.015881	***		0.070753	0.023547	**
nodefactor.page2.1	-0.03744	0.013334	**		0.092189	0.010179	***		0.069835	0.012514	***
nodefactor.author_number2.1	0.020085	0.016745			0.031895	0.01131	**		0.015959	0.013444	
gwesp.fixed.0.2									5.094352	0.032007	***
Sig.: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1											

Table 4.7 ERGM Results for Full and Core Citation Networks

In this essay, we have built three models. Model 1 and Model 2 are basic full and core networks, respectively. Model 3 is the core network considering the geometrically weighted edgewise shared partner (gwesp).

In Model 1, we can see that for the citing paper (Sender Effect), the number of their keywords and whether they have funding are significant. Publications with more keywords and without funding are more likely to cite. For the cited paper (Receiver Effect), their page number is significant. Publications with fewer pages are more likely to be cited.

In Model 2, we can see that for the citing paper (Sender Effect), their funding situation and page number are significant. Publications with funding and fewer pages are more likely to cite. For the cited paper (Receiver Effect), all the covariates are significant. Publications with fewer keywords, with funding, have more pages and authors are more likely to be cited.

In Model 3, we can see that for the citing paper (Sender Effect), their funding situation and author number are significant. Publications with funding and more authors are more likely to cite. For the cited paper (Receiver Effect), publications with funding and have more are more likely to receive citations. For the structure, we can see that the coefficient is positive and significant, indicating that publications are more likely to cite their reference's reference, which is consistent with what we find in the network statistics.

Model 1 Goodness-of-fit for model statistics					
	obs	min	mean	max	MC p-value
Edges	18202	17774	18193.04	18521	0.98
nodefactor.key1.1	11126	10765	11094.71	11414	0.84
nodefactor.fund1.1	6577	6340	6579.99	6826	0.88
nodefactor.page1.1	13790	13518	13786.7	14119	0.9
nodefactor.author_number1.1	9231	8930	9206.91	9414	0.86
nodefactor.key2.1	4863	4691	4873.03	5039	0.88
nodefactor.fund2.1	1028	926	1032.98	1087	0.9
nodefactor.page2.1	8766	8570	8759.2	9020	1
nodefactor.author_number2.1	4444	4284	4464.8	4611	0.68
Model 2 Goodness-of-fit for model statistics					
	obs	min	mean	max	MC p-value
Edges	20559	20067	20458.66	20816	0.46
nodefactor.key1.1	21772	21282	21672.84	22100	0.56
nodefactor.fund1.1	14874	14481	14815.8	15216	0.82
nodefactor.page1.1	20797	20301	20694.25	21170	0.56
nodefactor.author_number1.1	12312	11970	12271.13	12563	0.78
nodefactor.key2.1	13543	13185	13472.43	13786	0.64
nodefactor.fund2.1	4803	4629	4802.66	4975	1
nodefactor.page2.1	21749	21205	21651.58	22158	0.6
nodefactor.author_number2.1	11281	10908	11222.43	11526	0.62
Model 3 Goodness-of-fit for model statistics					
	obs	min	mean	max	MC p-value
Edges	20559	21810	24610.35	24963	0
nodefactor.key1.1	21772	23088	26114.01	26572	0
nodefactor.fund1.1	14874	15838	17996.42	18315	0
nodefactor.page1.1	20797	22002	24817.08	25294	0
nodefactor.author_number1.1	12312	13211	14970.3	15213	0
nodefactor.key2.1	13543	14335	16389.51	16730	0
nodefactor.fund2.1	4803	5155	5831.83	5986	0
nodefactor.page2.1	21749	23077	26021.65	26421	0
nodefactor.author_number2.1	11281	12077	13422.67	13739	0
gwesp.fixed.0.2	4604.092	4558.936	4635.728	4702.958	0.52

Table 4.8 Goodness-of-Fit for Model 1, 2, and 3 Statistics

Table 4.8 shows us the goodness of fit for models 1, 2, and 3. Before looking at the statistics, we want to understand how we can use goodness-of-fit to evaluate models. When we have very high MC p-values, we can say that the network our model has simulated is not different from the observed one. When we have low MC p-values, we may find that the network our model has simulated is significantly different from the observed one, indicating that we need to adjust our model.

In Table 4.8, we can see that MC p values of goodness-of-fit for model 1, and 2 are much larger than 0.05; even larger than 0.5, implying that we find no evidence that the simulated models do not accurately represent the observed network characteristics. MC p values for model 3 are smaller than 0.05, except for gwesp, implying that the simulated model does not fit the data well. Other goodness-of-fit tables are presented in the appendix.

4.6 Discussion and Conclusion

This paper provides some information on data science in academic business disciplines using descriptive statistics and citation network analysis with networks of authors, articles, and journals. In our dataset, the most prolific journals are ISOM journals, while the most cited journals are ISOM and statistics journals. Although statistics journals do not publish many papers related to data science, some of the most cited scholars are statisticians. From the descriptive statistics and ERGM results of the core and full networks, we observe that the citation network is sparse. The publications that cite many papers often are not highly cited. In the full network (Model 1), publications with more keywords and without funding support are more likely to cite; publications with fewer pages are more likely to be cited. In the core network without gwesp structure (Model 2), publications with funding and fewer pages are more likely to cite; publications with fewer keywords, more pages, more authors, and funding support are more likely to be cited. In the core network with gwesp structure (Model 3), publications with funding support and more authors are more likely to cite; publications with funding support and more pages are more likely to be cited; also, publications are more likely to cite the sources that their references cite.

However, questions remain unanswered. For example, why do the number of keywords, the number of authors, the number of pages, and whether the paper has funding have a positive/negative influence on citations? What other factors may affect the citations? We may use future surveys to shed light on these questions. Also, we may use a citation network to analyze coauthorship in data science for business disciplines. Thus, we can add more detail to our landscape of data science.

Chapter 5 General Conclusions

The motivation of the dissertation is generally to explore the contribution of statistics to academic business research in the era of business analytics. The first essay uses citation analysis and text analytics to describe knowledge sharing among 36 elite statistics and business journals as reflected in the similarity of their citation patterns and the words used in abstracts from their publications in each of the years 2000, 2005, 2010, and 2015. Using multivariate methods, multiple dimensional scaling and factor analysis, we find the not surprising result that economics journals are the link connecting business and statistics journals. Business and statistics journals seem to have more similarities in citations and to share more research interests in 2015 than in the earlier years we observed.

The second essay reaches similar conclusions from the same data set using a different tool, citation network analysis and the log multiplicative model. We find that statistics acts as a highly influential knowledge source rather than a knowledge storer. Finance plays a role both as a highly influential knowledge source and storer. Again, we conclude in the second essay that during the time when business analytics emerged as a force in the practice of business, academic knowledge sharing among business and statistics seems somewhat enhanced as evidenced by the network of directed citations among these journals.

Essay 3 presents the landscape of data science from the perspective of business and statistics journals using a new larger dataset of publications with resulting network analysis of citations for journals, authors, and publications with ERGM models,. In our journal set, we find that ISOM journals publish the most articles related to data science, while statistics journals publish the fewest. However, the discipline of statistics has a great influence on data science evidenced by the frequency of citations for publications by statisticians among other things. Some elite business journals, such as *Management Science, MIS Quarterly*, and *Journal of Finance* are also well-cited by data science related publications, indicating that business research is contributing to data science. However, both the full and core networks are quite sparse, indicating the knowledge sharing among articles on data science is not frequent in business and statistics.

Thus, we surmise that statistics has indeed had a profound influence on the foundations of data science and in turn on business analytics, but that this influence is still not immediately apparent in the direct exchange of knowledge between the academic disciplines of business and statistics.

Appendix A

	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7	Factor8	Factor9
AMR	-0.29043	-0.17794	-0.02026	0.028148	0.085049	-0.0809	0.057762	0.105022	0.924664
AMJ	-0.28257	-0.18164	-0.02295	0.051619	0.079327	-0.09741	0.053327	0.119194	0.923761
ASQ	-0.29727	-0.14786	-0.05585	-0.00237	0.073723	-0.05001	0.061313	0.093915	0.900915
SMJ	-0.3124	-0.14086	0.000907	0.068994	0.089298	-0.05841	0.069461	0.094958	0.89346
DS	-0.35407	-0.18504	0.046488	0.455277	0.062858	-0.08404	0.076177	0.750267	0.222697
MISQ	-0.28904	-0.19724	-0.01007	0.187424	0.078993	-0.08661	0.064606	0.8837	0.202569
POM	-0.28212	-0.20979	-7.3E-05	0.85168	0.100223	-0.13507	0.059903	0.279454	0.198722
JOM	-0.26728	-0.19062	0.889343	-0.02153	0.062834	-0.11498	0.045405	0.023429	0.175618
ISR	-0.3116	-0.14883	0.073101	0.391756	0.10963	-0.12281	0.084961	0.822428	0.093908
MGS	-0.33781	-0.03097	0.122097	0.869376	0.048616	-0.06348	0.079706	0.297557	0.05394
JMR	-0.15438	-0.11088	0.977055	0.024071	0.06237	-0.10317	0.037789	0.011135	-0.03063
MKS	-0.22392	0.066717	0.906118	0.214916	0.069177	-0.12822	0.081176	0.082657	-0.07389
RFS	-0.27841	0.240855	-0.15622	-0.10334	-0.06205	0.89897	0.063936	-0.07382	-0.08879
JFE	-0.26277	0.183011	-0.16155	-0.10747	-0.06328	0.914965	0.066289	-0.07356	-0.0896
OPR	-0.18133	-0.17097	0.00126	0.938073	0.093223	-0.1239	0.037538	0.137359	-0.09005
JFN	-0.26637	0.223719	-0.15862	-0.1063	-0.05413	0.906024	0.06614	-0.07556	-0.0907
AER	-0.32637	0.733456	-0.08358	-0.09357	0.048249	0.054597	0.178607	-0.07773	-0.10206
RES	-0.11195	0.968486	-0.07909	-0.09958	0.027489	0.073756	0.115963	-0.08299	-0.12273
EM	0.022453	0.949545	-0.06798	-0.05133	-0.04572	0.101256	-0.08586	-0.07772	-0.12691
ACR	-0.27591	-0.02082	-0.11777	-0.11025	-0.92855	0.041868	0.080688	-0.08692	-0.14182
JCR	-0.22399	-0.16072	0.824287	-0.07899	0.08255	-0.10614	0.045048	-0.02415	-0.14258
JOE	0.252479	0.899798	-0.08054	-0.08978	-0.0255	0.165393	-0.07829	-0.09455	-0.14488
BIO	0.94651	-0.03823	-0.11666	-0.11265	0.069861	-0.0886	0.049579	-0.10038	-0.14751
AS	0.809239	0.088517	-0.1207	-0.10287	0.058252	-0.09924	-0.41566	-0.09664	-0.14952
RSSB	0.95992	0.036173	-0.11321	-0.10614	0.066461	-0.08933	-0.06982	-0.10025	-0.15432
BES	0.20477	0.851095	-0.11992	-0.10238	-0.02293	0.393939	-0.02547	-0.09982	-0.15798
SSC	0.94325	-0.04661	-0.12528	-0.12089	0.08167	-0.0972	0.074631	-0.10847	-0.15868
ASA	0.957019	0.046223	-0.11005	-0.11195	0.066517	-0.08329	-0.09463	-0.10478	-0.15929
BMK	0.950605	0.03062	-0.12315	-0.10795	0.071182	-0.09485	-0.1152	-0.10641	-0.15938
RSSA	0.879431	0.054765	-0.11429	-0.11895	0.071209	-0.08935	0.076498	-0.10804	-0.15996
JAR	-0.27989	0.019523	-0.1612	-0.11473	-0.91077	0.113507	0.079007	-0.09414	-0.16134
RSSC	0.953981	-0.03965	-0.13025	-0.09939	0.07638	-0.10182	0.050388	-0.11237	-0.16443
JSPI	0.912499	0.062465	-0.13152	-0.10375	0.075587	-0.10667	-0.24603	-0.10756	-0.16933
AMS	0.887336	-0.00762	-0.13357	-0.13518	0.099945	-0.11116	0.085307	-0.12359	-0.18017
ANP	0.0629	-0.10497	-0.19372	-0.14757	0.160018	-0.16945	-0.67476	-0.1451	-0.20514
TEM	0.476562	-0.14182	-0.19709	-0.16282	0.172825	-0.16899	0.117068	-0.17394	-0.22716

Table A.1 2000 Citing-Cited Factor Analysis for 36 Journals

	Factor	Factor	Factor	Factor	Factor	Factor	Factor	Factor
ACR	-0.2814	-0.1545	-0.1703	-0.176	-0.075	-0.1261	-0.0506	0.88942
JAR	-0.2916	-0.1449	-0.1848	-0.1653	-0.0451	-0.1432	-0.0327	0.88608
POM	-0.2393	-0.0787	-0.0521	0.02117	-0.0745	0.09137	0.9143	0.03446
RSSC	0.93917	0.17997	-0.1158	-0.0921	-0.0647	-0.0501	-0.1001	0.00467
RSSA	0.95103	-0.0388	-0.11	-0.0934	-0.0689	-0.0574	-0.0596	-0.0145
JFE	-0.257	0.16836	-0.0864	-0.1654	0.90719	-0.1246	-0.1221	-0.0183
JFN	-0.2502	0.20178	-0.115	-0.1647	0.90036	-0.1244	-0.1149	-0.0194
BIO	0.94837	-0.1035	-0.0962	-0.0947	-0.0604	-0.0589	-0.0919	-0.0204
RFS	-0.2237	0.2168	-0.1618	-0.1638	0.89582	-0.1253	-0.1167	-0.0229
OPR	-0.1853	-0.113	-0.1041	-0.0228	-0.1076	0.04529	0.91423	-0.0298
EM	-0.004	0.94049	-0.1456	-0.131	0.19389	-0.1205	-0.0536	-0.0325
MGS	-0.3615	-0.1345	0.16454	0.10403	-0.124	0.20472	0.86441	-0.0405
JOE	0.12481	0.93495	-0.1558	-0.0866	-0.0117	-0.0845	-0.1037	-0.0428
AER	-0.3056	0.62127	0.08847	-0.0865	0.45307	-0.0964	-0.0172	-0.0453
AMS	0.83937	0.0469	-0.1495	-0.1124	-0.0722	-0.0953	-0.1287	-0.0539
MKS	-0.2192	-0.064	-0.0495	0.91801	-0.1239	-0.06	0.17556	-0.0543
BES	0.06043	0.96548	-0.148	-0.0262	0.04551	-0.0903	-0.0863	-0.059
JCR	-0.2177	-0.1108	-0.0881	0.89338	-0.1001	-0.0476	-0.0757	-0.0602
AMJ	-0.2604	-0.0949	0.94958	-0.0249	-0.0788	-0.0149	-0.0098	-0.0625
AMR	-0.2518	-0.0985	0.94712	-0.01	-0.0788	-0.0298	-0.0256	-0.0661
ASQ	-0.2679	-0.0863	0.94997	-0.0027	-0.0744	-0.0303	0.00678	-0.0668
SSC	0.95355	-0.0383	-0.1393	-0.124	-0.0988	-0.0995	-0.113	-0.0677
JMR	-0.2195	-0.0889	-0.0073	0.95284	-0.1153	-0.063	-0.0039	-0.0696
JOM	-0.2625	-0.1138	0.10885	0.90679	-0.1135	-0.0536	-0.0073	-0.0705
SMJ	-0.2568	-0.0602	0.94392	-0.0008	-0.0532	-0.064	-0.0165	-0.0709
DS	-0.3204	-0.1775	-0.0163	-0.0719	-0.1502	0.84119	0.31322	-0.0723
RSSB	0.95534	-0.0056	-0.142	-0.1292	-0.1022	-0.1078	-0.1117	-0.074
RES	-0.2274	0.86154	0.09884	-0.086	0.30994	-0.0765	-0.0824	-0.0745
MISQ	-0.2531	-0.1585	-0.0733	-0.1022	-0.1293	0.92663	-0.0063	-0.0792
ISR	-0.267	-0.1553	-0.0876	-0.099	-0.1303	0.91546	0.08783	-0.0814
BMK	0.94406	-0.0343	-0.1576	-0.1403	-0.114	-0.1217	-0.1197	-0.093
ASA	0.94354	-0.002	-0.1679	-0.133	-0.108	-0.1263	-0.1236	-0.0971
AS	0.81971	-0.0266	-0.2327	-0.218	-0.2055	-0.2136	-0.1598	-0.2119
TEM	0.6777	-0.1865	-0.2231	-0.207	-0.1964	-0.2202	-0.1355	-0.2246
JSPI	0.58909	-0.1782	-0.2621	-0.273	-0.2565	-0.2765	-0.1822	-0.3054
ANP	-0.0727	-0.182	-0.3403	-0.3546	-0.3811	-0.3868	-0.2236	-0.4564

Table A. 2 2000 Cited-Citing Factor Analysis for 36 Journals

Journal	X	Y	Discipline
ACR	0.96	1.4	Accounting
AER	0.37	0.81	Economics
AMJ	1.63	-0.14	Management
AMR	1.77	-0.11	Management
AMS	-1.48	0.15	Statistics
ANP	-1.63	-1.41	Probability
AS	-1.62	0.24	Statistics
ASA	-1.17	-0.07	Statistics
ASQ	1.7	0.18	Management
BES	-0.41	0.42	Statistics
BIO	-1.61	-0.07	Statistics
BMK	-1.36	-0.14	Statistics
DS	1.25	-0.39	ISOM
EM	-0.32	0.52	Economics
ISR	0.98	-0.56	ISOM
JAR	0.65	1.63	Accounting
JCR	0.71	-1.64	Marketing
JFE	0.33	1.27	Finance
JFN	0.35	1.26	Finance
JMR	0.35	-0.7	Marketing
JOE	-0.56	0.57	Economics
JOM	1.65	-0.95	Marketing
JSPI	-1.16	-0.32	Statistics
MGS	0.66	-0.14	ISOM
MISQ	1.63	-0.47	ISOM
MKS	0.34	-0.46	Marketing
OPR	0.23	-1.23	ISOM
POM	1.38	-1.13	ISOM
RES	-0.22	0.73	Economics
RFS	0.47	1.3	Finance
RSSA	-1.35	0.4	Statistics
RSSB	-1.27	-0.09	Statistics
RSSC	-1.33	-0.18	Statistics
SMJ	1.43	0.06	Management
SSC	-1.57	-0.12	Statistics
TEM	-1.79	-0.61	Statistics

Table A. 3 2000 Citing-Cited Multidimensional Scaling for 36 Journals

Journa	X	Y	Discipline
ACR	1.06	1.33	Accounting
AER	0.47	0.56	Economics
AMJ	1.6	0	Management
AMR	1.66	-0.1	Management
AMS	-1.46	0.39	Statistics
ANP	-1.57	-1.19	Probability
AS	-1.36	-0.29	Statistics
ASA	-1.19	-0.03	Statistics
ASQ	1.54	-0.03	Management
BES	-0.36	0.19	Statistics
BIO	-1.79	-0.07	Statistics
BMK	-1.33	-0.11	Statistics
DS	1.4	-0.6	ISOM
EM	-0.22	0.35	Economics
ISR	1.63	-0.86	ISOM
JAR	1.06	1.46	Accounting
JCR	0.84	-1.43	Marketing
JFE	0.26	1.28	Finance
JFN	0.18	1.26	Finance
JMR	0.57	-0.8	Marketing
JOE	-0.72	0.6	Economics
JOM	0.96	-0.94	Marketing
JSPI	-1.84	-0.52	Statistics
MGS	0.76	-0.2	ISOM
MISQ	1.77	-0.91	ISOM
MKS	0.46	-0.52	Marketing
OPR	0.14	-0.87	ISOM
POM	1.22	0.47	ISOM
RES	0.14	0.34	Economics
RFS	-0.29	1.52	Finance
RSSA	-1.21	-0.15	Statistics
RSSB	-1.28	-0.02	Statistics
RSSC	-1.57	0.41	Statistics
SMJ	1.59	0.17	Management
SSC	-1.63	0.05	Statistics
TEM	-1.46	-0.74	Statistics

Table A. 4 2000 Cited-Citing Multidimensional Scaling for 36 Journals

	Factor	Factor	Factor	Factor	Factor	Factor	Factor
BIO	0.962	-0.128	0.13	0.048	-0.052	0.039	-0.025
ASA	0.96	-0.153	0.136	0.061	-0.057	0.048	0.002
RSSB	0.934	-0.183	0.156	0.099	-0.078	0.067	0.027
RSSC	0.932	-0.075	0.098	0.01	-0.075	-0.019	-0.038
BMK	0.91	-0.211	0.181	0.133	-0.056	0.082	0.021
AMS	0.884	-0.118	0.176	0.052	-0.04	-0.011	0.069
TEM	0.865	-0.149	0.162	0.065	-0.082	0.041	0.108
SSC	0.861	-0.028	0.17	0.046	-0.058	0.027	0.043
AS	0.818	-0.301	0.227	0.176	-0.127	0.062	0.024
RSSA	0.813	0.013	0.049	0.003	0.012	-0.07	-0.139
BES	0.79	-0.146	-0.232	0.028	-0.114	0.089	-0.202
EM	0.612	-0.206	-0.012	0.032	-0.247	0.008	-0.479
RES	0.34	0.114	-0.352	-0.045	-0.095	-0.073	-0.712
OPR	0.291	-0.13	0.052	0.007	-0.838	-0.048	-0.057
JSPI	0.264	-0.33	0.26	0.267	0.09	0.786	0.104
JOE	0.262	-0.301	0.145	0.236	0.111	0.85	-0.091
MGS	0.213	0.151	-0.235	-0.279	-0.82	-0.05	-0.19
DS	0.187	0.363	-0.05	-0.141	-0.759	-0.051	0.011
ANP	0.166	-0.523	0.387	0.317	-0.145	-0.303	-0.012
ISR	0.04	0.638	-0.047	-0.166	-0.486	-0.011	0.018
JMR	0.013	-0.028	0.002	-0.931	0.01	-0.092	0.012
MKS	-0.002	-0.045	-0.102	-0.811	-0.218	-0.086	-0.192
MISQ	-0.019	0.76	0.043	-0.124	-0.356	-0.062	0.045
POM	-0.089	0.1	0.101	0.048	-0.775	-0.118	0.029
RFS	-0.104	-0.075	-0.74	-0.074	-0.101	0.041	-0.379
AER	-0.122	0.029	-0.121	-0.011	0.012	0.138	-0.878
JCR	-0.174	0.132	0.059	-0.776	-0.004	-0.117	0.023
JFE	-0.203	0.006	-0.843	-0.004	-0.047	0.055	-0.334
AMJ	-0.242	0.832	-0.092	-0.097	-0.092	-0.165	-0.088
ACR	-0.248	0.036	-0.696	0.056	0.063	-0.167	0.103
AMR	-0.255	0.754	0.162	0.025	-0.008	-0.152	0.033
ASQ	-0.266	0.761	0.034	-0.014	-0.005	-0.178	-0.072
JAR	-0.273	-0.005	-0.832	-0.004	0.009	-0.055	0.002
JOM	-0.288	0.231	0	-0.665	-0.108	-0.15	0.12
SMJ	-0.306	0.454	-0.064	0.097	0.061	-0.234	0.021
JFN	-0.336	-0.166	-0.181	0.19	0.174	0.842	-0.156

Table A. 5 2000 Abstract Factor Analysis for 36 Journals

Journal	X	Y	Discipline
ACR	1.69	1.3	Accounting
AER	0.24	1.23	Economics
AMJ	1.19	-0.09	Management
AMR	1.68	-1.3	Management
AMS	-1.08	-0.37	Statistics
ANP	-2.57	-0.55	Probability
AS	-1.35	0.05	Statistics
ASA	-0.88	-0.04	Statistics
ASQ	1.64	-0.35	Management
BES	-0.47	0.31	Statistics
BIO	-0.83	-0.06	Statistics
BMK	-1.16	0.09	Statistics
DS	0.17	-0.32	ISOM
EM	-0.47	0.43	Economics
ISR	0.45	-0.49	ISOM
JAR	1.46	1.45	Accounting
JCR	1.01	-1.37	Marketing
JFE	0.79	0.86	Finance
JFN	0.3	2.23	Finance
JMR	0.77	-0.66	Marketing
JOE	-1.16	1.08	Economics
JOM	1.65	-0.78	Marketing
JSPI	-2.04	0.9	Statistics
MGS	0.15	-0.04	ISOM
MISQ	0.54	-0.93	ISOM
MKS	0.6	0.05	Marketing
OPR	-0.35	-0.72	ISOM
POM	0	-1.58	ISOM
RES	0.13	0.44	Economics
RFS	0.58	0.88	Finance
RSSA	-0.81	-0.63	Statistics
RSSB	-1.16	-0.05	Statistics
RSSC	-0.76	-0.24	Statistics
SMJ	2.33	0.06	Management
SSC	-1	-0.53	Statistics
TEM	-1.29	-0.25	Statistics

Table A. 6 2000 Abstract Multidimensional Scaling for 36 Journals

	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7	Factor8	Factor9
AER	-0.30713	0.364079	-0.10679	0.752137	-0.05455	-0.12071	0.00898	-0.03145	-0.36217
RES	-0.1887	0.179474	-0.09852	0.895645	-0.07774	-0.10299	-0.01511	-0.02549	-0.31424
AMS	0.881043	-0.07019	-0.15955	-0.017	-0.17277	-0.1195	-0.04238	-0.05186	-0.10481
BIO	0.935865	-0.11795	-0.14097	-0.03086	-0.16153	-0.11739	-0.03878	-0.03433	-0.06631
RSSA	0.892772	-0.11005	-0.16802	0.260556	-0.17209	-0.12622	-0.03877	-0.03852	-0.04823
RSSC	0.954609	-0.11893	-0.14579	-0.01056	-0.16057	-0.11803	-0.0408	-0.03548	-0.04292
MGS	-0.39808	-0.00774	0.069602	0.095458	0.901622	0.114962	-0.00166	0.044299	-0.04057
JFN	-0.29847	0.901693	-0.13464	0.143496	-0.09051	-0.17444	0.128479	-0.03713	-0.03904
JCR	-0.2693	-0.14532	-0.1731	-0.19886	-0.14098	0.634126	-0.0771	0.128398	-0.03545
JFE	-0.29463	0.903402	-0.13454	0.122468	-0.092	-0.17716	0.144673	-0.03738	-0.0234
ISR	-0.37451	-0.15409	0.206194	-0.15303	0.646651	0.226019	-0.03013	0.518106	-0.018
TEM	0.884353	-0.13653	-0.15964	-0.05431	-0.16695	-0.12435	-0.05594	-0.04696	-0.01444
SMJ	-0.34319	-0.096	0.868092	-0.14372	0.177591	-0.02709	-0.05338	0.079836	-0.0141
AMR	-0.30355	-0.10652	0.924939	-0.15863	0.022751	-0.07694	-0.04592	0.042444	-0.00657
ACR	-0.32834	0.352875	-0.15305	-0.06784	-0.12589	-0.20565	0.824343	-0.03173	0.002059
OPR	-0.18633	-0.08656	-0.06137	-0.13382	0.923912	-0.01703	-0.04956	-0.05369	0.004371
MISQ	-0.34807	-0.18879	0.470138	-0.21517	0.426144	0.13412	-0.06738	0.610166	0.005863
AMJ	-0.28804	-0.14952	0.924225	-0.16833	0.069488	-0.05763	-0.05158	0.04462	0.007316
JAR	-0.32989	0.595419	-0.18527	-0.01852	-0.13506	-0.2151	0.660013	-0.04072	0.011426
MKS	-0.27474	-0.1479	-0.08769	-0.0382	0.315696	0.785054	-0.06211	-0.07777	0.012149
POM	-0.30812	-0.042	0.095108	-0.13536	0.928068	0.102823	-0.03799	0.024154	0.012325
ASQ	-0.30104	-0.09112	0.922216	-0.16233	0.053547	-0.08199	-0.04173	0.009967	0.013246
JMR	-0.28331	-0.16075	-0.14353	-0.02939	0.140286	0.925686	-0.07198	0.000418	0.020839
DS	-0.34914	-0.14745	0.352187	-0.20124	0.787936	0.149707	-0.05437	0.174818	0.02143
RFS	-0.26649	0.8849	-0.14243	0.260266	-0.09817	-0.17539	0.115591	-0.03745	0.021662
JOM	-0.33101	-0.18295	0.132164	-0.20638	0.057133	0.810489	-0.07412	0.077196	0.022897
SSC	0.948839	-0.05799	-0.178	0.088454	-0.16755	-0.14856	-0.04522	-0.03996	0.044488
BMK	0.949447	-0.12413	-0.15142	0.024303	-0.16618	-0.12877	-0.04853	-0.02978	0.04937
RSSB	0.945362	-0.12688	-0.15904	0.045992	-0.17066	-0.13314	-0.0535	-0.03182	0.05798
ASA	0.947886	-0.12764	-0.16182	0.081312	-0.16367	-0.13003	-0.05109	-0.03366	0.058625
JSPI	0.93852	-0.13537	-0.1638	0.003319	-0.17309	-0.14381	-0.06219	-0.03496	0.06688
EM	0.011906	0.066148	-0.14696	0.961859	-0.04635	-0.07941	-0.00749	-0.02695	0.078264
BES	0.248908	0.108186	-0.17671	0.91998	-0.12077	-0.05645	-0.00085	-0.04025	0.126172
AS	0.88464	-0.1491	-0.1727	0.052882	-0.17587	-0.15469	-0.07393	-0.03325	0.152552
ANP	-0.18962	-0.28201	-0.3069	-0.13641	-0.22747	-0.34733	-0.29434	-0.11666	0.217627
JOE	0.416506	-0.02381	-0.17063	0.8396	-0.14033	-0.10028	-0.02084	-0.0271	0.234744

Table A. 7 2005 Citing-Cited Factor Analysis for 36 Journals

	Factor	Factor	Factor	Factor	Factor	Factor	Factor	Factor
ACR	-0.3108	-0.1676	-0.1235	0.06189	-0.1835	-0.1404	-0.0975	0.87656
JAR	-0.3083	-0.1594	-0.1145	0.07584	-0.186	-0.1584	-0.1069	0.87478
JFE	-0.2819	-0.1095	0.0738	0.91268	-0.1598	-0.1194	-0.0995	0.08508
JFN	-0.2697	-0.1281	0.09602	0.91571	-0.1574	-0.1184	-0.0919	0.07487
RFS	-0.2314	-0.1576	0.1496	0.91101	-0.1558	-0.1149	-0.1054	0.02499
AER	-0.3123	0.10099	0.55313	0.62645	-0.0313	-0.0796	0.07916	0.02323
OPR	-0.1845	-0.062	-0.0315	-0.0377	0.05479	0.06203	0.87674	0.00937
RES	-0.1454	0.13565	0.93056	0.20287	-0.1151	-0.0821	-0.0535	-0.023
EM	-0.0539	-0.1372	0.9217	0.30114	-0.0739	-0.1013	0.02746	-0.0235
MGS	-0.4074	0.25208	-0.0488	-0.0592	0.15528	0.24097	0.78263	-0.0255
AMS	0.81637	-0.1302	-0.0355	-0.0871	-0.1139	-0.0787	-0.1041	-0.0333
RSSA	0.8136	-0.1399	0.20434	-0.1022	-0.1252	-0.0795	-0.1117	-0.0342
BIO	0.92459	-0.117	-0.057	-0.0895	-0.1075	-0.0717	-0.0889	-0.0344
MKS	-0.2415	-0.0687	-0.035	-0.0791	0.83503	-0.074	0.2362	-0.0458
RSSC	0.94393	-0.1294	-0.0856	-0.0986	-0.1216	-0.0873	-0.0964	-0.0509
ASQ	-0.2637	0.95007	-0.0736	-0.076	-0.0401	0.00009	0.0143	-0.0521
AMJ	-0.2585	0.95529	-0.0639	-0.0746	-0.0461	0.00363	-0.005	-0.0558
BES	0.07483	-0.1544	0.95262	0.00441	-0.1028	-0.0899	-0.1121	-0.0632
AMR	-0.2756	0.94031	-0.0945	-0.0922	-0.0179	0.05594	-0.0265	-0.0655
SMJ	-0.2919	0.92812	-0.0395	-0.0726	0.02615	0.04467	0.01778	-0.0721
JOE	0.14362	-0.139	0.94042	-0.0726	-0.0942	-0.098	-0.1163	-0.0755
ISR	-0.2972	0.03236	-0.1453	-0.136	-0.036	0.90744	0.07632	-0.078
JMR	-0.281	0.00697	-0.096	-0.1285	0.9252	-0.0129	0.03002	-0.0817
BMK	0.94325	-0.1488	0.01803	-0.1185	-0.1482	-0.1115	-0.1144	-0.0818
JOM	-0.2841	0.08007	-0.1455	-0.1353	0.85905	0.02824	-0.0525	-0.083
SSC	0.94452	-0.1547	-0.0283	-0.12	-0.136	-0.1127	-0.1127	-0.0833
MISQ	-0.2778	0.02538	-0.1498	-0.138	-0.025	0.9132	-0.0105	-0.0844
JCR	-0.2545	-0.1118	-0.1435	-0.1253	0.74474	0.00032	-0.1551	-0.0854
RSSB	0.9367	-0.161	0.02781	-0.1153	-0.1397	-0.1184	-0.1153	-0.0898
ASA	0.93086	-0.1641	0.0948	-0.1309	-0.1463	-0.1207	-0.1186	-0.0918
TEM	0.81095	-0.1554	-0.1253	-0.1287	-0.1571	-0.1331	-0.1209	-0.1107
JSPI	0.8617	-0.1657	-0.1	-0.144	-0.172	-0.1429	-0.1292	-0.1259
POM	-0.2766	-0.0932	-0.1563	-0.1358	-0.1232	0.00852	0.71038	-0.1344
DS	-0.3476	0.01674	-0.1884	-0.1793	-0.0287	0.67848	0.39258	-0.1389
AS	0.85864	-0.1901	0.10175	-0.165	-0.1865	-0.1554	-0.1407	-0.1436
ANP	0.0998	-0.3104	-0.1339	-0.338	-0.3734	-0.3771	-0.272	-0.4548

Table A. 8 2005 Cited-Citing Factor Analysis for 36 Journals

Journa	X	Y	Discipline
ACR	0.98	1.4	Accounting
AER	0.2	0.71	Economics
AMJ	1.72	-0.08	Management
AMR	1.79	0.27	Management
AMS	-1.33	0.5	Statistics
ANP	-1.51	-1.66	Probability
AS	-1.63	-0.24	Statistics
ASA	-1.26	-0.09	Statistics
ASQ	1.59	0.34	Management
BES	-0.42	0.2	Statistics
BIO	-1.81	0.15	Statistics
BMK	-1.58	0.03	Statistics
DS	1.38	-0.44	ISOM
EM	-0.27	0.33	Economics
ISR	1.24	-0.5	ISOM
JAR	0.67	1.54	Accounting
JCR	0.99	-1.87	Marketing
JFE	0.43	1.26	Finance
JFN	0.46	1.23	Finance
JMR	0.37	-1.03	Marketing
JOE	-0.63	0.23	Economics
JOM	1.13	-1.18	Marketing
JSPI	-1.62	-0.12	Statistics
MGS	0.66	-0.1	ISOM
MISQ	1.62	-0.69	ISOM
MKS	0.52	-1.01	Marketing
OPR	0.53	-0.6	ISOM
POM	1.17	-0.27	ISOM
RES	-0.07	0.57	Economics
RFS	0.16	1.01	Finance
RSSA	-1.04	0.21	Statistics
RSSB	-1.47	-0.05	Statistics
RSSC	-1.64	0.12	Statistics
SMJ	1.4	0.16	Management
SSC	-1.04	0.09	Statistics
TEM	-1.69	-0.45	Statistics

Table A. 9 2005 Citing-Cited Multidimensional Scaling for 36 Journals

Journal	X	Y	Discipline
ACR	1.05	1.38	Accounting
AER	0.39	0.43	Economics
AMJ	1.47	0.3	Management
AMR	1.49	0.15	Management
AMS	-1.76	0.27	Statistics
ANP	-1.55	-1.05	Probability
AS	-1.3	-0.15	Statistics
ASA	-1.1	-0.13	Statistics
ASQ	1.41	0.27	Management
BES	-0.69	0.44	Statistics
BIO	-1.82	0.04	Statistics
BMK	-1.29	-0.01	Statistics
DS	1.5	-0.57	ISOM
EM	-0.13	0.14	Economics
ISR	1.58	-0.5	ISOM
JAR	0.96	1.47	Accounting
JCR	1.02	-1.4	Marketing
JFE	0.37	1.16	Finance
JFN	0.19	1.12	Finance
JMR	0.81	-0.84	Marketing
JOE	-0.63	0.14	Economics
JOM	1.13	-1.02	Marketing
JSPI	-1.8	-0.3	Statistics
MGS	0.79	-0.14	ISOM
MISQ	1.61	-0.71	ISOM
MKS	0.67	-0.93	Marketing
OPR	0.35	-0.41	ISOM
POM	1.9	-0.12	ISOM
RES	-0.09	0.32	Economics
RFS	-0.14	1.18	Finance
RSSA	-1.59	0.46	Statistics
RSSB	-1.17	-0.15	Statistics
RSSC	-1.78	-0.13	Statistics
SMJ	1.35	0.08	Management
SSC	-1.43	-0.27	Statistics
TEM	-1.76	-0.52	Statistics

Table A. 10 2005 Cited-Citing Multidimensional Scaling for 36 Journals

	Factor	Factor	Factor	Factor	Factor	Factor	Factor
BIO	0.95549	-0.1251	0.00211	-0.0754	-0.0346	-0.1058	0.06937
RSSC	0.94129	-0.1114	0.01667	-0.0687	0.01772	-0.1036	0.06795
ASA	0.93507	-0.1885	0.01752	-0.1233	-0.0414	-0.1685	0.09302
RSSB	0.89777	-0.2143	0.00453	-0.1594	-0.0523	-0.1948	0.08942
BMK	0.88564	-0.2392	-0.0033	-0.166	-0.0607	-0.2086	0.12018
TEM	0.8533	-0.1803	0.09499	-0.1117	-0.0971	-0.1507	0.05228
BES	0.8116	-0.2352	-0.0138	0.00132	0.25154	-0.0379	0.13625
AS	0.80609	-0.2909	0.0144	-0.2175	-0.0532	-0.298	0.11505
RSSA	0.79708	0.08976	-0.0335	-0.0276	0.21286	-0.0298	-0.0395
AMS	0.65618	-0.2267	-0.0974	-0.1439	-0.2043	-0.1574	-0.1429
SSC	0.64273	-0.168	-0.1162	-0.1293	-0.1928	-0.0994	-0.147
EM	0.44828	-0.2838	0.16392	-0.1124	0.58613	-0.2622	0.03226
JSPI	0.36349	-0.2987	-0.1171	-0.2413	-0.1363	-0.2326	0.78584
OPR	0.35675	-0.1631	0.73838	-0.0939	0.24076	-0.232	-0.0171
JOE	0.3282	-0.2819	-0.127	-0.223	-0.0347	-0.1901	0.82121
ANP	0.23633	-0.4399	0.02961	-0.3877	-0.0127	-0.5914	-0.1584
RES	0.07262	0.12325	0.02818	0.04753	0.8269	0.15208	-0.0372
DS	0.01767	0.21755	0.8576	0.18114	-0.0323	0.05958	-0.0696
ISR	-0.0383	0.48351	0.4576	0.25932	0.11708	0.05977	-0.0409
MGS	-0.0451	0.07215	0.83006	0.27763	0.38949	0.06778	-0.0231
JMR	-0.0554	-0.0943	0.21929	0.89581	0.04555	-0.0385	-0.0805
AER	-0.09	0.03603	0.19751	0.10794	0.90452	0.07472	0.00741
MKS	-0.1262	-0.057	0.3482	0.77064	0.23246	0.03802	-0.0728
RFS	-0.1496	-0.1899	0.18549	-0.0009	0.63617	0.48359	0.10771
POM	-0.1552	0.13899	0.85834	0.15042	0.05317	0.07213	-0.0699
MISQ	-0.2147	0.67969	0.34852	0.10502	-0.1244	-0.0529	-0.0956
JCR	-0.2373	0.06417	-0.0866	0.78602	0.00006	-0.1748	-0.171
AMJ	-0.2472	0.83844	0.11215	0.01857	0.00289	0.0144	-0.1269
ASQ	-0.2598	0.781	-0.0863	-0.06	-0.003	-0.0139	-0.1324
AMR	-0.2716	0.769	0.06156	-0.0004	0.02358	-0.1038	-0.135
JOM	-0.2716	0.22405	0.22909	0.76022	-0.139	0.05815	-0.1098
JFE	-0.3542	-0.0612	0.11157	-0.0237	0.59322	0.58541	0.08925
JAR	-0.3662	-0.1133	-0.0597	-0.1568	0.16355	0.79931	-0.1292
JFN	-0.3705	-0.1596	-0.0465	-0.128	0.26752	0.28496	0.79665
ACR	-0.3896	-0.0413	0.05898	-0.1172	0.17446	0.79589	-0.1233
SMJ	-0.4051	0.36162	0.09047	-0.0656	-0.0495	0.21173	-0.1624

Table A. 11 2005 Abstract Factor Analysis for 36 Journals

Journal	X	Y	Discipline
ACR	1.43	1.08	Accounting
AER	0.4	0.48	Economics
AMJ	1.4	-0.43	Management
AMR	1.58	-0.69	Management
AMS	-1.66	-0.78	Statistics
ANP	-2.36	0.15	Probability
AS	-1.4	0.07	Statistics
ASA	-0.95	-0.05	Statistics
ASQ	2.01	-0.6	Management
BES	-0.67	0.3	Statistics
BIO	-0.94	-0.18	Statistics
BMK	-1.36	-0.01	Statistics
DS	0.3	-0.49	ISOM
EM	-0.6	0.64	Economics
ISR	0.64	-0.45	ISOM
JAR	1.67	1.67	Accounting
JCR	0.86	-1.93	Marketing
JFE	0.92	0.97	Finance
JFN	0.64	1.7	Finance
JMR	0.22	-1.19	Marketing
JOE	-1.32	0.95	Economics
JOM	1.13	-1.18	Marketing
JSPI	-1.78	0.79	Statistics
MGS	0.22	0.02	ISOM
MISQ	1	-0.8	ISOM
MKS	0.54	-0.2	Marketing
OPR	-0.34	0.08	ISOM
POM	0.74	-0.06	ISOM
RES	0.21	0.61	Economics
RFS	0.41	1.06	Finance
RSSA	-0.48	-0.26	Statistics
RSSB	-1.31	-0.07	Statistics
RSSC	-0.89	-0.1	Statistics
SMJ	2.22	0.26	Management
SSC	-1.34	-0.96	Statistics
TEM	-1.15	-0.41	Statistics

Table A. 12 2005 Abstract Multidimensional Scaling for 36 Journals

	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7	Factor8	Factor9
AER	-0.29235	0.194334	-0.09521	0.796356	0.011064	-0.1071	-0.01942	-0.02897	0.45692
RES	-0.27609	0.218256	-0.10895	0.831369	-0.018	-0.10944	-0.01359	-0.03519	0.390802
MGS	-0.45441	0.149602	0.143627	0.128735	0.825977	0.138648	0.01066	0.159071	0.074586
JFN	-0.26542	0.91772	-0.14631	0.165444	-0.0547	-0.12149	0.117354	-0.06163	0.042758
BIO	0.948742	-0.1233	-0.11543	-0.04664	-0.13788	-0.13635	-0.03927	-0.05597	0.036598
ISR	-0.36835	-0.16242	0.123738	-0.14795	0.492509	0.461599	-0.07743	0.579678	0.032337
RSSA	0.857635	0.175019	-0.15642	0.178542	-0.13281	-0.18487	-0.00545	-0.08056	0.027527
SMJ	-0.34969	-0.05212	-0.05566	-0.13955	0.169297	0.849438	-0.04929	0.156303	0.026868
AMS	0.937864	-0.1295	-0.11768	-0.01084	-0.14054	-0.14513	-0.04008	-0.06289	0.026083
SSC	0.960428	-0.12728	-0.11792	-0.00607	-0.13401	-0.143	-0.04125	-0.05073	0.01813
RSSC	0.961343	-0.12407	-0.11164	-0.03035	-0.13667	-0.14113	-0.04203	-0.05896	0.014762
JFE	-0.24921	0.926935	-0.14806	0.112035	-0.07121	-0.1157	0.142824	-0.06345	0.011757
DS	-0.3716	-0.17167	0.241297	-0.20487	0.617354	0.379176	-0.07129	0.430624	0.007517
RFS	-0.25006	0.926155	-0.14408	0.142933	-0.06469	-0.12066	0.121469	-0.06377	0.007094
MKS	-0.25702	-0.13304	0.771377	0.006279	0.358184	-0.09025	-0.05469	0.068874	0.006679
JCR	-0.25557	-0.13041	0.784173	-0.18145	-0.13	-0.1337	-0.07304	-0.00967	0.001443
JAR	-0.29518	0.617049	-0.1911	-0.0099	-0.1265	-0.15495	0.670155	-0.07154	0.000095
TEM	0.882383	-0.15398	-0.13695	-0.0571	-0.12818	-0.1573	-0.05521	-0.07234	-0.01056
EM	-0.08951	0.030507	-0.08536	0.969065	0.021754	-0.13632	0.00834	-0.05393	-0.01063
JOM	-0.30078	-0.14704	0.900534	-0.17137	0.072809	0.025658	-0.0695	0.096776	-0.01158
AMJ	-0.31452	-0.09982	-0.08785	-0.16629	0.030703	0.922937	-0.03784	0.065835	-0.01447
ASQ	-0.28985	-0.12741	-0.09282	-0.16697	-0.02358	0.922771	-0.05276	0.0291	-0.0146
MISQ	-0.30962	-0.16772	0.142344	-0.18743	0.316024	0.210371	-0.04548	0.801364	-0.01481
ACR	-0.2954	0.3619	-0.17812	-0.0592	-0.11327	-0.14874	0.840318	-0.05639	-0.01645
OPR	-0.21913	-0.10511	0.011773	0.006404	0.930635	-0.04738	-0.04726	0.016054	-0.01843
JMR	-0.26434	-0.12404	0.942818	-0.11988	0.122702	-0.09291	-0.04364	0.047805	-0.01961
AMR	-0.29997	-0.14474	-0.07726	-0.18837	0.027354	0.913154	-0.05459	0.067229	-0.02
POM	-0.25858	-0.12318	0.116831	-0.11655	0.924428	0.051079	-0.05266	0.125491	-0.02019
BMK	0.949456	-0.14287	-0.13122	0.003422	-0.14552	-0.15229	-0.05167	-0.06	-0.03917
ASA	0.955158	-0.1241	-0.12495	0.042939	-0.14203	-0.15746	-0.04712	-0.06276	-0.0431
RSSB	0.945207	-0.12358	-0.13797	0.015298	-0.13914	-0.1603	-0.05114	-0.06462	-0.06271
JSPI	0.930258	-0.14451	-0.14683	0.041453	-0.15303	-0.17378	-0.06438	-0.06929	-0.08181
AS	0.871302	-0.15873	-0.16122	0.048153	-0.15229	-0.18167	-0.07529	-0.07192	-0.13574
ANP	-0.16537	-0.24868	-0.30569	-0.20243	-0.21589	-0.30866	-0.2754	-0.13139	-0.15062
BES	0.299262	0.147123	-0.12063	0.881911	-0.06131	-0.19432	0.00278	-0.07492	-0.21498
JOE	0.3126	0.000759	-0.11989	0.888237	-0.08396	-0.18145	-0.0131	-0.07428	-0.22775

Table A. 13 2010 Citing-Cited Factor Analysis for 36 Journals

Journa	Factor	Factor	Factor	Factor	Factor	Factor	Factor
MISQ	-0.3054	-0.002	-0.1828	-0.0203	-0.1364	0.01674	0.89838
ISR	-0.3127	0.02348	-0.1672	0.01697	-0.1237	0.05891	0.88129
DS	-0.3611	-0.0024	-0.2074	0.04247	-0.1743	0.41076	0.59343
MGS	-0.442	0.27725	-0.0683	0.17099	-0.0483	0.75275	0.20905
POM	-0.2753	-0.0938	-0.131	-0.0457	-0.1195	0.81198	0.20599
JOM	-0.2654	0.01109	-0.1078	0.91766	-0.1164	-0.0247	0.05946
AMR	-0.2979	0.93341	-0.1198	-0.0267	-0.0845	-0.0132	0.05663
JMR	-0.2663	-0.0415	-0.0739	0.94095	-0.1107	0.02905	0.03888
SMJ	-0.2787	0.9368	-0.0744	-0.0374	-0.0388	0.02381	0.02588
MKS	-0.2479	-0.0685	-0.0178	0.88102	-0.0928	0.16377	0.00398
ASQ	-0.2715	0.94731	-0.0942	-0.0585	-0.0563	-0.0019	-0.0013
AMJ	-0.2634	0.95188	-0.0943	-0.051	-0.0623	-0.0185	-0.0027
JCR	-0.2094	-0.0791	-0.1133	0.88429	-0.0926	-0.0968	-0.0336
AER	-0.3395	0.088	0.5979	-0.0472	0.59658	0.07264	-0.0535
OPR	-0.1771	-0.0778	-0.0379	-0.0107	-0.0592	0.89633	-0.0757
JOE	0.18138	-0.1624	0.93325	-0.0949	-0.0231	-0.1017	-0.0816
RES	-0.1313	0.08034	0.88751	-0.0444	0.34487	-0.0174	-0.096
BIO	0.90406	-0.1434	-0.084	-0.1409	-0.084	-0.1082	-0.1004
RSSA	0.84982	-0.1393	-0.1279	-0.1328	-0.0433	-0.0543	-0.104
SSC	0.93278	-0.1731	0.02596	-0.1306	-0.1292	-0.1099	-0.1071
EM	-0.0062	-0.1328	0.9528	-0.0894	0.16614	-0.022	-0.1114
TEM	0.84082	-0.1753	0.04398	-0.1818	-0.2027	-0.1579	-0.1121
BMK	0.92054	-0.1789	0.0867	-0.1736	-0.1561	-0.1427	-0.1133
AMS	0.84565	-0.1689	-0.0195	-0.0728	-0.0812	-0.1179	-0.1134
JSPI	0.83663	-0.1807	0.0821	-0.1875	-0.2182	-0.1658	-0.1138
RSSC	0.93415	-0.163	-0.0362	-0.1457	-0.1121	-0.0967	-0.1142
ANP	0.40396	-0.1862	0.19768	-0.2033	-0.3336	-0.1789	-0.1158
RSSB	0.92189	-0.1775	0.10259	-0.1608	-0.1567	-0.1338	-0.1186
ASA	0.91613	-0.185	0.13612	-0.157	-0.1557	-0.1384	-0.1196
AS	0.85974	-0.1942	0.21698	-0.1894	-0.2057	-0.1584	-0.1203
BES	0.30162	-0.2118	0.89224	-0.0666	0.03834	-0.1416	-0.1219
RFS	-0.2783	-0.152	0.20866	-0.1755	0.87648	-0.1037	-0.1319
JFN	-0.301	-0.12	0.18377	-0.1734	0.87785	-0.1201	-0.1417
JFE	-0.302	-0.105	0.16745	-0.1804	0.87775	-0.1313	-0.1441
ACR	-0.5738	-0.306	-0.2194	-0.3533	-0.0183	-0.3124	-0.4132
JAR	-0.5812	-0.3051	-0.1939	-0.3626	0.09642	-0.3169	-0.4159

Table A. 14 2010 Cited-Citing Factor Analysis for 36 Journals

Journal	X	Y	Discipline
ACR	0.85	1.43	Accounting
AER	0.29	0.57	Economics
AMJ	1.71	0.19	Management
AMR	2.11	-0.13	Management
AMS	-1.46	-0.39	Statistics
ANP	-3.07	-0.09	Probability
AS	-1.41	0.18	Statistics
ASA	-1.18	-0.09	Statistics
ASQ	2.07	0.12	Management
BES	-0.39	0.27	Statistics
BIO	-1.63	-0.31	Statistics
BMK	-1.48	-0.07	Statistics
DS	1.38	-0.51	ISOM
EM	-0.2	0.42	Economics
ISR	0.99	-0.35	ISOM
JAR	0.44	1.4	Accounting
JCR	1.15	-1.81	Marketing
JFE	0.41	1.22	Finance
JFN	0.48	1.12	Finance
JMR	0.44	-0.9	Marketing
JOE	-0.55	0.38	Economics
JOM	0.96	-1.13	Marketing
JSPI	-1.29	0.01	Statistics
MGS	0.61	0.02	ISOM
MISQ	1.45	-0.77	ISOM
MKS	0.31	-0.85	Marketing
OPR	0.41	-0.45	ISOM
POM	0.77	-0.63	ISOM
RES	0.21	0.69	Economics
RFS	0.44	1.21	Finance
RSSA	-0.73	0.29	Statistics
RSSB	-1.22	0.07	Statistics
RSSC	-1.49	-0.28	Statistics
SMJ	1.36	0.14	Management
SSC	-1.29	-0.29	Statistics
TEM	-1.46	-0.71	Statistics

Table A. 15 2010 Citing-Cited Multidimensional Scaling for 36 Journals

Journal	X	Y	Discipline
ACR	1.06	1.51	Accounting
AER	0.4	0.44	Economics
AMJ	1.63	0.43	Management
AMR	1.57	0.22	Management
AMS	-1.35	-0.5	Statistics
ANP	-1.87	0.71	Probability
AS	-1.52	0.19	Statistics
ASA	-1.07	-0.09	Statistics
ASQ	1.57	0.41	Management
BES	-0.71	0.29	Statistics
BIO	-1.65	-0.33	Statistics
BMK	-1.33	-0.05	Statistics
DS	1.61	-0.51	ISOM
EM	-0.24	0.23	Economics
ISR	1.32	-0.77	ISOM
JAR	0.99	1.53	Accounting
JCR	0.78	-1.49	Marketing
JFE	0.3	1.2	Finance
JFN	0.29	1.13	Finance
JMR	0.64	-0.61	Marketing
JOE	-0.73	0.48	Economics
JOM	0.96	-1.03	Marketing
JSPI	-1.84	0.12	Statistics
MGS	0.73	-0.16	ISOM
MISQ	1.59	-0.87	ISOM
MKS	0.57	-0.71	Marketing
OPR	0.18	-1.1	ISOM
POM	1.48	-0.71	ISOM
RES	-0.03	0.31	Economics
RFS	0.09	1.2	Finance
RSSA	-1.41	-0.71	Statistics
RSSB	-1.14	-0.15	Statistics
RSSC	-1.52	-0.4	Statistics
SMJ	1.64	0.28	Management
SSC	-1.12	-0.44	Statistics
TEM	-1.89	-0.04	Statistics

Table A. 16 2010 Cited-Citing Multidimensional Scaling for 36 Journals

	Factor	Factor	Factor	Factor	Factor	Factor	Factor
JOE	0.34032	-0.2268	-0.3067	-0.222	-0.1027	-0.0359	0.81437
JFN	-0.3703	-0.1637	-0.1795	0.2921	-0.0608	0.16398	0.81413
JSPI	0.35287	-0.2489	-0.3309	-0.2603	-0.108	-0.1393	0.76744
BES	0.83598	-0.0977	-0.2015	-0.1039	0.05422	0.21663	0.18251
BMK	0.88435	-0.1803	-0.2183	-0.2205	0.01853	-0.0431	0.11892
AS	0.81853	-0.2453	-0.281	-0.3048	0.06192	-0.013	0.09221
RSSB	0.87951	-0.1748	-0.2014	-0.2178	-0.0253	-0.0562	0.08435
JFE	-0.3483	-0.0828	-0.0472	0.64294	0.1378	0.5368	0.07499
ASA	0.95056	-0.1076	-0.1589	-0.1746	0.01018	0.00009	0.0678
RFS	-0.2739	-0.0776	-0.0415	0.60837	0.12226	0.61963	0.05867
RSSC	0.93397	-0.0554	-0.0985	-0.1338	0.00088	0.10231	0.05502
BIO	0.95315	-0.0734	-0.123	-0.1592	-0.012	0.01368	0.0542
TEM	0.89311	-0.0788	-0.1453	-0.1354	0.08011	-0.0539	0.04213
EM	0.45862	-0.1	-0.1304	-0.2411	0.35572	0.54599	0.01535
RES	0.24176	0.1284	0.063	0.21301	0.07438	0.79446	0.00405
OPR	0.33576	-0.0204	-0.2017	-0.1695	0.80847	0.17756	-0.0223
AER	-0.0664	0.06407	0.03504	0.18775	0.21558	0.80843	-0.0295
RSSA	0.80344	0.04297	0.01052	-0.003	-0.0929	0.28309	-0.0305
MKS	-0.0018	0.74091	0.03844	0.04413	0.52831	0.2372	-0.0306
MGS	-0.0756	0.35812	0.17297	0.25771	0.76039	0.36404	-0.0384
POM	-0.0564	0.27153	0.0037	0.02156	0.86753	0.16396	-0.0599
SSC	0.83763	-0.0728	-0.0995	-0.0993	-0.0528	-0.1388	-0.0785
ISR	-0.1673	0.20196	0.5314	0.26211	0.54969	-0.0266	-0.0945
AMS	0.78602	-0.0751	-0.156	-0.1239	-0.0632	-0.1848	-0.0995
JAR	-0.4103	-0.1017	-0.041	0.77508	0.00198	0.18215	-0.1075
JMR	-0.0989	0.93898	0.00087	-0.0507	0.1497	0.00355	-0.1188
DS	-0.208	0.37604	0.45033	0.14266	0.59993	-0.0467	-0.12
MISQ	-0.0704	0.23876	0.62884	0.07423	0.28902	-0.1336	-0.1242
JOM	-0.234	0.89632	0.09346	-0.0032	0.19382	-0.0195	-0.1258
SMJ	-0.3776	-0.058	0.35139	0.4162	0.16081	-0.0993	-0.1293
ACR	-0.352	-0.0786	-0.0133	0.78297	0.04402	0.22414	-0.1369
AMR	-0.239	0.00156	0.83974	-0.1987	-0.0385	-0.0129	-0.14
AMJ	-0.3608	0.03868	0.7787	0.24174	0.04969	0.11513	-0.1402
JCR	-0.2295	0.85429	0.12394	-0.1071	0.07371	0.00761	-0.1493
ASQ	-0.2596	-0.0314	0.77929	-0.0726	-0.1616	0.09322	-0.165
ANP	0.09154	-0.3854	-0.4631	-0.6111	0.06611	-0.0518	-0.2541

Table A. 17 2010 Abstract Factor Analysis for 36 Journals

Journal	X	Y	Discipline
ACR	1.38	1.03	Accounting
AER	0.37	0.73	Economics
AMJ	1.36	-0.06	Management
AMR	1.65	-1.11	Management
AMS	-1.36	-0.79	Statistics
ANP	-2.85	-0.07	Probability
AS	-1.33	0.19	Statistics
ASA	-0.84	-0.1	Statistics
ASQ	1.77	-0.6	Management
BES	-0.75	0.4	Statistics
BIO	-0.91	-0.2	Statistics
BMK	-1.29	0.04	Statistics
DS	0.94	-0.46	ISOM
EM	-0.38	0.38	Economics
ISR	0.89	-0.14	ISOM
JAR	1.76	1.31	Accounting
JCR	0.83	-1.6	Marketing
JFE	0.96	1.13	Finance
JFN	0.58	1.88	Finance
JMR	0.38	-1.23	Marketing
JOE	-1.42	1	Economics
JOM	0.84	-1.23	Marketing
JSPI	-1.82	0.76	Statistics
MGS	0.34	0.06	ISOM
MISQ	0.88	-0.87	ISOM
MKS	0.28	-0.39	Marketing
OPR	-0.36	0.08	ISOM
POM	0.35	-0.19	ISOM
RES	0.12	0.46	Economics
RFS	0.72	0.87	Finance
RSSA	-0.62	-0.39	Statistics
RSSB	-1.49	-0.09	Statistics
RSSC	-0.92	-0.03	Statistics
SMJ	2.2	0.35	Management
SSC	-1.2	-0.76	Statistics
TEM	-1.05	-0.37	Statistics

Table A. 18 2010 Abstract Multidimensional Scaling for 36 Journals

	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7	Factor8	Factor9
ACR	-0.31512	0.756792	-0.1513	-0.03636	-0.06973	-0.11336	-0.08507	0.005577	0.52529
JAR	-0.30848	0.827799	-0.14511	-0.04815	-0.07845	-0.09681	-0.08582	0.012972	0.414794
EM	-0.05653	0.042016	-0.0479	0.9661	-0.00275	-0.12199	-0.04941	0.100346	0.048859
JOE	0.4984	0.065963	-0.13626	0.729357	-0.12007	-0.17331	-0.08025	0.274745	0.024552
RSSA	0.890575	-0.1636	-0.14855	0.17461	-0.153	-0.17096	-0.07826	-0.14742	0.011304
POM	-0.28692	-0.09704	0.113869	-0.05419	0.928146	0.092241	0.162386	-0.00816	0.000639
AMJ	-0.2923	-0.09452	-0.08155	-0.16323	0.017762	0.931225	0.076407	-0.00162	-0.001
DS	-0.31956	-0.14917	0.206129	-0.156	0.768402	0.314205	0.294195	0.00317	-0.00143
BES	0.510834	0.216189	-0.15672	0.738811	-0.1352	-0.18923	-0.09076	0.149901	-0.00234
AMR	-0.28144	-0.14432	-0.07839	-0.17466	-0.00142	0.916063	0.077581	-0.00276	-0.00353
RSSC	0.922257	-0.16743	-0.14691	-0.03852	-0.14873	-0.16041	-0.07913	-0.17864	-0.00423
OPR	-0.21039	-0.06635	0.029545	-0.0007	0.919288	-0.05441	0.046723	0.004897	-0.00538
AMS	0.773019	-0.18958	-0.16703	-0.07839	-0.16192	-0.17994	-0.09091	-0.23863	-0.00691
BIO	0.925622	-0.16771	-0.14863	-0.04238	-0.14962	-0.16175	-0.08107	-0.14512	-0.00739
MKS	-0.28673	-0.10874	0.776799	0.125855	0.356616	-0.09312	0.129642	-0.01418	-0.00789
ASA	0.943598	-0.16456	-0.15163	0.028316	-0.14938	-0.16906	-0.0856	0.015321	-0.00809
JCR	-0.25423	-0.15353	0.833859	-0.16021	-0.09095	-0.12977	-0.0325	-0.00435	-0.00989
ISR	-0.33369	-0.18831	0.218002	-0.09096	0.37802	0.192174	0.783556	-0.0152	-0.0121
SMJ	-0.34816	-0.02554	-0.05348	-0.12166	0.163527	0.864645	0.132372	-0.00927	-0.01224
BMK	0.94156	-0.16496	-0.15108	-0.01365	-0.14422	-0.16484	-0.08619	0.064186	-0.01546
MISQ	-0.2972	-0.12179	0.009793	-0.15443	0.189452	0.18136	0.895278	0.002449	-0.01557
RSSB	0.939581	-0.16256	-0.15263	-0.0071	-0.14494	-0.16693	-0.08757	0.079731	-0.01655
JMR	-0.27939	-0.10953	0.934986	-0.05902	0.14778	-0.10786	0.067757	-0.0134	-0.01655
TEM	0.903346	-0.16998	-0.1542	-0.0789	-0.12602	-0.16799	-0.09298	0.020303	-0.01805
SSC	0.934712	-0.16501	-0.15183	-0.0124	-0.14621	-0.16588	-0.08726	0.113574	-0.01821
JOM	-0.30794	-0.08457	0.927072	-0.14474	0.066896	0.006874	0.042902	0.015416	-0.01846
ASQ	-0.29879	-0.05875	-0.09958	-0.12571	0.04216	0.932061	0.063836	0.001603	-0.0205
JSPI	0.922639	-0.16405	-0.1585	0.009879	-0.14909	-0.17247	-0.09299	0.165964	-0.02359
MGS	-0.46783	0.457185	0.183571	0.263812	0.667686	0.032878	0.127547	-0.0542	-0.02994
AS	0.857097	-0.14842	-0.15115	-0.01081	-0.13673	-0.16094	-0.09122	0.300389	-0.03017
RES	-0.15991	0.152475	-0.02913	0.93731	0.038246	-0.11374	-0.03816	-0.15138	-0.03156
AER	-0.27692	0.219364	-0.01886	0.836835	0.038175	-0.11154	-0.04337	-0.16973	-0.04822
JFE	-0.28064	0.923121	-0.10488	0.203556	-0.03522	-0.06244	-0.06276	-0.00785	-0.08099
RFS	-0.2616	0.925747	-0.1006	0.20215	-0.04094	-0.07194	-0.06274	0.010084	-0.10059
JFN	-0.28306	0.908279	-0.09318	0.246079	-0.03594	-0.07563	-0.06248	-0.01266	-0.11578
ANP	-0.26861	-0.27014	-0.27287	-0.19264	-0.18277	-0.27553	-0.18082	0.166556	-0.19727

Table A. 19 2015 Citing-Cited Factor Analysis for 36 Journals

	Factor	Factor	Factor	Factor	Factor	Factor	Factor
MISQ	-0.2793	-0.1421	-0.1731	-0.0108	-0.0284	0.00214	0.91698
ISR	-0.3068	-0.1335	-0.1661	-0.0149	0.04683	0.08303	0.90532
DS	-0.3056	-0.2065	-0.2068	-0.0162	-0.0203	0.6157	0.3977
MGS	-0.4152	-0.0485	0.04919	0.27151	0.23178	0.80824	0.09392
MKS	-0.2763	-0.0117	-0.0164	-0.0826	0.8283	0.33809	0.0601
AMR	-0.279	-0.0998	-0.078	0.9418	-0.0587	0.00439	0.04418
JOM	-0.2855	-0.1258	-0.1192	0.00496	0.90622	0.07673	0.03912
POM	-0.2509	-0.1231	-0.1172	-0.0512	0.05655	0.92701	0.02925
JMR	-0.2722	-0.0697	-0.0776	-0.0538	0.93691	0.11777	0.02455
ASQ	-0.2691	-0.0784	-0.0503	0.95363	-0.0514	0.0018	-0.005
AMJ	-0.2595	-0.0888	-0.0616	0.95162	-0.0602	-0.0212	-0.0137
SMJ	-0.2733	-0.0555	-0.032	0.94328	-0.0367	0.02231	-0.0157
AER	-0.2643	0.55611	0.59881	0.0517	0.13124	0.12731	-0.0212
RSSA	0.83829	-0.0329	-0.0644	-0.1233	-0.0654	-0.0965	-0.0598
JFN	-0.2362	0.29007	0.86703	-0.0308	-0.0636	-0.0452	-0.061
BIO	0.92717	-0.1101	-0.1236	-0.1148	-0.1205	-0.12	-0.0624
RFS	-0.2017	0.34	0.84846	-0.0841	-0.0733	-0.0528	-0.0636
JCR	-0.2233	-0.1282	-0.1283	-0.0963	0.87282	-0.1371	-0.0651
RES	-0.0458	0.89885	0.34806	0.08228	-0.0164	-0.0491	-0.0729
RSSC	0.94175	-0.0735	-0.1418	-0.1369	-0.1395	-0.1342	-0.0766
JFE	-0.2604	0.22036	0.88601	-0.0052	-0.0812	-0.058	-0.0795
OPR	-0.2058	-0.0613	-0.0389	-0.0847	0.09136	0.90871	-0.0803
SSC	0.92712	0.1179	-0.1742	-0.1778	-0.1529	-0.1411	-0.0846
BES	0.21742	0.91008	0.03505	-0.1371	-0.143	-0.1412	-0.0872
TEM	0.80644	0.01402	-0.1742	-0.1588	-0.1548	-0.1383	-0.096
JOE	0.23359	0.88372	-0.0342	-0.1694	-0.1592	-0.1539	-0.0977
EM	0.12276	0.94326	0.13619	-0.1452	-0.0863	-0.0669	-0.0982
ASA	0.88823	0.2721	-0.1537	-0.1811	-0.1705	-0.1546	-0.099
AMS	0.45543	-0.1815	-0.1541	-0.1617	-0.1345	-0.1092	-0.1001
BMK	0.90727	0.20193	-0.1632	-0.1621	-0.168	-0.1528	-0.1007
RSSB	0.90675	0.19792	-0.1566	-0.1761	-0.1661	-0.1553	-0.1026
JSPI	0.84583	0.25173	-0.194	-0.1874	-0.1898	-0.161	-0.1178
AS	0.75973	0.4075	-0.1934	-0.2002	-0.2037	-0.1757	-0.1257
JAR	-0.3285	-0.2494	0.71556	-0.1446	-0.1957	-0.1484	-0.1881
ACR	-0.3137	-0.2846	0.64988	-0.1646	-0.2142	-0.1643	-0.1886
ANP	-0.1266	0.15706	-0.4597	-0.3108	-0.3228	-0.2798	-0.3606

Table A. 20 2015 Cited-Citing Factor Analysis for 36 Journals

Journal	X	Y	Discipline
ACR	1.16	-1.13	Accounting
AER	0.34	-0.69	Economics
AMJ	1.69	0.17	Management
AMR	2.02	0.54	Management
AMS	-1.78	0.21	Statistics
ANP	-2.62	1.78	Probability
AS	-1.49	-0.55	Statistics
ASA	-1.21	-0.21	Statistics
ASQ	1.47	-0.05	Management
BES	-0.4	-0.46	Statistics
BIO	-1.51	-0.32	Statistics
BMK	-1.36	-0.1	Statistics
DS	0.77	0.57	ISOM
EM	-0.14	-0.52	Economics
ISR	0.71	0.76	ISOM
JAR	1.32	-1.23	Accounting
JCR	0.73	1.92	Marketing
JFE	0.78	-1.01	Finance
JFN	0.84	-1.03	Finance
JMR	0.45	0.99	Marketing
JOE	-0.47	-0.44	Economics
JOM	1.01	1.06	Marketing
JSPI	-1.31	-0.04	Statistics
MGS	0.63	-0.08	ISOM
MISQ	1.38	0.78	ISOM
MKS	0.28	0.65	Marketing
OPR	0.34	0.38	ISOM
POM	1.01	0.51	ISOM
RES	0.09	-0.42	Economics
RFS	0.71	-1.06	Finance
RSSA	-0.98	-0.39	Statistics
RSSB	-1.31	-0.16	Statistics
RSSC	-1.49	-0.3	Statistics
SMJ	1.43	0.04	Management
SSC	-1.42	-0.07	Statistics
TEM	-1.7	-0.11	Statistics

Table A. 21 2015 Citing-Cited Multidimensional Scaling for 36 Journals

Journal	X	Y	Discipline
ACR	0.81	1.58	Accounting
AER	0.39	0.42	Economics
AMJ	1.53	0.55	Management
AMR	1.54	0.34	Management
AMS	-1.31	-1.31	Statistics
ANP	-2.1	0.98	Probability
AS	-1.57	0.29	Statistics
ASA	-1.12	-0.05	Statistics
ASQ	1.44	0.5	Management
BES	-0.62	0.36	Statistics
BIO	-1.65	-0.69	Statistics
BMK	-1.1	-0.06	Statistics
DS	1.58	-0.66	ISOM
EM	-0.34	0.22	Economics
ISR	1.37	-0.87	ISOM
JAR	0.85	1.43	Accounting
JCR	0.94	-1.59	Marketing
JFE	0.31	0.89	Finance
JFN	0.21	0.81	Finance
JMR	0.79	-0.58	Marketing
JOE	-0.88	0.55	Economics
JOM	1.15	-0.49	Marketing
JSPI	-1.54	0.08	Statistics
MGS	0.84	-0.02	ISOM
MISQ	1.64	-1.01	ISOM
MKS	0.74	-0.53	Marketing
OPR	0.46	-0.87	ISOM
POM	1.54	-0.42	ISOM
RES	-0.09	0.31	Economics
RFS	0.05	0.88	Finance
RSSA	-1.13	-0.61	Statistics
RSSB	-1.21	-0.02	Statistics
RSSC	-2.09	-0.28	Statistics
SMJ	1.4	0.58	Management
SSC	-1.1	-0.32	Statistics
TEM	-1.75	-0.36	Statistics

Table A. 22 2015 Cited-Citing Multidimensional Scaling for 36 Journals

	Factor	Factor	Factor	Factor	Factor	Factor
BIO	0.95549	-0.1407	-0.1082	-0.0986	0.02354	0.02877
RSSC	0.9374	-0.0951	-0.0934	-0.0609	0.0767	0.03395
ASA	0.92996	-0.2046	-0.1316	-0.1359	0.0163	0.02104
BMK	0.91302	-0.1761	-0.1838	-0.1617	0.10141	0.12554
RSSA	0.91242	0.0486	-0.0171	0.02523	0.02952	-0.0121
RSSB	0.8923	-0.2097	-0.2151	-0.1794	0.08514	0.07769
BES	0.88719	-0.0226	-0.1473	-0.1673	0.06341	0.16531
TEM	0.87578	-0.2407	-0.0899	-0.1131	0.04278	-0.0247
SSC	0.79856	-0.234	-0.1436	-0.1466	-0.0427	-0.1701
AS	0.79602	-0.2493	-0.279	-0.2303	0.20946	0.1139
EM	0.59372	0.27474	0.02554	-0.1684	0.44593	0.19675
AMS	0.57739	-0.2293	-0.0497	-0.1621	-0.2611	-0.3856
JOE	0.46313	-0.1483	-0.2657	-0.292	-0.0054	0.76371
OPR	0.44099	0.10935	0.18633	-0.0968	0.78213	0.00423
JSPI	0.42481	-0.2631	-0.2809	-0.2878	-0.0039	0.74459
RES	0.1745	0.68643	0.38879	0.05307	0.18691	-0.0168
ANP	0.15541	-0.4126	-0.3883	-0.3235	0.48484	-0.0766
AER	0.09392	0.74809	0.2776	0.00483	0.27851	0.00679
MKS	-0.0381	0.30017	0.87406	0.04897	0.20068	-0.0445
ISR	-0.0403	0.2637	0.61955	0.52687	0.20328	-0.1268
POM	-0.0797	0.30909	0.51288	0.11345	0.68287	-0.0697
DS	-0.0961	0.16276	0.58151	0.38767	0.41962	-0.1362
MISQ	-0.0974	0.0656	0.37312	0.74577	0.16875	-0.1292
MGS	-0.1196	0.62804	0.59507	0.22498	0.37109	-0.0167
JMR	-0.1969	0.07919	0.9297	0.03344	0.01643	-0.0685
AMR	-0.2042	-0.2281	-0.0129	0.81709	-0.0993	-0.0927
JCR	-0.2243	-0.1194	0.80847	0.22027	-0.0518	-0.1129
ASQ	-0.2373	0.27043	0.13431	0.78911	-0.121	-0.0773
AMJ	-0.2658	0.16691	0.19784	0.86468	-0.0377	-0.0971
JOM	-0.3196	0.13725	0.86632	0.11916	-0.0423	-0.079
RFS	-0.3287	0.88205	0.04147	0.06128	0.02618	0.10007
JFN	-0.347	0.40911	-0.0885	-0.1289	-0.1091	0.78454
JFE	-0.3601	0.862	0.0318	0.0546	0.04276	0.08823
ACR	-0.42	0.76591	0.04328	0.10795	-0.0745	-0.0968
JAR	-0.4434	0.75934	0.05662	0.08135	-0.0767	-0.0965
SMJ	-0.4485	0.23905	-0.0085	0.23458	-0.1017	-0.2034

Table A. 23 2015 Abstract Factor Analysis for 36 Journals

Journal	X	Y	Discipline
ACR	1.53	-0.84	Accounting
AER	0.3	-0.7	Economics
AMJ	1.1	0.37	Management
AMR	0.82	2.02	Management
AMS	-1.38	1.51	Statistics
ANP	-2.66	-0.53	Probability
AS	-1.45	-0.16	Statistics
ASA	-1.11	0.27	Statistics
ASQ	1.21	0.08	Management
BES	-0.88	-0.32	Statistics
BIO	-0.95	0.22	Statistics
BMK	-1.15	-0.06	Statistics
DS	0.6	0.63	ISOM
EM	-0.42	-0.52	Economics
ISR	0.49	0.35	ISOM
JAR	1.73	-1.01	Accounting
JCR	1.14	1.36	Marketing
JFE	1.12	-1.06	Finance
JFN	0.73	-1.79	Finance
JMR	1.02	0.8	Marketing
JOE	-1.31	-1.01	Economics
JOM	1.33	0.58	Marketing
JSPI	-1.73	-0.89	Statistics
MGS	0.39	-0.11	ISOM
MISQ	0.48	0.84	ISOM
MKS	0.48	0.05	Marketing
OPR	-0.36	-0.2	ISOM
POM	0.5	-0.23	ISOM
RES	0.23	-0.39	Economics
RFS	0.96	-0.91	Finance
RSSA	-0.6	0.2	Statistics
RSSB	-1.36	0.08	Statistics
RSSC	-0.9	0.11	Statistics
SMJ	2.59	-0.02	Management
SSC	-1.23	0.78	Statistics
TEM	-1.26	0.52	Statistics

Table A. 24 2015 Abstract Multidimensional Scaling for 36 Journals

				Citing						
		Accountin	Economics	Finance	ISOM	Managem	Marketing	Probability	Statistics	
	Accountin	338	0	32	41	4	2	0	2	419
	Economics	41	1698	423	125	162	106	0	277	2832
Cited	Finance	62	226	2602	68	157	6	0	79	3200
	ISOM	0	10	10	1584	166	126	0	29	1925
	Managem	3	5	5	283	3318	169	0	0	3783
	Marketing	10	0	0	148	95	1557	0	14	1824
	Probability	0	10	0	7	0	0	173	80	270
	Statistics	0	505	48	58	10	79	50	7151	7901

Table A. 25 2000 Cited-Citing Frequency for Eight Disciplines

				Cited						
		Accountin	Economics	Finance	ISOM	Managem	Marketing	Probability	Statistics	
	Accountin	338	41	62	0	3	10	0	0	454
	Economics	0	1698	226	10	5	0	10	505	2454
Citing	Finance	32	423	2602	10	5	0	0	48	3120
	ISOM	41	125	68	1584	283	148	7	58	2314
	Managem	4	162	157	166	3318	95	0	10	3912
	Marketing	2	106	6	126	169	1557	0	79	2045
	Probability	0	0	0	0	0	0	173	50	223
	Statistics	2	277	79	29	0	14	80	7151	7632

Table A. 26 2000 Citing-Cited Frequency for Eight Disciplines

				Citing					
		Accountin	Economics	Finance	ISOM	Managem	Marketing	Probability	Statistics
	Accountin	0.806683	0	0.076372	0.097852	0.009547	0.004773	0	0.004773
	Economics	0.014477	0.599576	0.149364	0.044138	0.057203	0.037429	0	0.097811
Cited	Finance	0.019375	0.070625	0.813125	0.02125	0.049063	0.001875	0	0.024688
	ISOM	0	0.005195	0.005195	0.822857	0.086234	0.065455	0	0.015065
	Managem	0.000793	0.001322	0.001322	0.074808	0.877082	0.044674	0	0
	Marketing	0.005482	0	0	0.08114	0.052083	0.853618	0	0.007675
	Probability	0	0.037037	0	0.025926	0	0	0.640741	0.296296
	Statistics	0	0.063916	0.006075	0.007341	0.001266	0.009999	0.006328	0.905075

Table A. 27 2000 Cited-Citing Relative Frequency for Eight Disciplines

				Cited					
		Accountin	Economics	Finance	ISOM	Manageme	Marketing	Probability	Statistics
	Accountin	0.744493	0.090308	0.136564	0	0.006608	0.022026	0	0
	Economics	0	0.691932	0.092095	0.004075	0.002037	0	0.004075	0.205786
Citing	Finance	0.010256	0.135577	0.833974	0.003205	0.001603	0	0	0.015385
	ISOM	0.017718	0.054019	0.029386	0.684529	0.122299	0.063959	0.003025	0.025065
	Manageme	0.001022	0.041411	0.040133	0.042434	0.84816	0.024284	0	0.002556
	Marketing	0.000978	0.051834	0.002934	0.061614	0.082641	0.761369	0	0.038631
	Probability	0	0	0	0	0	0	0.775785	0.224215
	Statistics	0.000262	0.036295	0.010351	0.0038	0	0.001834	0.010482	0.936976

Table A. 28 2000 Citing-Cited Relative Frequency for Eight Disciplines

	Citing	Cited	Difference
Accountin	74.45%	80.67%	6.22%
Economics	69.19%	59.96%	-9.24%
Finance	83.40%	81.31%	-2.08%
ISOM	68.45%	82.29%	13.83%
Manageme	84.82%	87.71%	2.89%
Marketing	76.14%	85.36%	9.22%
Probability	77.58%	64.07%	-13.50%
Statistics	0.936976	0.905075	-0.0319

Table A. 29 2000 Difference of Cited Relative Frequency and Citing Relative Frequency for Eight Disciplines

				Citing					
		Accountin	Economics	Finance	ISOM	Manageme	Marketing	Probability	Statistics
	Accountin	637	3	83	56	3	6	0	0
	Economics	67	2023	621	296	219	175	6	633
Cited	Finance	292	277	3117	144	128	12	0	101
	ISOM	4	23	19	1928	227	186	0	31
	Manageme	21	6	7	496	3487	221	0	0
	Marketing	4	2	2	392	89	2805	0	24
	Probability	0	8	0	2	0	0	170	88
	Statistics	0	629	53	29	13	48	12	8080

Table A. 30 2005 Cited-Citing Frequency for Eight Disciplines

		Cited							
		Accountin	Economics	Finance	ISOM	Manageme	Marketing	Probability	Statistics
	Accountin	637	67	292	4	21	4	0	0
	Economics	3	2023	277	23	6	2	8	629
Citing	Finance	83	621	3117	19	7	2	0	53
	ISOM	56	296	144	1928	496	392	2	29
	Manageme	3	219	128	227	3487	89	0	13
	Marketing	6	175	12	186	221	2805	0	48
	Probability	0	6	0	0	0	0	170	12
	Statistics	0	633	101	31	0	24	88	8080

Table A. 31 2005 Citing-Cited Frequency for Eight Disciplines

		Citing							
		Accountin	Economics	Finance	ISOM	Manageme	Marketing	Probability	Statistics
	Accountin	0.808376	0.003807	0.10533	0.071066	0.003807	0.007614	0	0
	Economics	0.016584	0.500743	0.153713	0.073267	0.054208	0.043317	0.001485	0.156683
Cited	Finance	0.071727	0.068042	0.76566	0.035372	0.031442	0.002948	0	0.02481
	ISOM	0.001654	0.009512	0.007858	0.797353	0.093879	0.076923	0	0.012821
	Manageme	0.004955	0.001416	0.001652	0.117036	0.822794	0.052147	0	0
	Marketing	0.001206	0.000603	0.000603	0.118143	0.026823	0.845389	0	0.007233
	Probability	0	0.029851	0	0.007463	0	0	0.634328	0.328358
	Statistics	0	0.070961	0.005979	0.003272	0.001467	0.005415	0.001354	0.911552

Table A. 32 2005 Cited-Citing Relative Frequency for Eight Disciplines

		Cited							
		Accountin	Economics	Finance	ISOM	Manageme	Marketing	Probability	Statistics
	Accountin	0.621463	0.065366	0.284878	0.003902	0.020488	0.003902	0	0
	Economics	0.00101	0.680916	0.093235	0.007742	0.00202	0.000673	0.002693	0.211713
Citing	Finance	0.021271	0.159149	0.798821	0.004869	0.001794	0.000513	0	0.013583
	ISOM	0.016751	0.088543	0.043075	0.576727	0.14837	0.11726	0.000598	0.008675
	Manageme	0.00072	0.052568	0.030725	0.054489	0.837014	0.021363	0	0.00312
	Marketing	0.001738	0.050681	0.003475	0.053866	0.064002	0.812337	0	0.013901
	Probability	0	0.031915	0	0	0	0	0.904255	0.06383
	Statistics	0	0.070671	0.011276	0.003461	0	0.002679	0.009825	0.902088

Table A. 33 2005 Citing-Cited Relative Frequency for Eight Disciplines

	Citing	Cited	Difference
Accountin	62.15%	80.84%	18.69%
Economics	68.09%	50.07%	-18.02%
Finance	79.88%	76.57%	-3.32%
ISOM	57.67%	79.74%	22.06%
Managem	83.70%	82.28%	-1.42%
Marketing	81.23%	84.54%	3.31%
Probability	90.43%	63.43%	-26.99%
Statistics	90.21%	91.16%	0.95%

Table A. 34 2005 Difference of Cited Relative Frequency and Citing Relative Frequency for Eight Disciplines

				Citing					
		Accountin	Economics	Finance	ISOM	Managem	Marketing	Probability	Statistics
	Accountin	1212	0	223	70	33	24	0	0
	Economics	124	2821	920	557	232	257	0	792
Cited	Finance	506	287	5291	333	246	70	0	198
	ISOM	18	32	38	3438	313	313	0	51
	Managem	45	8	23	869	4490	190	0	0
	Marketing	6	15	0	704	110	3955	0	25
	Probability	0	18	0	2	0	0	159	99
	Statistics	13	743	81	106	16	137	14	9215

Table A. 35 2010 Cited-Citing Frequency for Eight Disciplines

				Cited					
		Accountin	Economics	Finance	ISOM	Managem	Marketing	Probability	Statistics
	Accountin	1212	124	506	18	45	6	0	13
	Economics	0	2821	287	32	8	15	18	743
Citing	Finance	223	920	5291	38	23	0	0	81
	ISOM	70	557	333	3438	869	704	2	106
	Managem	33	232	246	313	4490	110	0	16
	Marketing	24	257	70	313	190	3955	0	137
	Probability	0	0	0	0	0	0	159	14
	Statistics	0	792	198	51	0	25	99	9215

Table A. 36 2010 Citing-Cited Frequency for Eight Disciplines

				Citing					
		Accountin	Economics	Finance	ISOM	Manageme	Marketing	Probability	Statistics
	Accountin	0.775928	0	0.142766	0.044814	0.021127	0.015365	0	0
	Economics	0.021743	0.494652	0.161319	0.097668	0.04068	0.045064	0	0.138874
Cited	Finance	0.073005	0.041408	0.763382	0.048045	0.035493	0.0101	0	0.028567
	ISOM	0.004283	0.007614	0.009041	0.817987	0.074471	0.074471	0	0.012134
	Manageme	0.008	0.001422	0.004089	0.154489	0.798222	0.033778	0	0
	Marketing	0.001246	0.003115	0	0.14621	0.022845	0.821391	0	0.005192
	Probability	0	0.064748	0	0.007194	0	0	0.571942	0.356115
	Statistics	0.001259	0.071961	0.007845	0.010266	0.00155	0.013269	0.001356	0.892494

Table A. 37 2010 Cited-Citing Relative Frequency for Eight Disciplines

				Cited					
		Accountin	Economics	Finance	ISOM	Manageme	Marketing	Probability	Statistics
	Accountin	0.629938	0.064449	0.262994	0.009356	0.023389	0.003119	0	0.006757
	Economics	0	0.718909	0.07314	0.008155	0.002039	0.003823	0.004587	0.189348
Citing	Finance	0.033911	0.139903	0.804592	0.005779	0.003498	0	0	0.012318
	ISOM	0.011515	0.091627	0.054779	0.565554	0.142951	0.115809	0.000329	0.017437
	Manageme	0.006066	0.042647	0.045221	0.057537	0.825368	0.020221	0	0.002941
	Marketing	0.004852	0.051961	0.014153	0.063283	0.038415	0.799636	0	0.027699
	Probability	0	0	0	0	0	0	0.919075	0.080925
	Statistics	0	0.076301	0.019075	0.004913	0	0.002408	0.009538	0.887765

Table A. 38 2010 Citing-Cited Relative Frequency for Eight Disciplines

	Citing	Cited	Difference
Accountin	62.99%	77.59%	14.60%
Economics	71.89%	49.47%	-22.43%
Finance	80.46%	76.34%	-4.12%
ISOM	56.56%	81.80%	25.24%
Manageme	82.54%	79.82%	-2.71%
Marketing	79.96%	82.14%	2.18%
Probability	91.91%	57.19%	-34.71%
Statistics	88.78%	89.25%	0.47%

Table A. 39 2010 Difference of Cited Relative Frequency and Citing Relative Frequency for Eight Disciplines

				Citing					
		Accountin	Economics	Finance	ISOM	Manageme	Marketing	Probability	Statistics
	Accountin	1292	15	241	123	66	4	0	0
	Economics	123	4360	983	835	283	293	0	751
Cited	Finance	822	698	4993	789	411	94	0	151
	ISOM	41	65	82	4740	497	267	0	22
	Manageme	42	6	50	905	5839	158	0	0
	Marketing	15	65	10	1065	117	3457	0	3
	Probability	0	31	0	0	0	0	235	74
	Statistics	8	1463	78	193	43	74	2	8192

Table A. 40 2015 Cited-Citing Frequency for Eight Disciplines

				Cited					
		Accountin	Economics	Finance	ISOM	Manageme	Marketing	Probability	Statistics
	Accountin	1292	123	822	41	42	15	0	8
	Economics	15	4360	698	65	6	65	31	1463
Citing	Finance	241	983	4993	82	50	10	0	78
	ISOM	123	835	789	4740	905	1065	0	193
	Manageme	66	283	411	497	5839	117	0	43
	Marketing	4	293	94	267	158	3457	0	74
	Probability	0	0	0	0	0	0	235	2
	Statistics	0	751	151	22	0	3	74	8192

Table A. 41 2015 Citing-Cited Frequency for Eight Disciplines

				Citing					
		Accountin	Economics	Finance	ISOM	Manageme	Marketing	Probability	Statistics
	Accounting	0.742102	0.008616	0.138426	0.070649	0.037909	0.002298	0	0
	Economics	0.016125	0.571578	0.128867	0.109465	0.0371	0.038411	0	0.098453
Cited	Finance	0.103292	0.08771	0.627419	0.099146	0.051646	0.011812	0	0.018975
	ISOM	0.007175	0.011376	0.014351	0.829541	0.086979	0.046727	0	0.00385
	Management	0.006	0.000857	0.007143	0.129286	0.834143	0.022571	0	0
	Marketing	0.00317	0.013736	0.002113	0.225063	0.024725	0.730558	0	0.000634
	Probability	0	0.091176	0	0	0	0	0.691176	0.217647
	Statistics	0.000796	0.145529	0.007759	0.019198	0.004277	0.007361	0.000199	0.814881

Table A. 42 2015 Cited-Citing Relative Frequency for Eight Disciplines

				Cited					
		Accounting	Economics	Finance	ISOM	Manageme	Marketing	Probability	Statistics
	Accounting	0.55143	0.052497	0.350832	0.017499	0.017926	0.006402	0	0.003414
	Economics	0.002238	0.650455	0.104132	0.009697	0.000895	0.009697	0.004625	0.21826
Citing	Finance	0.03744	0.152711	0.775672	0.012739	0.007768	0.001554	0	0.012117
	ISOM	0.01422	0.096532	0.091214	0.547977	0.104624	0.123121	0	0.022312
	Management	0.009096	0.039002	0.056643	0.068495	0.804713	0.016125	0	0.005926
	Marketing	0.00092	0.067403	0.021624	0.061422	0.036347	0.795261	0	0.017023
	Probability	0	0	0	0	0	0	0.991561	0.008439
	Statistics	0	0.081693	0.016426	0.002393	0	0.000326	0.00805	0.891113

Table A. 43 2015 Citing-Cited Relative Frequency for Eight Disciplines

	Citing	Cited	Difference
Accounting	55.14%	74.21%	19.07%
Economics	65.05%	57.16%	-7.89%
Finance	77.57%	62.74%	-14.83%
ISOM	54.80%	82.95%	28.16%
Manageme	80.47%	83.41%	2.94%
Marketing	79.53%	73.06%	-6.47%
Probability	99.16%	69.12%	-30.04%
Statistics	89.11%	81.49%	-7.62%

Table A. 44 2015 Difference of Cited Relative Frequency and Citing Relative Frequency for Eight Disciplines

Appendix B

	1	2	3	4	5	6	7	8	9
	Degree	2local	BetaCent	2Step	ARD	Closeness	Eigenvect	Between	2StepBet
AMJ	1.35	-5.056	349.53	23	22	69	0.329	2.834	1.877
AMR	1.61	-4.993	354.474	23	21.5	70	0.334	2.618	1.662
ACR	-0.77	-6.637	134.618	28	19.333	71	0.125	0	0
ASQ	1.07	-4.171	302.116	25	20.833	70	0.284	5.448	2.893
AER	2.03	1.057	144.387	35	25	55	0.139	41.519	21.869
ISR	0.73	-6.325	296.446	21	20.667	73	0.278	0.182	0.182
JAR	-0.22	-6.148	149.223	35	22	61	0.139	4.065	2.317
JCR	0.83	-4.128	244.322	21	18.167	78	0.23	0.091	0.091
JFN	1.13	-0.771	127.843	35	22.5	60	0.122	9.191	3.551
JFE	1.65	0.024	115.038	28	20.833	68	0.111	0.658	0.658
JOM	0.93	-6.35	330.885	21	21.667	71	0.31	1.951	1.951
JMR	0.98	-3.336	228.802	21	21.667	71	0.216	1.951	1.951
MGS	0.51	-7.282	331.29	35	25.5	54	0.31	49.316	12.311
MKS	2.2	-2.159	239.145	35	25	55	0.227	76.992	18.924
OPR	1.96	-0.78	159.826	30	23.667	61	0.153	34.545	19.159
POM	0.96	-4.599	256.603	21	20.667	73	0.241	0.182	0.182
RFS	1.77	-0.003	119.13	35	22.5	60	0.115	9.191	3.551
SMJ	1.69	-5.52	375.508	23	22.5	68	0.353	21.746	19.416
AMS	5.81	39.37	-1016.73	25	23.333	65	-0.935	4.646	2.986
ANP	2.63	20.879	-572.795	24	22.667	67	-0.528	0.986	0.653
AS	4.95	33.153	-889.427	24	22.667	67	-0.818	0.986	0.653
BIO	6.18	40.432	-1040.83	23	22	69	-0.957	0.083	0.083
DS	0.82	-8.661	378.531	21	21.167	72	0.354	0.668	0.668
EM	1.89	8.676	-138.809	35	25	55	-0.125	38.747	18.15
JOE	4.37	16.972	-286.315	35	29	47	-0.258	137.171	63.378
BES	3.61	14.26	-226.56	35	27.5	50	-0.204	64.918	30.719
ASA	5.43	39.482	-1056.43	24	22.667	67	-0.973	0.986	0.653
RSSA	5.16	37.646	-982.83	23	22	69	-0.905	0.083	0.083
RSSB	6.27	41.588	-1086.95	24	22.667	67	-1	0.986	0.653
RSSC	4.09	31.219	-802.589	23	22	69	-0.739	0.083	0.083
RES	2.09	5.82	3.328	35	24	57	0.008	26.791	12.303
SSC	5.12	37.184	-972.203	23	22	69	-0.895	0.083	0.083
TEM	4.07	31.299	-855.123	23	21.5	70	-0.788	0	0
MISQ	0.3	-7.625	316.652	21	21.167	72	0.296	0.668	0.668
JSPI	4.94	31.365	-792.014	25	23.333	65	-0.728	4.646	2.986
BMK	5.08	36.678	-978.936	24	22.667	67	-0.901	0.986	0.653

Table B.1 2000 Multiple Measures of Correlation Data

	Degree	2local	BetaCent	2Step	ARD	Closeness	Eigenvect	Between	2StepBe
AMJ	0.049	-4.88	3.759	0.743	0.629	0.522	0.107	0.009	0.004
AMR	0.039	-5.792	3.805	0.743	0.643	0.53	0.108	0.013	0.006
ACR	-0.001	-6.264	1.466	0.771	0.576	0.5	0.041	0.006	0.003
ASQ	0.034	-5.082	3.417	0.743	0.643	0.53	0.097	0.011	0.005
AER	0.065	0.102	1.612	1	0.714	0.636	0.047	0.048	0.024
ISR	0.033	-5.301	3.66	0.6	0.619	0.493	0.104	0.001	0.001
JAR	-0.002	-6.379	1.402	0.571	0.514	0.443	0.039	0	0
JCR	0.017	-5.641	2.629	0.6	0.576	0.473	0.074	0	0
JFN	0.027	-3.035	1.486	0.8	0.595	0.515	0.042	0.006	0.002
JFE	0.047	-1.722	1.413	1	0.657	0.593	0.041	0.018	0.007
JOM	0.028	-6.987	3.551	0.6	0.619	0.493	0.1	0.001	0.001
JMR	0.031	-5.058	2.824	0.6	0.605	0.486	0.08	0.001	0.001
MGS	0.045	-5.696	4.123	1	0.786	0.7	0.117	0.157	0.056
MKS	0.059	-3.448	3.108	1	0.686	0.614	0.088	0.058	0.012
OPR	0.085	2.35	2.25	0.829	0.686	0.574	0.065	0.043	0.025
POM	0.073	0.255	2.936	0.686	0.648	0.522	0.084	0.019	0.015
RFS	0.069	1.04	0.99	1	0.671	0.603	0.029	0.035	0.015
SMJ	0.058	-5.821	4.309	0.6	0.619	0.493	0.122	0.001	0.001
AMS	0.139	38.768	-9.178	0.6	0.619	0.493	-0.254	0	0
ANP	0.08	21.701	-5.324	0.771	0.676	0.556	-0.147	0.011	0.004
AS	0.167	41.573	-10.001	0.771	0.676	0.556	-0.277	0.011	0.004
BIO	0.177	44.527	-10.392	0.6	0.619	0.493	-0.288	0	0
DS	0.058	-4.127	4.133	0.6	0.619	0.493	0.117	0.001	0.001
EM	0.043	6.406	-0.91	1	0.7	0.625	-0.024	0.052	0.024
JOE	0.14	25.73	-4.67	1	0.786	0.7	-0.128	0.107	0.042
BES	0.114	18.7	-3.01	1	0.8	0.714	-0.082	0.165	0.061
ASA	0.146	41.405	-10.261	0.629	0.638	0.507	-0.284	0.002	0.001
RSSA	0.182	42.686	-9.489	0.771	0.676	0.556	-0.262	0.011	0.004
RSSB	0.137	38.726	-9.608	0.629	0.638	0.507	-0.266	0.002	0.001
RSSC	0.136	37.922	-8.757	0.6	0.619	0.493	-0.242	0	0
RES	0.073	6.446	-0.02	1	0.743	0.66	0.001	0.114	0.055
SSC	0.186	44.812	-10.237	0.686	0.648	0.522	-0.283	0.008	0.005
TEM	0.17	43.572	-10.334	0.6	0.619	0.493	-0.286	0	0
MISQ	0.031	-6.854	4.263	0.6	0.619	0.493	0.12	0.001	0.001
JSPI	0.156	40.146	-9.185	0.6	0.619	0.493	-0.254	0	0
BMK	0.146	39.915	-9.808	0.629	0.638	0.507	-0.272	0.002	0.001

Table B.2 2005 Multiple Measures of Correlation Data

	Degree	2local	BetaCent	2Step	ARD	Closeness	Eigenvect	Between	2StepBe
AMJ	0.041	-6.126	3.713	0.657	0.6	0.493	0.105	0.004	0.003
AMR	0.034	-6.633	3.7	0.657	0.6	0.493	0.105	0.004	0.003
ACR	0.005	-5.059	1.464	1	0.643	0.583	0.041	0.007	0.003
ASQ	0.018	-5.458	2.879	0.657	0.543	0.467	0.081	0.001	0.001
AER	0.05	-0.515	1.629	1	0.714	0.636	0.047	0.061	0.031
ISR	0.042	-5.34	3.926	0.6	0.619	0.493	0.111	0.005	0.005
JAR	0.002	-5.414	1.375	0.8	0.581	0.507	0.039	0	0
JCR	0.027	-3.905	2.499	0.571	0.529	0.449	0.071	0	0
JFN	0.031	-2.176	1.365	0.8	0.595	0.515	0.039	0	0
JFE	0.053	-1.144	1.387	1	0.657	0.593	0.04	0.006	0.003
JOM	0.034	-6.018	3.485	0.6	0.605	0.486	0.099	0.003	0.002
JMR	0.028	-4.985	3.049	0.6	0.562	0.467	0.086	0.001	0
MGS	0.042	-6.397	4.252	1	0.786	0.7	0.12	0.141	0.061
MKS	0.067	-2.455	3.098	1	0.7	0.625	0.088	0.07	0.017
OPR	0.095	3.443	2.263	1	0.729	0.648	0.066	0.094	0.029
POM	0.061	-0.306	2.925	0.6	0.59	0.479	0.084	0.001	0.001
RFS	0.057	0.446	1.079	1	0.671	0.603	0.031	0.015	0.007
SMJ	0.061	-5.552	4.069	0.743	0.657	0.538	0.115	0.025	0.018
AMS	0.147	39.499	-10.109	0.686	0.633	0.515	-0.28	0	0
ANP	0.096	24.302	-6.015	0.714	0.667	0.538	-0.166	0.005	0.004
AS	0.171	39.708	-9.904	0.714	0.667	0.538	-0.274	0.005	0.004
BIO	0.166	41.34	-10.451	0.686	0.633	0.515	-0.289	0	0
DS	0.031	-6.554	4.35	0.6	0.605	0.486	0.123	0.003	0.002
EM	0.049	7.475	-1.142	0.971	0.71	0.625	-0.031	0.037	0.021
JOE	0.128	21.049	-3.693	1	0.829	0.745	-0.101	0.159	0.068
BES	0.13	20.515	-3.535	1	0.843	0.761	-0.096	0.176	0.083
ASA	0.158	40.823	-10.508	0.686	0.648	0.522	-0.291	0.001	0.001
RSSA	0.146	35.272	-8.622	0.714	0.681	0.547	-0.239	0.015	0.013
RSSB	0.139	37.186	-9.579	0.686	0.648	0.522	-0.265	0.001	0.001
RSSC	0.133	38.017	-9.854	0.686	0.633	0.515	-0.273	0	0
RES	0.063	4.035	0.531	1	0.729	0.648	0.016	0.05	0.023
SSC	0.147	38.122	-9.635	0.686	0.633	0.515	-0.267	0	0
TEM	0.157	37.329	-9.253	0.686	0.648	0.522	-0.256	0.001	0.001
MISQ	0.015	-7.014	3.807	0.6	0.619	0.493	0.107	0.005	0.005
JSPI	0.151	36.954	-9.004	0.686	0.633	0.515	-0.249	0	0
BMK	0.165	40.856	-10.373	0.686	0.648	0.522	-0.287	0.001	0.001

Table B.3 2010 Multiple Measures of Correlation Data

	Degree	2local	BetaCent	2Step	ARD	Closeness	Eigenvect	Between	2StepBe
AMJ	0.037	-6.395	3.41	0.771	0.648	0.538	0.096	0.008	0.005
AMR	0.033	-6.252	3.238	0.657	0.586	0.486	0.092	0.001	0.001
ACR	0.022	-3.25	2.248	1	0.657	0.593	0.064	0.004	0.002
ASQ	0.034	-4.761	2.864	0.771	0.648	0.538	0.081	0.01	0.007
AER	0.079	5.483	1.725	1	0.757	0.673	0.05	0.057	0.028
ISR	0.017	-7.468	3.108	0.657	0.629	0.507	0.088	0.003	0.003
JAR	0.013	-3.9	2.108	1	0.643	0.583	0.06	0.004	0.001
JCR	0.009	-7.024	2.77	0.657	0.586	0.486	0.078	0.001	0.001
JFN	0.057	2.398	1.8	1	0.671	0.603	0.052	0.005	0.003
JFE	0.074	2.653	2.129	1	0.7	0.625	0.062	0.014	0.007
JOM	0.026	-9.072	3.81	0.657	0.643	0.515	0.107	0.004	0.004
JMR	0.022	-7.447	3.348	0.771	0.619	0.522	0.094	0.005	0.002
MGS	0.067	-3.48	4.195	1	0.814	0.729	0.119	0.094	0.045
MKS	0.069	-3.566	3.424	1	0.7	0.625	0.097	0.041	0.011
OPR	0.094	2.851	2.505	1	0.786	0.7	0.072	0.063	0.03
POM	0.062	-0.978	2.793	0.771	0.648	0.538	0.08	0.007	0.004
RFS	0.083	4.364	1.717	1	0.671	0.603	0.05	0.006	0.003
SMJ	0.052	-6.307	3.754	0.657	0.657	0.522	0.106	0.016	0.016
AMS	0.14	37.11	-9.058	0.686	0.619	0.507	-0.251	0	0
ANP	0.056	17.868	-4.401	0.8	0.624	0.53	-0.122	0.004	0.002
AS	0.151	36.287	-8.638	0.8	0.681	0.565	-0.239	0.007	0.004
BIO	0.163	41.941	-10.212	0.686	0.633	0.515	-0.283	0.001	0.001
DS	0.035	-5.862	3.474	0.657	0.629	0.507	0.098	0.003	0.003
EM	0.094	16.31	-2.249	1	0.743	0.66	-0.061	0.064	0.032
JOE	0.147	28.428	-4.545	1	0.829	0.745	-0.124	0.158	0.08
BES	0.172	30.655	-4.901	1	0.814	0.729	-0.134	0.106	0.061
ASA	0.164	43.083	-10.508	0.8	0.681	0.565	-0.291	0.007	0.004
RSSA	0.142	36.48	-8.467	0.8	0.652	0.547	-0.234	0.006	0.002
RSSB	0.161	41.978	-10.327	0.686	0.648	0.522	-0.286	0.001	0.001
RSSC	0.128	35.828	-8.873	0.686	0.619	0.507	-0.246	0	0
RES	0.104	12.897	-0.248	1	0.786	0.7	-0.005	0.113	0.064
SSC	0.166	43.432	-10.553	0.686	0.648	0.522	-0.292	0.001	0.001
TEM	0.16	42.216	-10.366	0.686	0.648	0.522	-0.287	0.001	0.001
MISQ	0.01	-7.961	3.11	0.657	0.629	0.507	0.088	0.003	0.003
JSPI	0.165	41.168	-9.657	0.686	0.648	0.522	-0.267	0.001	0.001
BMK	0.167	42.81	-10.514	0.686	0.648	0.522	-0.291	0.001	0.001

Table B.4 2015 Multiple Measures of Correlation Data

	OutDeg	Indeg	Out2local	In2local	OutBetaCe	InBetaCen	Out2Step	In2Step	OutARD	InARD	OutClose	InClose	OutEigen	InEigen	Between	2StepBet
AMJ	23.114	16	470631	470631	7.571	0.542	1	0.771	0.714	0.633	0.636	0.53	0.206	0.007	0.011	0.009
AMR	18.886	13.086	382236	382236	5.651	0.407	0.914	0.743	0.686	0.629	0.593	0.522	0.154	0.005	0.007	0.007
ACR	3.029	2.943	32198	32198	0.515	0.233	0.829	0.829	0.614	0.614	0.53	0.53	0.014	0.006	0.013	0.011
ASQ	5.143	20.857	126364	126364	1.625	0.536	0.886	0.743	0.638	0.629	0.556	0.522	0.044	0.007	0.004	0.004
AER	5.971	15.171	81391	81391	1.563	5.995	1	1	0.657	0.829	0.593	0.745	0.042	0.166	0.027	0.018
ISR	6.8	1.086	88582	88582	0.612	0.008	1	0.6	0.743	0.476	0.66	0.432	0.016	0	0.001	0.001
JAR	4.086	3.171	45619	45619	1.002	0.492	0.714	0.771	0.552	0.576	0.479	0.5	0.028	0.013	0.002	0.002
JCR	4.086	6.914	63379	63379	0.258	0.082	1	0.743	0.629	0.629	0.574	0.522	0.006	0.001	0.007	0.005
JFN	29.257	23.657	436349	436349	27.918	25.634	1	1	0.714	0.771	0.636	0.686	0.788	0.723	0.033	0.023
JFE	13.257	25.714	366913	366913	11.44	19.072	1	1	0.657	0.757	0.593	0.673	0.323	0.538	0.014	0.008
JOM	10.8	7.057	167768	167768	1.179	0.113	0.886	0.743	0.624	0.629	0.547	0.522	0.031	0.001	0.005	0.004
JMR	14.143	10.486	191639	191639	1.163	0.177	1	1	0.814	0.686	0.729	0.614	0.029	0.003	0.032	0.022
MGS	14.943	18.343	193171	193171	2.575	0.637	1	1	0.886	0.8	0.814	0.714	0.069	0.013	0.165	0.109
MKS	8.543	6.8	128874	128874	0.613	0.14	1	1	0.757	0.657	0.673	0.593	0.015	0.003	0.027	0.018
OPR	6.6	6.314	109995	109995	0.666	0.227	1	1	0.714	0.671	0.636	0.603	0.017	0.004	0.041	0.024
POM	3.114	0.114	48456	48456	0.319	0.003	0.886	0.6	0.581	0.448	0.522	0.422	0.009	0	0	0
RFS	14.114	9.543	335128	335128	8.544	6.798	1	1	0.671	0.657	0.603	0.593	0.241	0.192	0.016	0.009
SMJ	24.429	17.943	430030	430030	11.39	1.017	1	0.743	0.729	0.629	0.648	0.522	0.312	0.014	0.015	0.013
AMS	4.086	3.314	110668	110668	0.413	0.466	0.657	0.971	0.6	0.681	0.493	0.603	0.009	0.012	0.003	0.003
ANP	1.429	2.771	24809	24809	0.115	0.338	0.657	0.943	0.5	0.619	0.449	0.556	0.002	0.008	0.001	0
AS	8.857	33.514	241057	241057	1.231	6.101	0.657	1	0.6	0.757	0.493	0.673	0.025	0.151	0.009	0.008
BIO	26.543	15.257	628892	628892	3.624	3.357	0.686	0.971	0.619	0.667	0.507	0.593	0.074	0.082	0.007	0.006
DS	7.171	2.686	101209	101209	0.841	0.022	0.943	0.714	0.776	0.567	0.673	0.486	0.023	0	0.012	0.01
EM	5.629	28.857	97348	97348	1.174	6.165	1	1	0.7	0.914	0.625	0.854	0.031	0.169	0.062	0.039
JOE	25.171	6.829	395971	395971	4.909	1.47	0.829	1	0.729	0.757	0.603	0.673	0.129	0.039	0.034	0.026
BES	7	4.171	137873	137873	1.574	0.514	1	1	0.7	0.757	0.625	0.673	0.043	0.014	0.019	0.013
ASA	35.114	41.143	550587	550587	4.509	8.217	0.943	1	0.805	0.843	0.7	0.761	0.095	0.204	0.108	0.079
RSSA	1.571	2.343	42255	42255	0.156	0.303	0.657	0.943	0.543	0.633	0.467	0.565	0.003	0.007	0.001	0.001
RSSB	12.943	17.486	326194	326194	1.234	2.56	1	1	0.7	0.771	0.625	0.686	0.026	0.063	0.028	0.013
RSSC	6.457	0.543	141918	141918	0.477	0.089	0.829	0.771	0.629	0.519	0.538	0.473	0.01	0.002	0.004	0.002
RES	8.2	4.914	132454	132454	1.141	1.115	0.829	1	0.629	0.743	0.538	0.66	0.03	0.031	0.007	0.006
SSC	9.686	5.457	249376	249376	0.891	0.92	0.657	0.8	0.6	0.624	0.493	0.53	0.018	0.023	0.002	0.002
TEM	1.971	6.457	49723	49723	0.196	0.766	0.657	0.943	0.571	0.676	0.479	0.593	0.004	0.019	0.003	0.003
MISQ	5.2	4.171	88140	88140	0.848	0.021	0.886	0.657	0.681	0.5	0.583	0.449	0.023	0	0.002	0.002
JSPI	32.086	2.4	637182	637182	2.591	0.439	1	0.771	0.714	0.605	0.636	0.515	0.053	0.011	0.024	0.008
BMK	12.429	34.343	294401	294401	1.203	4.907	0.771	1	0.676	0.8	0.556	0.714	0.025	0.121	0.033	0.026

Table B.5 2000 Multiple Measures of Raw Data

	OutDeg	Indeg	Out2local	In2local	OutBetaCe	InBetaCen	Out2Step	In2Step	OutARD	InARD	OutClose	InClose	OutEigen	InEigen	Between	2StepBet
AMJ	22.486	19.743	488034	488034	4.508	0.478	1	0.771	0.714	0.633	0.636	0.53	0.119	0.006	0.01	0.008
AMR	14.629	16.314	336962	336962	2.825	0.287	0.857	0.771	0.633	0.633	0.547	0.53	0.075	0.003	0.003	0.002
ACR	12.286	4.8	215268	215268	3.837	0.912	0.857	0.8	0.662	0.595	0.565	0.515	0.107	0.025	0.009	0.007
ASQ	9.343	22.914	252066	252066	2.119	0.427	0.971	0.8	0.667	0.652	0.593	0.547	0.057	0.006	0.004	0.003
AER	12.171	26.429	250188	250188	5.071	8.69	1	1	0.729	0.886	0.648	0.814	0.14	0.239	0.044	0.033
ISR	6.571	2.971	133491	133491	0.676	0.025	0.886	0.686	0.724	0.533	0.614	0.467	0.018	0	0.002	0.002
JAR	8.057	8.771	195386	195386	3.426	1.079	0.686	0.829	0.548	0.6	0.473	0.522	0.096	0.03	0.001	0.001
JCR	4.314	10.886	86934	86934	0.758	0.217	1	0.743	0.629	0.6	0.574	0.507	0.019	0.003	0.002	0.002
JFN	25.571	39.971	654631	654631	22.503	26.914	1	1	0.686	0.814	0.614	0.729	0.632	0.752	0.024	0.017
JFE	27.086	28.229	704036	704036	20.51	19.167	1	1	0.686	0.8	0.614	0.714	0.576	0.536	0.018	0.013
JOM	21	9.057	373834	373834	2.757	0.191	1	0.914	0.771	0.686	0.686	0.593	0.07	0.002	0.023	0.017
JMR	12.314	18.4	205551	205551	0.974	0.237	1	0.943	0.714	0.69	0.636	0.603	0.024	0.003	0.021	0.015
MGS	25.171	26.486	412579	412579	5.265	1.024	1	1	0.886	0.829	0.814	0.745	0.142	0.023	0.126	0.081
MKS	15	10.429	289405	289405	1.628	0.297	1	0.971	0.729	0.681	0.648	0.603	0.041	0.006	0.021	0.015
OPR	6.057	6.457	173852	173852	1.216	0.238	1	1	0.686	0.686	0.614	0.614	0.032	0.005	0.029	0.018
POM	7.543	0.429	183413	183413	1.22	0.009	0.886	0.657	0.681	0.486	0.583	0.443	0.033	0	0.001	0.001
RFS	21.8	11.086	577237	577237	11.2	6.544	1	1	0.714	0.714	0.636	0.636	0.314	0.183	0.026	0.016
SMJ	30.143	19.686	650647	650647	9.321	0.592	1	0.829	0.786	0.671	0.7	0.565	0.25	0.008	0.024	0.019
AMS	3.571	2.914	95560	95560	0.256	0.083	0.886	0.8	0.667	0.624	0.574	0.53	0.006	0.002	0.008	0.005
ANP	0.514	2.8	10668	10668	0.036	0.187	0.6	0.857	0.476	0.576	0.432	0.515	0	0.004	0	0
AS	19.714	35.543	491109	491109	1.301	2.901	0.686	1	0.648	0.771	0.522	0.686	0.024	0.065	0.019	0.016
BIO	20.886	16.286	539243	539243	1.194	0.92	0.686	0.8	0.633	0.624	0.515	0.53	0.021	0.019	0.001	0.001
DS	8.943	1.771	210476	210476	1.225	0.015	0.886	0.771	0.752	0.562	0.636	0.493	0.032	0	0.007	0.005
EM	7.371	39.714	173137	173137	1.253	7.405	1	1	0.714	0.971	0.636	0.946	0.033	0.201	0.06	0.041
JOE	26.629	11.143	489530	489530	2.54	1.352	1	1	0.771	0.814	0.686	0.729	0.063	0.035	0.038	0.026
BES	12.886	6.086	283766	283766	1.525	0.655	1	1	0.714	0.743	0.636	0.66	0.04	0.017	0.033	0.02
ASA	31.714	49.171	646156	646156	1.948	3.018	1	1	0.786	0.871	0.7	0.795	0.038	0.067	0.066	0.045
RSSA	5.914	2.457	135964	135964	0.271	0.121	0.714	1	0.638	0.657	0.522	0.593	0.006	0.003	0.004	0.003
RSSB	11.429	25.229	290071	290071	0.506	1.437	0.829	1	0.7	0.814	0.583	0.729	0.009	0.033	0.028	0.022
RSSC	11.686	2.2	285909	285909	0.423	0.082	0.714	0.8	0.652	0.61	0.53	0.522	0.008	0.002	0.002	0.002
RES	8.486	7.914	148457	148457	1.326	1.06	0.943	1	0.662	0.771	0.583	0.686	0.036	0.028	0.013	0.009
SSC	15.457	5.629	374849	374849	1.149	0.258	1	1	0.8	0.686	0.714	0.614	0.027	0.006	0.023	0.013
TEM	7	5.543	182563	182563	0.306	0.246	0.829	0.8	0.629	0.624	0.538	0.53	0.005	0.005	0.008	0.005
MISQ	13.171	2.914	278746	278746	1.792	0.039	0.857	0.686	0.69	0.519	0.583	0.461	0.047	0.001	0	0
JSPI	35.686	3.886	841243	841243	1.566	0.285	0.771	1	0.676	0.643	0.556	0.583	0.029	0.006	0.004	0.003
BMK	15.857	34.2	411703	411703	0.767	1.683	0.686	1	0.633	0.814	0.515	0.729	0.014	0.037	0.026	0.021

Table B.6 2005 Multiple Measures of Raw Data

	OutDeg	Indeg	Out2local	In2local	OutBetaCe	InBetaCen	Out2Step	In2Step	OutARD	InARD	OutClose	InClose	OutEigen	InEigen	Between	2StepBet
AMJ	35.971	28.257	965330	965330	5.287	0.736	1	0.914	0.771	0.729	0.686	0.625	0.142	0.015	0.011	0.01
AMR	15.171	23.971	463891	463891	1.617	0.415	0.914	0.886	0.643	0.681	0.565	0.583	0.043	0.008	0.002	0.002
ACR	23	8.314	613927	613927	5.128	1.554	1	0.857	0.771	0.605	0.686	0.53	0.142	0.042	0.007	0.006
ASQ	5.686	33.057	213520	213520	0.664	0.678	0.914	0.886	0.629	0.724	0.556	0.614	0.018	0.014	0.005	0.004
AER	11.914	39.429	272514	272514	1.584	8.036	1	1	0.743	0.9	0.66	0.833	0.043	0.221	0.026	0.022
ISR	23.743	6.229	795476	795476	2.299	0.046	1	0.914	0.814	0.614	0.729	0.547	0.062	0.001	0.005	0.005
JAR	12.629	16.971	468877	468877	3.255	2.138	0.943	0.857	0.662	0.605	0.583	0.53	0.091	0.059	0.001	0.001
JCR	8.229	20.114	286685	286685	0.862	0.329	1	0.971	0.686	0.681	0.614	0.603	0.021	0.005	0.003	0.002
JFN	25.4	77.6	1215764	1215764	12.046	27.069	1	1	0.714	0.871	0.636	0.795	0.337	0.754	0.018	0.015
JFE	44.257	46.143	1687703	1687703	19.024	18.211	1	1	0.729	0.857	0.648	0.778	0.532	0.507	0.022	0.017
JOM	23.257	16.8	667495	667495	1.695	0.197	1	0.914	0.786	0.671	0.7	0.583	0.044	0.003	0.008	0.007
JMR	33.943	25.4	822184	822184	2.228	0.328	1	1	0.914	0.729	0.854	0.648	0.058	0.006	0.024	0.02
MGS	40.514	46.057	1157077	1157077	6.55	1.242	1	1	0.914	0.9	0.854	0.833	0.179	0.03	0.097	0.084
MKS	20.571	19.943	660664	660664	1.601	0.319	1	1	0.857	0.729	0.778	0.648	0.042	0.006	0.025	0.022
OPR	16.543	6.886	647310	647310	2.422	0.169	1	1	0.814	0.7	0.729	0.625	0.065	0.004	0.027	0.023
POM	13.771	3.171	490544	490544	1.429	0.044	1	0.829	0.8	0.529	0.714	0.486	0.038	0.001	0.002	0.002
RFS	67.286	23.343	2394307	2394307	23.294	10.255	1	1	0.729	0.8	0.648	0.714	0.651	0.286	0.016	0.013
SMJ	45.2	22.029	1358480	1358480	9.404	0.852	1	0.886	0.8	0.71	0.714	0.603	0.255	0.018	0.015	0.014
AMS	6.771	3.886	187213	187213	0.113	0.07	0.743	1	0.614	0.729	0.515	0.648	0.002	0.002	0.002	0.002
ANP	0.4	3.4	10610	10610	0.014	0.077	0.657	0.943	0.486	0.605	0.443	0.547	0	0.002	0	0
AS	20.486	42.343	608458	608458	1.005	1.255	1	1	0.771	0.8	0.686	0.714	0.025	0.03	0.026	0.019
BIO	24.286	17.714	668721	668721	0.546	0.319	0.829	1	0.657	0.729	0.556	0.648	0.012	0.007	0.007	0.006
DS	17.114	2.286	570800	570800	1.503	0.021	1	0.886	0.743	0.624	0.66	0.547	0.04	0	0.004	0.004
EM	6.714	59.086	199106	199106	0.633	6.436	1	1	0.729	0.971	0.648	0.946	0.017	0.175	0.03	0.026
JOE	44.514	16.057	886363	886363	2.746	1.794	1	1	0.786	0.814	0.7	0.729	0.072	0.048	0.02	0.018
BES	17.143	7	534414	534414	1.319	0.52	1	1	0.786	0.757	0.7	0.673	0.036	0.014	0.016	0.015
ASA	32.829	58.543	776654	776654	1.089	1.407	1	1	0.814	0.914	0.729	0.854	0.026	0.033	0.056	0.046
RSSA	5.143	2.857	154365	154365	0.375	0.034	1	1	0.743	0.686	0.66	0.614	0.01	0.001	0.007	0.005
RSSB	9.629	31.8	286780	286780	0.328	0.647	1	1	0.729	0.814	0.648	0.729	0.008	0.015	0.017	0.015
RSSC	8.571	4.229	221035	221035	0.134	0.06	0.886	0.943	0.667	0.676	0.574	0.593	0.003	0.001	0.004	0.004
RES	11.029	10.429	248274	248274	0.905	1.181	0.886	1	0.61	0.857	0.538	0.778	0.025	0.032	0.005	0.004
SSC	18.6	7.657	495935	495935	0.32	0.124	1	1	0.757	0.757	0.673	0.673	0.007	0.003	0.021	0.017
TEM	6.343	7.2	178529	178529	0.126	0.08	1	0.943	0.686	0.648	0.614	0.574	0.003	0.002	0.002	0.001
MISQ	15.057	8.514	467443	467443	1.311	0.065	1	0.943	0.771	0.648	0.686	0.574	0.035	0.001	0.011	0.01
JSPI	60.171	5.771	1533367	1533367	1.662	0.162	1	1	0.829	0.686	0.745	0.614	0.039	0.004	0.018	0.015
BMK	18.4	37.8	520900	520900	0.39	0.79	0.8	1	0.667	0.871	0.556	0.795	0.009	0.019	0.022	0.021

Table B.7 2010 Multiple Measures of Raw Data

	OutDeg	Indeg	Out2local	In2local	OutBetaCe	InBetaCen	Out2Step	In2Step	OutARD	InARD	OutClose	InClose	OutEigen	InEigen	Between	2StepBet
AMJ	37.743	38.429	1506690	1506690	13.075	4.412	1	0.743	0.843	0.686	0.761	0.556	0.366	0.116	0.012	0.012
AMR	16.543	28.914	665913	665913	4.077	2.32	0.943	0.743	0.662	0.671	0.583	0.547	0.114	0.061	0.002	0.002
ACR	29.6	11.171	1165166	1165166	3.426	1.908	1	0.971	0.786	0.681	0.7	0.603	0.092	0.053	0.01	0.007
ASQ	9.286	34.229	449780	449780	2.258	2.635	1	0.743	0.671	0.657	0.603	0.538	0.063	0.07	0.001	0.001
AER	19.514	49.8	592144	592144	1.515	12.601	1	0.971	0.743	0.881	0.66	0.795	0.04	0.35	0.024	0.019
ISR	21.857	10.914	893232	893232	2.784	0.161	1	0.743	0.843	0.586	0.761	0.5	0.077	0.004	0.003	0.003
JAR	15.829	17.057	726467	726467	1.746	2.053	0.943	0.943	0.676	0.69	0.593	0.603	0.047	0.057	0.005	0.003
JCR	8.743	19.4	258838	258838	0.555	0.818	1	0.914	0.643	0.729	0.583	0.625	0.015	0.021	0.004	0.003
JFN	28.714	85.2	1512176	1512176	4.066	22.397	1	1	0.7	0.857	0.625	0.778	0.109	0.625	0.013	0.011
JFE	56.4	56.771	2230158	2230158	7.598	17.454	1	1	0.757	0.814	0.673	0.729	0.204	0.487	0.017	0.011
JOM	22.286	18.257	678957	678957	2.051	0.604	1	0.886	0.8	0.695	0.714	0.593	0.056	0.016	0.009	0.008
JMR	22.457	28.114	636428	636428	1.241	0.958	1	0.971	0.814	0.781	0.729	0.686	0.033	0.025	0.028	0.02
MGS	66.886	62.629	2383516	2383516	7.897	3.526	1	1	0.943	0.843	0.897	0.761	0.214	0.094	0.072	0.054
MKS	22.257	20.971	759094	759094	1.395	0.832	1	0.971	0.886	0.695	0.814	0.614	0.038	0.022	0.018	0.014
OPR	14.743	12.743	839015	839015	1.87	0.416	1	0.971	0.8	0.681	0.714	0.603	0.051	0.011	0.029	0.021
POM	38.057	5.343	1982535	1982535	5.061	0.146	1	0.829	0.829	0.571	0.745	0.507	0.138	0.004	0.002	0.002
RFS	49.686	36.286	2216670	2216670	5.813	11.071	1	1	0.757	0.771	0.673	0.686	0.156	0.309	0.015	0.01
SMJ	68.657	23.343	2648761	2648761	28.694	4.248	1	0.857	0.871	0.705	0.795	0.593	0.803	0.112	0.016	0.015
AMS	4.857	1.943	152989	152989	0.048	0.048	1	0.971	0.671	0.681	0.603	0.603	0.001	0.001	0.01	0.007
ANP	0.057	3	1180	1180	0.004	0.178	0.514	1	0.433	0.629	0.407	0.574	0	0.005	0	0
AS	16.857	50.314	532820	532820	0.368	3.152	1	1	0.757	0.814	0.673	0.729	0.009	0.085	0.049	0.029
BIO	23.2	13.629	652025	652025	0.193	0.399	0.8	1	0.667	0.743	0.556	0.66	0.004	0.01	0.007	0.006
DS	21.257	2.543	1043730	1043730	3.054	0.045	1	0.943	0.857	0.633	0.778	0.565	0.084	0.001	0.018	0.015
EM	10.571	70.686	456093	456093	0.687	9.883	1	1	0.743	0.957	0.66	0.921	0.018	0.274	0.039	0.029
JOE	81.029	18.829	2120916	2120916	4.512	3.568	1	1	0.843	0.929	0.761	0.875	0.117	0.098	0.052	0.042
BES	19.971	9.371	851750	851750	0.899	0.878	1	1	0.743	0.786	0.66	0.7	0.023	0.024	0.012	0.01
ASA	37.086	54.829	882796	882796	0.506	2.654	1	1	0.786	0.929	0.7	0.875	0.012	0.072	0.035	0.03
RSSA	7.914	2.057	259758	259758	0.112	0.082	0.8	1	0.667	0.7	0.556	0.625	0.003	0.002	0.005	0.004
RSSB	14.971	30.8	439024	439024	0.141	1.135	0.857	1	0.719	0.843	0.603	0.761	0.003	0.031	0.017	0.015
RSSC	11.114	3.343	323108	323108	0.073	0.07	0.743	0.943	0.629	0.648	0.522	0.574	0.002	0.002	0.001	0.001
RES	15.057	13.286	526364	526364	0.743	1.966	1	1	0.743	0.857	0.66	0.778	0.02	0.054	0.023	0.017
SSC	10.114	8.457	280658	280658	0.084	0.251	0.743	1	0.643	0.743	0.53	0.66	0.002	0.007	0.004	0.004
TEM	9.829	4.943	258344	258344	0.073	0.162	0.8	0.943	0.624	0.676	0.53	0.593	0.002	0.004	0.003	0.002
MISQ	23.343	8.086	934783	934783	3.942	0.15	1	0.743	0.829	0.6	0.745	0.507	0.109	0.004	0.004	0.004
JSPI	22.086	7.657	608540	608540	0.225	0.295	0.8	1	0.695	0.7	0.574	0.625	0.005	0.008	0.004	0.004
BMK	19.629	34.857	578196	578196	0.198	1.29	0.857	1	0.705	0.914	0.593	0.854	0.004	0.035	0.023	0.022

Table B.8 2015 Multiple Measures of Raw Data

	Degree	nDegree
AMJ	1.35	0.039
AMR	1.61	0.047
ACR	-0.77	-0.022
ASQ	1.07	0.031
AER	2.03	0.059
ISR	0.73	0.021
JAR	-0.22	-0.006
JCR	0.83	0.024
JFN	1.13	0.033
JFE	1.65	0.048
JOM	0.93	0.027
JMR	0.98	0.029
MGS	0.51	0.015
MKS	2.2	0.064
OPR	1.96	0.057
POM	0.96	0.028
RFS	1.77	0.052
SMJ	1.69	0.049
AMS	5.81	0.169
ANP	2.63	0.077
AS	4.95	0.144
BIO	6.18	0.18
DS	0.82	0.024
EM	1.89	0.055
JOE	4.37	0.127
BES	3.61	0.105
ASA	5.43	0.158
RSSA	5.16	0.15
RSSB	6.27	0.183
RSSC	4.09	0.119
RES	2.09	0.061
SSC	5.12	0.149
TEM	4.07	0.119
MISQ	0.3	0.009
JSPI	4.94	0.144
BMK	5.08	0.148

Table B.9 2000 Degree Centralization of Correlation

	Degree	nDegree
AMJ	1.7	0.05
AMR	1.37	0.04
ACR	-0.04	-0.001
ASQ	1.19	0.035
AER	2.26	0.067
ISR	1.16	0.034
JAR	-0.07	-0.002
JCR	0.61	0.018
JFN	0.95	0.028
JFE	1.63	0.048
JOM	0.99	0.029
JMR	1.07	0.032
MGS	1.56	0.046
MKS	2.08	0.061
OPR	2.96	0.087
POM	2.56	0.075
RFS	2.4	0.071
SMJ	2.04	0.06
AMS	4.87	0.143
ANP	2.8	0.082
AS	5.84	0.172
BIO	6.21	0.183
DS	2.03	0.06
EM	1.5	0.044
JOE	4.91	0.145
BES	3.99	0.118
ASA	5.1	0.15
RSSA	6.36	0.187
RSSB	4.79	0.141
RSSC	4.76	0.14
RES	2.54	0.075
SSC	6.51	0.192
TEM	5.96	0.176
MISQ	1.07	0.032
JSPI	5.45	0.161
BMK	5.11	0.151

Table B10 2005 Degree Centralization of Correlation

	Degree	nDegree
AMJ	1.42	0.041
AMR	1.18	0.034
ACR	0.19	0.006
ASQ	0.62	0.018
AER	1.76	0.051
ISR	1.46	0.043
JAR	0.07	0.002
JCR	0.93	0.027
JFN	1.07	0.031
JFE	1.84	0.054
JOM	1.19	0.035
JMR	0.97	0.028
MGS	1.47	0.043
MKS	2.36	0.069
OPR	3.34	0.097
POM	2.13	0.062
RFS	1.99	0.058
SMJ	2.12	0.062
AMS	5.14	0.15
ANP	3.36	0.098
AS	5.98	0.174
BIO	5.8	0.169
DS	1.08	0.031
EM	1.72	0.05
JOE	4.47	0.13
BES	4.55	0.133
ASA	5.54	0.162
RSSA	5.1	0.149
RSSB	4.88	0.142
RSSC	4.66	0.136
RES	2.19	0.064
SSC	5.13	0.15
TEM	5.48	0.16
MISQ	0.53	0.015
JSPI	5.28	0.154
BMK	5.76	0.168

Table B11 2010 Degree Centralization of Correlation

	Degree	nDegree
AMJ	1.31	0.038
AMR	1.15	0.033
ACR	0.76	0.022
ASQ	1.19	0.034
AER	2.76	0.08
ISR	0.59	0.017
JAR	0.46	0.013
JCR	0.32	0.009
JFN	2.01	0.058
JFE	2.6	0.075
JOM	0.9	0.026
JMR	0.76	0.022
MGS	2.33	0.067
MKS	2.4	0.069
OPR	3.3	0.095
POM	2.16	0.062
RFS	2.89	0.083
SMJ	1.83	0.053
AMS	4.89	0.141
ANP	1.97	0.057
AS	5.28	0.152
BIO	5.72	0.165
DS	1.22	0.035
EM	3.29	0.095
JOE	5.13	0.148
BES	6.01	0.173
ASA	5.73	0.165
RSSA	4.97	0.143
RSSB	5.64	0.163
RSSC	4.49	0.13
RES	3.63	0.105
SSC	5.82	0.168
TEM	5.59	0.161
MISQ	0.34	0.01
JSPI	5.78	0.167
BMK	5.84	0.169

Table B12 2015 Degree Centralization of Correlation

	Outdeg	Indeg	nOutdeg	nIndeg
AMJ	809	560	0.045	0.031
AMR	661	458	0.037	0.025
ACR	106	103	0.006	0.006
ASQ	180	730	0.01	0.04
AER	209	531	0.012	0.029
ISR	238	38	0.013	0.002
JAR	143	111	0.008	0.006
JCR	143	242	0.008	0.013
JFN	1024	828	0.057	0.046
JFE	464	900	0.026	0.05
JOM	378	247	0.021	0.014
JMR	495	367	0.027	0.02
MGS	523	642	0.029	0.036
MKS	299	238	0.017	0.013
OPR	231	221	0.013	0.012
POM	109	4	0.006	0
RFS	494	334	0.027	0.018
SMJ	855	628	0.047	0.035
AMS	143	116	0.008	0.006
ANP	50	97	0.003	0.005
AS	310	1173	0.017	0.065
BIO	929	534	0.051	0.03
DS	251	94	0.014	0.005
EM	197	1010	0.011	0.056
JOE	881	239	0.049	0.013
BES	245	146	0.014	0.008
ASA	1229	1440	0.068	0.08
RSSA	55	82	0.003	0.005
RSSB	453	612	0.025	0.034
RSSC	226	19	0.013	0.001
RES	287	172	0.016	0.01
SSC	339	191	0.019	0.011
TEM	69	226	0.004	0.013
MISQ	182	146	0.01	0.008
JSPI	1123	84	0.062	0.005
BMK	435	1202	0.024	0.067

Table B13 2000 Degree Centralization of Raw Data

	Outdeg	Indeg	nOutdeg	nIndeg
AMJ	787	691	0.04	0.036
AMR	512	571	0.026	0.029
ACR	430	168	0.022	0.009
ASQ	327	802	0.017	0.041
AER	426	925	0.022	0.048
ISR	230	104	0.012	0.005
JAR	282	307	0.014	0.016
JCR	151	381	0.008	0.02
JFN	895	1399	0.046	0.072
JFE	948	988	0.049	0.051
JOM	735	317	0.038	0.016
JMR	431	644	0.022	0.033
MGS	881	927	0.045	0.048
MKS	525	365	0.027	0.019
OPR	212	226	0.011	0.012
POM	264	15	0.014	0.001
RFS	763	388	0.039	0.02
SMJ	1055	689	0.054	0.035
AMS	125	102	0.006	0.005
ANP	18	98	0.001	0.005
AS	690	1244	0.035	0.064
BIO	731	570	0.038	0.029
DS	313	62	0.016	0.003
EM	258	1390	0.013	0.071
JOE	932	390	0.048	0.02
BES	451	213	0.023	0.011
ASA	1110	1721	0.057	0.088
RSSA	207	86	0.011	0.004
RSSB	400	883	0.021	0.045
RSSC	409	77	0.021	0.004
RES	297	277	0.015	0.014
SSC	541	197	0.028	0.01
TEM	245	194	0.013	0.01
MISQ	461	102	0.024	0.005
JSPI	1249	136	0.064	0.007
BMK	555	1197	0.029	0.062

Table B14 2005 Degree Centralization of Raw Data

	Outdeg	Indeg	nOutdeg	nIndeg
AMJ	1259	989	0.033	0.026
AMR	531	839	0.014	0.022
ACR	805	291	0.021	0.008
ASQ	199	1157	0.005	0.03
AER	417	1380	0.011	0.036
ISR	831	218	0.022	0.006
JAR	442	594	0.012	0.016
JCR	288	704	0.008	0.018
JFN	889	2716	0.023	0.071
JFE	1549	1615	0.04	0.042
JOM	814	588	0.021	0.015
JMR	1188	889	0.031	0.023
MGS	1418	1612	0.037	0.042
MKS	720	698	0.019	0.018
OPR	579	241	0.015	0.006
POM	482	111	0.013	0.003
RFS	2355	817	0.062	0.021
SMJ	1582	771	0.041	0.02
AMS	237	136	0.006	0.004
ANP	14	119	0	0.003
AS	717	1482	0.019	0.039
BIO	850	620	0.022	0.016
DS	599	80	0.016	0.002
EM	235	2068	0.006	0.054
JOE	1558	562	0.041	0.015
BES	600	245	0.016	0.006
ASA	1149	2049	0.03	0.054
RSSA	180	100	0.005	0.003
RSSB	337	1113	0.009	0.029
RSSC	300	148	0.008	0.004
RES	386	365	0.01	0.01
SSC	651	268	0.017	0.007
TEM	222	252	0.006	0.007
MISQ	527	298	0.014	0.008
JSPI	2106	202	0.055	0.005
BMK	644	1323	0.017	0.035

Table B15 2010 Degree Centralization of Raw Data

	Outdeg	Indeg	nOutdeg	nIndeg
AMJ	1321	1345	0.042	0.042
AMR	579	1012	0.018	0.032
ACR	1036	391	0.033	0.012
ASQ	325	1198	0.01	0.038
AER	683	1743	0.022	0.055
ISR	765	382	0.024	0.012
JAR	554	597	0.017	0.019
JCR	306	679	0.01	0.021
JFN	1005	2982	0.032	0.094
JFE	1974	1987	0.062	0.063
JOM	780	639	0.025	0.02
JMR	786	984	0.025	0.031
MGS	2341	2192	0.074	0.069
MKS	779	734	0.025	0.023
OPR	516	446	0.016	0.014
POM	1332	187	0.042	0.006
RFS	1739	1270	0.055	0.04
SMJ	2403	817	0.076	0.026
AMS	170	68	0.005	0.002
ANP	2	105	0	0.003
AS	590	1761	0.019	0.055
BIO	812	477	0.026	0.015
DS	744	89	0.023	0.003
EM	370	2474	0.012	0.078
JOE	2836	659	0.089	0.021
BES	699	328	0.022	0.01
ASA	1298	1919	0.041	0.06
RSSA	277	72	0.009	0.002
RSSB	524	1078	0.017	0.034
RSSC	389	117	0.012	0.004
RES	527	465	0.017	0.015
SSC	354	296	0.011	0.009
TEM	344	173	0.011	0.005
MISQ	817	283	0.026	0.009
JSPI	773	268	0.024	0.008
BMK	687	1220	0.022	0.038

Table B16 2015 Degree Centralization of Raw Data

	Farness	nCloseness
JOE	47	74.468
BES	50	70
MGS	54	64.815
AER	55	63.636
EM	55	63.636
MKS	55	63.636
RES	57	61.404
JFN	60	58.333
RFS	60	58.333
JAR	61	57.377
OPR	61	57.377
JSPI	65	53.846
AMS	65	53.846
ANP	67	52.239
AS	67	52.239
BMK	67	52.239
RSSB	67	52.239
ASA	67	52.239
SMJ	68	51.471
JFE	68	51.471
AMJ	69	50.725
RSSC	69	50.725
SSC	69	50.725
RSSA	69	50.725
BIO	69	50.725
ASQ	70	50
AMR	70	50
TEM	70	50
ACR	71	49.296
JOM	71	49.296
JMR	71	49.296
MISQ	72	48.611
DS	72	48.611
ISR	73	47.945
POM	73	47.945
JCR	78	44.872

Table B17 2000 Farness and Closeness of Correlation Data for Each Journal

	Farness	nCloseness
Minimum	47	44.872
Average	65.333	54.287
Maximum	78	74.468
Sum	2352	1954.339
Standard Deviation	7.087	6.654
Variance	50.222	44.272
SSQ	155472	107689.3
MCSSQ	1808	1593.795
Euclidlidean Norm	394.299	328.161
Observations	36	36
Missing	0	0
Std Deviation (n-1)	7.187	6.748
Variance (n-1)	51.657	45.537
Binary valued	0	0
Negatives	0	0
Integer valued	1	0
Weighted Obs	36	36
Positives	36	36
Avg Positive Value	65.333	54.287

Table B.18 2000 Farness and Closeness Descriptive Statistics of Correlation Data

	Farness	nCloseness
BES	49	71.429
JOE	50	70
MGS	50	70
RES	53	66.038
AER	55	63.636
EM	56	62.5
MKS	57	61.404
RFS	58	60.345
JFE	59	59.322
OPR	61	57.377
ANP	63	55.556
RSSA	63	55.556
AS	63	55.556
ASQ	66	53.03
AMR	66	53.03
POM	67	52.239
AMJ	67	52.239
SSC	67	52.239
JFN	68	51.471
RSSB	69	50.725
BMK	69	50.725
ASA	69	50.725
ACR	70	50
ISR	71	49.296
RSSC	71	49.296
JSPI	71	49.296
MISQ	71	49.296
AMS	71	49.296
JOM	71	49.296
DS	71	49.296
BIO	71	49.296
SMJ	71	49.296
TEM	71	49.296
JMR	72	48.611
JCR	74	47.297
JAR	79	44.304

Table B19 2005 Farness and Closeness of Correlation Data for Each Journal

	Farness	nCloseness
Minimum	49	44.304
Average	65.278	54.397
Maximum	79	71.429
Sum	2350	1958.308
Standard Deviation	7.43	6.906
Variance	55.201	47.7
SSQ	155390	108244.2
MCSSQ	1987.222	1717.189
Euclidlidean Norm	394.195	329.005
Observations	36	36
Missing	0	0
Std Deviation (n-1)	7.535	7.004
Variance (n-1)	56.778	49.063
Binary valued	0	0
Negatives	0	0
Integer valued	1	0
Weighted Obs	36	36
Positives	36	36
Avg Positive Value	65.278	54.397

Table B20 2005 Farness and Closeness Descriptive Statistics of Correlation Data

	Farness	nCloseness
BES	46	76.087
JOE	47	74.468
MGS	50	70
RES	54	64.815
OPR	54	64.815
AER	55	63.636
EM	56	62.5
MKS	56	62.5
RFS	58	60.345
JFE	59	59.322
ACR	60	58.333
RSSA	64	54.688
AS	65	53.846
ANP	65	53.846
SMJ	65	53.846
TEM	67	52.239
RSSB	67	52.239
ASA	67	52.239
BMK	67	52.239
JFN	68	51.471
RSSC	68	51.471
BIO	68	51.471
AMS	68	51.471
JSPI	68	51.471
SSC	68	51.471
JAR	69	50.725
MISQ	71	49.296
AMR	71	49.296
ISR	71	49.296
AMJ	71	49.296
JOM	72	48.611
DS	72	48.611
POM	73	47.945
ASQ	75	46.667
JMR	75	46.667
JCR	78	44.872

Table B21 2010 Farness and Closeness of Correlation Data for Each Journal

	Farness	nCloseness
Minimum	46	44.872
Average	64.667	55.059
Maximum	78	76.087
Sum	2328	1982.106
Standard Deviation	7.962	7.669
Variance	63.389	58.813
SSQ	152826	111249.1
MCSSQ	2282	2117.285
Euclidlidean Norm	390.93	333.54
Observations	36	36
Missing	0	0
Std Deviation (n-1)	8.075	7.778
Variance (n-1)	65.2	60.494
Binary valued	0	0
Negatives	0	0
Integer valued	1	0
Weighted Obs	36	36
Positives	36	36
Avg Positive Value	64.667	55.059

Table B22 2010 Farness and Closeness Descriptive Statistics of Correlation Data

	Farness	nCloseness
JOE	47	74.468
MGS	48	72.917
BES	48	72.917
RES	50	70
OPR	50	70
AER	52	67.308
EM	53	66.038
MKS	56	62.5
JFE	56	62.5
JFN	58	60.345
RFS	58	60.345
ACR	59	59.322
JAR	60	58.333
ASA	62	56.452
AS	62	56.452
RSSA	64	54.688
AMJ	65	53.846
ASQ	65	53.846
POM	65	53.846
ANP	66	53.03
RSSB	67	52.239
TEM	67	52.239
SSC	67	52.239
BMK	67	52.239
JMR	67	52.239
JSPI	67	52.239
SMJ	67	52.239
JOM	68	51.471
BIO	68	51.471
RSSC	69	50.725
ISR	69	50.725
AMS	69	50.725
MISQ	69	50.725
DS	69	50.725
AMR	72	48.611
JCR	72	48.611

Table B23 2015 Farness and Closeness of Correlation Data for Each Journal

	Farness	nCloseness
Minimum	47	48.611
Average	62.167	57.184
Maximum	72	74.468
Sum	2238	2058.61
Standard Deviation	7.343	7.52
Variance	53.917	56.545
SSQ	141070	119754.3
MCSSQ	1941	2035.603
Euclidlidean Norm	375.593	346.055
Observations	36	36
Missing	0	0
Std Deviation (n-1)	7.447	7.626
Variance (n-1)	55.457	58.16
Binary valued	0	0
Negatives	0	0
Integer valued	1	0
Weighted Obs	36	36
Positives	36	36
Avg Positive Value	62.167	57.184

Table B24 2015 Farness and Closeness Descriptive Statistics of Correlation Data

	Infarness	Outfarness	Incloseness	Outcloseness
EM	41	56	85.366	62.5
ASA	46	50	76.087	70
AER	47	59	74.468	59.322
MGS	49	43	71.429	81.395
BMK	49	63	71.429	55.556
JFN	51	55	68.627	63.636
RSSB	51	56	68.627	62.5
AS	52	71	67.308	49.296
JFE	52	59	67.308	59.322
BES	52	56	67.308	62.5
JOE	52	58	67.308	60.345
RES	53	65	66.038	53.846
JMR	57	48	61.404	72.917
AMS	58	71	60.345	49.296
OPR	58	55	60.345	63.636
TEM	59	73	59.322	47.945
RFS	59	58	59.322	60.345
MKS	59	52	59.322	67.308
BIO	59	69	59.322	50.725
RSSA	62	75	56.452	46.667
ANP	63	78	55.556	44.872
AMJ	66	55	53.03	63.636
ACR	66	66	53.03	53.03
SSC	66	71	53.03	49.296
AMR	67	59	52.239	59.322
JCR	67	61	52.239	57.377
JOM	67	64	52.239	54.688
SMJ	67	54	52.239	64.815
ASQ	67	63	52.239	55.556
JSPI	68	55	51.471	63.636
JAR	70	73	50	47.945
DS	72	52	48.611	67.308
RSSC	74	65	47.297	53.846
MISQ	78	60	44.872	58.333
ISR	81	53	43.21	66.038
POM	83	67	42.169	52.239

Table B25 2000 Farness and Closeness of Raw Data for Each Journal

	Infarness	Outfarness	Incloseness	Outcloseness
Minimum	41	43	42.169	44.872
Average	60.778	60.778	59.183	58.639
Maximum	83	78	85.366	81.395
Sum	2188	2188	2130.604	2110.992
Standard Deviation	9.998	8.138	9.893	7.97
Variance	99.951	66.228	97.876	63.516
SSQ	136580	135366	129620	126072.4
MCSSQ	3598.222	2384.222	3523.537	2286.576
Euclidlidean Norm	369.567	367.921	360.028	355.067
Observations	36	36	36	36
Missing	0	0	0	0
Std Deviation (n-1)	10.139	8.254	10.034	8.083
Variance (n-1)	102.806	68.121	100.672	65.331
Binary valued	0	0	0	0
Negatives	0	0	0	0
Integer valued	1	1	0	0
Weighted Obs	36	36	36	36
Positives	36	36	36	36
Avg Positive Value	60.778	60.778	59.183	58.639

Table B26 2000 Farness and Closeness Descriptive Statistics of Raw Data

	Infarness	Outfarness	Incloseness	Outcloseness
EM	37	55	94.595	63.636
AER	43	54	81.395	64.815
ASA	44	50	79.545	70
MGS	47	43	74.468	81.395
JOE	48	51	72.917	68.627
RSSB	48	60	72.917	58.333
JFN	48	57	72.917	61.404
BMK	48	68	72.917	51.471
JFE	49	57	71.429	61.404
AS	51	67	68.627	52.239
RES	51	60	68.627	58.333
BES	53	55	66.038	63.636
RFS	55	55	63.636	63.636
SSC	57	49	61.404	71.429
OPR	57	57	61.404	61.404
JMR	58	55	60.345	63.636
MKS	58	54	60.345	64.815
RSSA	59	67	59.322	52.239
JOM	59	51	59.322	68.627
JSPI	60	63	58.333	55.556
SMJ	62	50	56.452	70
ASQ	64	59	54.688	59.322
AMJ	66	55	53.03	63.636
AMR	66	64	53.03	54.688
BIO	66	68	53.03	51.471
TEM	66	65	53.03	53.846
AMS	66	61	53.03	57.377
RSSC	67	66	52.239	53.03
JAR	67	74	52.239	47.297
ANP	68	81	51.471	43.21
ACR	68	62	51.471	56.452
JCR	69	61	50.725	57.377
DS	71	55	49.296	63.636
ISR	75	57	46.667	61.404
MISQ	76	60	46.053	58.333
POM	79	60	44.304	58.333

Table B27 2005 Farness and Closeness of Raw Data for Each Journal

	Infarness	Outfarness	Incloseness	Outcloseness
Minimum	37	43	44.304	43.21
Average	59.056	59.056	61.146	60.168
Maximum	79	81	94.595	81.395
Sum	2126	2126	2201.255	2166.047
Standard Deviation	10.058	7.367	11.269	7.362
Variance	101.164	54.275	126.999	54.205
SSQ	129194	127506	139169.8	132278.1
MCSSQ	3641.889	1953.889	4571.973	1951.391
Euclidlidean Norm	359.436	357.08	373.055	363.701
Observations	36	36	36	36
Missing	0	0	0	0
Std Deviation (n-1)	10.201	7.472	11.429	7.467
Variance (n-1)	104.054	55.825	130.628	55.754
Binary valued	0	0	0	0
Negatives	0	0	0	0
Integer valued	1	1	0	0
Weighted Obs	36	36	36	36
Positives	36	36	36	36
Avg Positive Value	59.056	59.056	61.146	60.168

Table B28 2005 Farness and Closeness Descriptive Statistics of Raw Data

	Infarness	Outfarness	Incloseness	Outcloseness
EM	37	54	94.595	64.815
ASA	41	48	85.366	72.917
AER	42	53	83.333	66.038
MGS	42	41	83.333	85.366
JFN	44	55	79.545	63.636
BMK	44	63	79.545	55.556
JFE	45	54	77.778	64.815
RES	45	65	77.778	53.846
RSSB	48	54	72.917	64.815
JOE	48	50	72.917	70
RFS	49	54	71.429	64.815
AS	49	51	71.429	68.627
SSC	52	52	67.308	67.308
BES	52	50	67.308	70
JMR	54	41	64.815	85.366
AMS	54	68	64.815	51.471
MKS	54	45	64.815	77.778
BIO	54	63	64.815	55.556
OPR	56	48	62.5	72.917
AMJ	56	51	62.5	68.627
RSSA	57	53	61.404	66.038
JSPI	57	47	61.404	74.468
ASQ	57	63	61.404	55.556
SMJ	58	49	60.345	71.429
JCR	58	57	60.345	61.404
RSSC	59	61	59.322	57.377
JOM	60	50	58.333	70
AMR	60	62	58.333	56.452
MISQ	61	51	57.377	68.627
TEM	61	57	57.377	61.404
ANP	64	79	54.688	44.304
DS	64	53	54.688	66.038
ISR	64	48	54.688	72.917
ACR	66	51	53.03	68.627
JAR	66	60	53.03	58.333
POM	72	49	48.611	71.429

Table B29 2010 Farness and Closeness of Raw Data for Each Journal

	Infarness	Outfarness	Incloseness	Outcloseness
Minimum	37	41	48.611	44.304
Average	54.167	54.167	66.2	65.796
Maximum	72	79	94.595	85.366
Sum	1950	1950	2383.216	2368.667
Standard Deviation	8.184	7.581	10.653	8.617
Variance	66.972	57.472	113.489	74.26
SSQ	108036	107694	161855.5	158522.9
MCSSQ	2411	2069	4085.603	2673.361
Euclidlidean Norm	328.688	328.168	402.313	398.149
Observations	36	36	36	36
Missing	0	0	0	0
Std Deviation (n-1)	8.3	7.689	10.804	8.74
Variance (n-1)	68.886	59.114	116.732	76.382
Binary valued	0	0	0	0
Negatives	0	0	0	0
Integer valued	1	1	0	0
Weighted Obs	36	36	36	36
Positives	36	36	36	36
Avg Positive Value	54.167	54.167	66.2	65.796

Table B30 2010 Farness and Closeness Descriptive Statistics of Raw Data

	Infarness	Outfarness	Incloseness	Outcloseness
EM	38	53	92.105	66.038
ASA	40	50	87.5	70
JOE	40	46	87.5	76.087
BMK	41	59	85.366	59.322
AER	44	53	79.545	66.038
RES	45	53	77.778	66.038
JFN	45	56	77.778	62.5
RSSB	46	58	76.087	60.345
MGS	46	39	76.087	89.744
AS	48	52	72.917	67.308
JFE	48	52	72.917	67.308
BES	50	53	70	66.038
JMR	51	48	68.627	72.917
RFS	51	52	68.627	67.308
SSC	53	66	66.038	53.03
BIO	53	63	66.038	55.556
JSPI	56	61	62.5	57.377
RSSA	56	63	62.5	55.556
JCR	56	60	62.5	58.333
MKS	57	43	61.404	81.395
ACR	58	50	60.345	70
JAR	58	59	60.345	59.322
OPR	58	49	60.345	71.429
AMS	58	58	60.345	60.345
TEM	59	66	59.322	53.03
SMJ	59	44	59.322	79.545
JOM	59	49	59.322	71.429
ANP	61	86	57.377	40.698
RSSC	61	67	57.377	52.239
DS	62	45	56.452	77.778
AMJ	63	46	55.556	76.087
AMR	64	60	54.688	58.333
ASQ	65	58	53.846	60.345
POM	69	47	50.725	74.468
MISQ	69	47	50.725	74.468
ISR	70	46	50	76.087

Table B31 2015 Farness and Closeness of Raw Data for Each Journal

	Infarness	Outfarness	Incloseness	Outcloseness
Minimum	38	39	50	40.698
Average	54.361	54.361	66.108	65.94
Maximum	70	86	92.105	89.744
Sum	1957	1957	2379.903	2373.837
Standard Deviation	8.564	8.839	11.102	9.844
Variance	73.342	78.12	123.261	96.913
SSQ	109025	109197	161769	160019.6
MCSSQ	2640.306	2812.306	4437.412	3488.884
Euclidlidean Norm	330.189	330.45	402.205	400.024
Observations	36	36	36	36
Missing	0	0	0	0
Std Deviation (n-1)	8.685	8.964	11.26	9.984
Variance (n-1)	75.437	80.352	126.783	99.682
Binary valued	0	0	0	0
Negatives	0	0	0	0
Integer valued	1	1	0	0
Weighted Obs	36	36	36	36
Positives	36	36	36	36
Avg Positive Value	54.361	54.361	66.108	65.94

Table B32 2015 Farness and Closeness Descriptive Statistics of Raw Data

	Betweenness	nBetweenness
JOE	137.171	23.054
MKS	76.992	12.94
BES	64.918	10.911
MGS	49.316	8.288
AER	41.519	6.978
EM	38.747	6.512
OPR	34.545	5.806
RES	26.791	4.503
SMJ	21.746	3.655
JFN	9.191	1.545
RFS	9.191	1.545
ASQ	5.448	0.916
AMS	4.646	0.781
JSPI	4.646	0.781
JAR	4.065	0.683
AMJ	2.834	0.476
AMR	2.618	0.44
JMR	1.951	0.328
JOM	1.951	0.328
ASA	0.986	0.166
RSSB	0.986	0.166
AS	0.986	0.166
ANP	0.986	0.166
BMK	0.986	0.166
DS	0.668	0.112
MISQ	0.668	0.112
JFE	0.658	0.111
ISR	0.182	0.031
POM	0.182	0.031
JCR	0.091	0.015
RSSC	0.083	0.014
RSSA	0.083	0.014
BIO	0.083	0.014
SSC	0.083	0.014
TEM	0	0
ACR	0	0

Table B33 2000 Betweenness of Correlation Data for Each Journal

	Betweenness	nBetweenness
Mean	15.167	2.549
Std Dev	28.385	4.771
Sum	546	91.765
Variance	805.704	22.758
SSQ	37286.34	1053.212
MCSSQ	29005.34	819.302
Euclid Norm	193.097	32.453
Minimum	0	0
Maximum	137.171	23.054
N of Obs	36	36

Table B34 2000 Betweenness Descriptive Statistics of Correlation Data

	Betweenness	nBetweenness
BES	98.208	16.505
MGS	93.516	15.717
RES	68.066	11.44
JOE	63.775	10.719
MKS	34.331	5.77
EM	31.185	5.241
AER	28.316	4.759
OPR	25.866	4.347
RFS	20.928	3.517
POM	11.554	1.942
JFE	10.438	1.754
AMR	7.826	1.315
AS	6.477	1.089
RSSA	6.477	1.089
ANP	6.477	1.089
ASQ	6.389	1.074
AMJ	5.225	0.878
SSC	5.045	0.848
ACR	3.393	0.57
JFN	3.322	0.558
RSSB	1.176	0.198
BMK	1.176	0.198
ASA	1.176	0.198
ISR	0.801	0.135
MISQ	0.801	0.135
DS	0.801	0.135
JOM	0.801	0.135

SMJ	0.801	0.135
JMR	0.476	0.08
JCR	0.174	0.029
BIO	0	0
RSSC	0	0
TEM	0	0
JAR	0	0
JSPI	0	0
AMS	0	0

Table B35 2005 Betweenness of Correlation Data for Each Journal

	Betweenness	nBetweenness
Mean	15.139	2.544
Std. Dev	25.524	4.29
Sum	545	91.597
Variance	651.468	18.402
SSQ	31703.55	895.517
MCSSQ	23452.85	662.463
Euclid Norm	178.055	29.925
Minimum	0	0
Maximum	98.208	16.505
N of Obs	36	36

Table B36 2005 Betweenness Descriptive Statistics of Correlation Data

	Betweenness	nBetweenness
BES	104.563	17.574
JOE	94.502	15.883
MGS	84.097	14.134
OPR	56.197	9.445
MKS	41.627	6.996
AER	36.492	6.133
RES	29.533	4.964
EM	22.049	3.706
SMJ	15.003	2.522
RFS	8.864	1.49
RSSA	8.846	1.487
ACR	4.195	0.705
JFE	3.783	0.636
MISQ	3.054	0.513
ISR	3.054	0.513
ANP	2.906	0.488
AS	2.906	0.488
AMR	2.193	0.369
AMJ	2.193	0.369
JOM	1.544	0.26
DS	1.544	0.26
ASA	0.716	0.12
RSSB	0.716	0.12
TEM	0.716	0.12
BMK	0.716	0.12
ASQ	0.641	0.108
POM	0.633	0.106
JMR	0.345	0.058
JFN	0.25	0.042
JAR	0.125	0.021
JCR	0	0
AMS	0	0
BIO	0	0
RSSC	0	0
JSPI	0	0
SSC	0	0

Table B37 2010 Betweenness of Correlation Data for Each Journal

	Betweenness	nBetweenness
Mean	14.833	2.493
Std. Dev	27.418	4.608
Sum	534	89.748
Variance	751.75	21.234
SSQ	34984.01	988.179
MCSSQ	27063.01	764.438
Euclid Norm	187.04	31.435
Minimum	0	0
Maximum	104.563	17.574
N of Obs	36	36

Table B38 2010 Betweenness Descriptive Statistics of Correlation Data

	Betweenness	nBetweenness
JOE	94.255	15.841
RES	67.417	11.331
BES	63.137	10.611
MGS	55.949	9.403
EM	37.938	6.376
OPR	37.223	6.256
AER	33.977	5.71
MKS	24.494	4.117
SMJ	9.619	1.617
JFE	8.525	1.433
ASQ	6.149	1.033
AMJ	4.667	0.784
AS	4.398	0.739
ASA	4.398	0.739
POM	4.336	0.729
RFS	3.567	0.6
RSSA	3.563	0.599
JFN	2.789	0.469
JMR	2.773	0.466
ANP	2.549	0.428
ACR	2.496	0.42
JAR	2.274	0.382
JOM	2.111	0.355
ISR	1.576	0.265
MISQ	1.576	0.265
DS	1.576	0.265

RSSB	0.835	0.14
SSC	0.835	0.14
TEM	0.835	0.14
JSPI	0.835	0.14
BMK	0.835	0.14
AMR	0.635	0.107
JCR	0.444	0.075
BIO	0.413	0.069
RSSC	0	0
AMS	0	0

Table B39 2015 Betweenness of Correlation Data for Each Journal

	Betweenness	nBetweenness
Mean	13.583	2.283
Std. Dev	22.876	3.845
Sum	489	82.185
Variance	523.327	14.782
SSQ	25482.04	719.781
MCSSQ	18839.79	532.16
Euclid Norm	159.631	26.829
Minimum	0	0
Maximum	94.255	15.841
N of Obs	36	36

Table B40 2015 Betweenness Descriptive Statistics of Correlation Data

	Betweenness	nBetweenness
MGS	196.212	16.488
ASA	128.456	10.795
EM	73.857	6.206
OPR	49.133	4.129
JOE	40.869	3.434
BMK	39.296	3.302
JFN	38.773	3.258
JMR	38.12	3.203
RSSB	33.586	2.822
MKS	32.383	2.721
AER	32.008	2.69
JSPI	28.951	2.433
BES	22.802	1.916
RFS	19.485	1.637
SMJ	18.277	1.536
JFE	16.392	1.377
ACR	15.345	1.29
DS	14.129	1.187
AMJ	12.808	1.076
AS	11.14	0.936
AMR	8.52	0.716
JCR	8.462	0.711
RES	8.426	0.708
BIO	8.265	0.694
JOM	5.573	0.468
ASQ	5.294	0.445
RSSC	4.455	0.374
AMS	4.13	0.347
TEM	3.565	0.3
JAR	2.563	0.215
MISQ	1.961	0.165
SSC	1.909	0.16
RSSA	1.096	0.092
ISR	0.955	0.08
ANP	0.804	0.068
POM	0	0

Table B41 2000 Betweenness of Raw Data for Each Journal

	Betweenness	nBetweenness
Mean	25.778	2.166
Std. Dev	37.93	3.187
Sum	928	77.983
Variance	1438.662	10.159
SSQ	75713.6	534.663
MCSSQ	51791.83	365.736
Euclid Norm	275.161	23.123
Minimum	0	0
Maximum	196.212	16.488
N of Obs	36	36

Table B42 2000 Betweenness Descriptive Statistics of Raw Data

	Betweenness	nBetweenness
MGS	149.384	12.553
ASA	78.66	6.61
EM	71.405	6
AER	52.892	4.445
JOE	45.312	3.808
BES	39.712	3.337
OPR	34.394	2.89
RSSB	33.719	2.834
RFS	30.967	2.602
BMK	30.58	2.57
SMJ	28.67	2.409
JFN	28.367	2.384
JOM	27.793	2.336
SSC	26.864	2.258
MKS	25.523	2.145
JMR	24.597	2.067
AS	22.894	1.924
JFE	20.862	1.753
RES	15.708	1.32
AMJ	11.913	1.001
ACR	10.578	0.889
AMS	9.415	0.791
TEM	8.951	0.752
DS	7.926	0.666

JSPI	5.219	0.439
ASQ	4.655	0.391
RSSA	4.373	0.367
AMR	3.406	0.286
JCR	2.971	0.25
ISR	2.661	0.224
RSSC	2.499	0.21
BIO	1.135	0.095
JAR	0.869	0.073
POM	0.643	0.054
MISQ	0.482	0.041
ANP	0	0

Table B43 2005 Betweenness of Raw Data for Each Journal

	Betweenness	nBetweenness
Mean	24.056	2.021
Std. Dev	28.667	2.409
Sum	866	72.773
Variance	821.796	5.803
SSQ	50416.75	356.025
MCSSQ	29584.65	208.916
Euclid Norm	224.537	18.869
Minimum	0	0
Maximum	149.384	12.553
N of Obs	36	36

Table B44 2005 Betweenness Descriptive Statistics of Raw Data

	Betweenness	nBetweenness
MGS	115.672	9.72
ASA	66.207	5.564
EM	35.128	2.952
OPR	32.416	2.724
AER	30.948	2.601
AS	30.378	2.553
MKS	30.152	2.534
JMR	28.028	2.355
BMK	26.289	2.209
JFE	25.991	2.184
SSC	24.485	2.058
JOE	24.1	2.025

JFN	21.908	1.841
JSPI	21.835	1.835
RSSB	20.09	1.688
BES	19.078	1.603
RFS	18.505	1.555
SMJ	17.774	1.494
MISQ	13.36	1.123
AMJ	12.808	1.076
JOM	9.003	0.757
RSSA	8.662	0.728
BIO	8.188	0.688
ACR	7.844	0.659
ISR	6.023	0.506
ASQ	5.876	0.494
RES	5.363	0.451
RSSC	4.826	0.406
DS	4.785	0.402
JCR	3.214	0.27
AMS	2.76	0.232
AMR	2.612	0.22
TEM	2.587	0.217
POM	1.948	0.164
JAR	1.159	0.097
ANP	0	0

Table B45 2010 Betweenness of Raw Data for Each Journal

	Betweenness	nBetweenness
Mean	19.167	1.611
Std. Dev	21.172	1.779
Sum	690	57.983
Variance	448.262	3.165
SSQ	29362.42	207.347
MCSSQ	16137.42	113.957
Euclid Norm	171.355	14.4
Minimum	0	0
Maximum	115.672	9.72
N of Obs	36	36

Table B46 2010 Betweenness Descriptive Statistics of Raw Data

	Betweenness	nBetweenness
MGS	85.425	7.179
JOE	61.35	5.155
AS	57.75	4.853
EM	46.089	3.873
ASA	41.11	3.455
OPR	34.439	2.894
JMR	33.862	2.846
AER	29.015	2.438
BMK	27.883	2.343
RES	27.445	2.306
MKS	21.964	1.846
DS	21.556	1.811
RSSB	19.967	1.678
JFE	19.751	1.66
SMJ	18.83	1.582
RFS	18.163	1.526
JFN	15.881	1.335
AMJ	14.396	1.21
BES	13.745	1.155
AMS	11.641	0.978
ACR	11.539	0.97
JOM	10.969	0.922
BIO	8.254	0.694
JAR	5.589	0.47
RSSA	5.518	0.464
JSPI	5.314	0.447
JCR	5.253	0.441
SSC	5.164	0.434
MISQ	4.571	0.384
ISR	4.084	0.343
TEM	3.485	0.293
POM	2.786	0.234
AMR	2.254	0.189
ASQ	1.089	0.092
RSSC	0.87	0.073
ANP	0	0

Table B47 2015 Betweenness of Raw Data for Each Journal

	Betweenness	nBetweenness
Mean	19.361	1.627
Std. Dev	19.116	1.606
Sum	697	58.571
Variance	365.434	2.581
SSQ	26650.3	188.195
MCSSQ	13155.61	92.9
Euclid Norm	163.249	13.718
Minimum	0	0
Maximum	85.425	7.179
N of Obs	36	36

Table B48 2015 Betweenness Descriptive Statistics of Raw Data

	2000	2005	2010	2015
Avg Degree	12.944	13.5	13.333	14.278
Indeg H-Index	14	14	14	14
Deg Centralization	0.304	0.227	0.323	0.264
Out-Central	0.296	0.22	0.313	0.256
In-Central	0.296	0.22	0.313	0.256
Density	0.37	0.386	0.381	0.408
Components	1	1	1	1
Component Ratio	0	0	0	0
Connectedness	1	1	1	1
Fragmentation	0	0	0	0
Closure	0.766	0.767	0.742	0.726
Avg Distance	1.867	1.865	1.848	1.776
SD Distance	0.767	0.786	0.766	0.736
Diameter	3	3	3	3
Wiener Index	2352	2350	2328	2238
Dependency Sum	1092	1090	1068	978
Breadth	0.354	0.349	0.348	0.327
Compactness	0.646	0.651	0.652	0.673
Small Worldness	1.858	1.764	1.75	1.634
Mutuals	0.37	0.386	0.381	0.408
Asymmetrics	0	0	0	0
Nulls	0.63	0.614	0.619	0.592
Arc Reciprocity	1	1	1	1
Dyad Reciprocity	1	1	1	1

Table B 49 Network Cohesion Measures using the correlation data

	2000	2005	2010	2015
Avg Degree	13.333	14.611	17.222	17.778
Indeg H-Index	13	14	16	17
Deg Centralization	0.413	0.375	0.356	0.4
Out-Central	0.402	0.364	0.346	0.389
In-Central	0.46	0.54	0.464	0.418
Density	0.381	0.417	0.492	0.508
Components	1	1	1	1
Component Ratio	0	0	0	0
Connectedness	1	1	1	1
Fragmentation	0	0	0	0
Closure	0.631	0.648	0.693	0.709
Avg Distance	1.737	1.687	1.548	1.553
SD Distance	0.655	0.651	0.572	0.608
Diameter	3	3	3	3
Wiener Index	2188	2126	1950	1957
Dependency Sum	928	866	690	697
Breadth	0.329	0.309	0.261	0.256
Compactness	0.671	0.691	0.739	0.744
Small- World- Ness	1.519	1.472	1.325	1.286
Mutuals	0.246	0.279	0.343	0.357
Asymmetrics	0.27	0.276	0.298	0.302
Nulls	0.484	0.444	0.359	0.341
Arc Reciprocity	0.646	0.669	0.697	0.703
Dyad Reciprocity	0.477	0.503	0.535	0.542

Table B50 Network Cohesion Measures using the raw data

Appendix C

Rank	Author	Pubs	Rank	Author	Pubs
1	ZHANG Y	71	29	KIM S	24
2	LIU Y	65	29	LEE CH	24
3	SHI Y	53	29	LEE H	24
4	HONG TP	52	29	LI DC	24
5	CHEN Y	42	29	LIAO SH	24
5	LI X	42	35	LIU F	23
5	LI Y	42	36	CHEN J	22
8	WANG Y	40	36	LI G	22
9	CHEN YL	38	36	WANG L	22
10	VAN DEN POEL D	37	39	FRIEDMAN C	21
11	CHEN HC	35	39	LU J	21
11	WANG J	35	39	PEDRYCZ W	21
13	KIM J	34	39	WEI CP	21
13	LI H	34	43	KIM SB	20
15	LI J	33	43	LEE C	20
15	WANG H	33	43	PARK SC	20
15	ZHANG L	33	43	PIRAMUTHU S	20
18	LEE S	32	43	SONG M	20
19	ZHANG J	31	43	TSUJII J	20
20	LEE J	30	49	CHEN H	19
21	DELEN D	29	49	CHEN X	19
22	PARK Y	28	49	CHEN YJ	19
23	LI L	27	49	KIM K	19
23	XU H	27	49	MARTENS D	19
23	YANG J	27	49	OSEI-BRYSON KM	19
26	ANANIADOU S	26	49	PARK H	19
26	KOSTOFF RN	26	49	WU CH	19
28	PORTER AL	25	49	YANG Y	19
29	BAESENS B	24			

Table C1 The Most Proflic Authors

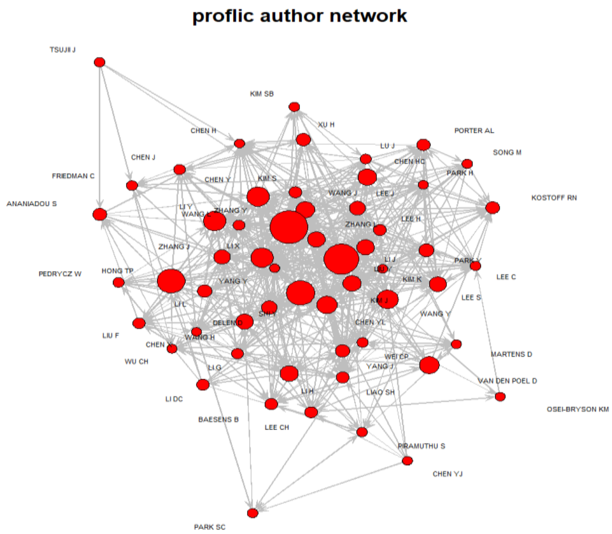


Figure C2 The Most Prolific Authors Network

Goodness-of-fit for in-degree					
	obs	min	mean	max	MC p-value
0	3962	1092	1181.86	2327	0
1	2124	2298	2374	2745	0
2	948	1676	2394.02	2504	0
3	536	868	1620.61	1710	0
4	333	443	827.51	905	0
5	202	266	342.93	373	0
6	177	89	117.36	144	0
7	110	20	36.11	112	0.02
8	91	3	10.67	69	0
9	75	0	2.9	42	0
10	52	0	1.22	35	0
11	31	0	0.86	32	0.02
12	32	0	0.52	25	0
13	36	0	0.41	23	0
14	24	0	0.33	21	0
15	12	0	0.27	12	0.02
16	16	0	0.2	8	0
17	13	0	0.1	8	0
18	8	0	0.2	9	0.04
19	13	0	0.1	5	0
20	7	0	0.09	6	0
21	10	0	0.1	7	0
22	7	0	0.08	6	0
23	11	0	0.09	6	0

24	10	0	0.03	2	0
25	7	0	0.06	6	0
26	4	0	0.04	2	0
27	5	0	0.06	4	0
28	3	0	0.03	2	0
29	2	0	0.03	1	0
30	6	0	0.02	1	0
31	6	0	0.03	2	0
32	3	0	0.01	1	0
33	2	0	0.01	1	0
34	7	0	0	0	0
36	2	0	0.02	1	0
37	2	0	0	0	0
38	2	0	0.02	2	0.02
39	1	0	0	0	0
40	2	0	0	0	0
41	1	0	0	0	0
42	1	0	0	0	0
43	0	0	0.01	1	1
44	2	0	0.01	1	0
45	1	0	0.01	1	0.02
46	1	0	0	0	0
50	0	0	0.01	1	1
51	2	0	0	0	0
52	1	0	0.01	1	0.02
53	1	0	0	0	0
57	1	0	0	0	0
59	0	0	0.01	1	1
61	0	0	0.01	1	1
63	1	0	0	0	0
65	0	0	0.01	1	1
69	0	0	0.01	1	1
73	1	0	0	0	0
76	1	0	0	0	0
83	1	0	0	0	0
87	1	0	0	0	0
93	0	0	0.01	1	1
98	1	0	0	0	0
111	1	0	0	0	0
123	1	0	0	0	0

Table C3 Goodness-of-fit for in-degree for model 1

Goodness-of-fit for out-degree					
	obs	min	mean	max	MC p-value
0	2189	1098	1176.11	1673	0
1	3026	2269	2362.14	2701	0
2	1412	1957	2404.15	2491	0
3	811	1168	1624.06	1715	0
4	474	633	832.21	885	0
5	328	276	343.7	391	0.38
6	179	96	119.77	180	0.02
7	123	22	36.1	131	0.02
8	101	3	9.75	59	0
9	56	0	2.93	48	0
10	50	0	0.89	23	0
11	41	0	0.38	20	0
12	25	0	0.2	12	0
13	28	0	0.15	7	0
14	13	0	0.06	4	0
15	11	0	0.07	2	0
16	4	0	0.05	3	0
17	8	0	0.05	2	0
18	7	0	0.03	3	0
19	7	0	0.03	1	0
20	2	0	0.01	1	0
21	2	0	0	0	0
22	1	0	0.02	1	0.04
23	1	0	0.03	2	0.04
24	3	0	0.03	1	0
25	0	0	0.01	1	1
26	1	0	0	0	0
28	0	0	0.01	1	1
29	2	0	0.02	2	0.02
32	1	0	0	0	0
34	1	0	0	0	0
35	1	0	0	0	0
40	0	0	0.01	1	1
41	0	0	0.01	1	1
43	1	0	0	0	0
44	2	0	0	0	0
67	0	0	0.02	2	1
93	1	0	0	0	0
107	1	0	0	0	0

Table C4 Goodness-of-fit for out-degree for model 1

Goodness-of-fit for edgewise shared partner					
	obs	min	mean	max	MC p-value
esp0	14431	16929	18166.38	18513	0
esp1	2624	3	23.76	1011	0
esp2	659	0	2.15	184	0
esp3	275	0	0.54	42	0
esp4	101	0	0.17	17	0
esp5	63	0	0.03	3	0
esp6	30	0	0.01	1	0
esp7	13	0	0	0	0
esp8	6	0	0	0	0

Table C5 Goodness-of-fit for edgewise shared partner for model 1

Goodness-of-fit for minimum geodesic distance					
	obs	min	mean	max	MC p-value
1	18202	17774	18193.04	18521	0.98
2	30574	35455	37200.52	38669	0
3	41648	70845	75958.8	80663	0
4	46004	133151	154654.7	168003	0
5	38675	244268	313044.8	346431	0
6	23888	432875	626012	705151	0
7	11373	729064	1223105	1398704	0
8	4314	1142841	2287821	2644454	0
9	1273	1653079	3963364	4596233	0
10	242	2182161	6081001	6991777	0
11	29	2609845	7892958	8848331	0
12	1	2838446	8415332	9040660	0
13	0	2830122	7356687	7714911	0
14	0	2614627	5393860	5820183	0
15	0	2256943	3435803	3930049	0
16	0	1610932	1971987	2532384	0
17	0	801807	1051105	1584843	0
18	0	383915	532036.7	1059415	0
19	0	165899	259570.3	757355	0
20	0	67179	123384	525344	0
21	0	24938	57526.66	350588	0
22	0	8556	26457.65	227443	0
23	0	2773	12091.96	144194	0
24	0	843	5506.88	88482	0
25	0	189	2534.37	53384	0
26	0	25	1189.57	31417	0
27	0	5	585.09	18252	0
28	0	0	297.14	10382	0.02
29	0	0	152.49	5659	0.18
30	0	0	77.48	3053	0.6
31	0	0	38.69	1640	1
32	0	0	18.86	843	1
33	0	0	9.19	439	1
34	0	0	4.05	200	1
35	0	0	1.58	82	1
36	0	0	0.67	39	1
37	0	0	0.34	23	1
38	0	0	0.12	10	1
39	0	0	0.02	2	1

Table C6 Goodness-of-fit for minimum geodesic distance for model 1

Goodness-of-fit for in-degree					
	obs	min	mean	max	MC p-value
0	4568	1040	1160.37	2702	0
1	1908	2284	2401.83	2779	0
2	965	1695	2528.9	2663	0
3	553	903	1797.39	1900	0
4	369	457	970.68	1112	0
5	220	287	425.95	478	0
6	184	124	155.05	201	0.06
7	150	33	51.65	119	0
8	99	5	15.69	86	0
9	75	0	5.5	63	0
10	57	0	1.92	36	0
11	49	0	1.21	29	0
12	43	0	0.94	31	0
13	26	0	0.57	26	0.02
14	29	0	0.52	21	0
15	22	0	0.37	14	0
16	19	0	0.26	9	0
17	15	0	0.29	10	0
18	12	0	0.24	12	0.02
19	10	0	0.24	15	0.02
20	14	0	0.15	8	0
21	8	0	0.17	7	0
22	15	0	0.14	11	0
23	6	0	0.11	4	0
24	6	0	0.06	6	0.02
25	9	0	0.03	2	0
26	7	0	0.17	8	0.02
27	4	0	0.06	3	0
28	5	0	0.03	3	0
29	6	0	0.01	1	0
30	4	0	0.03	2	0
31	6	0	0.02	1	0
32	3	0	0.02	2	0
33	6	0	0.03	1	0
34	1	0	0.05	3	0.04
35	6	0	0.03	2	0
36	3	0	0.01	1	0
37	4	0	0.02	1	0
38	4	0	0	0	0
39	2	0	0.01	1	0
40	2	0	0.01	1	0

41	1	0	0.02	1	0.04
43	0	0	0.01	1	1
44	2	0	0.04	2	0.02
45	1	0	0.02	1	0.04
46	2	0	0.01	1	0
47	1	0	0	0	0
48	0	0	0.01	1	1
49	1	0	0.01	1	0.02
50	0	0	0.01	1	1
51	1	0	0	0	0
52	1	0	0.01	1	0.02
53	0	0	0.01	1	1
54	1	0	0	0	0
56	1	0	0.01	1	0.02
57	1	0	0	0	0
58	1	0	0.01	1	0.02
60	2	0	0	0	0
61	2	0	0.02	1	0
70	1	0	0	0	0
71	0	0	0.01	1	1
73	1	0	0.02	1	0.04
79	1	0	0	0	0
82	0	0	0.02	2	1
84	0	0	0.01	1	1
94	1	0	0	0	0
102	1	0	0	0	0
104	1	0	0	0	0
114	0	0	0.01	1	1
115	0	0	0.01	1	1
118	1	0	0	0	0
163	1	0	0	0	0
167	1	0	0	0	0

Table C7 Goodness-of-fit for in-degree for model 2

Goodness-of-fit for out-degree					
	obs	min	mean	max	MC p-value
0	2189	1072	1141.05	1811	0
1	3215	2308	2396.11	2683	0
2	1530	2097	2539.1	2664	0

3	887	1270	1803.88	1901	0
4	525	665	981.85	1057	0
5	377	374	427.67	486	0.02
6	205	119	157.96	207	0.02
7	142	33	49.54	128	0
8	120	6	15.89	94	0
9	67	0	4.66	57	0
10	57	0	1.42	40	0
11	53	0	0.56	27	0
12	31	0	0.35	19	0
13	35	0	0.16	11	0
14	16	0	0.19	11	0
15	14	0	0.13	6	0
16	4	0	0.07	4	0.02
17	11	0	0.06	3	0
18	9	0	0.03	2	0
19	9	0	0.06	3	0
20	3	0	0.02	1	0
21	2	0	0	0	0
22	1	0	0.05	2	0.06
23	1	0	0.02	1	0.04
24	3	0	0.03	1	0
25	0	0	0.01	1	1
26	2	0	0.01	1	0
28	0	0	0.01	1	1
29	4	0	0.01	1	0
30	0	0	0.02	1	1
31	0	0	0.01	1	1
32	1	0	0	0	0
34	2	0	0.01	1	0
35	1	0	0	0	0
38	0	0	0.01	1	1
43	1	0	0	0	0
44	2	0	0	0	0
45	0	0	0.01	1	1
47	0	0	0.01	1	1
59	0	0	0.01	1	1
67	0	0	0.01	1	1
72	0	0	0.01	1	1
93	1	0	0	0	0
107	1	0	0	0	0

Table C8 Goodness-of-fit for out-degree for model 2

Goodness-of-fit for edgewise shared partner					
	obs	min	mean	max	MC p-value
esp0	16217	18773	20421.02	20804	0
esp1	3011	5	32.92	1389	0
esp2	749	0	3.33	255	0
esp3	325	0	0.86	71	0
esp4	115	0	0.39	34	0
esp5	74	0	0.1	9	0
esp6	37	0	0.04	4	0
esp7	21	0	0	0	0
esp8	10	0	0	0	0

Table C9 Goodness-of-fit for edgewise shared partner for model 2

Goodness-of-fit for minimum geodesic distance					
	obs	min	mean	max	MC p-value
1	20559	20067	20458.66	20816	0.46
2	35472	41322	44156.66	45957	0
3	49215	78433	95121.43	101520	0
4	55496	140653	204165.6	223206	0
5	47155	243884	435247.5	487931	0
6	29461	406267	914551.3	1049392	0
7	14257	646651	1865787	2181548	0
8	5539	973376	3592833	4236353	0
9	1616	1374156	6239539	7288805	0
10	305	1804805	9215114	10395053	0
11	35	2205531	10985447	11766337	0
12	1	2506076	10343773	10841950	0
13	0	2644404	7816555	8706227	0
14	0	2599823	4934968	6111916	0
15	0	2216976	2726400	3726319	0
16	0	1080069	1372354	2118910	0
17	0	488117	649104.1	1760174	0
18	0	205055	295205.3	1418942	0
19	0	76072	131580.6	1105040	0
20	0	26293	58613.9	835576	0
21	0	7994	26685.07	617067	0
22	0	2066	12740.88	447527	0
23	0	493	6516.24	321266	0
24	0	99	3589.34	228094	0
25	0	14	2114.72	160613	0
26	0	0	1308.18	111594	0.02
27	0	0	845.49	77525	0.18

28	0	0	558.58	53389	0.64
29	0	0	368.59	36025	1
30	0	0	239.56	23671	1
31	0	0	153.26	15219	1
32	0	0	96.25	9592	1
33	0	0	60.61	6053	1
34	0	0	37.49	3748	1
35	0	0	22.92	2292	1
36	0	0	13.72	1372	1
37	0	0	7.96	796	1
38	0	0	4.75	475	1
39	0	0	2.71	271	1
40	0	0	1.55	155	1
41	0	0	0.84	84	1
42	0	0	0.42	42	1
43	0	0	0.2	20	1
44	0	0	0.1	10	1
45	0	0	0.02	2	1

Table C10 Goodness-of-fit for minimum geodesic distance for model 2

Goodness-of-fit for in-degree					
	obs	min	mean	max	MC p-value
0	4568	1235	1359.41	3061	0
1	1908	2236	2374.07	2777	0
2	965	1491	2215.53	2338	0
3	553	769	1513.17	1616	0
4	369	406	866.51	970	0
5	220	264	447.62	515	0
6	184	186	236.09	275	0
7	150	108	133.73	156	0.12
8	99	67	84.26	115	0.12
9	75	42	56.66	76	0.02
10	57	27	42.8	64	0.04
11	49	20	32.32	46	0
12	43	16	24.13	39	0
13	26	7	18.97	30	0.18
14	29	4	14.49	27	0
15	22	6	13.84	21	0
16	19	5	12.6	23	0.1
17	15	4	9.53	17	0.14
18	12	3	7.26	13	0.08
19	10	1	6.54	17	0.26

20	14	2	6.4	15	0.02
21	8	1	5.75	13	0.48
22	15	0	4.52	12	0
23	6	0	2.75	13	0.18
24	6	0	2.1	6	0.02
25	9	0	2.57	8	0
26	7	0	2.05	8	0.02
27	4	0	1.9	9	0.22
28	5	0	1.69	6	0.04
29	6	0	1.58	4	0
30	4	0	1.76	5	0.12
31	6	0	1.71	5	0
32	3	0	1.59	7	0.38
33	6	0	1.32	4	0
34	1	0	1.51	4	1
35	6	0	0.96	6	0.02
36	3	0	0.58	4	0.08
37	4	0	0.81	3	0
38	4	0	0.66	3	0
39	2	0	0.6	3	0.2
40	2	0	0.89	3	0.48
41	1	0	0.73	3	1
42	0	0	0.36	2	1
43	0	0	0.41	2	1
44	2	0	0.36	2	0.02
45	1	0	0.32	2	0.58
46	2	0	0.41	2	0.1
47	1	0	0.24	2	0.44
48	0	0	0.2	2	1
49	1	0	0.15	1	0.3
50	0	0	0.23	2	1
51	1	0	0.26	1	0.52
52	1	0	0.23	1	0.46
53	0	0	0.24	2	1
54	1	0	0.19	2	0.36
55	0	0	0.09	1	1
56	1	0	0.09	2	0.16
57	1	0	0.03	1	0.06
58	1	0	0.03	1	0.06
60	2	0	0.03	2	0.02
61	2	0	0.03	1	0
62	0	0	0.01	1	1
63	0	0	0.01	1	1

64	0	0	0.01	1	1
65	0	0	0.02	1	1
67	0	0	0.02	1	1
68	0	0	0.01	1	1
70	1	0	0	0	0
73	1	0	0.01	1	0.02
74	0	0	0.01	1	1
79	1	0	0.02	1	0.04
81	0	0	0.07	1	1
82	0	0	0.12	2	1
83	0	0	0.1	1	1
84	0	0	0.23	2	1
85	0	0	0.12	2	1
86	0	0	0.08	2	1
87	0	0	0.12	2	1
88	0	0	0.16	2	1
89	0	0	0.12	1	1
90	0	0	0.16	1	1
91	0	0	0.11	1	1
92	0	0	0.06	1	1
93	0	0	0.07	1	1
94	1	0	0.07	1	0.14
95	0	0	0.06	2	1
96	0	0	0.02	1	1
97	0	0	0.06	1	1
98	0	0	0.05	1	1
99	0	0	0.02	1	1
100	0	0	0.05	1	1
101	0	0	0.06	2	1
102	1	0	0	0	0
103	0	0	0.01	1	1
104	1	0	0	0	0
105	0	0	0.01	1	1
106	0	0	0.01	1	1
107	0	0	0.01	1	1
110	0	0	0.01	1	1
112	0	0	0.01	1	1
113	0	0	0.01	1	1
115	0	0	0.11	1	1
116	0	0	0.09	1	1
117	0	0	0.04	1	1
118	1	0	0.04	1	0.08
119	0	0	0.03	1	1

120	0	0	0.05	1	1
121	0	0	0.01	1	1
122	0	0	0.04	1	1
123	0	0	0.07	1	1
124	0	0	0.05	1	1
125	0	0	0.05	1	1
126	0	0	0.03	1	1
127	0	0	0.02	1	1
128	0	0	0.04	1	1
129	0	0	0.14	1	1
130	0	0	0.04	1	1
131	0	0	0.03	1	1
132	0	0	0.03	1	1
133	0	0	0.03	1	1
135	0	0	0.03	1	1
136	0	0	0.01	1	1
137	0	0	0.01	1	1
142	0	0	0.01	1	1
143	0	0	0.02	1	1
147	0	0	0.01	1	1
152	0	0	0.01	1	1
163	1	0	0	0	0
167	1	0	0	0	0

Table C11 Goodness-of-fit for in-degree for model 3

Goodness-of-fit for out-degree					
	obs	min	mean	max	MC p-value
0	2189	1148	1234.18	1918	0
1	3215	2043	2182.57	2605	0
2	1530	1938	2141.6	2247	0
3	887	1229	1571.79	1691	0
4	525	631	985.9	1067	0
5	377	413	576.96	633	0
6	205	253	327.59	375	0
7	142	142	184.17	213	0.02
8	120	84	111.1	139	0.3
9	67	51	66.28	88	0.9
10	57	28	43.91	58	0.12
11	53	15	27.66	46	0
12	31	10	17.96	30	0
13	35	5	14.22	24	0
14	16	4	10.27	17	0.04

15	14	2	7.11	13	0
16	4	1	5.12	11	0.88
17	11	0	2.99	10	0
18	9	0	1.64	5	0
19	9	0	0.91	4	0
20	3	0	0.51	3	0.04
21	2	0	0.36	3	0.08
22	1	0	0.38	3	0.6
23	1	0	0.48	3	0.86
24	3	0	0.44	2	0
25	0	0	0.91	5	0.82
26	2	0	0.98	3	0.56
27	0	0	0.62	3	1
28	0	0	0.26	2	1
29	4	0	0.08	2	0
30	0	0	0.02	2	1
31	0	0	0.02	1	1
32	1	0	0	0	0
34	2	0	0	0	0
35	1	0	0	0	0
37	0	0	0.01	1	1
43	1	0	0	0	0
44	2	0	0	0	0
66	0	0	0.02	1	1
68	0	0	0.01	1	1
69	0	0	0.11	1	1
70	0	0	0.07	1	1
71	0	0	0.07	1	1
72	0	0	0.04	1	1
73	0	0	0.09	1	1
74	0	0	0.11	1	1
75	0	0	0.09	1	1
76	0	0	0.06	1	1
77	0	0	0.04	1	1
78	0	0	0.01	1	1
79	0	0	0.06	1	1
80	0	0	0.06	1	1
81	0	0	0.06	1	1
82	0	0	0.07	1	1
83	0	0	0.05	1	1
84	0	0	0.1	1	1
85	0	0	0.15	1	1
86	0	0	0.06	1	1

87	0	0	0.15	1	1
88	0	0	0.14	1	1
89	0	0	0.13	1	1
90	0	0	0.04	1	1
91	0	0	0.06	1	1
92	0	0	0.03	1	1
93	1	0	0.05	1	0.1
94	0	0	0.01	1	1
98	0	0	0.02	1	1
99	0	0	0.02	1	1
101	0	0	0.01	1	1
103	0	0	0.01	1	1
107	1	0	0	0	0

Table C12 Goodness-of-fit for out-degree for model 3

Goodness-of-fit for edgewise shared partner					
	obs	min	mean	max	MC p-value
esp0	16217	17454	20138.8	20472	0
esp1	3011	3131	3617	3761	0
esp2	749	564	591.89	740	0
esp3	325	135	163.3	286	0
esp4	115	47	54.43	103	0
esp5	74	22	26.77	53	0
esp6	37	8	10.83	21	0
esp7	21	4	5.25	16	0
esp8	10	0	1.51	6	0
esp9	0	0	0.57	1	0.86

Table C13 Goodness-of-fit for edgewise shared partner for model 3

Goodness-of-fit for minimum geodesic distance					
	obs	min	mean	max	MC p-value
1	20559	21810	24610.35	24963	0
2	35472	45956	69253.7	73571	0
3	49215	88404	192537.8	216570	0
4	55496	161003	521281.4	619833	0
5	47155	278544	1331628	1654625	0
6	29461	460036	3058950	3885227	0
7	14257	721659	5954212	7462402	0
8	5539	1043397	9288764	11038302	0
9	1616	1386551	11198940	12367522	0
10	305	1702658	10393893	11160879	0

11	35	1932474	7644764	8677888	0
12	1	2041950	4677095	6275823	0
13	0	1774039	2505537	4470584	0
14	0	779303	1228737	3147640	0
15	0	313622	571698.4	2283175	0
16	0	114439	260060.1	1553782	0
17	0	36770	118966.9	1227682	0
18	0	9932	56105.61	977889	0
19	0	2379	27773.67	752760	0
20	0	474	14558.68	560147	0
21	0	83	8033.08	401623	0
22	0	4	4665.17	282321	0
23	0	0	2788.57	191996	0.02
24	0	0	1702.84	126269	0.18
25	0	0	1058.86	80783	0.5
26	0	0	678.4	50658	0.9
27	0	0	451.21	30987	1
28	0	0	310.48	18819	1
29	0	0	211.89	11154	1
30	0	0	141.66	7572	1
31	0	0	92.07	5167	1
32	0	0	55.31	3094	1
33	0	0	30.53	1643	1
34	0	0	15.78	809	1
35	0	0	7.03	362	1
36	0	0	3.02	160	1
37	0	0	1.31	83	1
38	0	0	0.49	33	1
39	0	0	0.17	12	1
40	0	0	0.02	2	1

Table C14 Goodness-of-fit for minimum geodesic distance for model 3

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